TECHNICKÁ UNIVERSITA V LIBERCI

FAKULTA TEXTILNÍ

Habilitační práce

METODY HODNOCENÍ PLOŠNÉ NESTEJNOMĚRNOSTI NETKANÝCH TEXTILIÍ

OBOR: TEXTILNÍ TECHNIKA A MATERIÁL. INŽEN

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Obsah

1. Úvod

Netkané textilie, zejména pro technické aplikace, musí vedle nominálně definovaných hodnot fyzikálních vlastností, také obecně splňovat požadavky kladené na jejich stejnoměrnost. Dosavadní vývoj v oboru netkaných textilií potvrzuje předpoklady, že díky neustálým inovacím a velké variantnosti surovinových, technologických a výrobních možností, roste s garantovanou stejnoměrností vlastností netkaných textilií také jejich uplatňování v náročnějších podmínkách nejen konečné spotřeby, ale i v mnoha zpracovatelských oborech. V teoretické oblasti je proto aktuální zpřesňovat specifické definice vlastního pojmu stejnoměrnosti, případně nestejnoměrnosti vlastností netkaných textilií a systematicky doplňovat matematicko-statistickými metodami popis jejich hodnocení přispívající k zvýšení reprezentativnosti studovaných metod měření z pohledu praktické použitelnosti.

K popisu nestejnoměrnosti nebo variability vlastností plošných textilních útvarů je možno přistupovat z různých hledisek. Jednotliví autoři obvykle vycházejí z určitých zjednodušení možných definic stejnoměrnosti struktury plošných textilií. K praktickému hodnocení stejnoměrnosti netkaných textilií, V_{NT}, je potřeba zvolit vlastnost dostatečně reprezentativní, snadno měřitelnou, s jednoduchým vztahem ke struktuře netkané textilie. U netkaných textilií může být základní charakteristikou pro statistickou analýzu například objemová hmotnost, $\rho_{NT} = m/V$ [kg.m^{-3}], která je podílem hmotnosti, m [kg] a objemu, V [m], v každém elementu prostorově uspořádané struktury.

Soubor publikovaných prací navazuje na disertační práci autora této habilitační práce a rozpracovává metodami prostorové statistické analýzy experimentální výsledky hodnocení nestejnoměrnosti chemicky pojené textilie, používané v elektrotechnickém průmyslu k ochraně kabelů při porušení isolace proti znehodnocení vodou. Výrobní i uživatelské vlastnosti pro tento účel vyžadují zaručenou podélnou pevnost a tažnost, elektrickou průraznou pevnost, nasákavost, a pevnost v přetrhu. Všechny tyto vlastnosti přímo úzce souvisejí se stejnoměrností uspořádání základních komponent, viskózových vláken, akrylátového pojiva a superabsorpční složky, aplikované formou pěnové disperze. Z tohoto hlediska je zřejmé, že výsledky provedených měření mohou být vhodným zdrojem informací pro další zkoumání a hodnocení prostorové variability tohoto typu netkaných textilií.

Habilitační práce prohlubuje získané poznatky z hodnocení nestejnoměrnosti pojené textilie obchodního názvu Perlan. Základní statistické charakteristiky vybraných vlastností z měření gravimetrickou metodou a z měření vzhledové nestejnoměrnosti chemicky pojené textilie jsou využity pro rozšíření popisu plošné nestejnoměrnosti či prostorové variability, prostřednictvím strukturálních funkcí. Postupně jsou diskutovány možnosti využití statistické variability náhodných polí a jsou popsány některé způsoby konstrukce strukturálních charakteristik z experimentálních dat. Navržené postupy se dají dále modifikovat pro různé parametry a vlastnosti vystihující strukturní uspořádání netkaných textilií a variabilitu sledovaných vlastností. Odkazy na použitou literaturu jsou uvedeny u jednotlivých zveřejněných prací v příloze.

2. Nestejnoměrnost netkaných textilií

K hodnocení vlastností netkaných textilií se používá podle okolností jak pojmu stejnoměrnost, tak nestejnoměrnost. Použitím přívlastku stejnoměrnost je vyjádřen požadavek na dosažení přibližně konstantní hodnoty vlastnosti netkané textilie, V_{NT}. Při použití výrazu nestejnoměrnost je zdůrazněna skutečnost, že netkaná textilie bude vykazovat vyšší variaci hodnot měřené vlastnosti od požadované hodnoty. Variabilita netkaných textilií, jako zvláštních druhů porézních materiálů, je jejich základní strukturní charakteristikou. Obecně je známo, že strukturní stejnoměrnost, případně nestejnoměrnost se přenáší i na stejnoměrnost či nestejnoměrnost všech jejich vlastností. Podle toho, které charakteristiky se sledují, lze nestejnoměrnost rozdělit do těchto základních skupin:

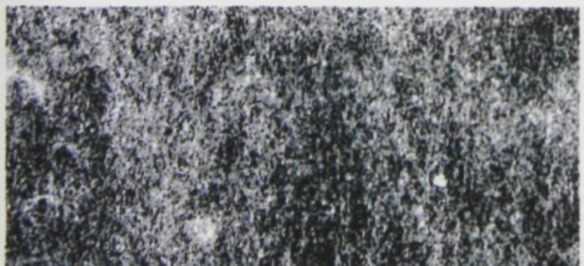
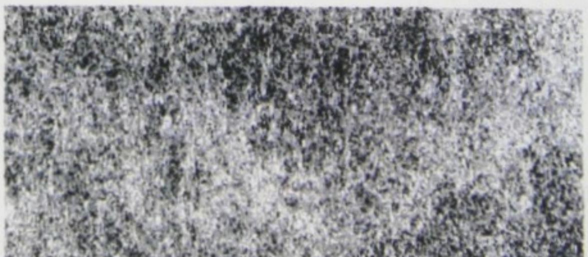
- hmotná nestejnoměrnost
- strukturní nestejnoměrnost

- vizuální (optická) nestejnoměrnost
- nestejnoměrnost mechanických a fyzikálních vlastností
- vzhledová nestejnoměrnost.

Pro spojité prostorové útvary obecně platí, že v každém elementu může být jejich vlastnost popsána jednou, skalární, veličinou, je-li tato hodnota v jeho okolí jen málo odlišná nebo stejná. V souladu s technickými a fyzikálními možnostmi měření volbou přiměřené velikosti zkoumaného elementu dostáváme možnost definovat nestejnoměrnost objemové hmotnosti, ρ_{NT}. U plošných textilií se běžně osvědčilo, vedle objemové hmotnosti, ρ_{NT}, používat plošnou hmotnost $m_A = f(A)$, která je odvozena od charakteristické plochy, A, netkané textilie. Lokální plošná hmotnost, m_A, je definována jako střední hodnota v ploše, nebo i jako infinitezimální hodnota (1). Objemová hmotnost elementu netkané textilie, ρ_A, se stanoví jako podíl hmotnosti elementu, m, a jeho objemu, V_A, daného součinem zvolené velikosti plochy, A, a tloušťky, t.

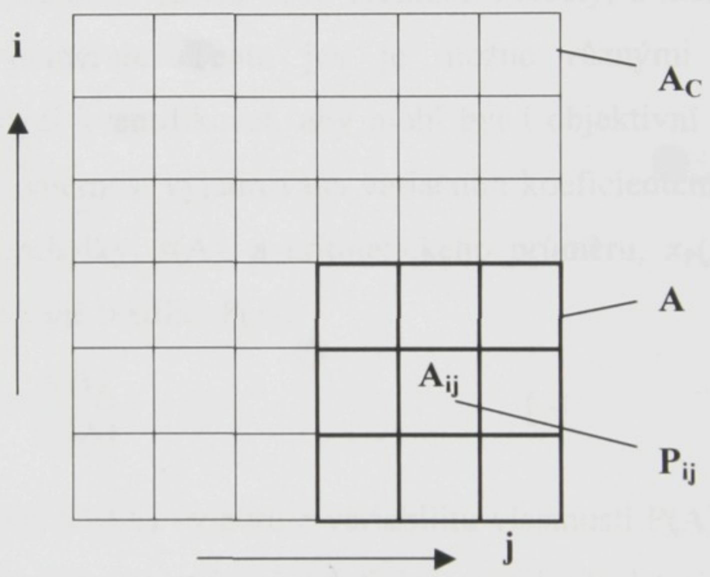
$$\bar{m}_A = \Delta m / \Delta A = \rho_A \,.\, t \quad ; \quad dm_A = dm / dA \qquad [\,\mathrm{kg\ m^{-2}}] \qquad (1)$$

Plošná hmotnost, $\bar{m}_A$, byla použita k porovnání experimentálních výsledků získaných dále popsanými metodami hodnocení nestejnoměrnosti pojené textilie.

Obr. 1 Nestejnoměrnosti uspořádání komponent v pojené textilii plošné hmotnosti 40 g m^{-2} a 50 g m^{-2}

Měření byla provedena tak, aby se na vzorcích pojené textilie plošné hmotnosti 30, 40, 50 a 60 g m^{-2} využila možnost, hodnotit specifickou strukturní a hmotnostní nestejnoměrnost, mrakovitost, která se vzhledově projevuje zvláště ve velkých plochách (obr. 1). Na obrázku 2 je znázorněna definice elementární buňky struktury,A_{ij}, v rektangulární síti. Rozdělení plochy vzorku, A_C, na elementární buňky, A_{ij}, o celkovém počtu *N*x*M*, umožňuje pro různé charakteristiky, P_{ij}, vyhodnocení celkové nestejnoměrnosti a hodnocení nestejnoměrnosti ve dvou vzájemně na sebe kolmých směrech, i, j. Změnou velikosti pracovní matice, a vytvoření dílčích úseků o ploše A, s určitým počtem elementárních buněk, A_{ij}, lze popsat nestejnoměrnost uvnitř vzorku o ploše, A_C, mezi plochami A.



Obr. 2 Vytvoření pracovní sítě s elementární buňkou velikosti plochy, A_{ij}

Pro popis vzhledové nestejnoměrnosti byly jako charakteristiky, P_{ij}, zvoleny: počet slabých míst, M, v základní buňce struktury,A_{ij} a relativní velikost plochy slabých míst, $\sum_{k}^{M} S_k / A_{ij}$, kde S_k je plocha k-tého slabého místa, a hmotnost m_{ij}.

Pro porovnání vizuální a gravimetrické metody byla použita metoda analýzy obrazu, která se ukázala jako vhodná pro popis vzhledové nestejnoměrnosti určením počtu slabých míst v netkané textilii. Výhodou metody je snadná definice velikosti slabého (prázdného) místa bez vláken a pojiva (póru) přes počet pixelů v digitálním zobrazení. Pro všechny tři použité charakteristiky stejnoměrnosti je možné pro grafické vyjádření použít vrstevnicový diagram, z kterého je možno identifikovat převládající směr nestejnoměrnosti, tak rozložení charakteristik P_{ij}.

Podle způsobu výroby mají netkané textilie velmi rozličné uspořádání struktury. Například vpichovaná textilie má až 90% volného prostoru a obvykle se jeví vzhledově jako stejnoměrná. U chemicky pojených netkaných textilií se naopak setkáváme s vizuální a hmotnostní nestejnoměrností hodnocenou jako mrakovitost. Tato vzhledová charakteristika vystihuje plošné rozdělení hmotnosti v závislosti na surovinových, technologických a výrobních faktorech tvorby vlákenné vrstvy a dalšího postupu zpevňování chemicky pojené netkané textilie.

Měřítkem pro stanovení odchylky stejnoměrnosti od požadovaného hodnoty jsou nejčastěji zjednodušené slovní nebo fyzikální modely, s kterými se reálně vyrobená textilie poměřuje. Tento jev je možno různými matematicko-statistickými metodami kvantifikovat, aby mohl být i objektivní mírou jakosti. Nejčastěji je nestejnoměrnost vyjadřována variačním koeficientem, CV(A), jako podíl směrodatné odchylky, s(A), a aritmetického průměru, $x_P(A)$, zjištěných hodnot vlastnosti netkané textilie, P(A).

$$CV(A) = \frac{s(A)}{x_P(A)} \qquad [-] \qquad (2)$$

Variační koeficient CV(A) vyjadřuje variabilitu vlastnosti P(A) průměrované přes plochu A. Jde tedy o variační koeficient mezi plochami A_C. Variační koeficient CV(A), vypočítaný ze zjištěných hodnot naměřených standardní metodou, nevyjadřuje dostatečně charakteristické rozdělení hmotnosti v ploše a průřezu zkoumané netkané textilie. Vedle hodnot celkového variačního koeficientu CV(A), lze také vypočítat variační koeficienty ve směru podélném a ve směru příčném CV_L, CV_{HL}, resp. CV_H, , CV_{LH} využitím rozkladu rozptylu. Pro případ elementárních buněk, A_{ij}, lze průměrnou hodnotu, x_p, zvolené charakteristiky, P_{ij}, (například počet děr v elementární buňce, A_{ij}) určit ze vztahu

$$x_P = \frac{1}{NM} \sum_i \sum_j (P_{ij}) \qquad (3)$$

a pro celkový rozptyl s^2 platí

$$s^2 = \frac{1}{NM-1}\sum_i \sum_j (P_{ij} - x_P)^2 \qquad (4)$$

Celkový rozptyl, s^2, se použitím dílčích průměrů m_{io} (ve směru osy stroje) a m_{oj} (ve směru příčném) dá vyjádřit vztahy (5) až (12). Symbol „o" určuje index přes který se sumuje.

Pro podélný směr lze nalézt rozklad celkového rozptylu ve tvaru

$$s^2 = s^2_L + s^2_{HL} \qquad (5)$$

$$s^2_L = \frac{1}{N}\sum_i (m_{io} - m)^2 \qquad (6)$$

$$s^2_{HL} = \frac{1}{NM}\sum_i \sum_j (P_{ij} - m_{io})^2 \qquad (7)$$

$$m_{io} = \frac{1}{M}\sum_j P_{ij} \qquad (8)$$

kde s^2_L je rozptyl ve směru stroje a s^2_{HL} je doplňkový rozptyl pro příčný směr.

Podobně pro příčný směr lze definovat rozklad celkového rozptylu, kde s^2_H je rozptyl ve směru příčném a s^2_{LH} je doplňkový rozptyl pro směr osy stroje.

$$s^2 = s^2_H + s^2_{LH} \qquad (9)$$

$$s^2_H = \frac{1}{M}\sum_j (m_{oj} - m)^2 \qquad (10)$$

$$s^2_{LH} = \frac{1}{NM}\sum_i \sum_j (P_{ij} - m_{oj})^2 \qquad (11)$$

$$m_{oj} = \frac{1}{N}\sum_i P_{ij} \qquad (12)$$

Výše uvedené vztahy jsou analogické rozkladu na vnější a vnitřní nestejnoměrnost.

Další možností posuzování vzhledové nestejnoměrnosti je interpretace charakteristiky, P_{ij}, jako diskrétní presentace dvourozměrného náhodného pole pro úrovně dvou faktorů odpovídajících příčnému a podélnému směru výroby.

$$P_{ij} = \mu_{ij} + \varepsilon_{ij} \tag{13}$$

kde μ_{ij} je střední hodnota a ε_{ij} je náhodná chyba v ij-té buňce pole.

Člen μ_{ij} se dá dále rozložit na efekty β_j odpovídající podélnému směru, efekty α_i odpovídající příčnému směru a interakční člen $\alpha_i\beta_j$ pomocí vztahu

$$\mu_{ij} = \alpha_i + \beta_j + c\,\alpha_i\,\beta_j \tag{14}$$

kde c je koeficient neaditivity.

Pro případ čistě aditivních efektů je interakce $\tau_{ij}=c\,\alpha_i\beta_j=0$ a pak

$$\alpha = \frac{1}{M}\sum_j (P_{ij} - m) \tag{15}$$

$$\beta = \frac{1}{N}\sum_i (P_{ij} - m) \tag{16}$$

kde m je celkový průměr definovaný rovnicí (3).

Z reziduí $\hat{e}_{ij} = P_{ij} - m - \alpha_i - \beta_j$ lze vyčíslit odhad parametru c

$$c = \frac{\sum_i \sum_j e_{ij} P_{ij} \alpha_i \beta_j}{\sum_i \sum_j \alpha_i^2 \beta_j} \tag{17}$$

Stejnoměrnost ve směru osy stroje je pak ekvivalentní platnosti hypotézy: H_0: $\beta_j = 0$, j = 1…M a stejnoměrnost v příčném směru je rovna platnosti H_0: $\alpha_i = 0$, i

= 1...N. Pro testování těchto hypotéz byla použita standardní dvoustupňová analýza rozptylu (ANOVA) s pevnými efekty bez opakování.

3. Hodnocení vizuální nestejnoměrnosti

S využitím jednoduchého opticko-mechanického zařízení MEOFLEX byl navržen polokvantitativní způsob vizuálního vyhodnocení nestejnoměrnosti plošné hmotnosti na základě kolísání počtu slabých míst. Oko pracuje jako receptor a snímá maximální a minimální hodnoty intenzity osvětlení v místech nahromaděných vláken a v řídkých místech vlákenné vrstvy. Nestejnoměrnost plošné hmotnosti je pak funkcí kontrastu, K, podle vztahu (18), subjektivně vyhodnoceným na základě rozdílu jasu L_{max} a L_{min}. Abychom mohli takto postupovat je nutný dostatečný rozdíl mezi jasnými a tmavými místy. Definujeme-li kontrast, K, pro dvě místa s rozdílným hmotnostním rozložením vláken a s dostatečně rozdílnou hodnotou, L_{max} a L_{min}, vztahem (18), bude pro průhledné místo hodnota L_{min} rovna L_{max} a kontrast $K = 0$. Pro neprůhlednou část netkané textilie bude $L_{min} = 0$ a $K = 1$.

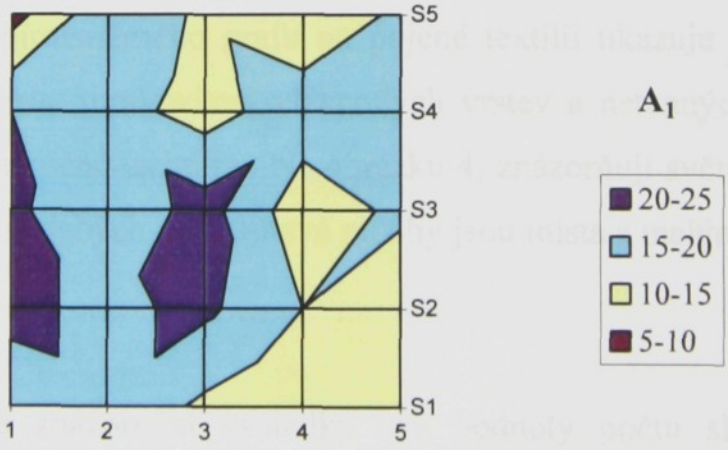
$$K = \frac{L_{max} - L_{min}}{L_{max} + L_{min}} \qquad [-] \qquad K(0;1) \qquad (18)$$

Tímto způsobem je možno hodnotit alespoň částečně transparentní netkané textilie. Citlivost oka na různé kvantitativní poměry rozložení těchto oblastí je podle zkušeností možno stanovit v rozsahu 5.10^{-4} až 0,1 metru. Při faktoru zvětšení 21x přístroje MEOFLEX se sníží dolní hranice citlivosti vizuální metody o další řád na 5.10^{-5} [m]. Horní hranice je dána propustností světelného toku netkaných textilií nebo vlákenných vrstev vyšších hmotností. Podle zkušeností autora je omezena plošnou hmotností 0,1 kg m^{-2}. Rozlišitelnost místních vad je od 0,025 mm. Kvantifikace vizuálního hodnocení podle navrženého experimentu spočívá v identifikaci slabých míst v každé z 25 elementárních buněk, A_{ij}, uspořádaných do pracovní matice, A. Skutečný rozměr každé elementární buňky je 2x2 mm z odebraného vzorku 10x10 mm. Pozorovatel spočítá oblasti s hodnotami kontrastu K=0, které definují místa s minimální hodnotou plošné hmotnosti, A_k.

Tabulka 1. Kvantifikace lokálních hodnot slabých míst pojené textilie, A_k, ve vzorku A_1

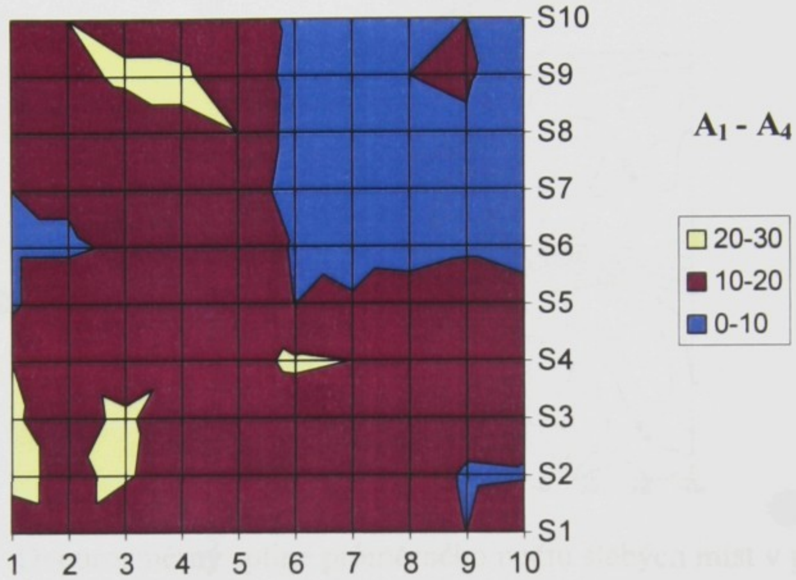
A_{ij}				
18	19	14	10	12
21	19	21	15	11
21	16	22	12	16
20	17	13	18	18
8	19	14	11	16

Počet hodnot	25	
Střední hodnota	16,04	[-]
Maximální hodnota	22	[-]
Minimální hodnota	8	[-]
Rozpětí	14	[-]
Směrodatná odchylka	3,8312	[-]
Variační koeficient	23,88	[%]



Obr. 3 Grafické znázornění počtu slabých míst ve vzorku 60 g m^{-2}, hodnocených vizuální metodou na přístroji Meoflex ve vzorku A_1

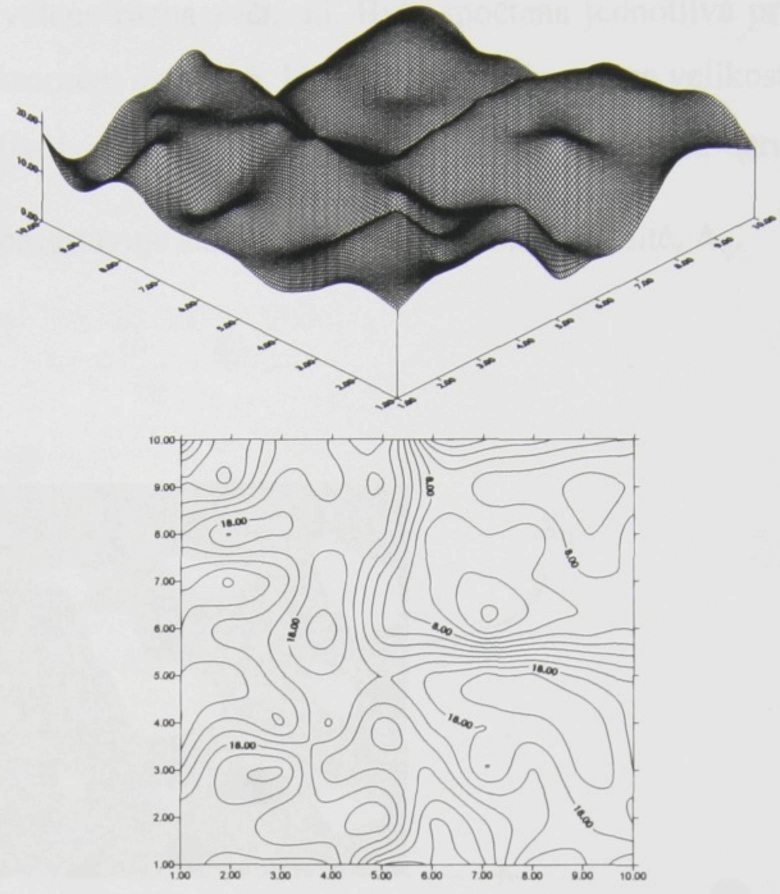
Pro grafické vyjádření nestejnoměrnosti ve větších plochách lze uspořádat hodnoty, M_k, zjištěné v jednotlivých elementárních buňkách, A_{ij}, do navazujících pracovních matic (A_1 – A_4), odpovídajících v tomto případě velikosti plochy vzorku, A_C, 20x20mm.



Obr. 4 Grafické znázornění počtů slabých míst čtyř hodnocených ploch A, velikosti (10x10 mm) pojené textilie 60 g m^{-2}

Grafické vyjádření výsledků polokvantitativního hodnocení nestejnoměrnosti pomocí řezu trojrozměrného grafu na pojené textilii ukazuje směr, kterým by bylo možno popsat mrakovitost vlákenných vrstev a netkaných textilií nižších hmotností bez náročné techniky. Na obrázku 4, znázorňují světlé plochy oblasti s velkým počtem slabých míst, tmavé plochy jsou místa s malým počtem slabých míst.

Jiné grafické znázornění výsledku pro hodnoty počtu slabých míst, A_k, pracovních matic A_1- A_4, čtyř vzorků je na obrázku 5a),b). Podstatou této metody je lokální vyhlazení dat dvourozměrnou kubickou funkcí spline tak, aby zobrazované úseky na sebe v uzlových bodech hladce navazovaly (obr. 5a). Na grafu (obr. 5b) je pak možno sledovat izolinie povrchu anizotropie hodnoceného vzorku.

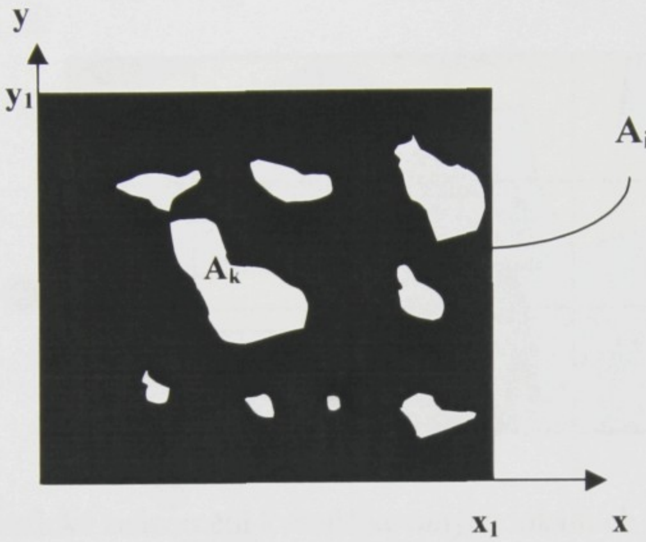


Obr. 5a), b) Dvourozměrný spline průměrného počtu slabých míst v pojené textilii plošné hmotnosti 60 g m^{-2}

4. Hodnocení nestejnoměrnosti metodou analýzy obrazu

Metoda analýzy obrazu, pomocí CCD kamery a počítače, odstraňuje vysokou míru subjektivity při vizuálním hodnocení stejnoměrnosti transparentních netkaných textilií. Zpřesňuje podmínky měření, zrychluje vyhodnocení a má další výhody. Metoda umožnila vyjádřit stejnoměrnost pojené textilie dalšími dvěma charakteristikami, velikostí plochy slabého místa a podílem velikosti plochy slabého místa k celkovému plošnému obsahu měřeného úseku vzorku (porosita). Pro zpracování digitalizovaného obrazu bylo použito softwareového systému LUCIA M, pro zpracování a analýzu digitálních obrazů High Color (3x5 bitů) s rozlišením 752x524 bodů.

Metodou analýzy obrazu byly hodnoceny pojené textilie plošných hmotností 30, 40 a 50 g m^{-2}, u kterých již okem nelze dostatečně rozlišit kontrast slabých a silných míst. Při hodnocení stejnoměrnosti snímku netkané textilie pořízeného kamerou, byla volena různá zvětšení. Byla spočtena jednotlivá průhledná místa (díry) podle znázornění na obr. 6. U každé díry byla určena velikost plochy, A_k, a stanovena relativní velikost (porosita), $\sum_k A_k / A_{ij}$, elementu struktury pojené textilie, kterou představuje základní buňka rektangulární sítě, A_{ij}.



Obr. 6 Systém analýzy obrazu vzorku pojené textilie plošného obsahu, A

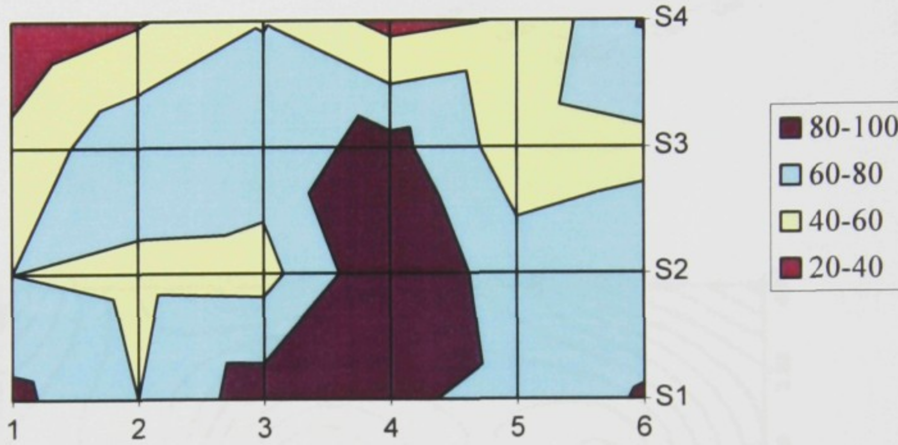
Vybrané výsledky hodnocení nestejnoměrnosti pojené textilie navrženou metodou analýzy obrazu jsou uvedeny v tabulkách 2 až 4 a na obrázcích 7 až 11. Celková plocha vzorku, A_C = 58,59 mm^2, pojené textilie 30 g m^{-2} byla rozdělena na 24 elementárních buněk plochy A_{ij} = 2,44 mm^2.

Hodnoty zvolených charakteristik nestejnoměrnosti, P_{ij}, graficky vyjadřují řezy trojrozměrného grafu a vyhlazený dvourozměrný kubický spline, z kterých je možno identifikovat jak převládající směr nestejnoměrnosti, tak rozložení hodnot.

Tabulka 2. Počet slabých míst pojené textilie 30 g m^{-2}

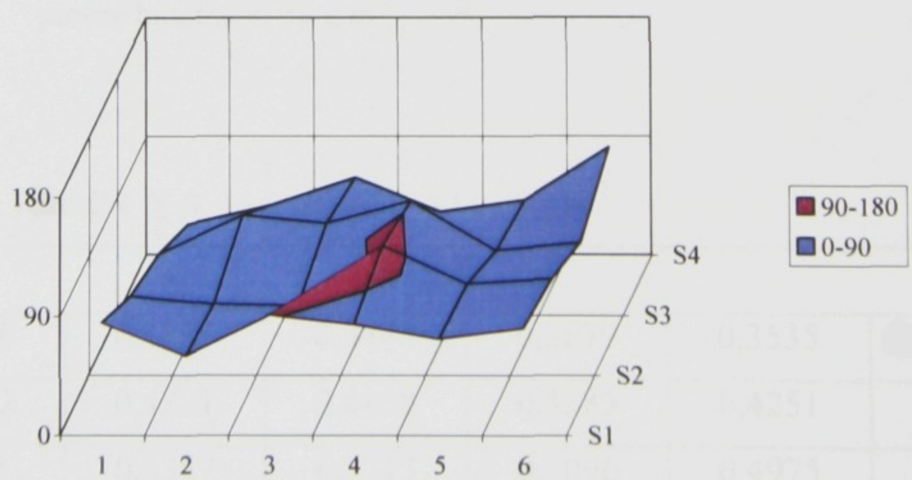
A_{ij}					
85	60	91	84	73	81
60	54	53	98	69	73
46	76	70	87	49	55
23	38	59	33	42	82

Počet hodnot	24	
Střední hodnota	64,208	[–]
Maximální hodnota	98	[–]
Minimální hodnota	23	[–]
Rozpětí	75	[–]
Směrodatná odchylka	19,3045	[–]
Variační koeficient	30,06	[%]

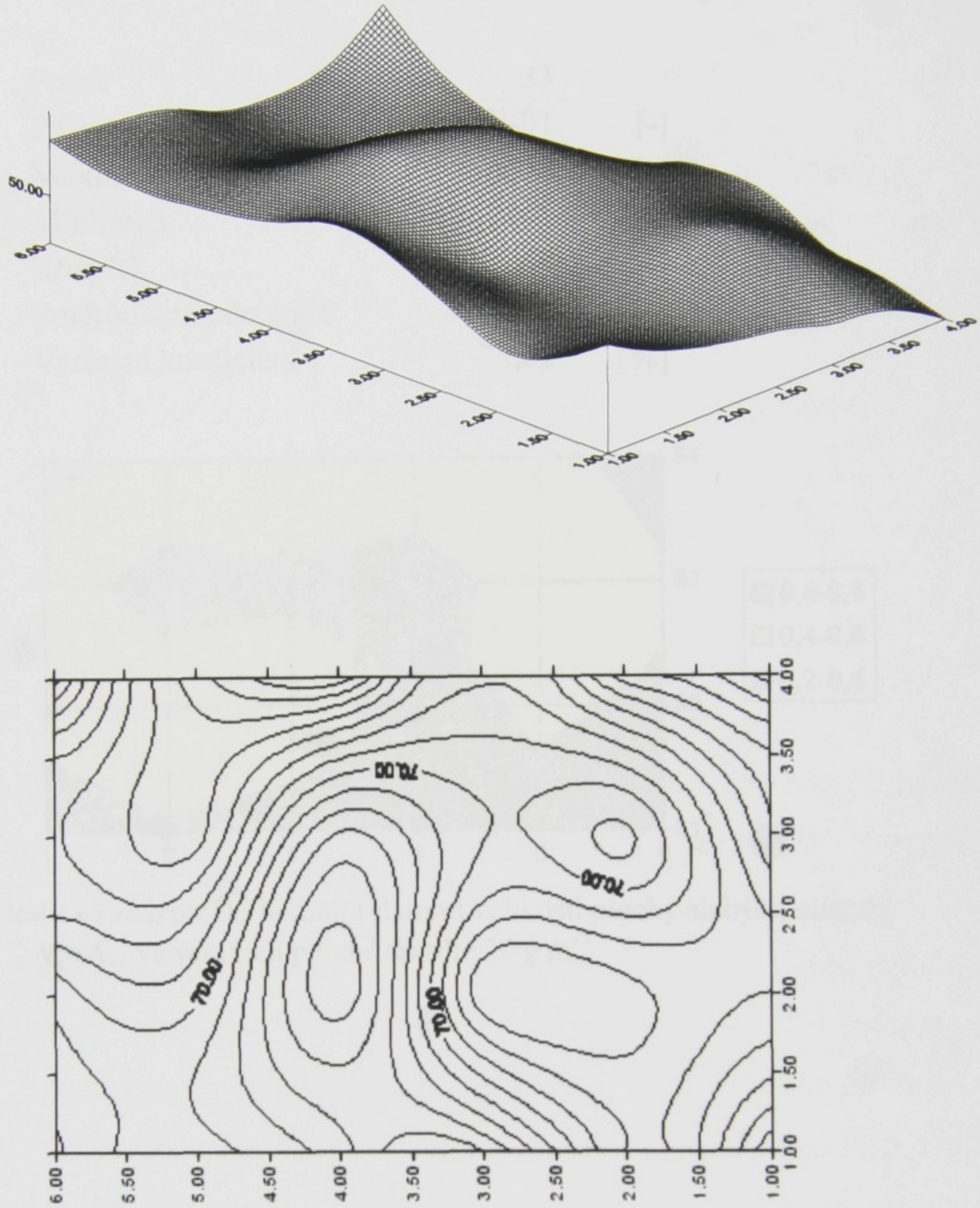


Obr. 7 Grafické znázornění kvantifikovaných lokálních hodnot slabých míst pojené textilie 30 g m^{-2}

Vyjádření výsledků počtu slabých míst pomocí řezů trojrozměrných grafů zjednodušuje orientaci v určování kritických míst v pojené textilii. Například volbou hranice citlivosti hodnot větších než 90 slabých míst v měřeném úseku pojené textilie, byla vyznačena tmavou plochou informace o kritickém místě (obr. 8).



Obr. 8 Způsob identifikace kritické oblasti slabých míst v pojené textilii 30 g m^{-2}

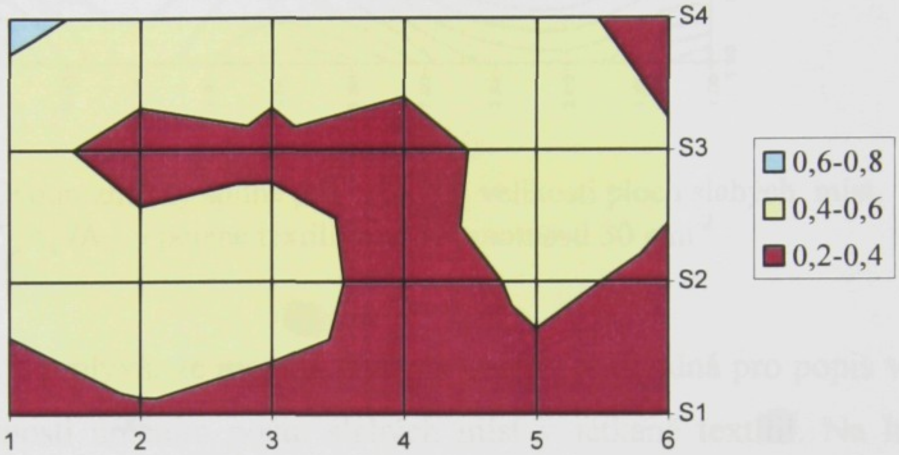


Obr. 9a),b) Dvourozměrný spline pro počet slabých míst v pojené textilii plošné hmotnosti 30 g m^{-2}

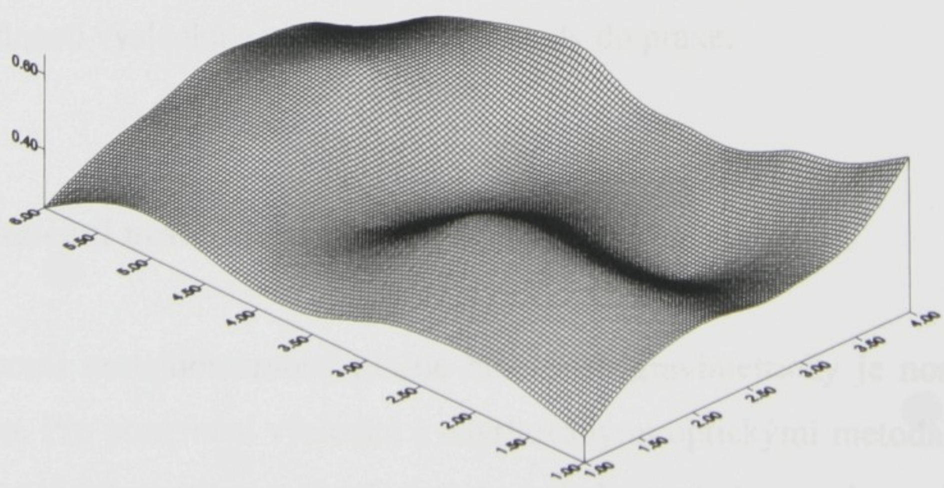
Tabulka 3. Porosita, $\sum_k A_k / A_{ij}$, pojené textilie 30 g m^{-2}

A_{ij}					
0,3146	0,3885	0,3447	0,2879	0,3535	0,2461
0,4612	0,4821	0,4858	0,3285	0,4251	0,3741
0,457	0,3387	0,3717	0,3096	0,4975	0,4318
0,6524	0,5302	0,4595	0,5342	0,4822	0,3046

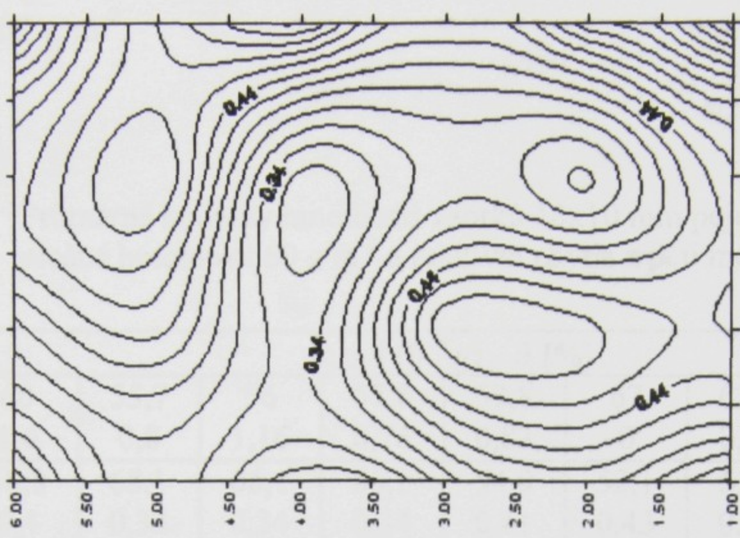
Počet	24	
Průměr	4,11E-01	[-]
Maximum	0,6524	[-]
Minimum	0,2461	[-]
Rozpětí	0,4063	[-]
Směrodatná odchylka	0,09462	[-]
Variační koeficient	23,02	[%]



Obr. 10 Grafické znázornění hodnot relativní velikosti plochy slabých míst, $\sum_k A_k / A_{ij}$, ve vzorcích pojené textilie 30 g m^{-2}



Obr. 11 a) Dvourozměrný spline pro relativní velikosti ploch slabých míst, $\sum_k A_k / A_{ij}$, v pojené textilii plošné hmotnosti 30 g m^{-2}



Obr. 11 b) Dvourozměrný spline pro relativní velikosti ploch slabých míst, $\sum_{k} A_k / A_{ij}$, v pojené textilii plošné hmotnosti 30 g m^{-2}

Z výsledků vyplývá, že metoda analýzy obrazu je vhodná pro popis vzhledové nestejnoměrnosti určením počtu slabých míst v netkané textilii. Na hodnocení relativním podílem plochy (porosita) nebo velikostí plochy slabých míst v netkané textilii je možno dále rozpracovat. Výhodou metody je snadná definice velikosti slabého (prázdného) místa bez vláken a pojiva (póru) přes počet pixelů v digitálním zobrazení. Metoda analýzy obrazu ukazuje další směr možnosti hodnocení stejnoměrnosti plošných vlákenných útvarů, zejména transparentních netkaných textilií. Při standardizaci podmínek je možné v budoucnu počítat se srovnatelností výsledků a se zavedením metody do praxe.

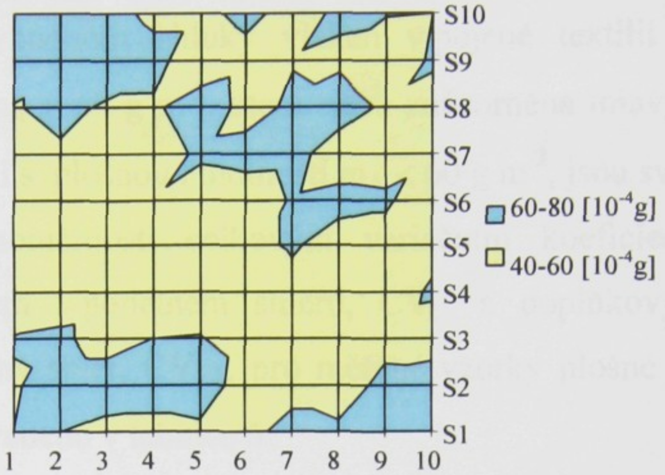
5. Hodnocení nestejnoměrnosti gravimetrickou metodou

Hodnocení nestejnoměrnosti plošné hmotnosti gravimetricky je normovaným postupem. Pro porovnání výsledků s navrhovanými optickými metodami, kde se pracuje s řádově menšími měřenými plošnými obsahy byl proveden pokus vážení vzorků 10x10 mm s hmotností 10^{-4} g. Kontrola vlivu chyby rozměru a vážení je uvedena v tabulce 5, která shrnuje výsledky pro vzorek pojené textilie plošné hmotnosti 60 g m^{-2}.

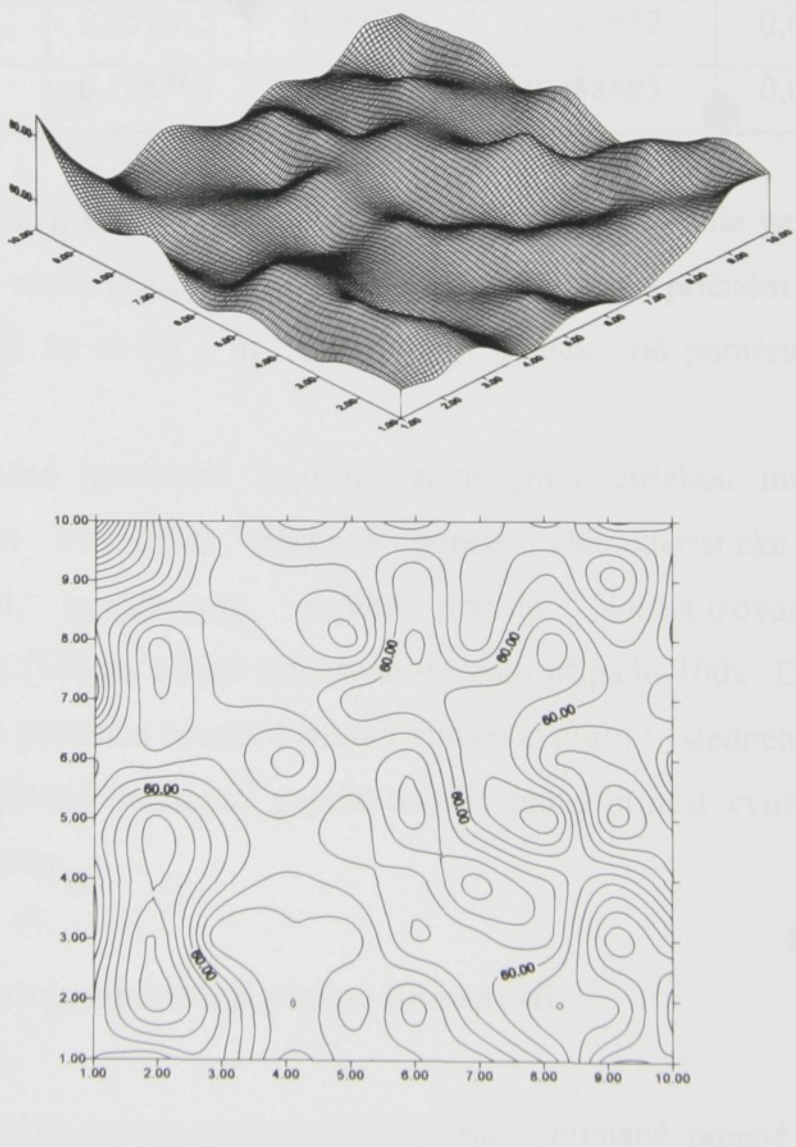
Tabulka 5. Průměrné hodnoty hmotnosti vzorků 10x10 mm pojené textilie plošné hmotnosti 60 g m^{-2} a relativní chyba z pěti měření

$\overline{m}_{Aij}$ $[10^{-4}$ g$]$ ± ϑ [%]									
60 1,02	60 1,6	55,7 0,8	56 1,16	57,8 0,76	53,8 0,83	67 0	62,7 0,71	69,2 0,39	63,2 0,43
58,1 0,39	68,8 0,4	68,1 0,33	66,1 0,34	66,1 0,34	54,9 0,41	52,1 0,43	51,8 0,49	64,2 0,43	65,3 0,42
61,1 0,37	63 0	53,4 0,4	60,1 0,37	60,4 0,37	56,1 0,4	56 0	57 0	55,7 0,49	55 0
51,1 0,44	51,9 0,43	53,8 0,51	55,4 0,4	56,1 0,4	51 0	57,1 0,39	54,8 0,5	55,4 0,4	61,4 0,36
55,5 0	57,1 0,4	53,1 0,42	56,8 0,48	59,7 0,75	57,2 0,48	61 0	51,6 0,43	55,8 0,49	57,1 0,39
54,8 0,5	51,2 0,54	60 0	59,1 0,38	53,1 0,42	54,6 0,41	61 0	62,7 0,44	61,6 0,36	52,1 0,43
52,4 0,79	58,2 0,47	59,2 0,46	53,1 0,42	62,2 0,44	63,4 0,66	63,2 0,43	54,8 0,5	54,8 0,46	58 0
59 0	63,9 0,35	58,1 0,39	58 0	67 0	56,3 0,49	61,8 0,44	65 0	58,1 0,39	53,5 0
70 0	63,4 0,35	71 0	64,3 0,43	51,3 0,53	56 0	59,5 0	58 0	51 0	62,2 0,44
69,3 0,4	73 0	65 0	57 0	57,2 0,48	63 0	56 0	62 0	61 0	60 0

Počet hodnot	100	
Střední hodnota	58,8767	$[10^{-4}$ g$]$
Maximální hodnota	73	$[10^{-4}$ g$]$
Minimální hodnota	51	$[10^{-4}$ g$]$
Rozpětí	22	$[10^{-4}$ g$]$
Směrodatná odchylka	5,1002	$[10^{-4}$ g$]$
Variační koeficient	8,66	[%]



Obr. 12 Grafické znázornění hodnot hmotnosti, m_A, pojené textilie 60 g m^{-2} zjištěných gravimetricky



Obr. 13a),b) Dvourozměrný spline pro hodnoty hmotnosti, m_A,pojené textilie 60 g m^{-2} zjištěné gravimetricky

Z obrázku 12 lze vyhodnotit shluky vláken v pojené textilii tvořící místa s plošnou hmotností $m_A > 60$ g m^{-2}, která jsou znázorněna tmavými plochami. Místa v pojené textilii s plošnou hmotností $m_A < 60$ g m^{-2}, jsou světlá.

Hodnocení nestejnoměrnosti celkovým variačním koeficientem, CV, a variačním koeficientem v podélném směru, CV_L, a doplňkovým variačním koeficientem pro příčný směr, CV_{HL}, pro měřené vzorky plošné hmotnosti 30, 40, 50 a 60 g m^{-2} je uvedeno v tabulce 6.

Tabulka 6. Variační koeficienty hodnot hmotnosti vzorků měřených gravimetricky

Charakteristika	**m_A [g m^{-2}]**			
hmotnost	**30**	**40**	**50**	**60**
CV	0,136615	0,105927	0,100945	0,086634
CV_L	0,051815	0,043055	0,047852	0,018719
CV_{HL}	0,126407	0,096782	0,088883	0,084588

Z hodnot variačních koeficientů ve směru výroby pojené textilie ve stroji, CV_L, je zřejmé, že ve všech případech je větší nestejnoměrnost v příčném směru a pro plošné hmotnosti 30 až 60 g m^{-2} se pohybují hodnoty od poměru 1:1, 85 do poměru 1:4,51.

Měřením plošné hmotnosti modifikovanou gravimetrickou metodou byla naznačen jeden z možných postupů popisu charakteristické vzhledové nestejnoměrnosti, mrakovitosti, pojené textilie. Normalizovaná velikost měřených úseků ($100 cm^2$) byla zmenšena v tomto případě 100x. Další diskuse ověření přímého odečítání rozměrů shluků vláken z grafu výsledného hodnocení stejnoměrnosti plošné hmotnosti pojené textilie může přinést využití výsledků k provozním účelům.

6. Analýza nestejnoměrnosti plošné hmotnosti

Pro účely analýzy nestejnoměrnosti vlastností zkoumané pojené textilie, byl zaveden pojem plošné hustoty, $z(\mathbf{x})=z(x,y)$. V místě $\mathbf{x} = (x,y)$ je definována hodnota z(**x**) jako hmotnost M(S) dělená plochou dS =4dxdy elementárního čtverce tj. plochou příčného řezu objemového elementu o tloušťce odpovídající tloušťce textilie a příčných rozměrech x ± dx a y ± dy, s objemovou hustotou textilie ρ(x,y).

Současně je uvažováno náhodné pole $z(\boldsymbol{x})$ se složkami $z_i = z(\boldsymbol{x}_i) = z(x_i, y_i)$ určené v *p- tici* bodů $\boldsymbol{x}_i$ umístěných v oblasti *D*, kterou tvoří rektangulární rovnoměrnou síť. Náhodné pole $z(\boldsymbol{x})$ je jednoznačně charakterizováno p rozměrnou hustotou pravděpodobnosti

$$p_n(z_1, z_2, ..z_n) = P\{z_i \leq z(\mathbf{x}_i) \leq z_i + dz_i,\ \ i = 1..n\} \qquad (19)$$

Střední hodnota $m(\boldsymbol{x}_i) = E(z_i)$ náhodného pole v místě $\boldsymbol{x}_i$ je definována vztahem

$$E(z_i) = \int z_i\, p(z_i)\, dz_i \qquad (20)$$

Pro vyjádření variability bylo standardně použito druhého smíšeného centrálního momentu, *kovariance*, podle vztahu (18)

$$C_{ij} = \iint (z_i - E(z_i)(z_j - E(z_j)\, p(z_i, z_j)\, dz_i\, dz_j$$

resp.

$$C_{ij} = E(z(x_i) * z(x_j)) - E(z(x_i) * E(z(x_j)) \qquad (21)$$

Speciálně pro vyjádření prostorové nepodobnosti mezi hodnotami v místech $\boldsymbol{x}_i$ a $\boldsymbol{x}_j$ byl využit *variogram* resp. *semivariogram,* který je definován jako polovina rozptylu přírůstku $(z(\boldsymbol{x}_i) - z(\boldsymbol{x}_j))$

$$\Gamma_{ij} = 0.5 * D[z(x_i) - z(x_j)]$$

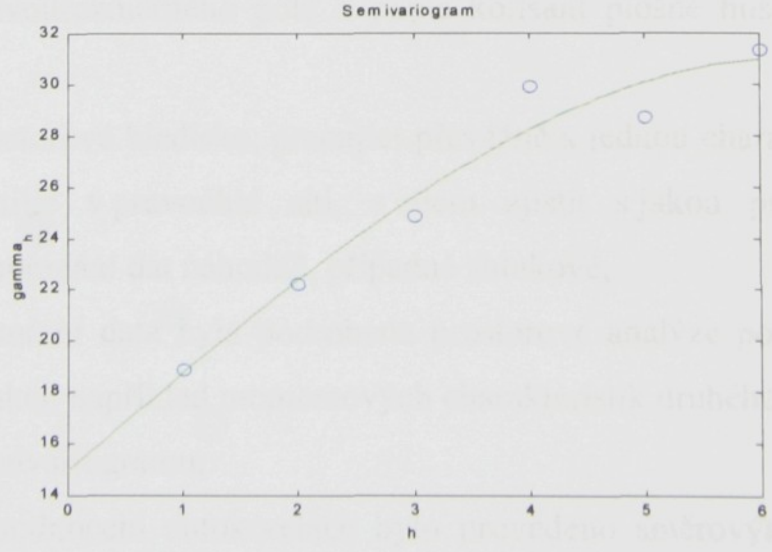
resp.

$$\Gamma_{ij} = 0.5 * [E(z(x_i) - z(x_j))^2 - (E(z(x_i) - z(x_j))^2] \qquad (22)$$

Pro mřížkové uspořádání byl zvolen přírůstkový vektor jako násobek délky a výšky jednotkové elementární buňky. *Výběrový směrový variogram* ve směru přírůstkového vektoru ***h*** byl počítán obecně ze vztahu

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \tag{23}$$

kde $N(\boldsymbol{h})$ je počet dvojic bodů oddělených o vzdálenost h a orientovaných podle směru vektoru ***h***. Pro mřížkové uspořádání jsou možné pouze tři směry, a délka přírůstkového vektoru je násobkem velikosti elementární cely. Bylo tedy možné počítat směrový variogram ve směru podélném 0^o $(\boldsymbol{h} = c*[1,0])$, diagonálním 45^o $(\boldsymbol{h} = c*[1,1])$, a příčném 90^o $(\boldsymbol{h} = c*[1,0])$ pro násobky $c = 1,2,3$.... Průměrování variogramů ve všech směrech vedlo k tzv. všesměrovému variogramu (*omnidirectional variogram)*. Pro grafické vyjádření prostorové variability byl konstruován *variogramový povrch*. Jde o soustavu variogramů uspřádaných do buněk čtvercové sítě. Počátkem je centrální buňka, která má nulový přírůstkový vektor. Další buňky mají přírůstkový vektor ***h*** vytvořený jako násobek centrální buňky ve směru x a y. Na tomto povrchu bylo možno sledovat orientačně uvedené tři základní směry anizotropie, ve kterých je variogram nejvíce informativní. Obrázek 14 znázorňuje sférický model všesměrového variogramu. Diskontinuita v počátku indikuje nesplnění stacionarity druhého řádu.



Obr. 14 Všesměrový variogram plošné hustoty pojené textilie 60 g m^2

V předchozích částech této práce byly stručně shrnuty výsledky disertační práce autora, s uvedením příkladů a jejich vizualizace. Dále jsou uvedeny základní statistické charakteristiky nestejnoměrnosti. Vedle celkového variačního koeficientu CV, byly počítány také hodnoty variačního koeficientu ve směru výroby CV_L a CV_{HL}. Závěrečným krokem u všech měření byla interpretace charakteristik, P_{ij}, počtu slabých míst a velikosti plochy slabých míst A_k, a hmotnosti vzorku m_{ij}, jako diskrétní presentace dvourozměrného náhodného pole podle vztahů (13) až (17), včetně analýzy rozptylu ANOVA. Uvedené postupy hodnocení nestejnoměrnosti vizuální metodou, metodou analýzy obrazu a modifikovanou gravimetrickou metodou, reprezentují tři různé způsoby posuzování nestejnoměrnosti plošné hmotnosti pojených textilií. Popis nestejnoměrnosti netkaných textilií, lze za určitých předpokladů, rozšířit o statistickou prostorovou analýzu dat, která může přispět k vysvětlení procesů, které vedly ke vzniku nestejnoměrnosti popisované vlastnosti netkané textilie. Jednou z těchto možností je vyjádření plošné nestejnoměrnosti využitím širšího aparátu náhodných polí. V prostorové analýze dat z různých oborů se obecně využívá indexů prostorové autokorelace nebo kovariance a variogramu.

Prostorová analýza

V souboru publikovaných studií [1] až [16], které jsou přílohou habilitační práce, bylo v oboru hodnocení nestejnoměrnosti netkaných textilií užito pro statistickou analýzu dvourozměrného pole a popis kolísání plošné hustoty pojené textilie zejména:

- prostorové hledisko, pracující převážně s jednou charakteristikou netkané textilie v pravoúhlé síti, s cílem zjistit s jakou pravděpodobností je uspořádání dat náhodné, případně shlukové;
- primární data byla podrobena prostorové analýze pomocí strukturálních funkcí, například momentových charakteristik druhého řádu, variogramu a semivariogramu;
- vyhodnocení autokorelace bylo provedeno směrovými semivariogramy, kterými je popsána anizotropie povrchové hustoty;

- k informaci o variabilitě povrchové hustoty je navrhován odhad kovarianční funkce, všesměrový variogram a konstrukce variogramového povrchu;
- ke kvantifikaci prostorové kontinuity dat variogramu, byla použita také indikátorová funkce dvourozměrného rozdělení;
- identifikace shluků a hodnocení prostorové závislosti dat byly provedeny ověřením multivariační špičatosti;
- využití hodnot všesměrového variogramu je použito k určení fraktální dimenze, která charakterizuje komplexně složitost zkoumaného povrchu.

Diskuse výsledků analýzy nestejnoměrnosti zkoumané pojené textilie je postupně rozvedena v souboru zveřejněných prací, včetně využití dalších charakteristik prostorové statistiky k vyjádření kolísání lokální plošné hmotnosti netkaných textilií. Jsou v nich podrobně uvedeny základní teoretické možnosti popisu dat, která jsou chápána jako náhodná pole a odkazy na relevantní odbornou literaturu. Prakticky jsou využita primární data z disertační práce autora k demonstraci provedení statistické analýzy na příkladech a k vyjádření různých způsobů vyhodnocení variability plošné hmotnosti, objemové či povrchové hustoty, až po definici fraktálního rozměru povrchu pojené textilie.

7. Komentář dosažených výsledků

Výsledky analýzy nestejnoměrnosti vlastností pojené textilie, podrobně popsané v disertační práci autora z let 1998-2000, jsou stručně představeny v této práci v kapitole 1. až 5. Podle koncepce uvedené v kapitole 6. jsou postupně rozvinuty další aplikace nástrojů prostorové statistiky, prezentované přiloženým souborem studií [1] až [16].

Vzhledová nestejnoměrnost netkaných textilií

Způsob vizuálního hodnocení vzhledové nestejnoměrnosti subjektivní metodou a objektivního měření s využitím systému LUCIA pro analýzu obrazů (kapitola 3. a 4.) je systematicky rozpracován v práci [1] až [4]. Pro popis vzhledové nestejnoměrnosti vzorku pojené textilie 60 g m^{-2} jsou využity tyto charakteristiky, P_{ij}:

- počet bílých míst subjektivně pozorovaných hodnotitelem, WS_{ij}
- počet bílých míst objektivně snímaných kamerou, WO_{ij}
- relativní podíl bílých míst, porosita, PO_{ij}
- relativní podíl míst s konstantní úrovni šedi, SO_{ij}.

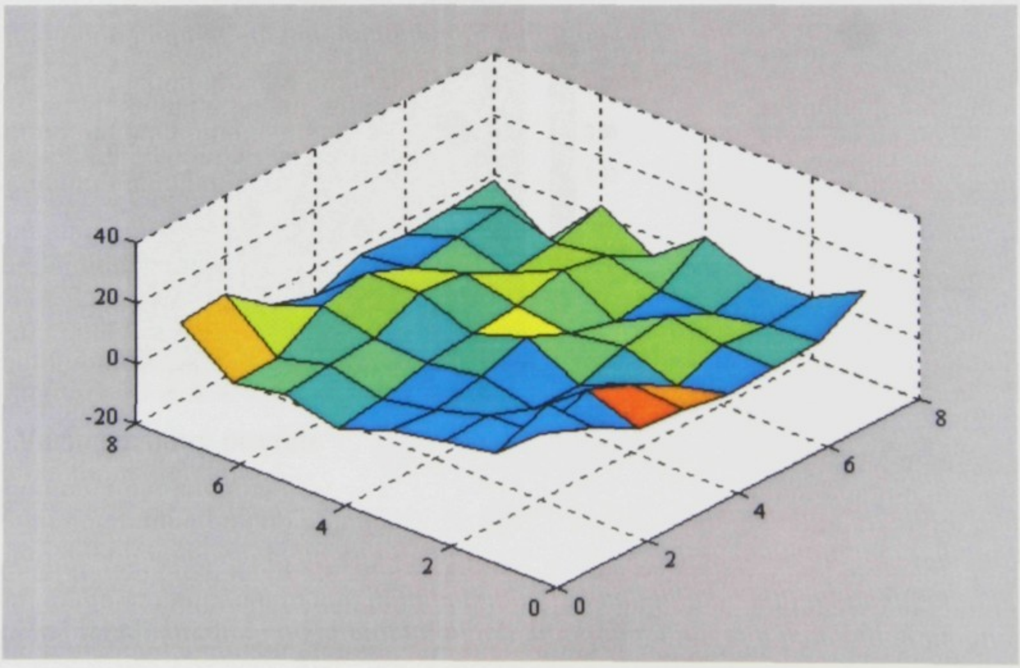
Je popsáno použití rozkladu rozptylů pro vyjádření složek nestejnoměrnosti ve směru osy stroje a směru příčném, pro posouzení významnosti kolísání charakteristik zaplnění, počet bílých míst WS a počet děr WO. Na hodnotách variačních koeficientů, celkového CV, ve směru výroby CV_L a v příčném směru, CV_H, je pro výše uvedené charakteristiky ukázáno na rozdíly v subjektivním a objektivním posuzování bílých míst WS a WO. Výsledek přijetí hypotéz H_0 na hladině významnosti 0.95, při testování hypotéz standardní analýzou rozptylu pro relativní porositu, PO, a počet bílých míst WS resp. WO, potvrdil, že variabilita žádné sledované charakteristiky není statisticky významná.

K prozkoumání prostorové souvislosti sousedních hodnot zjištěných vizuálním hodnocením, bílých míst, WS_{ij}, v pravoúhlé síti, byl proveden výpočet autokorelačního indexu, I, podle Morana [4]. Výsledek potvrdil přímou lokální prostorovou souvislost hodnot WS_{ij}, nejbližších sousedních buněk.

Nestejnoměrnost plošné hmotnosti netkaných textilií

K popisu nestejnoměrnosti plošné hmotnosti je využit způsob hodnocení modifikovanou gravimetrickou metodou (kapitola 5.), který je rozšířen o teoretický popis použití prostorové kovariance a variogramu k vyjádření kolísání globální a lokální variability plošné hmotnosti. Dále je ukázán způsob vyjádření anizotropie těchto náhodných polí jako možného popisu plošné nestejnoměrnosti při analýze gravimetrických měření. Výsledky jsou doloženy zpracováním experimentálních dat vzorku pojené textilie 60 g m^{-2}.

Pro popis plošné nestejnoměrnosti netkaných textilií se doporučuje zavést, v kap. 6 definovaný pojem plošná hustota, z(x)=z(x,y). Informace o náhodných polích se získávají na základě náhodné sekvence povrchových hustot z(i,j) určených na pravoúhlé síti, kde i,j (i = 1...m, j = 1...n) definuje ij-tou buňku. Jako základní charakteristika nehomogenity povrchové hustoty se používá koeficient anizotropie, An=Km/Lm, kde Km a Lm jsou intervaly korelace, při znalosti odhadu korelační funkce R(K,L) je možné určit charakteristiku anizotropie i parametry Gaussovského pole.

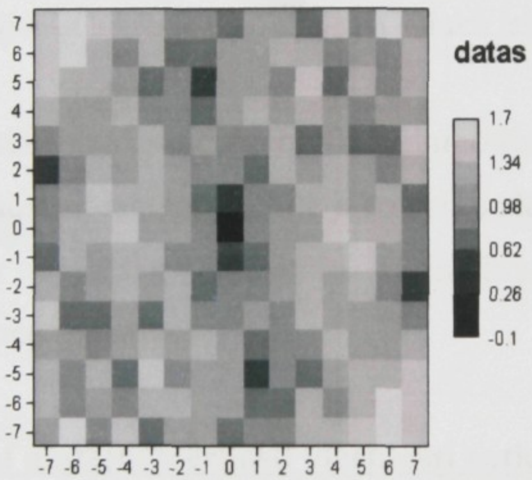


Obr. 15 Odhad korelační funkce R(K,L) pro K=0,1.....7 a L=0,1...7.

V příspěvku [5] bylo ukázáno použití pole povrchové hustoty pro hodnocení povrchové nestejnoměrnosti netkaných textilií. Z výsledků bylo zjištěno, že pole povrchové hustoty zkoumaného vzorku pojené textilie je mírně anizotropní a vykazuje lokální neregularity.

K prozkoumání prostorové souvislosti sousedních hodnot plošné hmotnosti, m_{ij} v pravoúhlé síti, byl proveden výpočet autokorelačního indexu, c, podle Gearyho [6]. Výsledek rovněž potvrdil přímou lokální prostorovou souvislost hodnot plošné hmotnosti, m_{ij}, nejbližších sousedních buněk.

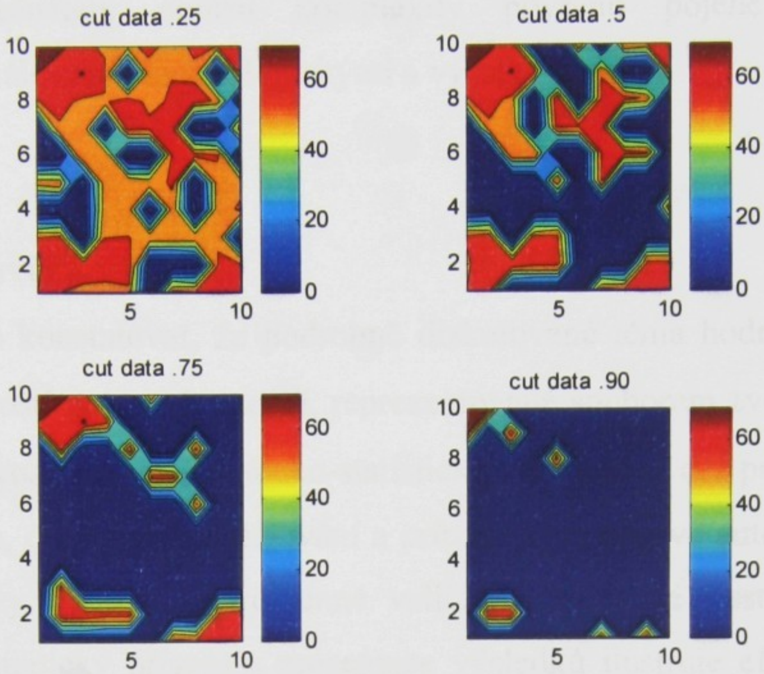
Aplikací směrového variogramu ve směru podélném, příčném a diagonálním, včetně jejich kombinace byla na sférickém přechodovém modelu všesměrového variogramu plošné hustoty potvrzena prostorová závislost plošné hmotnosti malého dosahu a náhodnost kolísání plošné hmotnosti ve větším měřítku (obr. 14). Pro grafické vyjádření prostorové variability byl zkonstruován variogramový povrch (obr. 16), jako soustava variogramů uspořádaných do buněk čtvercové sítě, na kterém je možno orientačně sledovat směry anizotropie [7, 8, 9].



Obr.16 Variogramový povrch

Lokální nestejnoměrnost netkaných textilií

V práci [10] a [11] je rozšířen způsob hodnocení nestejnoměrnosti zkoumané pojené textilie o další charakterizaci izotropních povrchů použitím fraktálního rozměru, D, vypočítaného z plochy variogramů pro směr řádků, sloupců a diagonální směr pravoúhlé sítě. Zavádí se výpočet indikátorové funkce, včetně grafického znázornění řezů, k vizualizaci závislostí lokálních shluků dat naměřených modifikovanou gravimetrickou metodou (kapitola 5.).



Obr. 17 Vybrané kvantily indikátorové funkce náhodné variability znázorňují souvislost lokálních dat a výskyt shluků jako lokálních anomálilí

Hodnota zjištěného všesměrového fraktálního rozměru, D=2,86 popisuje plošnou nestejnoměrnost zkoumané textilie jako velmi složitý povrch. Na obrázku 17 jsou prezentovány výsledky indikátoru variability, který orientačně znázorňuje povrchovou heterogenitu.

Hodnocení nestejnoměrnosti vlastností netkaných textilií

Hlavním cílem příspěvků [12] až [16] je prezentace teorie i výsledků dříve postupně představovaných metod hodnocení nestejnoměrnosti vlastností netkaných textilií, založeném na použití teorie náhodných polí, jako uceleného systému hodnocení. Doložené výsledky na datech zjištěných měřením vybrané charakteristické vlastnosti, plošné či objemové hmotnosti, představují v pravoúhlé síti aplikaci různých všesměrových charakteristik prostorové variability, variogramu, kovariance, korelogramu a madogramu. Ověření prostorové závislosti malého dosahu a náhodnosti ve větším měřítku je modelováno pomocí přechodového typu sférického modelu variogramu. Rovněž je ukázána vhodnost kombinace variogramu a jeho fraktálního rozměru k zdokonalení popisu komplexity povrchu pojené textilie, generované materiálovými, technologickými a výrobními vlivy.

8. Závěr

Lze konstatovat, že podrobně diskutované téma hodnocení nestejnoměrnosti vlastností pojených textilií, reprezentované souborem zveřejněných prací [1] až [16], rozšířilo matematicko-statistické zpracování dat použité v disertační práci autora, o postupy modelování a průzkum prostorové autokorelace a o provedení analýzy variability proměnné veličiny, objemové hustoty, v náhodném poli. Systematický přístup a prezentace výsledků ilustruje efektivní využití nástrojů prostorové statistiky k popisu různých charakteristik zkoumané vlastnosti pojené textilie a zpřehledňuje orientaci v dalších možnostech zdokonalování způsobů hodnocení nestejnoměrnosti vlastností plošných vlákenných útvarů. Další prohloubení poznatků uvedených v této práci, může vést podle představené koncepce, k obecnému rozšíření hodnocení a popisu strukturálních a povrchových vlastností plošných textilií.

Poděkování

Děkuji při této příležitosti všem spoluautorům za jejich příspěvek k dalšímu rozvinutí poznatků mojí disertační práce a výsledků mého doktorandského studia v letech 1998 – 2000.

Zvláště děkuji Prof. Ing. Jiřímu Militkému, CSc., vedoucímu Katedry textilních materiálů, Fakulty textilní, Technické univerzity v Liberci, za jeho odborné vedení a za mnohaletou podporu prezentace nových poznatků, bez které by se téma hodnocení nestejnoměrnosti netkaných textilií nedostalo na současnou úroveň.

9. Seznam zveřejněných vědeckých prací

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Příloha - Soubor zveřejněných vědeckých prací

Vzhledová nestejnoměrnost netkaných textilií

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Václav Klička, BASATEX Ústí nad Orlicí

1. Úvod

Vzhled textilií úzce souvisí s jejich stejnoměrností. Pojmem vzhledová nestejnoměrnost obyčejně zahrnuje charakteristiky související s lokálními změnami hustoty zaplnění mezi elementárními plochami určenými na základě rozlišovací schopnosti hodnotitele. Uvnitř těchto plochy se uvažuje stejná hustota zaplnění.

Vzhledová nestejnoměrnost patří mezi důležité charakteristiky jak textilií pro oděvní účely, tak i pro textilie technické. Tato charakteristika souvisí velmi úzce s řadou dalších charakteristik sledovaných lokálně a vyjádřených např. jako variační koeficient (průhlednost, odrazivost, plošná hmotnost). Ovlivňuje také řadu charakteristik transportních (prodyšnost vzduchu, šíření tepla, propustnost vodních par atd.) Ve všech uvedených případech jde vlastně o charakteristiky související s lokální variací struktury (resp. „zaplnění") plošných textilií.

Podle toho, které charakteristiky se sledují (s ohledem na jejich variabilitu), lze nestejnoměrnost rozdělit do těchto základních skupin:

- hmotná nestejnoměrnost
- strukturní nestejnoměrnost
- vizuální (optická) nestejnoměrnost
- nestejnoměrnost mechanických a fyzikálních vlastností
- vzhledová nestejnoměrnost.

Lze snadno zjistit, že mezi výše uvedenými skupinami existuje velmi úzká vazba.
Byl např. odvozen vztah mezi hmotnou nestejnoměrností a optickou nestejnoměrností pro netkané textilie [1].

Podobně jako u lineárních textilních útvarů, kde se lokální variace jemnosti (hmotnosti, průřezu) vyjadřují pomocí variačního koeficientu a jeho závislosti na délce lze pro výše uvedené charakteristiky použít variační koeficient a jeho závislost na ploše[2].

Cílem této práce je objektivní vizuální hodnocení vzhledové nestejnoměrnosti vybraných netkaných textilií s využitím systému LUCIA pro analýzu obrazů. Je ukázáno použití rozkladu rozptylů pro vyjádření složek nestejnoměrnosti ve směru osy stroje a směru příčném. Pro posouzení významnosti kolísání charakteristik zaplnění je použito analýzy rozptylu.

2. Princip vizuálního hodnocení vzhledové nestejnoměrnosti

Při subjektivním hodnocení vzhledu netkaných textilií se obyčejně postupuje tímto způsobem [5]:

1. Na mikroskopický obraz textilie se promítne čtvercová síť složená z celkového počtu NxM buněk (cel sítě). Každá buňka má velikost P. Ve směru osy stroje - index i (osnova u tkanin) je celkem N buněk a ve směru příčném- index j (útek) je celkem M buněk.
2. Ve všech buňkách Cij se určí počet bílých skvrn (úseků bez textilního materiálu) WS_{ij}.
3. Pomocí standardní statistické analýzy se určí celkový variační koeficient,

$$CV(P) = \frac{s}{m} \qquad (1)$$

Pro průměrný počet bílých skvrn je

$$m = \frac{1}{NM}\sum_i \sum_j WS_{ij} \qquad (2)$$

a pro celkový rozptyl s^2 platí

$$s^2 = \frac{1}{NM-1}\sum_i \sum_j (WS_{ij} - m)^2 \qquad (3)$$

Hodnota CV(P) charakterizuje celkovou variabilitu počtu bílých skvrn mezi úseky velikosti P (analogie vnější kvadratické nestejnoměrnosti).
Pokud je počet buněk dostatečně veliký lze provádět jejich slučování a počítat funkci CV(P) pro různá P. Tímto postupem lze zjišťovat nestejnoměrnost i mezi většími plochami (mrakovitost).
Minimální velikost posuzované bílé skvrny závisí na rozlišitelnosti lidského oka.

Toto subjektivní hodnocení je zatíženo řadou nepřesností (identifikace bílých skvrn) a je časově náročné.

Pro objektivní vizuální hodnocení lze s výhodou využít systém pro analýzu obrazu LUCIA. Příprava vzorku k měření je prakticky stejná (obraz textilie se rozdělí čtvercovou sítí na buňky velikosti P). Pro charakterizaci vzhledové nestejnoměrnosti je možné určovat

- počet bílých míst (skvrn) WO_{ij}
- relativní podíl bílých míst (porosita) PO_{ij}
- relativní podíl míst s konstantní úrovní šedi (odpovídá přibližně lokální tloušťce materiálu) SO_{ij}

Snadno lze také definovat minimální velikost elementu (skvrny, velikosti póru atd.) přes minimální počet pixelů v digitálním zobrazení

3. Experimentální část

Pro experiment byly použity vzorky chemicky pojených netkaných textilií (obchodní název Perlan). Ve velkých plochách je vizuálně patrná nepravidelnost rozdělení počtu vláken tzv. mrakovitost (viz obr.1)

Obr. 1 Testovaná textilie.

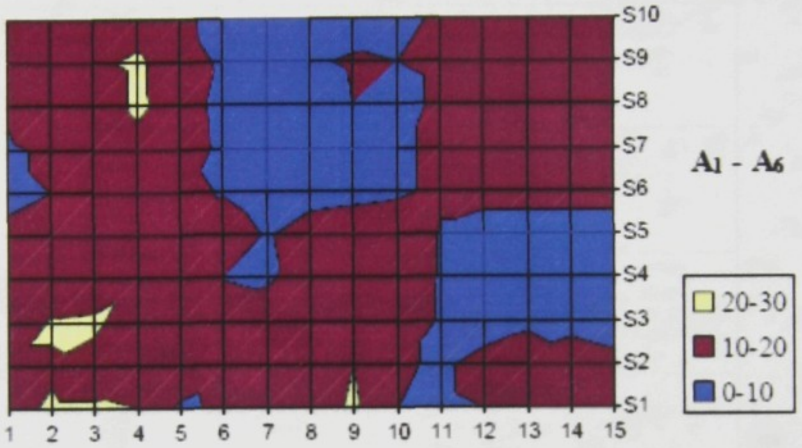
Subjektivní vizuální vyhodnocení [11]

Vzorek pozorovaný pod mikroskopem byl rozdělen na 5x5 (25) buněk pravoúhlou sítí, velikost buňky byla 2x2 mm^2. Použité zvětšení bylo 21x a tak bylo dosaženo zvýšení citlivosti oka na 0,05 mm. Hodnotitel zjišťoval počet míst s největší úrovní jasu WS_{ij} v každé jedné buňce[5]. Základní statistické charakteristiky pro veličinu WS jsou:

výběrový průměr = 12.38 bílých skvrn

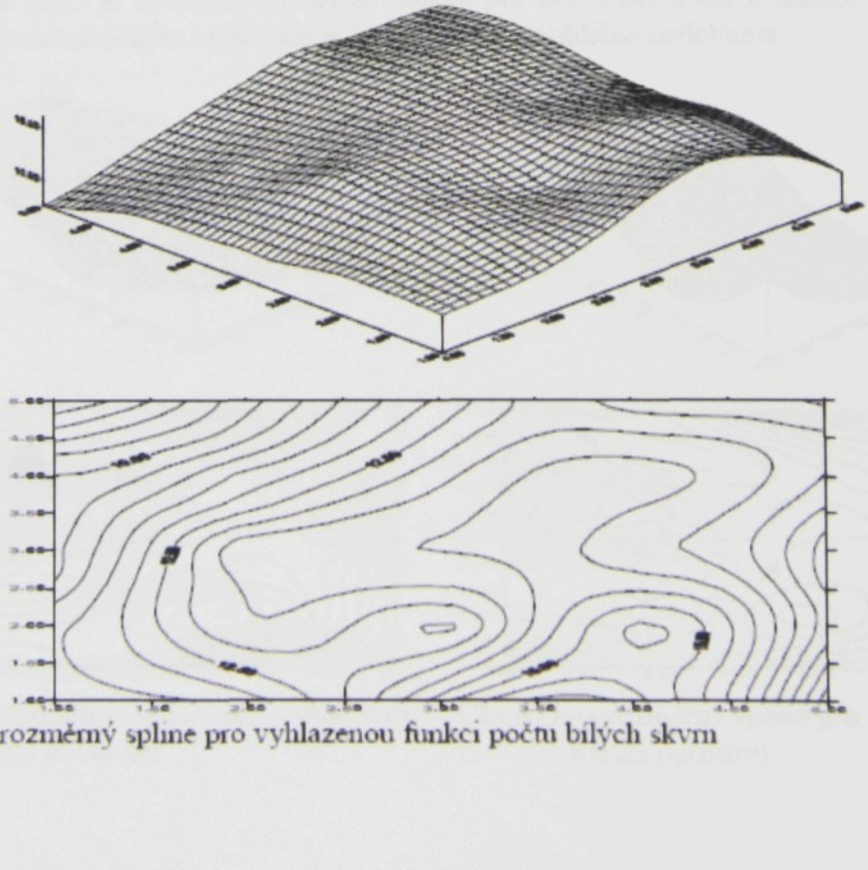
variační koeficient CV_u = 15.78 %.

Z kombinace výsledků pro šest vzorků byly sestaveny povrchy stejných úrovní počtu bílých skvrn (viz.obr 2)



Obr.2 Plochy stejných úrovní bílých skvrn.

Na obr.3 je uvedena vyhlazená funkce pro počet bílých skvrn na jednom vzorku (vyhlazení dvourozměrným kubickým spline)

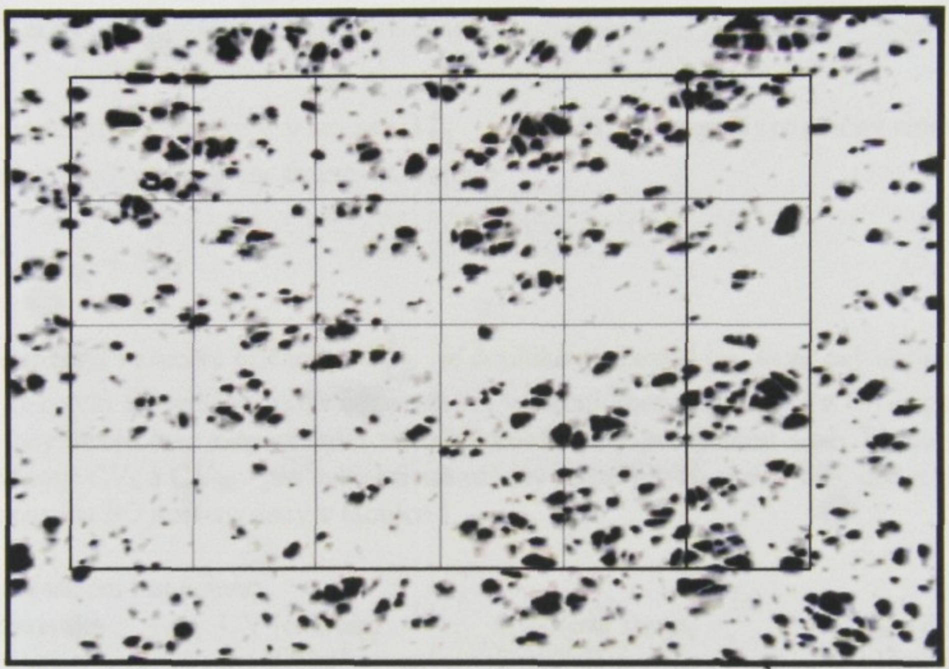


Obr.3 Dvourozměrný spline pro vyhlazenou funkci počtu bílých skvrn

Objektivní měření pomocí systému LUCIA

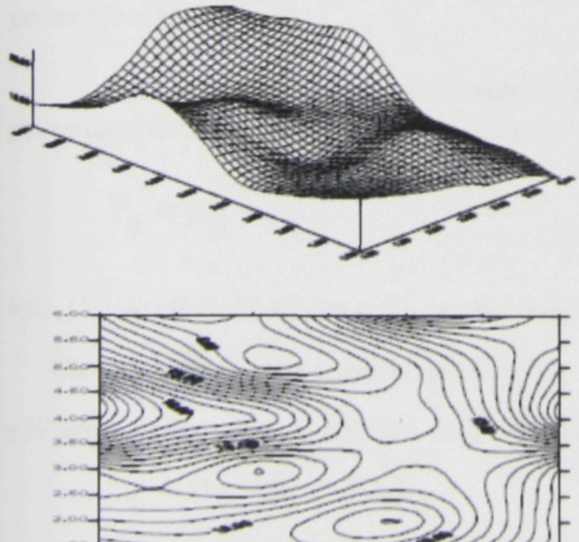
Mikroskopický pohled snímaný kamerou byl rozdělen jako u subjektivní metody. Použití jiného zvětšení, než u subjektivní metody a získání obdélníkového zorného pole způsobilo poněkud odlišné uspořádání a počet buněk viz. obr.4. V každé buňce byly zjišťovány tyto parametry:

- počet děr (skvrn)
- relativní porosita

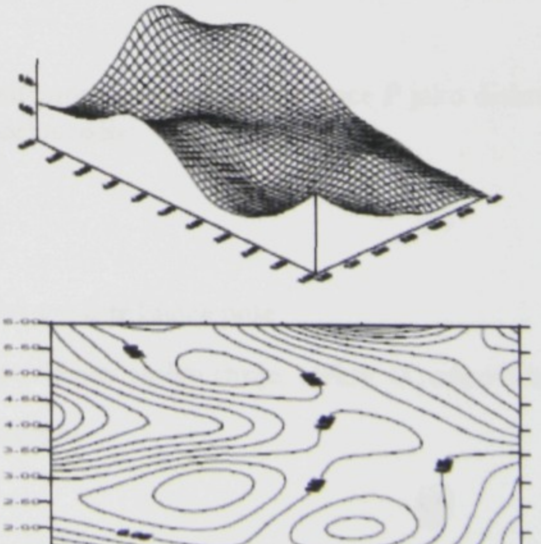


Obr.4 Invertovaný obraz zkoušeného vzorku (plošná hmotnost 60 $g.m^{-2}$)

Na obr.5 je uvedena vyhlazená funkce pro počet děr a obr.6 funkce pro porositu (vyhlazení dvourozměrným kubickým spline) Je patrná přibližná podobnost.



Obr.5 Dvourozměrný spline pro vyhlazenou funkci počtu děr



Obr.6 Dvourozměrný spline pro vyhlazenou funkci porosity)

4. Analýza výsledků

Označme Pij vybranou vizuální charakteristiku vzhledu (WS_{ij} WO_{ij} PO_{ij} SO_{ij}). Kromě celkového variačního koeficientu CV(P) lze také počítat variační koeficienty ve směru osy stroje a ve směru příčném[3]. Vychází se z rozkladu celkového rozptylu s využitím dílčích průměrů) m_{io} (ve směru osy stroje) a m_{oj} (ve směru příčném). Symbol „o" určuje index přes který se sumuje.

Pro směr osy stroje lze nalézt rozklad celkového rozptylu ve tvaru

$$s^2 = s_L^2 + s_{HL}^2 \tag{4}$$

kde s_L^2 je rozptyl ve směru osy stroje a s_{HL}^2 je doplňkový rozptyl pro příčný směr.

Podobně pro příčný směr lze definovat rozklad

$$s^2 = s_H^2 + s_{LH}^2 \tag{5}$$

kde s_H^2 je rozptyl ve směru příčném a s_{LH}^2 je doplňkový rozptyl pro směr osy stroje.
Z hodnot rozptylů lze snadno určit odpovídající variační koeficienty CV_L a CV_{HL} pro rozklad ve směru osy stroje resp odpovídající variační koeficienty pro příčný směr.Tímto postupem určené hodnoty CV_L a CV_{HL} pro subjektivně určený počet bílých skvrn WS, počet děr WO a relativní porositu PO jsou uvedeny v tabulce I.

Tabulka I. Variační koeficienty

Charakteristika	CV (celkem)	CV_L (osa stroje)	CV_{HL} (doplněk)
WS	0.1494245	0.0609795	0.1364155
WO	0.3944114	0.2029876	0.3381662
PO	0.5806934	0.2569274	0.520762

Je zřejmé, že počet bílých skvrn určených subjektivně příliš nekoresponduje s počtem děr určených obrazovou analýzou. Ukazuje to na rozdíly v subjektivní a objektivním posuzování bílých míst.

Další možností posuzování vzhledové nestejnoměrnosti je interpretace P jako diskrétní presentace dvourozměrného náhodného pole modelovaného vztahem[4]

$$P_{ij} = \mu_{ij} + \varepsilon_{ij} \tag{6}$$

kde μ_{ij} je střední hodnota a ε_{ij} je náhodná chyba v v ij-té buňce pole.

Člen μ_{ij} se dá dále rozložit na efekty β_j odpovídající směru stroje, efekty α_i odpovídající příčnému směru a interakční člen $\alpha_i\beta_j$ pomocí vztahu

$$\mu_{ij} = \alpha_i + \beta_j + c\alpha_i\beta_j \tag{7}$$

kde c je koeficient neaditivity

Pro případ čistě aditivních efektů je interakce $\tau_{ij} = c.\alpha_i.\beta_j = 0$ a pak

$$\hat{\alpha}_i = \frac{1}{M}\sum_j (P_{ij} - m) \qquad \hat{\beta}_j = \frac{1}{N}\sum_i (P_{ij} - m)$$

kde m celkový průměr definovaný rov. (2).

Z reziduí $\hat{e}_{ij} = P_{ij} - m - \hat{\alpha}_i - \hat{\beta}_j$ lze pak snadno vyčíslit odhad parametru c

$$c = \frac{\sum_i \sum_j \hat{e}_{ij}.\hat{\alpha}_i.\hat{\beta}_j}{\sum_i \sum_j \hat{\alpha}_i^2.\hat{\beta}_j^2}$$

Stejnoměrnost ve směru osy stroje je pak ekvivalentní platnosti hypotézy:

$$H_0 : \beta_j = 0, \quad j = 1...M$$

a stejnoměrnost v příčném směru je rovna platnosti

$$H_0 : \alpha_i \equiv 0, \quad i = 1...N.$$

Pro testování těchto hypotéz je možno použít standardní analýzu rozptylu (ANOVA) [4]. Výsledky pro relativní porositu PO jsou :

POROSITA

Průměry a efekty:

Celkový průměr = 6.3421E-02
Residuální rozptyl = 1.3626E-03

Faktor A:

Úroveň	Průměr	Efekt
1	9.0583E-02	2.7163E-02
2	4.8533E-02	-1.4888E-02
3	6.5917E-02	2.4958E-03
4	4.8650E-02	-1.4771E-02
5	7.3675E-02	1.0254E-02
6	7.9725E-02	1.6304E-02

Faktor B:

Úroveň	Průměr	Efekt
1	5.8900E-02	-4.5208E-03
2	4.5650E-02	-1.7771E-02
3	4.0350E-02	-2.3071E-02
4	8.2225E-02	1.8804E-02

Parametr neaditivity c = -8.3761

ANOVA model s interakcí

Zdroj rozptylu	Stupeň volnosti	Suma čtverců	Prům. čtverec	Test. kriterium	Závěr H_0 je
úrovně A	3	7.1031E-03	2.3677E-03	1.738	přijata
úrovně B	5	6.3723E-03	1.2745E-03	0.935	přijata
Interakce	1	1.3232E-04	1.3232E-04	0.097	přijata
Residua	14	1.9076E-02	1.3626E-03		
celkem	23	3.2551E-02	1.4153E-03		

Také pro subjektivně určený počet bílých skvrn WS a objektivně stanovený počet děr WO byly všechny hypotézy H_0 přijaty na hladině významnosti 0.95. Analýza rozptylu tedy ukazuje, že variabilita žádné sledované charakteristiky není statisticky významná.

5. ZÁVĚR

Navržený postup hodnocení vzhledové nestejnoměrnosti se dá snadno modifikovat pro jiné charakteristiky jako jsou plocha pórů, relativní tloušťka atd.

Je možné použít jak rozkladu celkové variability tak i analýzy rozptylu resp. regrese v případě nenáhodných trendů P_{ij}.

***PODĚKOVÁNÍ:** Tato práce vznikla s podporou České národní grantové agentury (grant No. 106/97/0372)*

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APPLICATION OF IMAGE ANALYSIS FOR NONWOVENS UNIFORMITY EVALUATION

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ABSTRACT

Surface appearance or uniformity is important characteristics of textile structures . This characteristics is closely connected to the variation function for transparency, reflectivity, planar mass and to the another properties as e.g. air permeability.
Corresponding to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness of planar structures.
There exists a lot of methods for evaluation of uniformity (or unevenness). Modern ones uses the image analysis systems.
The main aim of this work is attempt to describe uniformity of appearance of light weight nonwoven textile structures. Visual and subjective methods for evaluation of surface appearance irregularity of chemically bonded nonwovens are compared. The image analysis system LUCIA is used for estimation of characteristics describing appearance. The analysis of subjective and objective estimates of surface appearance irregularity is realized by the coefficient of variation and by the ANOVA type model.

.KEYWORDS

Surface Appearance, Visual Irregularity, Porosity, Image Analysis

1. INTRODUCTION

Surface appearance irregularity is interesting for woven structures and in some cases for nonwovens as well. This characteristics is closely connected to the variation function for transparency, reflectivity, planar mass and to the another properties as e.g. air permeability.

Corresponding to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity.

The unevenness can be categorized according to the investigated characteristics to the following main groups:

- mass unevenness (mostly used)
- structural unevenness
- visual (optical) unevenness
- mechanical or physical properties unevenness
- appearance unevenness.

There are some connections between above mentioned categories of unevenness.
The main aim of this work is attempt to describe uniformity of appearance of light weight nonwoven textile structure. For quantification of appearance uniformity the characteristics of visual unevenness are used. These characteristics are measured by the image analysis and subjectively by the human eye. The evaluation of appearance uniformity is based on the variation coefficient estimation and on the ANOVA (analysis of variance) model.

2. UNEVENNESS CHARACTERIZATION

Traditional methods of uneveness characterization in two dimensions are based on the measurement of relative variance (variation coefficient) of some geometrical quantities between selected (rectangular) cells dividing the investigated area. The same principle can be used for appearance nonuniformity estimation. In this work, the nonuniformity of appearance has been evaluated from selected visual characteristics measured in cells of defined size (see Fig.1). These rectangular cells divide the microscopic image of sample and create rectangular net.

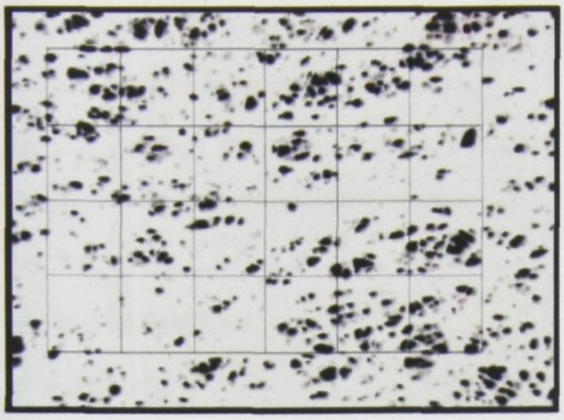


Figure 1
Inverted Image of tested sample (planar weight is 60g/m^2). White spots are here black.

As the visual characteristics of appearance unevenness in individual cells the following ones were selected:

- - number of white spots evaluated by the human eye *NE*
- - number of white objects *NW* evaluated by the image analysis (see white areas in the Fig.2)
- - relative surface porosity (portion of white area) *AF* defined on the fig 2.

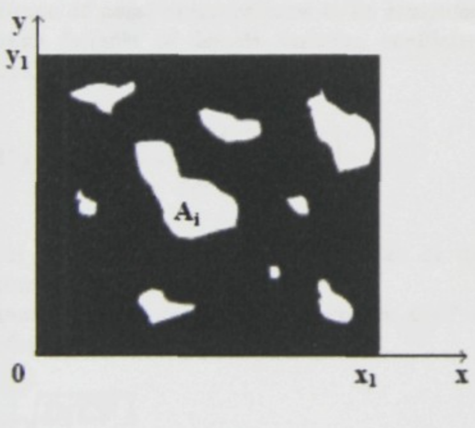


Figure 2
Definition of relative surface porosity (A_i is the area of white object)

The characteristics AF is computed from relations(see fig. 2)

$$AP = \sum A_i$$

$$AE = x_i . y_i$$

$$AF = \frac{A_P}{A_E}$$

Samples (cells) were oriented in the following way (see Fig.1).

- Direction X is equivalent to the <u>machine direction</u> (cells denoted i). In this direction is *N* cells.
- Direction y is equivalent to the <u>cross direction</u> (cells denoted j). In this direction is *M* cells.

Results of evaluation are rectangular data arrays NE_{ij}, NW_{ij}, AF_{ij}, $i = 1...n, j = 1...m$.
Appearance uniformity is analyzed by the following methods:

a) Coefficient of variation (CV)
b) Analysis of variance (ANOVA

Traditional method based on the variation coefficient is more suitable for characterization of degree of overall unevenness. Analysis based on the analysis of variance is useful for testing of evenness in selected orthogonal directions.

2.1 Analysis based on CV

Coefficient of variation is traditionally used as the characteristics of unevenness. According to the common definitions we can simply computed the overall mean

$$m = \frac{1}{MN}\sum_i \sum_j (P_{ij}) \qquad (1)$$

variance

$$s^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m)^2 \qquad (2)$$

and coefficient of variation

$$CV = \frac{s}{m} \qquad (3)$$

Here P_{ij} is selected visual characteristic of appearance (NE_{ij} or NW_{ij} or AF_{ij}).
The quantity CV is external variation coefficient CB(F) between cell areas F
The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{io} = \frac{1}{M}\sum_j P_{ij}$$

$$m_{oj} = \frac{1}{N}\sum_j P_{ij}$$

Symbol „*o*" denotes index used for summation *i.e.* m_{io} is mean value for i th position in the machine direction. For the <u>machine direction</u> (expansion of eqn.(2) by using of the m_{io}) the following relation results [1]

$$s^2 = s_L^2 + s_{HL}^2 \quad (4)$$

where the variance in the machine direction is

$$s_L^2 = \frac{1}{N}\sum_i (m_{io} - m)^2 \quad (5)$$

and the variance in the transversal direction is

$$s_{HL}^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m_{io})^2 \quad (6)$$

For the cross direction is

$$s^2 = s_H^2 + s_{LH}^2 \quad (7)$$

where the variance in the cross-direction is

$$s_H^2 = \frac{1}{M}\sum_j (m_{oj} - m)^2 \quad (8)$$

and the variance in the longitudinal direction is

$$s_{LH}^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m_{oj})^2 \quad (9)$$

Dividing the corresponding standard deviations by the mean m the coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} results.
These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals the variance of point estimates have to be computed. The rough formula of sample variation coefficient variance D(CV) has the form[2]

$$D(CV) = CV^2\left(\frac{n + CV^2(2n+1)}{2n(n-1)}\right)$$

where n = (N or M) is number of cells in the corresponding direction.
Asymptotic 95 %th confidence interval for CVP is then defined as

$$CV \pm 2\sqrt{D(CV)}$$

The coefficients of variation are statistically different in the cases when corresponding confidence intervals are not intersecting.

2.2 Analysis by the ANOVA

The P_{ij} can be interpreted as discrete presentations of random field on the discrete two dimensional integer valued rectangular mesh [1]. Let the P_{ij} are described by the following model[2]

$$P_{ij} = \mu_{ij} + \varepsilon_{ij} \quad (10)$$

where μ_{ij} is true value in the ij cell and ε_{ij} is random error. The term μ_{ij} can be decomposed to the terms

$$\mu_{ij} = \mu + \alpha_i + \beta_j + c.\alpha_i.\beta_j \quad (11)$$

where μ is total mean α_i **are effects in the cross direction**, β_j **are effects in the machine direction** and c is constant of Tukey one degree of freedom non - additivity.[2].
Uniformity in the machine direction is equal to validity of hypotheses $H_0: \beta_j = 0, j = 1 \ldots M$
and uniformity in the cross direction is equal to validity of hypotheses
$H_0: \alpha_i = 0, i = 1 \ldots N$.
Testing of these hypotheses can be realized by the ANOVA (model with a single observation per cell).
For the ANOVA model the following constraints are imposed

$$\sum_i \alpha_i = 0,\ \sum_{j=1} \beta_j = 0,\ \sum_i \alpha_i\beta_j = 0,$$
$$\sum_j \alpha_i\beta_j = 0 \ .$$

For the pure additive effects the interactions $\tau_{ij} = c.\alpha_i.\beta_j = 0$ and then

$$\hat{\alpha}_i = \frac{1}{M}\sum_j (P_{ij} - m)$$

$$\hat{\beta}_j = \frac{1}{N}\sum_i (P_{ij} - m)$$

where m is estimator of the total mean defined by the eqn.(1).
From residuals $\hat{e}_{ij} = P_{ij} - m - \hat{\alpha}_i - \hat{\beta}_j$ the parameter c can be simply estimated

$$c = \frac{\sum_i \sum_j \hat{e}_{ij}.\hat{\alpha}_i.\hat{\beta}_j}{\sum_i \sum_j \hat{\alpha}_i^2.\hat{\beta}_j^2} \quad (12)$$

For ANOVA testing the sum of squares due to machine direction (effects $\hat{\beta}_j$), cross direction (effects $\hat{\alpha}_i$) and due to interaction are computed and compared with total sum of squares $s * M * N$. Statistical tests based on the F-criterion may be performed [2]. According to the results of testing of the null hypothesis $H_0\ (\beta_j = 0 \text{ or } \alpha_i = 0)$ the statistical uniformity in the machine and cross direction can be accepted or not.

When eqn. (10) is considered as the special regression model, the diagonal elements of projection matrix have the same value[2]

$$H_{ii} = \frac{N + M - 1}{N.M}$$

Outlying cells may be then detected by the standardized residuals

$$e_{S_{ij}} = \frac{e_{ij}}{\sqrt{\sigma_R^2 (1 - H_{ii})}}$$

where σ_R^2 is variance of error term estimated from residual sum of squares divided by corresponding degrees of freedom (NM-N-N). Roughly, if $e_{S_{ij}} > 3$, the given cell is taken as an outlier.

3. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibers (VS) was prepared. Starting lap of planar weight 60 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding. The qualitative visual appearance unevenness of final structure is clearly visible on the Fig 3.

Figure 3
Tested nonwoven structure

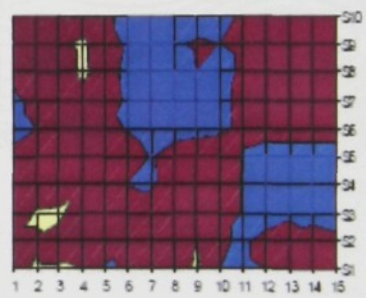
The rectangular samples of dimensions 100 x 100 mm (area A_j = 100 mm^2 and weight 6 mg) were cut for further analysis [3].

3.1 Subjective Visual Appearance

Subjective visual estimation of appearance is based on the evaluation of number of local maximal illumination L_m in individual mesh of defined rectangular net by the human eye. The maximal illumination corresponds to the spots without material. The human eye is able to distinguish the spots of dimension higher than approximately the
m = 0.5 mm By using of the microscope MEOFLEX (magnification 21 times) is lower bound of visible spots approximately equal to the 0.05 mm.
This subjective visual evaluation was used for above mentioned nonwoven structure.
The microscope image of sample was divided to the net consisted of the 25 rectangular mesh (dimension 2 x 2 mm). The number of spots NE_{ij} in the ij - th mesh having maximal illumination was evaluated by the direct visual inspection [3].
The basic statistical characteristics of NE are:

- sample mean = 12.38 spots
- coefficient of variation CV_n = 15.78 %.

From the combination of six microscope images the areas of the same level of local numbers of white spots are shown graphically on the fig. 4.



$A_1 - A_6$

Figure 4
Areas of the same levels of numbers of white spots.

From the fig 4 the areas of the same level of white spots concentration are visible.
For creation of the smooth surface of white spots concentration the cubic bivariate spline smoothing technique has been used.
The smoothed surface of NE for one image is shown on the fig 5.

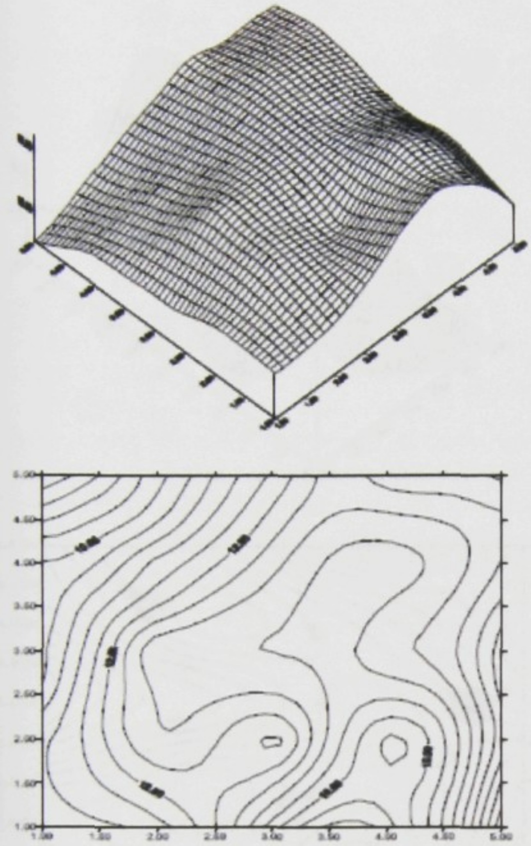


Figure 5

Bivariate spline smoothed surface of NE

3.2 Application of the Image Analysis

Subjective visual evaluation of white spots number is very tedious and subjected by the errors. The image analysis system is suitable for objective visual estimation. The system consists of microscope, CCD camera and personal computer has been used.

The treatment of digital images were made by the software LUCIA-M. This software is designed for analysis of the high color (3x5 bits) images having resolution of 752x524 pixels. The threshold value 62 (all gray patterns are converted to the black ones) has been chosen. The rectangular net dividing the image into equal cells has been defined by the same way as at subjective visual evaluation.

The following characteristics of appearance uniformity have been evaluated in each cell:

- number of white spots NW
- relative porosity AF

Bivariate spline smoothed surface of NW is shown on the fig 6 and for AF on the fig. 7.

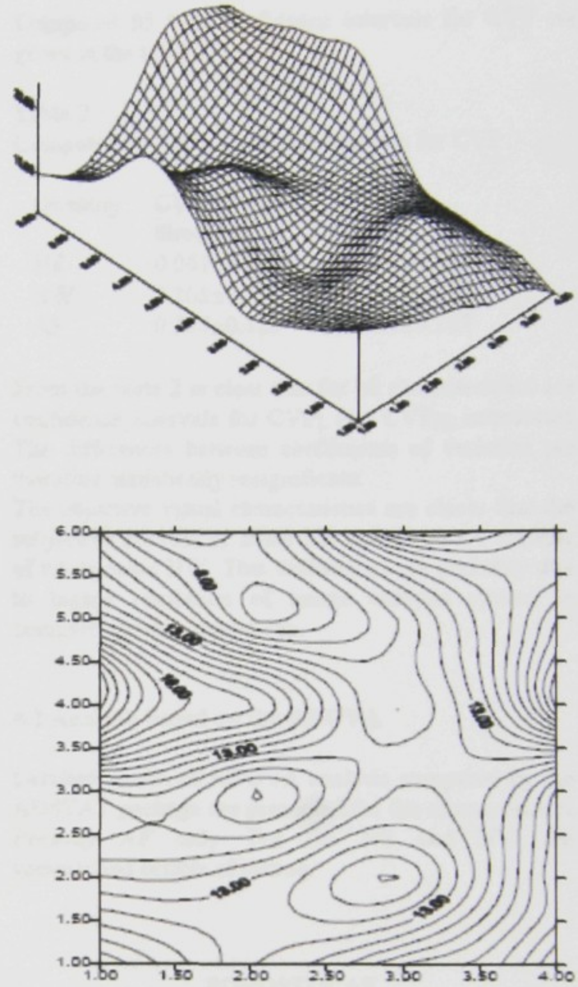


Figure 6

Bivariate spline smoothed surface of NW

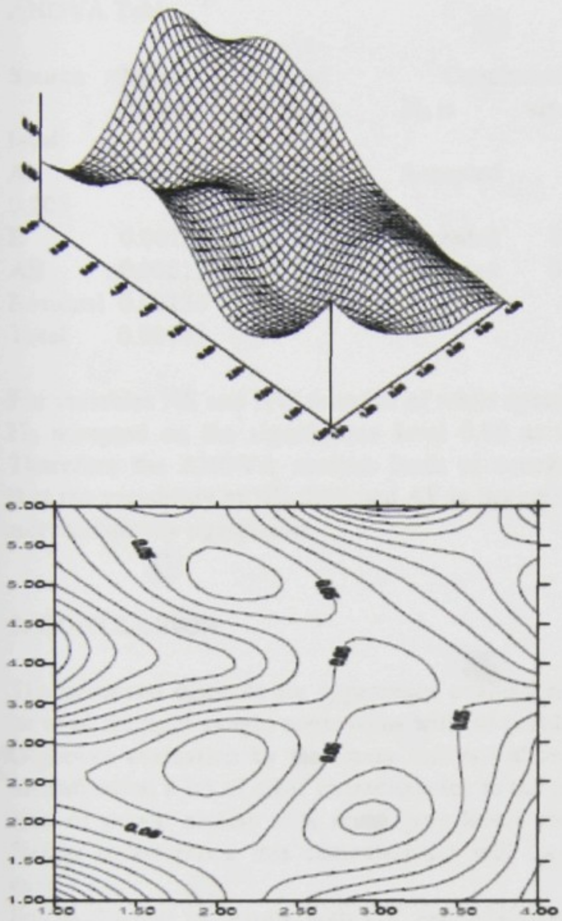


Fig. 7
Bivariate spline smoothed surface of AF

From the surfaces of NE, NW and AF is possible to identify the local variation of these characteristics.

4. UNIFORMITY EVALUATION

.Quantification of appearance uniformity has been realized by the analysis of coefficient of variation CV and analysis of variance ANOVA.

4.1 Analysis based on the CV

The values of CV, CV_L and CV_{HL} computed from above defined relations are given in the table 1.

Table 1
Coefficients of variation

Quantity	CV (total)	CV_L(machine direction)	CV_{HL} (transversal)
NE	0.1494245	0.0609795	0.1364155
NW	0.3944114	0.2029876	0.3381662
AF	0.5806934	0.2569274	0.520762

Computed 95 %th confidence intervals for CVP are given in the table 2

Table 2
Computed 95 %th confidence intervals for CVP

Quantity	CV_L(machine direction)	CV_{HL} (transversal)
NE	0.061±0.044	0.136±0.041
NW	0.203±0.150	0.338±0.109
AF	0.257±0.189	0.521±0.187

From the table 2 is clear that for all characteristics are confidence intervals for CVP_L and CVP_{HL} intersected The differences between coefficients of variation are therefore statistically insignificant.
The objective visual characteristics are closer that the subjective number of holes NE and objective number of white areas NW. This differences are probably due to higher resolution of image analysis system in comparison with human eye.

4.2 Analysis based on the ANOVA

Detailed results of ANOVA analysis computed by the ADSTAT package are presented for the characteristics ***Porosity AF*** only. For the NE and NW are summarized results of testing.

POROSITY AF

Basic characteristics are summarized in the table 3.

Table 3
Means and Level Effects

FACTOR A:			FACTOR B:		
Level	Mean	Effect	Level	Mean	Effect
1	0.09068	0.0272	1	0.0589	-0.0045
2	0.04853	-0.0148	2	0.0456	-0.0177
3	0.06591	0.0025	3	0.0403	-0.0231
4	0.04865	-0.0147	4	0.0822	0.0188
			5	0.0736	0.0102
			6	0.0797	0.0163

Computed characteristics for ANOVA model are

Total mean = 6.3421E-02

Residual variance = 1.3626E-03

Tukey's one degree of non - additivity C = -8.3761

In the table 4 is ANOVA table for full model with Tukey one degree of non additivity interaction

Table 4
ANOVA Table

Source	Mean square	Testing criterion	Conclusion H$_0$ is	sig. level
A	0.00236	1.738	Accepted	0.205
B	0.00127	0.935	Accepted	0.488
AB	0.00013	0.097	Accepted	0.760
Residual	0.00136			
Total	0.00142			

For variables NE and NW (number of white spots) are H_0 accepted on the significance level 0.95 as well. Therefore the ANOVA analysis leads to conclusion that the variability of NE, NW and AF in the cells are ***not statistically significant***.

5. CONCLUSION

The proposed methods for appearance evaluation can be used for light weight nonwovens without problems. Objective evaluation by the image analysis allows to identification a lot of other characteristics as the mean area of pores, objects with some gray levels etc. In further investigation this characteristics will be also used.
For evaluation of results both CV and ANOVA are suitable. The behavior of effects in the machine and cross directions computed by the ANOVA can be analyzed by the regression methods (trends, nonlinearitiers etc.).

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Surface appearance irregularity of nonwovens

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Keywords *Textiles, Structures*

Abstract *Visual and subjective methods for evaluation of surface appearance irregularity of chemically bonded nonwovens are compared. The image analysis system LUCIA is used for estimation of characteristics describing appearance. The analysis of subjective and objective estimates of surface appearance irregularity is realized by the coefficient of variation and by the ANOVA type model.*

1. Introduction

Surface appearance irregularity is interesting for woven structures and in some cases for nonwovens as well. This characteristic is closely connected to the variation function for transparency, reflectivity, planar mass and to other properties, for example, air permeability.

Corresponding to the description of unevenness of linear textile structures by the length variation function, a surface variation function can be constructed for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity.

The unevenness can be categorized according to the investigated characteristics in the following main groups:

- mass unevenness (mostly found);
- structural unevenness;
- visual (optical) unevenness;
- mechanical or physical properties unevenness;
- appearance unevenness.

There are some connections between the above mentioned categories of unevenness. For example, Huang and Bresee (1993) derived a connection between mass unevenness and optical unevenness (characterized in both cases by the coefficient of variation).

The main aim of this work is to attempt to describe uniformity of appearance of lightweight nonwoven textile structure. For quantification of appearance uniformity the characteristics of visual unevenness are used. These characteristics are measured by the image analysis and subjectively by the

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human eye. The evaluation of appearance uniformity is based on the variation coefficient estimation and on the ANOVA (analysis of variance) model.

2. Appearance unevenness characterization

Nonuniformity of appearance has been evaluated from selected visual characteristics measured in cells of defined size (see Figure 1). These rectangular cells divide the microscopic image of sample and create a rectangular net.

As the visual characteristics of appearance unevenness the following were selected:

- number of white spots evaluated by the human eye NE;
- number of white objects NW evaluated by the image analysis (see white areas in Figure 2);
- relative surface porosity (portion of white area) AF defined in Figure 2.

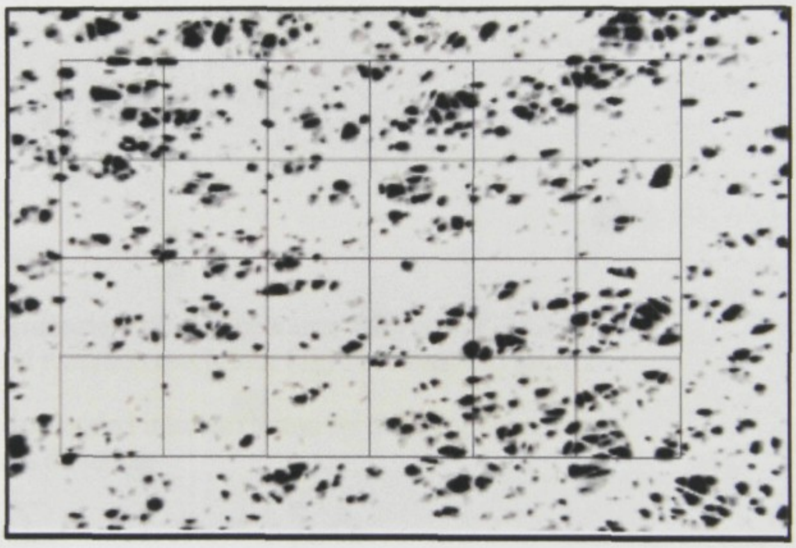


Figure 1.
Inverted image of tested sample (planar weight 60g/m^2). White spots are shown here as black

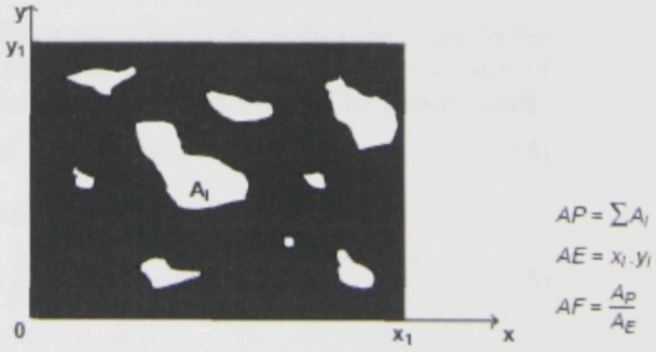


Figure 2.
Definition of relative surface porosity (A_i is the area of white objects)

Samples were oriented in the following way (see Figure 1).

Direction X is equivalent to the machine direction (cells denoted i). In this direction is N cells. Direction y is equivalent to the cross direction (cells denoted j). In this direction is M cells.

Results of evaluation are data arrays NE_{ij}, NW_{ij}, AF_{ij}, $i = 1 \ldots n, j = 1 \ldots m$.

Appearance uniformity is described by the following methods:

- Coefficient of variation (CV)
- Analysis of variance (ANOVA)

Analysis based on CV

Coefficient of variation is traditionally used as the characteristic of unevenness. According to the common definitions we can simply compute the overall mean

$$m = \frac{1}{MN}\sum_i \sum_j (P_{ij}) \tag{1}$$

variance

$$s^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m)^2 \tag{2}$$

and coefficient of variation

$$CV = \frac{s}{m} \tag{3}$$

Here P_{ij} is the selected visual characteristic of appearance (NE_{ij} or NW_{ij} or AF_{ij}).

The quantity CV is external variation coefficient CB(F) between cell areas F (Wegener, 1986).

The total variance s^2 can be divided into two terms by the use of means in the machine direction and cross direction:

$$m_{io} = \frac{1}{M}\sum_j P_{ij} \qquad m_{oj} = \frac{1}{N}\sum_j P_{ij}.$$

Symbol "o" denotes the index used for summation, i.e. m_{io} is the mean value for the ith position in the machine direction. For the machine direction (expansion of equation (2) by the use of the m_{io}) the following relation results (Cherkassky, 1998):

$$s^2 = s_L^2 + s_{HL}^2 \tag{4}$$

where the variance in the machine direction is

$$s_L^2 = \frac{1}{N}\sum_i (m_{io} - m)^2 \tag{5}$$

and the variance in the transversal direction is

$$s_{HL}^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m_{io})^2. \quad (6)$$

For the cross direction it is

$$s^2 = s_H^2 + s_{LH}^2 \quad (7)$$

where the variance in the cross direction is

$$s_H^2 = \frac{1}{M}\sum_j (m_{oj} - m)^2 \quad (8)$$

and the variance in the longitudinal direction is

$$s_{LH}^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m_{oj})^2. \quad (9)$$

Dividing the corresponding standard deviations by the mean m the coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} result.

Analysis by the ANOVA

The P_{ij} can be interpreted as a discrete presentation of the random field on the discrete two-dimensional integer valued rectangular mesh (Cherkassky, 1998). Let P_{ij} be described by the following model

$$P_{ij} = \mu_{ij} + \varepsilon_{ij} \quad (10)$$

where μ_{ij} is the true value in the ij cell and ε_{ij} is random error. The term μ_{ij} can be decomposed to the terms

$$\mu_{ij} = \alpha_i + \beta_j + c.\alpha_i.\beta_j \quad (11)$$

where α_i are effects in the cross direction, β_j are effects in the machine direction and c is the constant of Tukey one degree of freedom non-additivity.

Uniformity in the machine direction is equal to validity of the hypothesis

$$H_0: \beta_j = 0,\ j = 1 \ldots M$$

and uniformity in the cross direction is equal to the validity of the hypothesis

$$H_0: \alpha_i \equiv 0,\ i = 1 \ldots N.$$

Testing of these hypotheses can be realized by the ANOVA (model with a single observation per cell). For the ANOVA model the following constraints are imposed

$$\sum_i \alpha_i = 0, \sum_{j=1} \beta_j = 0, \sum_i \alpha_i \beta_j = 0, \sum_j \alpha_i \beta_j = 0.$$

For the pure additive effects the interactions $\tau_{ij} = c.\alpha_i.\beta_j = 0$ and then

$$\hat{\alpha}_i = \frac{1}{M}\sum_j (P_{ij} - m) \qquad \hat{\beta}_j = \frac{1}{N}\sum_i (P_{ij} - m)$$

where m is the total mean defined by equation (1).

From residuals $\hat{e}_{ij} = P_{ij} - m - \hat{\alpha}_i = \hat{\beta}_j$ the parameter c can be simply estimated

$$c = \frac{\sum_i \sum_j \hat{e}_{ij}.\hat{\alpha}_i.\hat{\beta}_j}{\sum_i \sum_j \hat{\alpha}_i^2.\hat{\beta}_j^2}. \tag{12}$$

For ANOVA testing the sum of squares due to machine direction (effects $\hat{\beta}_j$), to cross direction (effects $\hat{\alpha}_i$) and to interaction is computed and compared with the total sum of squares $s * M * N$. Statistical tests based on the F-criterion may be performed (Meloun *et al.*, 1992). According to the results of testing of the null hypothesis $H_0(\beta_j = 0 \text{ or } \alpha_i = 0)$ the statistical uniformity in the machine and cross direction can be accepted or not.

3. Experimental part

The chemically bonded (by the acrylate binder) nonwoven from viscose fibers (VS) was prepared. Starting lap of planar weight 60gm^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 per cent) was applied by padding. The qualitative visual appearance unevenness of the final structure is clearly visible in Figure 3.

The rectangular samples of dimensions 100×100mm (area A_j (100mm^2 and weight 6mg)) were cut for further analysis (Klička, 1998).

Subjective visual appearance

Subjective visual estimation of appearance is based on the evaluation of the number of local maximal illumination L_m in individual mesh of defined rectangular net by the human eye. The maximal illumination corresponds to the spots without material.

The human eye is able to distinguish the spots of dimension to a greater degree than approximately m = 0.5mm. By using the microscope MEOFLEX (21 times magnification) the lower bound of visible spots is found to be approximately equal to 0.05mm.

This subjective visual evaluation was used for the above mentioned nonwoven structure. The microscope image of the sample was divided into the net consisting of the 25 rectangular mesh (dimension 2×2mm). The number of

Figure 3.
Tested nonwoven structure

spots NE_{ij} in the ijth mesh having maximum illumination was evaluated by direct visual inspection (Klička, 1998). The basic statistical characteristics of NE are: sample mean = 12.38 spots and coefficient of variation CV_n = 15.78 per cent. From the combination of six microscope images the areas of the same level of local numbers of white spots are shown graphically in Figure 4.

The bivariate spline smoothed surface of NE for one image is shown in Figure 5.

Application of the image analysis

Subjective visual evaluation of the number of white spots is very tedious and subject to errors. The image analysis system is suitable for objective visual estimation. The system consist of microscope, CCD camera and personal computer has been used.

The treatment of digital images was made using the software LUCIA-M. This software is designed for analysis of the high color (3×5 bits) images having a resolution of 752×524 pixels. The threshold value 62 (all gray patterns are converted to black) has been chosen. The rectangular net dividing the image into equal cells has been defined by the same means as at subjective visual evaluation.

The following characteristics of appearance uniformity have been evaluated in each cell:

- number of white spots NW;
- relative porosity AF.

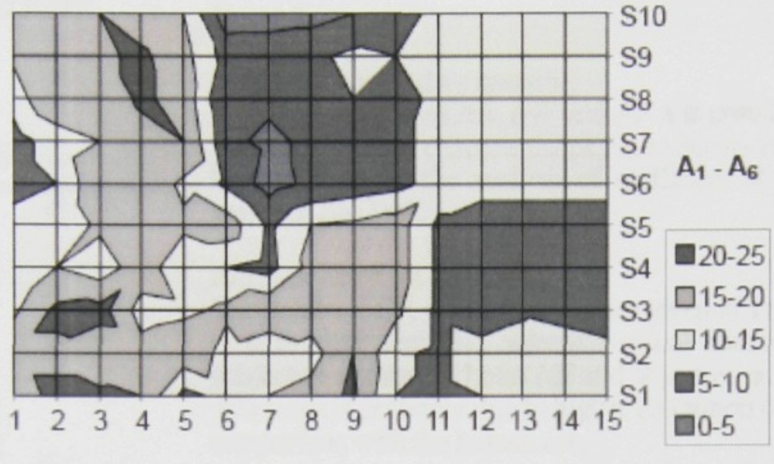


Figure 4. Areas of the same levels of numbers of white spots

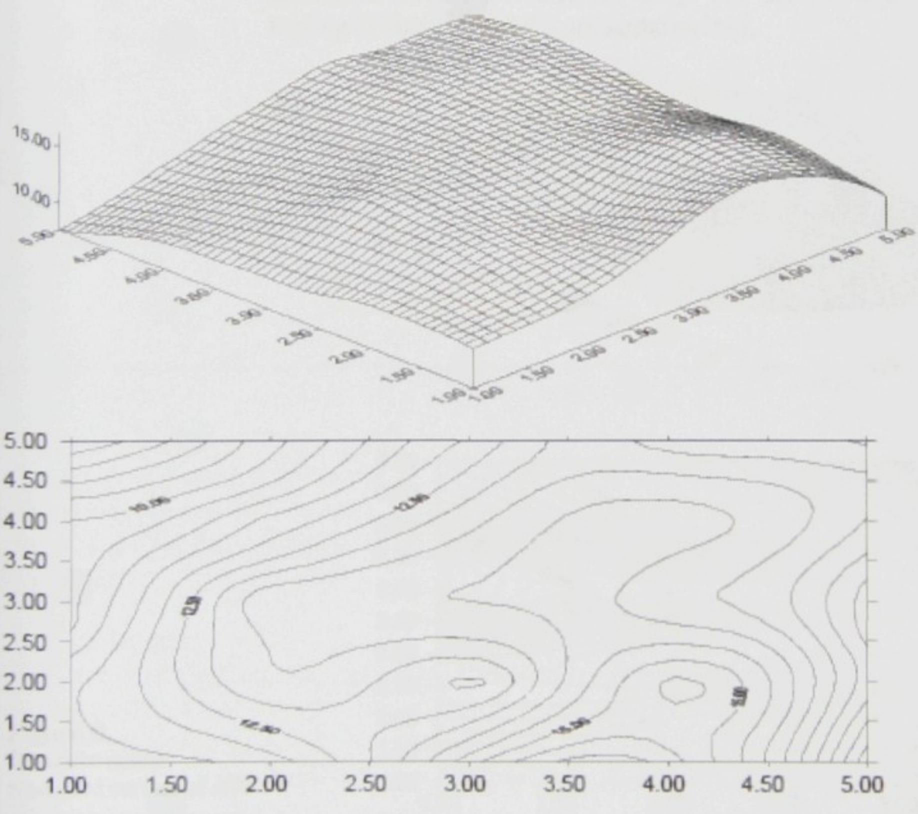


Figure 5. Bivariate spline smoothed surface of *NE*

Bivariate spline smoothed surface of *NW* is shown in Figure 6 and for *AF* in Figure 7.

4. Results and discussion

From the surfaces of *NE*, *NW* and *AF* it is possible directly to identify the local variation of these characteristics. Quantification of appearance uniformity has been realized by the analysis of coefficient of variation *CV* and analysis of variance ANOVA.

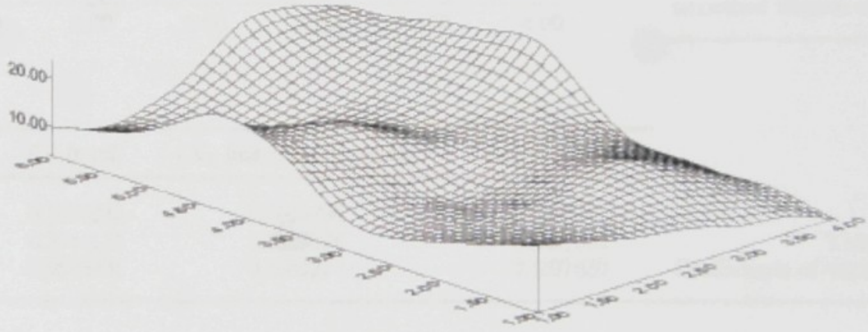
Analysis based on the CV

The values of CV, CV_L and CV_{HL} are given in Table I.

It is clear that the objective visual characteristics are closer than the subjective number of holes *NE* and objective number of white areas *NW*. This difference is probably due to higher resolution of the image analysis system in comparison with the human eye.

Analysis based on the ANOVA

Detailed results of ANOVA analysis computed by the ADSTAT package are presented for the porosity *AF* only. For the *NE* and *NW* only the results of testing (Tables II and III) are summarized.



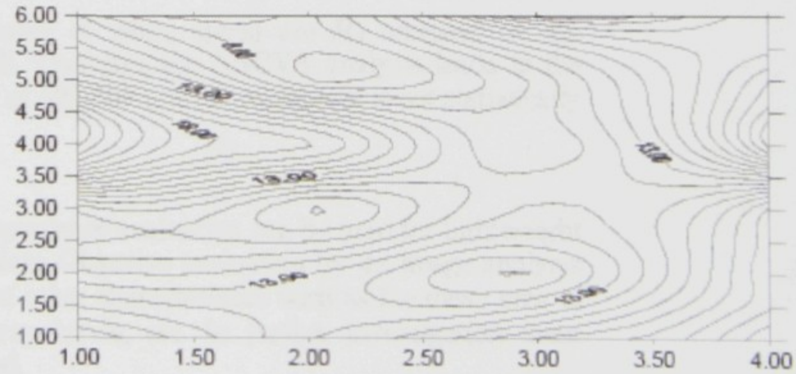


Figure 6.
Bivariate spline smoothed surface of *NW*

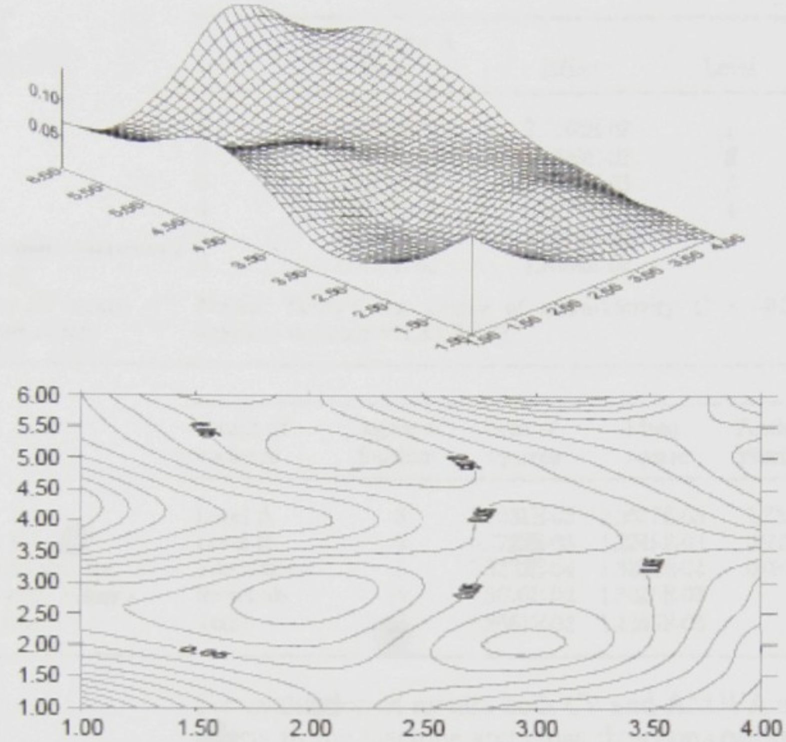


Figure 7.
Bivariate spline smoothed surface of *AF*

Characteristics	CV (total)	CV_L (machine direction)	CV_{HL} (transversal)
NE	0.1494245	0.0609795	0.1364155
NW	0.3944114	0.2029876	0.3381662
AF	0.5806934	0.2569274	0.5207620

Table I.
Coefficients of variation

Variables *NE* and *NW* (number of white spots) are H_0 accepted on the significance level 0.95 as well. Therefore the ANOVA analysis leads to the conclusion that the variability of *NE*, *NW* and *AF* in the cells is not statistically significant.

5. Conclusion

The proposed methods for appearance evaluation can be used for lightweight nonwovens without any problem. Objective evaluation by the image analysis allows identification of a lot of other characteristics such as the mean area of pores, objects with some gray levels, etc. In further investigation these characteristics will be also used.

Table II.
Porosity AF means and level effects

Factor A Level	Factor A Mean	Factor A Effect	Factor B Level	Factor B Mean	Factor B Effect
1	9.0583E-02	2.7163E-02	1	5.8900E-02	–4.5208E-03
2	4.8533E-02	–1.4888E-02	2	4.5650E-02	–1.7771E-02
3	6.5917E-02	2.4958E-03	3	4.0350E-02	–2.3071E-02
4	4.8650E-02	–1.4771E-02	4	8.2225E-02	1.8804E-02
5	7.3675E-02	1.0254E-02			
6	7.9725E-02	1.6304E-02			

Notes: Tukey's one degree of non-additivity $C = -8.3761$; Total mean = 6.3421E-02; Residual variance = 1.3626E-03

Table III.
ANOVA table for model with Tukey's interaction

Source of variance	Degree of freedom	Sum of squares	Mean square	Testing criterion	Conclusion H_0 is	Computed significant level
Level A	3	7.1031E-03	2.3677E-03	1.738	Accepted	0.205
Level B	5	6.3723E-03	1.2745E-03	0.935	Accepted	0.488
Interactions	1	1.3232E-04	1.3232E-04	0.097	Accepted	0.760
Residuals	14	1.9076E-02	1.3626E-03			
Total	23	3.2551E-02	1.4153E-03			

For evaluation of results both CV and ANOVA are suitable. The behavior of effects in the machine and cross directions computed by the ANOVA can be analyzed by regression methods (trends, nonlinearities, etc.).

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APPLICATION OF IMAGE ANALYSIS FOR NONWOVENS VISUAL IRREGULARITY EVALUATION

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The main aim of this work is attempt to describe visual irregularity (surface appearance) of light weight nonwoven textile structures. Visual and subjective methods for evaluation of visual irregularity of chemically bonded nonwovens are compared. The image analysis system LUCIA is used for estimation of characteristics describing visual irregularity. The analysis of subjective and objective estimates of visual irregularity is realized by the variation coefficient and by the ANOVA type model. The Moran's spatial autocorrelation index is used for identification of organized pattern in data.

KEYWORDS
Surface Appearance, Visual Irregularity, Porosity, Image Analysis

1. INTRODUCTION

Surface appearance (visual irregularity) is interesting for woven structures and in some cases for nonwovens as well. This characteristic is closely connected to the variation function for transparency, reflectivity, planar mass and to the another properties as e.g. air permeability.
Corresponding to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity.
The unevenness can be categorized according to the investigated characteristics to the following main groups:

- Mass unevenness (mostly used)
- Structural unevenness
- Visual (optical) unevenness
- Mechanical or physical properties unevenness
- Appearance unevenness.

There are some connections between above-mentioned categories of unevenness.
The main aim of this work is attempt to describe uniformity of appearance of light weight nonwoven textile structure. For quantification of appearance uniformity the characteristics of visual unevenness are used. These characteristics are measured by the image analysis and subjectively by the human eye. The evaluation of appearance uniformity is based on the variation coefficient estimation and on the ANOVA (analysis of variance) model. The organized patterns in data are checked by the Moran's spatial autocorrelation index.

2. UNEVENNESS CHARACTERIZATION

Traditional methods of uneveness characterization in two dimensions are based on the measurement of relative variance (variation coefficient) of some geometrical quantities between selected (rectangular) cells dividing the investigated area. The same principle can be used for visual irregularity estimation. In this work, the visual irregularity has been evaluated from selected visual characteristics measured in cells of defined size (see Fig.1). These rectangular cells divide the microscopic image of sample and create rectangular net.

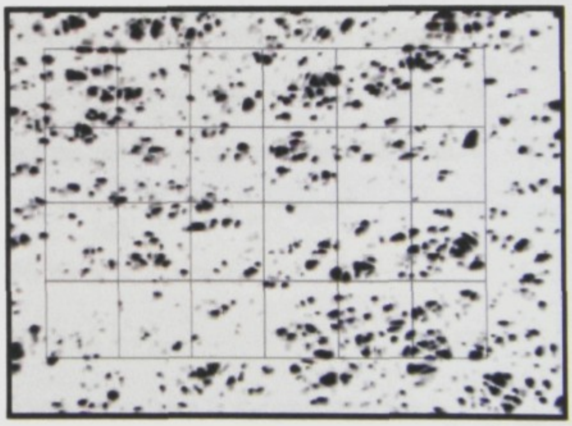

Figure 1 Inverted Image of tested sample (planar weight is $60 g/m^2$). White spots are here black.

As the visual characteristics of appearance unevenness in individual cells the following ones were selected:

- Number of white spots evaluated by the human eye NE
- Number of white objects NW evaluated by the image analysis (see white areas in the Fig.2)
- Relative surface porosity (portion of white area) AF defined on the Fig 2.

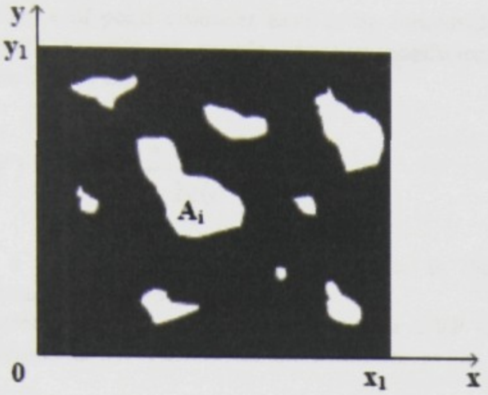

Figure 2 Definition of relative surface porosity (A_i is the area of white object)

The characteristics AF is computed from relations (see Fig. 2)

$$AP = \sum A_i$$

$$AE = x_i . y_i$$

$$AF = \frac{A_P}{A_E}$$

Samples (cells) were oriented in the following way (see Fig.1).

- Direction X is equivalent to the machine direction (cells denoted i). In this direction are N cells.
- Direction Y is equivalent to the cross direction (cells denoted j). In this direction are M cells.

Results of evaluation are rectangular data arrays NE_{ij}, NW_{ij}, AF_{ij}, $i = 1...n, j = 1...m$.
Appearance uniformity is analyzed by the following methods:

a) Coefficient of variation (CV)
b) Analysis of variance (ANOVA

Traditional method based on the variation coefficient is more suitable for characterization of degree of overall unevenness. Analysis based on the analysis of variance is useful for testing of evenness in selected orthogonal directions.

2.1 Analysis based on CV

Coefficient of variation is traditionally used as the characteristics of unevenness. According to the common definitions we can simply computed the overall mean

$$m = \frac{1}{MN}\sum_i \sum_j (P_{ij}) \quad (1)$$

variance

$$s^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m)^2 \quad (2)$$

and coefficient of variation

$$CV = \frac{s}{m} \quad (3)$$

Here P_{ij} is selected visual characteristic of appearance (NE_{ij} or NW_{ij} or AF_{ij}).
The quantity CV is external variation coefficient CB(F) between cell areas F
The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{io} = \frac{1}{M}\sum_j P_{ij}$$

$$m_{oj} = \frac{1}{N}\sum_j P_{ij}$$

Symbol „o" denotes index used for summation *i.e.* m_{io} is mean value for i th position in the machine direction. For the <u>machine direction</u> (expansion of eqn.(2) by using of the m_{io}) the following relation results [1]

$$s^2 = s_L^2 + s_{HL}^2 \quad (4)$$

where the variance in the machine direction is

$$s_L^2 = \frac{1}{N}\sum_i (m_{io} - m)^2 \quad (5)$$

and the variance in the transversal direction is

$$s_{HL}^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m_{io})^2 \quad (6)$$

For the <u>cross direction</u> is

$$s^2 = s_H^2 + s_{LH}^2 \quad (7)$$

where the variance in the cross-direction is

$$s_H^2 = \frac{1}{M}\sum_j (m_{oj} - m)^2 \quad (8)$$

and the variance in the longitudinal direction is

$$s_{LH}^2 = \frac{1}{MN}\sum_i \sum_j (P_{ij} - m_{oj})^2 \quad (9)$$

Dividing the corresponding standard deviations by the mean m the variation coefficients CV_L, CV_{HL}, CV_H and CV_{LH} results.
These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals

the variance of point estimates have to be computed. The rough formula of sample variation coefficient variance D(CV) has the form[2]

$$D(CV) = CV^2\left(\frac{c + CV^2(2c+1)}{2c(c-1)}\right)$$

where c = (N or M) is number of cells in the corresponding direction.

Asymptotic 95 %th confidence interval for CVP is then defined as

$$CV \pm 2\sqrt{D(CV)}$$

The coefficients of variation are statistically different in the cases when corresponding confidence intervals are not intersecting.

2.2 Analysis by the ANOVA

The P_{ij} can be interpreted as discrete presentations of random field on the discrete two-dimensional integer valued rectangular mesh [1]. Let the P_{ij} are described by the following model [2]

$$P_{ij} = \mu_{ij} + \varepsilon_{ij} \tag{10}$$

where μ_{ij} is true value in the ij cell and ε_{ij} is random error. The term μ_{ij} can be decomposed to the terms

$$\mu_{ij} = \mu + \alpha_i + \beta_j + c.\alpha_i.\beta_j \tag{11}$$

where μ is total mean α_i **are effects in the cross direction**, β_j **are effects in the machine direction** and c is constant of Tukey one degree of freedom non - additivity.[2]

Uniformity in the machine direction is equal to validity of hypotheses $H_0: \beta_j = 0, j = 1...M$

and uniformity in the cross direction is equal to validity of hypotheses

$H_0: \alpha_i = 0, i = 1...N$.

Testing of these hypotheses can be realized by the ANOVA (model with a single observation per cell). For the ANOVA model the following constraints are imposed

$$\sum_i \alpha_i = 0, \ \sum_{j=1} \beta_j = 0, \ \sum_i \alpha_i \beta_j = 0,$$

$$\sum_j \alpha_i \beta_j = 0$$

For the pure additive effects the interactions $\tau_{ij} = c.\alpha_i.\beta_j = 0$ and then

$$\hat{\alpha}_i = \frac{1}{M}\sum_j (P_{ij} - m)$$

$$\hat{\beta}_j = \frac{1}{N}\sum_i (P_{ij} - m)$$

where m is estimator of the total mean defined by the eqn.(1).

From residuals $\hat{e}_{ij} = P_{ij} - m - \hat{\alpha}_i - \hat{\beta}_j$ the parameter c can be simply estimated

$$c = \frac{\sum_i \sum_j \hat{e}_{ij}.\hat{\alpha}_i.\hat{\beta}_j}{\sum_i \sum_j \hat{\alpha}_i^2.\hat{\beta}_j^2} \tag{12}$$

For ANOVA testing the sum of squares due to machine direction (effects $\hat{\beta}_j$), cross direction (effects $\hat{\alpha}_i$) and due to interaction are computed and compared with total sum of squares $s * M * N$. Statistical tests based on the F-criterion may be performed [2]. According to the results of testing of the null hypothesis $H_0\ (\beta_j = 0 \ or\ \alpha_i = 0)$ the statistical uniformity in the machine and cross direction can be accepted or not.

When eqn. (10) is considered as the special regression model, the diagonal elements of projection matrix have the same value[2]

$$H_{ii} = \frac{N + M - 1}{N.M}$$

Outlying cells may be then detected by the standardized residuals

$$e_{Sij} = \frac{e_{ij}}{\sqrt{\sigma_R^2(1 - H_{ii})}}$$

where σ_R^2 is variance of error term estimated from residual sum of squares divided by corresponding degrees of freedom (NM-N-N). Roughly, if $e_{Sij} > 3$, the given cell is taken as an outlier.

2.3 Spatial autocorelation index

The spatial autocorrelation can be used for identification of association between values in neighboring cells. If the high values at one cell are associated with high values at neighboring cells the spatial autocorrelation is positive and when high values and low values alternates the spatial autocorrelation is negative. Lack of spatial autocorrelation means that there is no connection between cell values. The autocorrelation indices are simply cross products of spatial weights W_{ij} (connectivity or measures of contiguity between i-th and j-th cell) and some measures of proximity (distances between values P_i and P_j in the i-th and j-th cell). The original cell array P_{ij} is here replaced by the vector of length n = N*M where P_{ij} are included row-wise. The spatial weights depends on the research question. Standard is so called kings case when neighborhood of adjacent eight cells to the i-th one have $W_{ij} = 1$ and other cells have $W_{ij} = 0$. [5].

Moran [4] introduced the measure I analogous to the conventional correlation coefficient suitable for ordinal ratio and interval data.

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} * \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} * (P_i - \overline{P}) * (P_j - \overline{P})}{\sum_{i=1}^{n}\sum_{j=1}^{n} (P_i - \overline{P})^2} \tag{13}$$

Symbol $\overline{P}$ denotes arithmetic mean. Like a correlation coefficient the values of I range from −1 to 1 , where 0 meaning random pattern.

Under normality assumption is the mean value E(I) equal to

$$E(I) = \frac{-1}{n-1} \tag{14}$$

and variance D(I) is expressed in the form [5]

$$D(I) = \left(\frac{1}{S_0^2 (n-1)} (n^2 S_1 - n S_2 + 3 S_0^2 \right) - E(I)^2 \tag{15}$$

The following variables in the variance equation are defined as

$$S_0 = \sum_i \sum_j W_{ij}$$

$$S_1 = \frac{\sum_i \sum_j (W_{ij} + W_{ji})^2}{2}$$

$$S_3 = \sum_i (W_{i*} + W_{*i})^2$$

where W_{*i} is i-th row and W_{i*} is i-th column mean. The z score is then in the form

$$z = \frac{(I - E(I))}{\sqrt{D(I)}} \tag{16}$$

The random variable z has standardized normal distribution. If abs(z) > 2 is the assumption of spatial randomness rejected on the significance level 0.05.

3. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibers (VS) was prepared. Starting lap of planar weight 60 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding. The qualitative visual appearance unevenness of final structure is clearly visible on the Fig 3.

Figure 3 Tested nonwoven structure

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m = 0.5 mm By using of the microscope MEOFLEX (magnification 21 times) is lower bound of visible spots approximately equal to the 0.05 mm.

This subjective visual evaluation was used for above-mentioned nonwoven structure.

The microscope image of sample was divided to the net consisted of the 25 rectangular mesh (dimension 2 x 2 mm). The number of spots NE_{ij} in the ij - th mesh having maximal illumination was evaluated by the direct visual inspection [3].

The basic statistical characteristics of NE are:

- sample mean = 12.38 spots
- coefficient of variation CV_n = 15.78 %.

From the combination of six microscope images the areas of the same level of local numbers of white spots are shown graphically on the fig. 4.

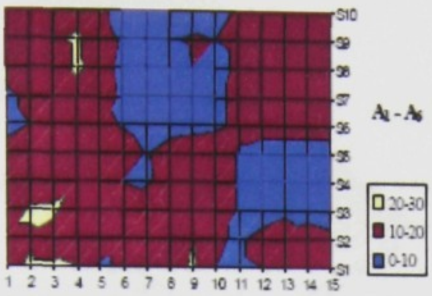

Figure 4 Areas of the same levels of numbers of white spots.

From the fig 4 the areas of the same level of white spots concentration are visible.

For creation of the smooth surface of white spots concentration the cubic bivariate spline smoothing technique has been used. The smoothed surface of NE for one image is shown on the fig 5.

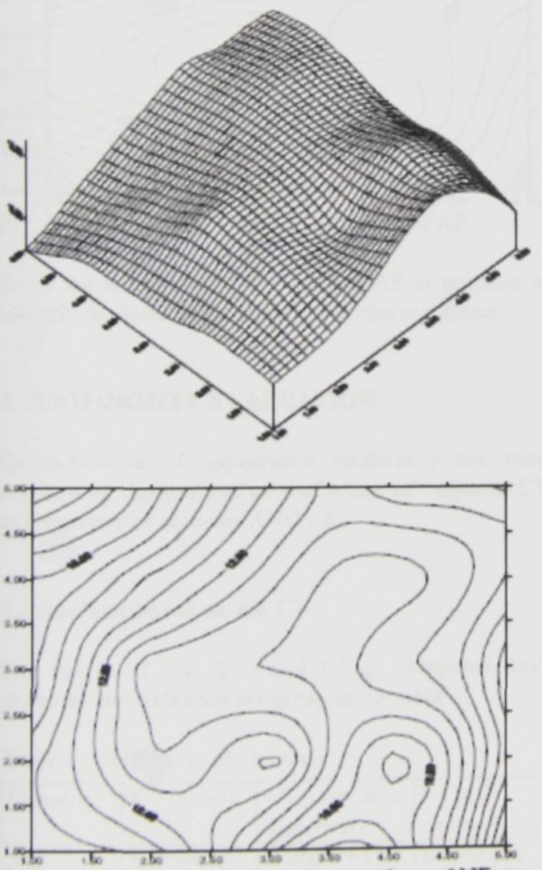

Figure 5 Bivariate spline smoothed surface of NE

3.2 Application of the Image Analysis

Subjective visual evaluation of white spots number is very tedious and subjected by the errors. The image analysis system is suitable for objective visual estimation. The system consists of microscope, CCD camera and personal computer has been used.

The treatments of digital images were made by the software LUCIA-M. This software is designed for analysis of the high color (3x5 bits) images having resolution of 752x524 pixels. The threshold value 62 (all gray patterns are converted to the black ones) has been chosen. The rectangular net dividing the image into equal cells has been defined by the same way as at subjective visual evaluation.

The following characteristics of appearance uniformity have been evaluated in each cell:

- number of white spots NW
- relative porosity AF

Bivariate spline smoothed surface of NW is shown on the fig 6 and for AF on the fig. 7.

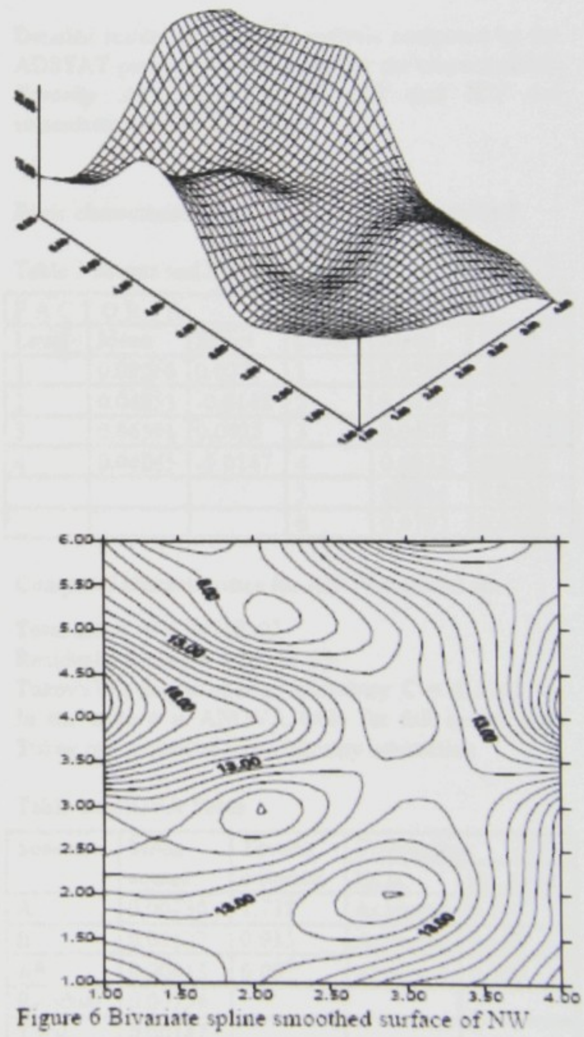

Figure 6 Bivariate spline smoothed surface of NW

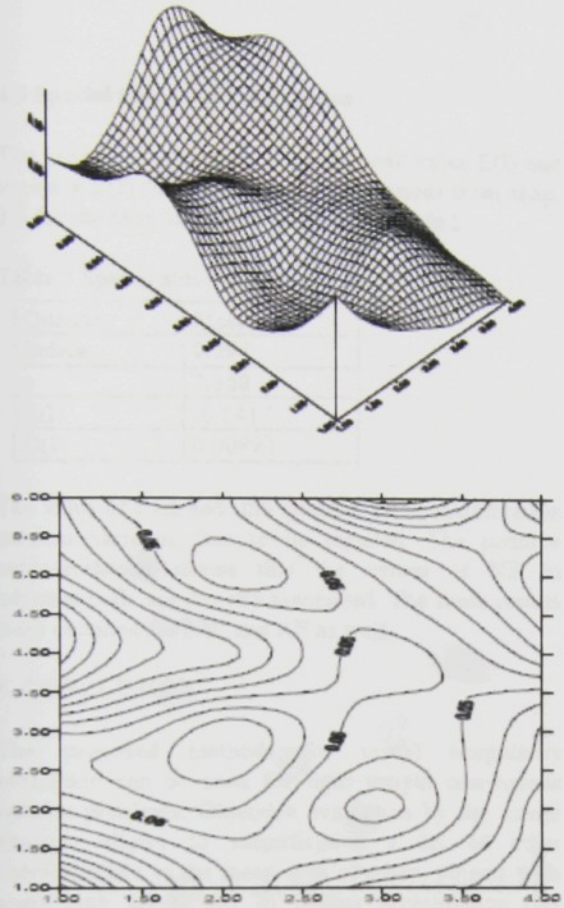

Fig. 7 Bivariate spline smoothed surface of AF

From the surfaces of NE, NW and AF is possible to identify the local variation of these characteristics.

4. UNIFORMITY EVALUATION

Quantification of appearance uniformity has been realized by the analysis of coefficient of variation CV and analysis of variance ANOVA.

4.1 Analysis based on the CV

The values of CV, CV_L and CV_{HL} computed from above defined relations are given in the table 1.

Table 1 Coefficients of variation

Quantity	CV (total)	CV_L(machine direction)	CV_{HL} (transversal)
NE	0.1494245	0.0609795	0.1364155
NW	0.3944114	0.2029876	0.3381662
AF	0.5806934	0.2569274	0.520762

Computed 95 %th confidence intervals for CVP are given in the table 2

Table 2 Computed 95 %th confidence intervals for CVP

Quantity	CV_L(machine direction)	CV_{HL} (transversal)
NE	0.061±0.044	0.136±0.041
NW	0.203±0.150	0.338±0.109
AF	0.257±0.189	0.521±0.187

From the table 2 is clear that for all characteristics are confidence intervals for CVP_L and CVP_{HL} intersected The differences between coefficients of variation are therefore statistically insignificant.
The objective visual characteristics are closer that the subjective number of holes NE and objective number of white areas NW. This differences are probably due to higher resolution of image analysis system in comparison with human eye.

4.2 Analysis based on the ANOVA

Detailed results of ANOVA analysis computed by the ADSTAT package are presented for the characteristics ***Porosity AF*** only. For the NE and NW are summarized results of testing.

POROSITY AF

Basic characteristics are summarized in the table 3.

Table 3 Means and Level Effects

FACTOR A			FACTOR B		
Level	Mean	Effect	Level	Mean	Effect
1	0.09068	0.0272	1	0.0589	-0.0045
2	0.04853	-0.0148	2	0.0456	-0.0177
3	0.06591	0.0025	3	0.0403	-0.0231
4	0.04865	-0.0147	4	0.0822	0.0188
			5	0.0736	0.0102
			6	0.0797	0.0163

Computed characteristics for ANOVA model are

Total mean = 6.3421E-02
Residual variance = 1.3626E-03
Tukey's one degree of non - additivity C = -8.3761
In the table 4 is ANOVA table for full model with Tukey one degree of non additivity interaction

Table 4 ANOVA Table

Source	Mean square	Testing criterion	Conclusion: H_0 is	sig. level
A	0.00236	1.738	Accepted	0.205
B	0.00127	0.935	Accepted	0.488
AB	0.00013	0.097	Accepted	0.760
Residual	0.00136			
Total	0.00142			

For variables NE and NW (number of white spots) are H_0 accepted on the significance level 0.95 as well. Therefore the ANOVA analysis leads to conclusion that the variability of NE, NW and AF in the cells are ***not statistically significant***.

4.3 Spatial autocorrelation index

The Moran's I and corresponding mean value E(I) and variance D(I) computed according relations from chap. 2.3 for the case of NE are given in the table 5.

Table 5 Spatial autocorrelation index for NE

Quantity	Moran
Indice	0.294
z	3.368
E(I)	-0.0417
D(I)	0.00993

The value of z exceeds the quantity 2 and therefore the random variation has to be rejected. The positive autocorrelation shows that the values of NE in adjacent cells are directly associated. The same results were obtained for NW and AF as well.

5. CONCLUSION

The proposed methods for visual irregularity evaluation can be used for light weight nonwovens without problems. Objective evaluation by the image analysis allows to identification a lot of other characteristics as the mean area of pores, objects with some gray levels etc. In further investigation this characteristics will be also used.

For evaluation of results both CV and ANOVA are suitable. The behavior of effects in the machine and cross directions computed by the ANOVA can be analyzed by the regression methods (trends, nonlinearitiers etc.). The spatial autocorrelation index I can be used for check of random variation of visual irregularity characteristics in cells.

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VYJÁDŘENÍ PLOŠNÉ NESTEJNOMĚRNOSTI NETKANÝCH TEXTILIÍ

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Abstrakt: V příspěvku je uveden způsob popisu nestejnoměrnosti netkaných textilií vycházející z teorie náhodných polí. Pro vyjádření základních charakteristik těchto polí je využito stanovení druhých momentů. Je ukázán způsob vyjádření anizotropie těchto náhodných polí. Tento způsob popisu plošné nestejnoměrnosti je použit pro analýzu gravimetrických měření.

1. Úvod

Dosavadní vývoj v oboru netkaných textilií potvrdil, že díky stále nevyčerpaným výrobkovým inovacím a velké variantnosti surovinových, technologických a výrobních možností, poroste také jejich široké uplatňování v náročnějších podmínkách nejen konečné spotřeby, ale i v mnoha zpracovatelských oborech.

U netkaných textilií pro technické aplikace jsou kladeny stále vyšší požadavky na stejnoměrnost hodnot jejich základních vlastností.

Byly vypracovány metody určování anizotropie, textury a dalších specifických parametrů charakterizujících strukturu netkaných textilií.[1] V literatuře existuje značné množství informací z oblasti stejnoměrnosti vlastností lineárních textilií a některých analogicky používaných poznatků pro jednotlivé případy řešení stejnoměrnosti vlastností netkaných textilií. V práci [4] je uvedena studie, která se zabývá problematikou kontinuálního a diskontinuálního měření stejnoměrnosti plošné hmotnosti netkaných textilií. Průmyslové použití kontinuálních měřících zařízení se stalo snadno dostupné a tvoří on-line integrované měřící a regulační systémy výrobních linek.

Hodnocení stejnoměrnosti plošné hmotnosti gravimetricky je v současné době základním normovaným postupem. Proto bylo v tomto příspěvku použito pro demonstraci využití aparátu náhodných polí pro popis plošné nerovnoměrnosti.

2. Náhodné pole plošné nestejnoměrnosti

Pro popis plošné nestejnoměrnosti netkaných textilií je vhodné zavést pojem plošná hustota [2]. Plošná hustota z(x,y) v místě o souřadnicích x,y je definována jako limita podílu hmotnosti M(S) a plochy S =4dxdy elementárního kvádru o výšce rovné tloušťce textilie t a příčných rozměrech x ± dx a y ± dy

$$z\,(x,y) = \lim_{S \to 0} \frac{M\,(S)}{S} = t * \rho\,(x,y) \qquad (1)$$

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kde $\rho(x,y)$ je hustota plošné textilie v místě x,y. Veličina $z(x,y)$ je náhodná funkce dvou proměnných označovaná také jako náhodné pole.
Ze statistického hlediska je náhodné pole úplně popsáno n - rozměrnou hustotou pravděpodobnosti

$$p_n(z_1, z_2, .. z_n) = P\{z_i \le z(x_i, y_i) \le z_i + dz_i, \quad i = 1..n\} \tag{2}$$

Pokud je p_n invariantní vůči posunu obou souřadnic jde o *homogenní náhodné pole*. Pokud je p_n invariantní vůči posunu souřadnic pouze ve směru osy x jde o *příčnou homogenitu* a pokud je invariantní vůči posunu souřadnic pouze ve směru osy y jde o *podélnou homogenitu*.
Pro vyjádření variability náhodného pole se používá korelační funkce $R(x_1,x_2,y_1,y_2)$, pro kterou platí

$$R(x_1, x_2, y_1, y_2) = \iint (z_1 - E(z_1))(z_2 - E(z_2))\, p_2(z_1, z_2)\, dz_1\, dz_2 \tag{3}$$

kde střední hodnota $E(z_1)$ je z definice rovna

$$E(z) = \int z\, p_1(z)\, dz \tag{4}$$

Pro homogenní náhodná pole je korelační funkce závislá pouze na vzdálenosti mezi body (x_1,y_1) a (x_2,y_2), tedy

$$R(x_1, x_2, y_1, y_2) = R(x_2 - x_1, y_2 - y_1) \tag{5}$$

Analogické vztahy platí pro příčnou a podélnou homogenitu. Pro izotropní náhodné pole je korelační funkce invariantní vůči rotaci a zrcadlovému otočení a závisí tedy pouze na délce vektoru $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$, tedy

$$R(x_1, x_2, y_1, y_2) = R(d) \tag{6}$$

Informace o náhodných polích se získávají na základě náhodné sekvence povrchových hustot $z(i,j)$ určených na pravoúhlé síti, kde i,j (i = 1...m, j = 1...n)definuje i,j -tou celu. Pro odhad korelační funkce pak platí [3]

$$R(K, L) = \frac{1}{(m-K)(n-L)-1} \sum_{i=1}^{m-K} \sum_{j=1}^{n-L} (z(i+K, j+L) - \bar{z})(z(i,j) - \bar{z}) \tag{7}$$

kde

$$\bar{z} = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} z(i,j) \tag{8}$$

je průměrná hodnota plošné hustoty. Je zřejmé, že korelační funkce R(0,0) = D(z(i,j)). Zde symbol D(z(i,j)) označuje výběrový rozptyl plošné hustoty.
Pro Gaussovské náhodné pole má korelační funkce tvar [2]

$$R(d_x, d_y) = \exp(-a|d_x| - b|d_y|) \qquad (9)$$

kde $d_x=x_2-x_1$ a $d_y=y_2-y_1$ a koeficienty a,b jsou parametry náhodného pole.

Jako základní charakteristika nehomogenity povrchové hustoty se používá koeficient anizotropie An definovaný vztahem

$$An = \frac{Km}{Lm} \qquad (9)$$

kde Km a Lm jsou intervaly korelace t.j. minimální hodnoty K a L pro které platí, že

$$R(Km,0) \leq 0.05 * R(0,0) \quad \text{resp.} \quad R(0,Lm) \leq 0.05 * R(0,0)$$

Lze ukázat, že Km a Lm souvisejí s parametry Gaussovského pole podle vztahů

$$a = \frac{3}{Km} \quad \text{resp.} \quad b = \frac{3}{Lm}$$

Je zřejmé, že při znalosti odhadu korelační funkce je možné poměrně snadno určit charakteristiku anizotropie i parametry Gaussovského pole.

Pro výpočet odhadu korelační funkce z rov. (7) a určení intervalů korelace Km, Lm byl sestaven program v jazyce MATLAB 5.3.

3. Experimentální část

K hodnocení stejnoměrnosti byly použity chemicky pojené textilie obchodního názvu Perlan, vyrobené ze 100% viskózové střiže, dvou jemností, zpevněné akrylátovým pojivem. Jejich technická aplikace, například v elektrotechnickém průmyslu pro výrobu hydroizolačních pásek, je podmíněna zaručenou spolehlivostí v podélné pevnosti a tažnosti. V upraveném stavu jsou u této netkané textilie požadovány zaručené hodnoty v elektrické průrazné pevnosti, nasákavosti a pevnosti v přetrhu. Všechny tyto vlastnosti souvisejí se stejnoměrností uspořádání vlákenných složek a pojiva.

Vlákenná vrstva za pneumatickým rouno tvořičem byla v hmotnostním poměru 67/33 (VSs 3,1 dtex/60 mm a 1,6 dtex/40mm). Nanášení zpěněné akrylátové disperze bylo provedeno na fuláru se sušením se na bubnové sušárně.[4]

Složení hotové netkané textilie je uvedeno v tabulce 1. Odhad anizotropie uspořádání vlákenných složek vychází na základě poměru hodnot příčné a podélné pevnosti v rozmezí 1:2 až 1:3. Vybarvovací zkouška akrylátového podílu pojiva potvrdila, že rozložení pojiva kopíruje vstupní stejnoměrnosti vlákenné vrstvy.

Tabulka 1 Složení pojené textilie Perlan

Složka	hodnota
pojená textilie	30, 40, 50, 60 g/m^2
vlákno - VSs 3,1 dtex	49 %
vlákno - VSs 1,6 dtex	25 %
sušina pojiva - Sokrat 4924	20 %
vlhkost - voda	6 %

Nestejnoměrnost vzhledu je dobře patrná z obr.1

Obr. 1 Stejnoměrnost vlákenné vrstvy v pojené textilii plošné hmotnosti 60 g m^{-2}

Vzorky pro gravimetrická měření byly odebrány ve tvaru čtverců rozměrů 100 x 100 mm. Tyto vorky byly rozděleny na rektangulární síť o velikosti cely 10 x 10 mm. Pro textilii o plošné hmotnosti 60 g/m^2 má cela plošného obsahu S_j = 100 mm^2 hmotnost kolem 6 mg. Kontrola přesnosti přípravy cel, byla provedena na náhodném výběru 25 vzorků.. Relativní chyba velikosti cely se pohybovala od 0,88% do 1,22%. Hmotnost každé cely m_{ij} byla určena jako průměr z pěti vážení. Maximální relativní chyba vážení u vzorku 60 g/m^2 byla 1,606%.

V tab. 2 jsou uvedeny hodnoty m_{ij} pro vzorek pojené textilie plošné hmotnosti 60 g m^{-}

Tabulka 2 Průměrné hmotnosti cel pojené textilie plošné hmotnosti 60 g m^{-2}

Průměrná hmotnost m_{ij} [10^{-4} g]									
60	60	55.7	56	57.8	53.8	67	62.7	69.2	63.2
58.1	68.8	68.1	66.1	66.1	54.9	52.1	51.8	64.2	65.3
61.1	63	53.4	60.1	60.4	56.1	56	57	55.7	55
51.1	51.9	53.8	55.4	56.1	51	57.1	54.8	55.4	61.4
55.5	57.1	53.1	56.8	59.7	57.2	61	51.6	55.8	57.1
54.8	51.2	60	59.1	53.1	54.6	61	62.7	61.6	52.1
52.4	58.2	59.2	53.1	62.2	63.4	63.2	54.8	54.8	58
59	63.9	58.1	58	67	56.3	61.8	65	58.1	53.5
70	63.4	71	64.3	51.3	56	59.5	58	51	62.2
69.3	73	65	57	57.2	63	56	62	61	60

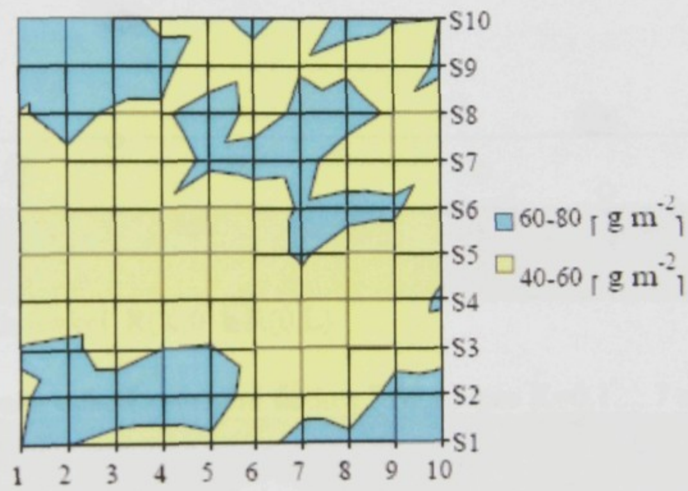
4. Výsledky a diskuse

Vzhledem k tomu, že byla použita stejná velikost cel o ploše $S_j = 100$ mm^2 je p hustota $z_{ij} = m_{ij} / S_j$ v [g m^{-2}] číselně rovna hodnotám v tab. 2. Základní statistické charakteristiky tohoto pole plošná hustoty jsou uvedeny v tab. 3

Tabulka 3. Základní statistické charakteristiky plošné hustoty

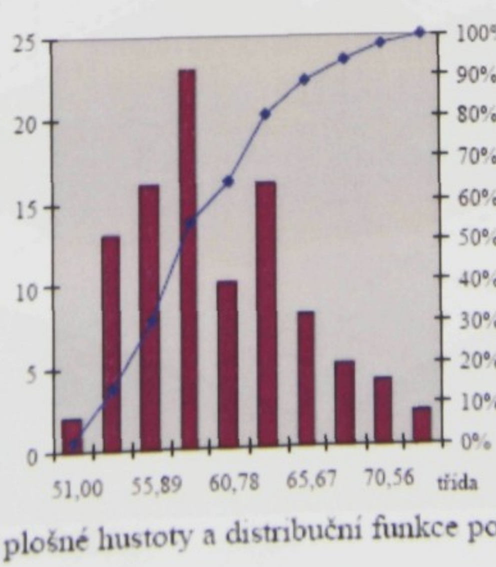
Počet hodnot	100	rozměr
Průměr	58.92	[g m^{-2}]
Maximální hodnota	73	[g m^{-2}
Minimální hodnota	51	[1 g m^{-2}]
Směrodatná odchylka	5,12	[g m^{-2}]
Variační koeficient	8.68	[%]

Graficky je kolísání povrchové hustoty znázorněno na obr. 2



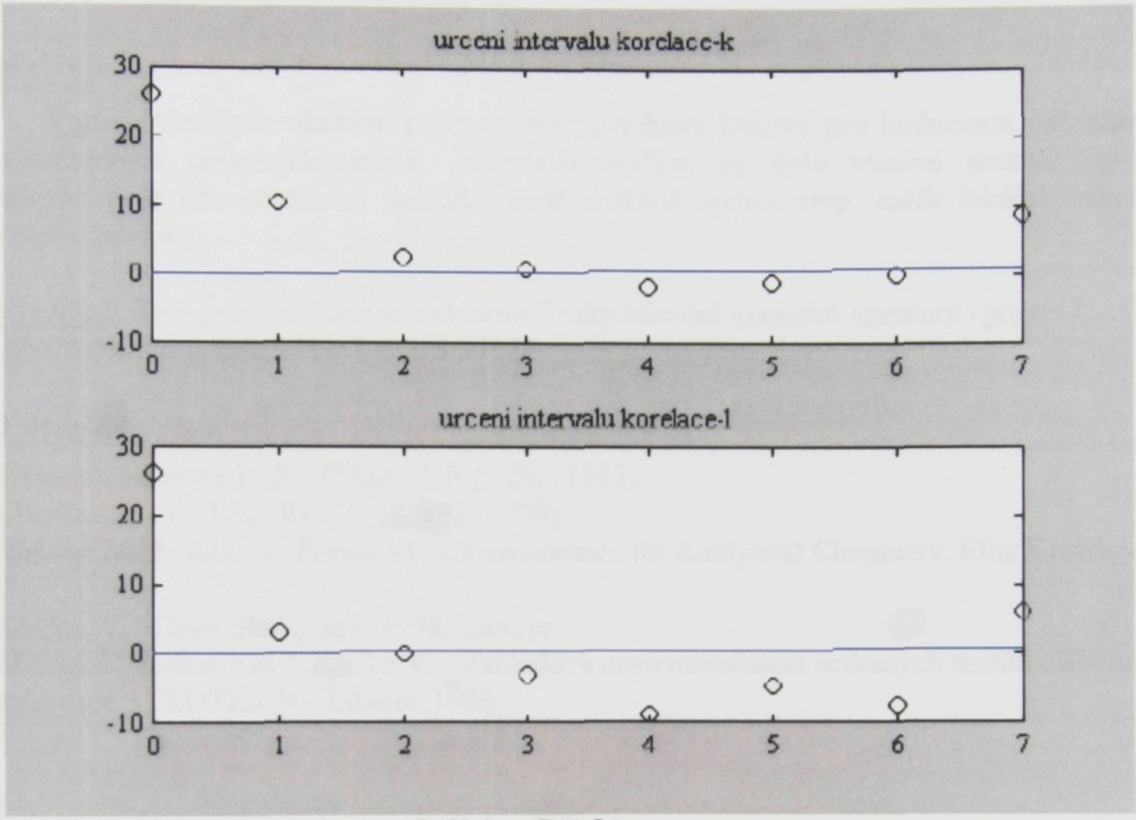
Obr. 2 Kolísání plošné hustoty pojené textilie 60 g m^{-2}

Na obr.3 je uveden histogram plošné hustoty naměřených hodnot a distribuční funkce



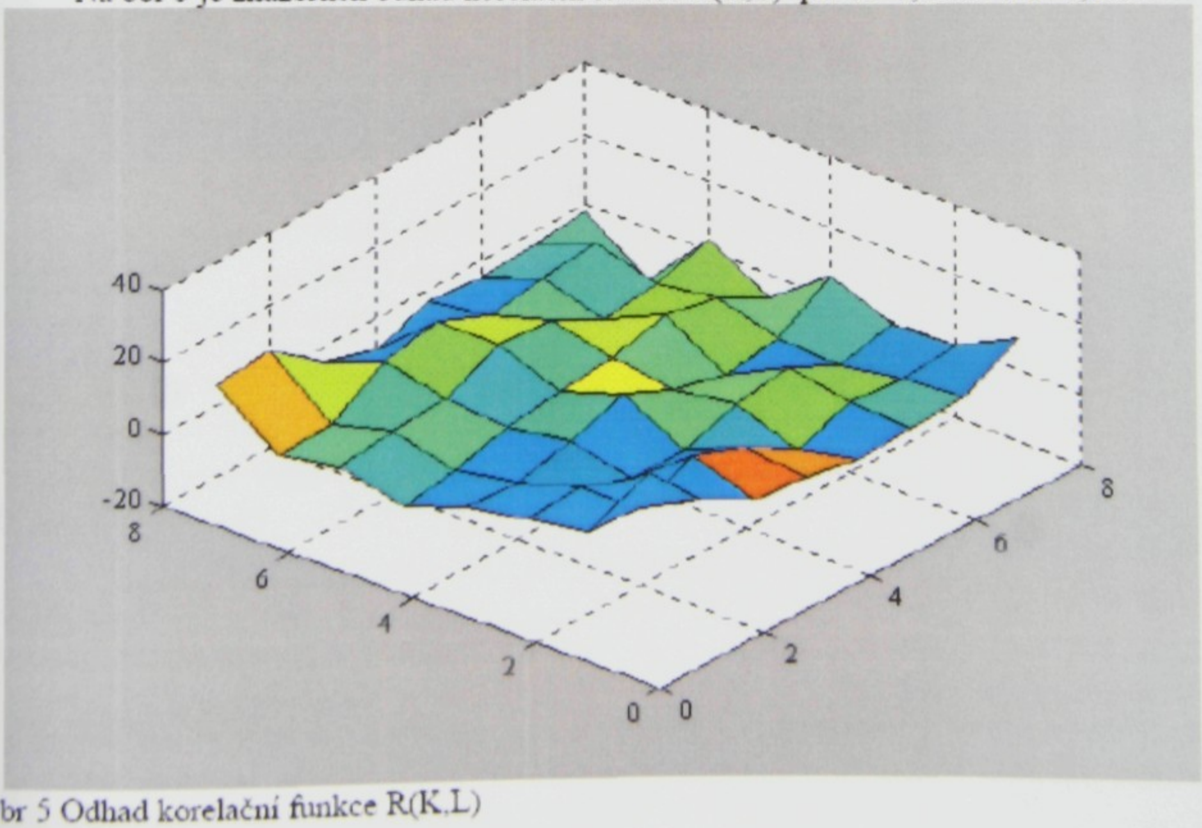
Obr. 3 Rozdělení četnosti plošné hustoty a distribuční funkce pojené textilie 60 g m^{-2}

Na obr 4 jsou uvedeny průběhy korelačních funkcí R(K,0) a R(0,L) spolu s limit hodnotou 0.005*R(0,0). Je patrné, že intervaly korelace jsou Km=3 a Lm=2. Inde anizotropie je pak podle rov.(9) roven An=1.5.



Obr 4. Průběhy korelačních funkcí R(K,0) a R(0,L)

Na obr 5 je znázorněn odhad korelační funkce R(K,L) pro K=0,1.....7 a L=0,1...7.



Obr 5 Odhad korelační funkce R(K,L)

Z uvedeného je patrné, že pole povrchové hustoty je mírně anizotropní a vykazuje lokální neregularity. To bylo potvrzeno také analýzou založenou na vizuální nestejnoměrnosti [2]. Index anizotropie převyšuje jedničku, ale velmi nevýrazně. Na druhé straně hraje roli poměrně malý počet buněk rektangulární sítě.

6. Závěr

V příspěvku bylo ukázáno použití pole povrchové hustoty pro hodnocení povrchové nestejnoměrnosti netkaných textilií. Pro další analýzu by bylo vhodné sestavit model náhodného pole pro strukturní jednotky dané netkané textilie resp. měřit lokální kolísání povrchové hustoty.

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SPATIAL VARIATION OF NONWOVENS SURFACE DENSITY

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1. INTRODUCTION

The products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exists a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1,2]. Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation [4]. Basic on is direct measurement of local planar mass variation by weighting (gravimetric method). The extension of linear textiles uniformity based on the variation coefficient CV to the planar case is frequently used [2].

In this contribution the planar uniformity is described on the base of random field theory and spatial autocorrelation indices.

2. RANDOM FIELD OF PLANAR UNEVENNESS

The planar density z(x,y) describes sufficiently the planar uniformity or unevenness [2]. The quantity z(x,y) in thec point x,y is defined as limit of mass M(S) divided by the area S =4dxdy of elementary rectangle i.e. the cross sectional area of volume element having thickness t (thickness of nonwoven) and perpendicular dimensions x ± dx and y ± dy. Formally

$$z(x,y) = \lim_{S \to 0} \frac{M(S)}{S} = t * \rho(x,y) \tag{1}$$

where $\rho(x,y)$ is planar textile density in the point x,y. Quantity z(x,y) is random function of two variables called random field. This random field is fully described by the n variate probability density function

$$p_n(z_1, z_2, .. z_n) = P\{z_i \le z(x_i, y_i) \le z_i + dz_i, \quad i = 1..n\} \tag{2}$$

Homogeneous random field has property of invariance according to the translation. *Variability* of random field is characterized by the correlation function

$$R(x_1, x_2, y_1, y_2) = \iint (z_1 - E(z_1)(z_2 - E(z_2)\, p_2(z_1, z_2)\, dz_1\, dz_2 \tag{3}$$

The mean value $E(z_1)$ is defined as

$$E(z) = \int z\, p_1(z)\, dz \tag{4}$$

For *homogeneous random field* is correlation function dependent on the distance between poins (x_1, y_1) and (x_2, y_2) only. For this case is valid

$$R(x_1, x_2, y_1, y_2) = R(x_2 - x_1, y_2 - y_1) \tag{5}$$

For isotropic random field is correlation function invariant against rotation and mirroring . This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore

$$R(x_1, x_2, y_1, y_2) = R(d) \tag{6}$$

For computation of correlation function the experimentally determined values of planar densities z(i,j) of i,j th cell (i = 1...m, j = 1...n) of the rectangular net are used. The estimate of the correlation function is then defined by the relation [3]

$$R(K, L) = \frac{1}{(m-K)(n-L)-1} \sum_{i=1}^{m-K} \sum_{j=1}^{n-L} (z(i+K, j+L) - \overline{z})(z(i, j) - \overline{z}) \tag{7}$$

The arithmetic mean of surface density has the form

$$\overline{z} = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} z(i, j) \tag{8}$$

It is simple to derive that correlation function R(0,0) = D(z(i,j)) is equal to the variance D(z(i,j)) of the surface density. For the Gauss random field is correlation function dependent on the differences $d_x = x_2 - x_1$ a $d_y = y_2 - y_1$ only [2]

$$R(d_x, d_y) = \exp(-a|d_x| - b|d_y|) \tag{9}$$

For characterization of the random field non homogeneity the anisotropy coefficient An defined by relation

$$An = \frac{Km}{Lm} \tag{9}$$

is used. The Km and Lm correlation are intervals i.e. minimal values K and L for which is valid

$$R(Km, 0) \le 0.05 * R(0,0) \quad \text{resp.} \quad R(0, Lm) \le 0.05 * R(0,0) \tag{10}$$

The parameters Km and Lm are connected with parameters of the Gauss random field by relations

$$a = \frac{3}{Km} \quad \text{and.}\ b = \frac{3}{Lm} \tag{11}$$

Based on the estimate of correlation function is therefore straightforward to describe anisotropy characteristics An. For estimation of the correlation function and computation of anisotropy characteristics the program in MATLAB 5.3 language has been created.

2. SPATIAL AUTOCORELATION

The spatial randomness in the plane can be expressed by the spatial autocorrelation indices. For definition of spatial autocorrelation some measure of contiguity is required. Simple contiguity measures are defined as neighborhood relations. The kings case considering neighborhood of eight cells was used in this work. The connectivity (spatial weight) matrix W contains elements Wij = 1, if i-th and j-th cell are neighborhood or Wij = 0 if i-th and j-th cell are far each other.

Let the value Zk = z(i,j) for k = i + m*(j-1) are surface densities z(i,j) arranged columnwise. The Geary autocorrelation index is defined by relation [3]

$$c = \frac{N-1}{2*\sum_i\sum_j W_{ij}} * \frac{\sum_i\sum_j W_{ij}*(Z_i - Z_j)^2}{\sum_i (Z_i - Zm)^2}$$

(12)

where Zm is arithmetic mean of all cells surface densities. The statistics c is defined in the range from 0 to 2. Negative spatial autocorrelation is for c>1 and positive spatial autocorrelation is for c<1. Mean value (spatial randomness) is equal to E(c) = 1. Variance D(c) based on the approximate normality is defined as

$$D(c) = \frac{(N-1)*(2*S_1 + S_2) - 4*S_0^2}{S_0^2*2*(N+1)} \qquad (13)$$

Individual symbols in eqn. (13) are defined as

$$S_0 = \sum_i\sum_j W_{ij} \quad S_1 = \frac{1}{2}\sum_i\sum_j (W_{ij} + W_{ji})^2 \quad S_2 = \sum_i (W_{i*} + W_{*i})^2$$

Symbol Wi* denotes i-th row and W*i denotes i-th column of matrix W. Random variable

$$Z(c) = \frac{c-1}{\sqrt{D(c)}}$$

has approximately standardized normal distribution. If absolute value abs(Z(c))≥2 the significant autocorrelation occurs

3. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibers (VS) was prepared. Starting lap of planar weight 60 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding

The rectangular samples of dimensions 100 x 100 mm (area Aj = 100 mm^2 and weight 6 mg) were cut for further analysis [3].These samples were divided to the rectangular net having dimensions of individual cells 10 x 10 mm. Relative error of cell dimensions was in the interval from 0.88% to 1,22%. The weight m_{ij} of i,j th cell has been computed as mean from five parallel weightings. Maximal relative error of weighing was 1,606%.

4. RESULTS AND DISCUSSION

From the weights m_{ij} and cell area S_j = 100 mm^2 the surface densities z_{ij} = m_{ij} / S_j v [g m^{-2}] have been computed. Basic statistical characteristics of resulted random field of surface density are given in the table 1

Number of values	100	dimension
Mean	58.92	[g m^{-2}]
Standard deviation	5,12	[g m^{-2}]
Variation coefficient	8.68	[%]

The intervals of correlation are Km=3 a Lm=2 and therefore An=1.5.The bivariate autocorrelation unction R(K,L) for K=0,1.....7 and L=0,1...7 is given on the fig.2.

It is clear that the random field of surface density is slightly anisotropic and has local nonregularities. The index of anisotropy is not so far from one. The Geary index c = 0.768, D(c)= 0.0037and the standard normal one is Z= -3.79 The value of c is below 1 and therefore the random variation has to be rejected. The positive autocorrelation shows that the values of surface densities z(i,j) in adjacent cells are directly associated. The spatial randomness has to be therefore omitted

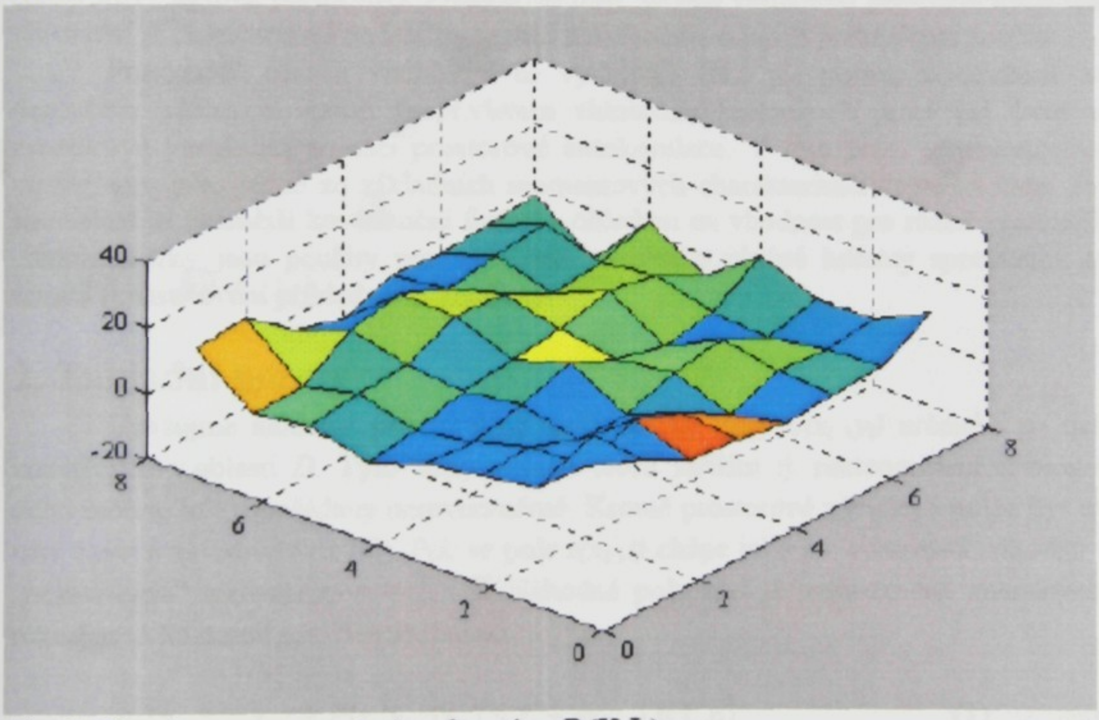

Fig. 2 Bivariate autocorrelation function R(K,L)

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PROSTOROVÁ STATISTIKA A NESTEJNOMĚRNOST PLOŠNÉ HMOTNOSTI NETKANÝCH TEXTILIÍ

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Abstrakt: Jsou uvedeny základní možnosti popisu fyzikálních vlastností, u kterých hraje významnou roli prostorové uspořádání textilií. Tato data se chápou jako náhodné pole a pro vyjádření jeho variability se používá momentových charakteristik druhého řádu. Je diskutováno použití *prostorové kovariance* (globální variabilita) a méně známého *variogramu* (lokální variabilita) resp. jeho variant. Jsou popsány způsoby konstrukce těchto charakteristik z experimentálních dat. Jsou uvedeny možnosti parametrickmého vyjádření variogramu. Tyto charakteristiky jsou použity pro vyjádření kolísání lokální plošné hmotnosti netkaných textilií.

1. Úvod

Celá řada fyzikálních vlastností plošných textiliích je závislá na místě a někdy i na čase (prostorově časové proměnné). Prostorová resp. plošná variabilita geometrických resp. jiných vlastností je charakteristikou kvality textilií a rozhoduje o jejich praktickém použití.

Prostorově časová variabilita se vyskytuje také při popisu opotřebení, stárnutí a degradace plošných textilií (např.vlivem slunečního záření). V práci [1] byla sledována prostorová variabilita pomocí prostorové autokorelace. V této práci je diskutováno použití variogramu jako jedné ze základních momentových charakteristik druhého řádu. Je ukázána souvislost se známější kovarianční funkcí s ohledem na vhodnost pro různé situace. Navržené charakteristiky jsou použity pro vyjádření variability plošné hustoty speciálních netkaných textilií (pokračování příkladu z práce [1].)

2. Základní pojmy

Uvažujme náhodné pole $z(x)$ se složkami $z_i= z(x_i)=z(x_i ,y_i)$ určené v *p- tici* bodů x_i umístěných v oblasti D. Tyto body mohou tvořit mřížku tj. rektangulární rovnoměrnou síť nebo mohou být uspořádány nerovnoměrně. Kromě prostorové závislosti může být uvažována také časová závislost (viz [2]). Pak se pole $z(x_i ,t)$ chápe jako p – rozměrná náhodná veličina s „nezávislými" realizacemi $t = 1,\ T$. Náhodné pole $z(x)$ je jednoznačně charakterizováno p rozměrnou hustotou pravděpodobnosti

$$p_n(z_1, z_2,..z_n) = P\{z_i \le z(\mathbf{x}_i) \le z_i + dz_i,\ \ i = 1..n\} \qquad (1)$$

Důležitý je pojem *homogennní náhodné pole* , které je invariantní vůči posunu. V případě prostorově-časových polí se obyčejně uvažuje časová homogenita.
Střední hodnota $m(x_i) = E(z_i)$ náhodného pole v místě x_i je definována vztahem

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$$E(z_i) = \int z_i \, p(z_i) \, dz_i \tag{2}$$

Pro vyjádření variability se standardně používá *kovariance* jako druhý smíšený centrální moment

$$C_{ij} = \iint (z_i - E(z_i))(z_j - E(z_j)) \, p(z_i, z_j) \, dz_i \, dz_j$$

resp.

$$C_{ij} = E(z(x_i) * z(x_j)) - E(z(x_i) * E(z(x_j)) \tag{3}$$

Pro případ, kdy jsou oba body x_i a x_j totožné resultuje z rov. (3) rozptyl $D(x_i)$, který lze vyjádřit ve tvaru

$$D(z(x_i)) = C_{ii} = E(z(x_i)^2) - (E(z(x_i)))^2 \tag{4}$$

Speciálně pro vyjádření prostorové nepodobnosti mezi hodnotami v místech x_i a x_j byl zaveden *variogram* resp. *semivariogram*, který je definován jako polovina rozptylu přírůstku $(z(x_i) - z(x_j))$

$$\Gamma_{ij} = 0.5 * D[z(x_i) - z(x_j)]$$

resp.

$$\Gamma_{ij} = 0.5 * [E(z(x_i) - z(x_j))^2 - (E(z(x_i) - z(x_j))^2]$$

Pro *stacionární* náhodné pole je střední hodnota v jednotlivých bodech konstantní tj. $E(z(x_i)) = m$. *Pak je*

$$\Gamma_{ij} = 0.5 * E(z(x_i) - z(x_j))^2 \tag{5}$$

Pro *homogenní náhodné pole* je kovariance funkcí pouze vzdálenosti mezi body $x_i = (x_i, y_i)$, $x_j = (x_j, y_j)$ a pro isotropní náhodné pole je kovariance invariantní vůči rotaci a zrcadlení. Závisí pak pouze na délce $d = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$

Důležitou vlastností řady náhodných polí je *stacionarita druhého řádu*. Náhodné pole $z(x)$ má vlastnosti stacionarity druhého řádu pokud platí, že

- Průměrná hodnota je konstantní, tj.nezávislá na poloze vektoru x. Tedy $E(x) = m$.
- Pro každou dvojici náhodných proměnných $z(x)$ a $z(x + h)$ závisí kovariance pouze na přírůstkovém vektoru h

$$C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x}+\mathbf{h})] - m^2 \tag{6}$$

Pro rozptyl pak platí, že

$$D(z(\mathbf{x})) = C(\mathbf{h}=0) = C(0) \tag{7}$$

a variogram souvisí přímo s kovariancí podle vztahu

$$\Gamma(h) = C(0) - C(h)$$

resp.

$$C(0) = C(h) + \Gamma(h) \tag{8}$$

Pro případ satacionarity druhého řádu je tedy celková variabilita vyjádřená rozptylem $C(0)$ součtem <u>globální složky</u> vyjádřené prostorovou kovariancí $C(h)$ a <u>lokální složky</u> vyjádřené variogramem $\Gamma(h)$. Až na násobivou konstantu je poměr $\Gamma(h)/C(0)$ roven Gearyho autokorelačnímu koeficientu a poměr $C(h)/C(0)$ je roven Moranovu autokorelačnímu koeficientu. Je tedy patrné , že stacionarita druhého řádu umožňuje nalezení souvislosti mezi složkami prostorové variability a prostorové autokorelace. Jde pak o prakticky ekvivalentní nástroje pro popis náhodných polí.. V obecném případě však tyto vztahy neplatí a je třeba volit vhodné vyjádření prostorové variability. Pokud neplatí předpoklad konstantnosti střední hodnoty je „necentrovaný" variogram méně vhodný, protože je vychýlený. Dá se použít jeho centrovaná verse

$$\Gamma_{ij} = 0.5 * D[(z(x_i) - E(z_i)) - (z(x_j) - E(z_j))] \tag{9}$$

která již nevyžaduje prostorovou konstantnost střední hodnoty.
Rov.(8) indikuje, že stacionarita druhého řádu vede k požadavku spojitosti variogramu v počátku, protože $\Gamma(0) = 0$. Pokud vyjde, že $\Gamma(0) = c_0 > 0$, znamená to neplatnost stacionarity druhého řádu. Parametr c_0 se označuje jako nugget efekt (důsledek variací malého dosahu v blízkosti počátku). Pokud je $\Gamma(h) = const.$ pro všechna h je náhodné pole $z(.)$ v tomto směru nekorelované.

Závislost $\Gamma(h)$ na h se dá vyjádřit celou řadou parametrických modelů Často se používá sférický model vyjádřitelný ve tvaru

$$\begin{aligned} &\Gamma(h) = c_0 + c[1.5(h/a) - 0.5(h/a)^3] \quad \text{for } 0 \le h \le a \\ &\Gamma(h) = c_0 + c \quad \text{for } h > a \end{aligned} \tag{10}$$

kde h je délka vektoru $\boldsymbol{h}$. Rozdělení variogramu a jeho vlastnosti jsou popsány v knize [5], kde jsou také uvedeny způsoby jeho odhadu

Pokud je sledované náhodné pole důsledkem kombinace několika nezávislých zdrojů s přibližně stejným rozdělením je možno popsat $z(x)$ pomocí vícerozměrného ***Gaussova*** (normálního) rozdělení.Pak má tedy rozdíl $[z(x) - z(x+h)]$ normální rozdělení s nulovou střední hodnotou a rozptylem $2\Gamma(h)$.

Pro odhad variogramu lze v případě prostorově časových dat použít sumarizaci přes časovou proměnnou a nalézt odhad ve tvaru,

$$\gamma_{ij} = \frac{1}{2T}\sum_{t=1}^{T}(z(x_i,t) - z(x_j,t))^2 \tag{11}$$

Jeho rozptyl je roven

$$D(\gamma_{ij}) = \frac{2}{T}\Gamma_{ij}^2 \tag{12}$$

Pro případ konstantní střední hodnoty je pak

$$D(\gamma_{ij}) = \frac{2}{T}(0.5*(c_{ii}^2 + c_{jj}^2) - c_{ij})^2 \tag{13}$$

Odhad kovariance se v tomto případě vyčísluje podle vztahu

$$c_{ij} = \frac{1}{T}\sum_{t=1}^{T}(z(x_i,t) - z_{pi})*(z(x_j,t) - z_{pj}) \tag{14}$$

Odhad střední hodnoty je počítán ze vztahu

$$z_{pi} = \frac{1}{T}\sum_{t=1}^{T}(z(x_i,t) \tag{15}$$

Pro rozptyl odhadu kovariance platí, že

$$D(c_{ij}) = \frac{1}{T}(c_{ii}^2 * c_{jj}^2 + c_{ij}^2) \tag{16}$$

Dá se ukázat, že pro případ vysoké korelace mezi složkami náhodného pole (již od korelačního koeficientu 0.27) je výhodnější použít variogram, protože jeho odhad je efektivnější. Takto definované odhady umožňují posouzení variabity resp. míry neshody mezi jednotlivými body v oblasti D.

Pro případ, kdy se sleduje pouze prostorová proměnná (nejsou k dispozici opakování v různých časech) se provádí sumace s ohledem na délku a orientaci přírůstkového vektoru (obyčejně se volí pro neregulární síť tolerance délek a směrů, které se považují za přibližně stejné). Takto počítané odhady již posuzují spíše prostorovou autokorelaci, protože se počítají přes celou oblast D. Pro mřížkové uspořádání je volen přírůstkový vektor jako násobek délky a výšky jednotkové cely, takže odpadá potřeba stanovení tolerance. *Výběrový směrový variogram* ve směru přírůstkového vektoru $\boldsymbol{h}$ se počítá obecně ze vztahu

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}[z(x_i) - z(x_i + \mathbf{h})]^2 \qquad (17)$$

kde $N(h)$ je počet dvojic bodů oddělených o vzdálenost h a orientovaných podle vektoru $\boldsymbol{h}$. Pro mřížkové uspořádání jsou možné pouze tři směry, a délka přírůstkového vektoru je násobkem velikosti elementární cely. Je tedy možné počítat směrový variogram ve směru podélném 0° ($h = c*[1,0]$), diagonálním 45° ($h = c*[1,1]$), a příčném 90° ($h = c*[1,0]$) pro násobky $c = 1,2,3....$ Průměrování variogramů ve všech směrech vede k tzv. všesměrovému variogramu (*omnidirectional variogram*).

Místo variogramu lze použít výběrového mandrogramu $M(h)$, který má pro přírůstkový vektor $\boldsymbol{h}$ tvar

$$M(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}\left|z(\mathbf{x}_i) - z(\mathbf{x}_i + \mathbf{h})\right| \qquad (18)$$

Pokud má náhodné pole $z(x)$ vícerozměrné Gaussovo rozdělení platí jednoduchý vztah

$$\frac{\sqrt{\gamma(\mathbf{h})}}{M(\mathbf{h})} = \sqrt{\pi} \qquad (19)$$

Je možné také poměrně jednoduše definovat *výběrový standardizovaný variogram* pro přírůstkový vektor $\boldsymbol{h}$

$$\gamma_s(h) = \frac{\gamma(\mathbf{h})}{\sigma_1\sigma_h} \qquad (20)$$

kde

$$\sigma_1^2 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i)^2 - m_1^2 \text{ and } \quad m_1 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) \qquad (21)$$

a

$$\sigma_h^2 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h})^2 - m_h^2 \text{ and } \quad m_h = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h}) \qquad (22)$$

Všesměrový standardizovaný variogram souvisí úzce s korelogramem $\rho(\mathbf{h}) = 1 - \gamma(\mathbf{h})$.

Pro výpočet standardizované kovariance s ohledem na přírůstkový vektor $\boldsymbol{h}$ se používá vztah

$$C(\mathbf{h}) = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) * z(\mathbf{x}_i + \mathbf{h}) - m_1 * m_h \qquad (23)$$

Pro grafické vyjádření prostorové variability je možno konstruovat *variogramový povrch*. Jde o soustavu variogramů uspřádaných do buněk čtvercové sítě. Začíná se od centrální buňky, která má nulový přírůstkový vektor. Další buňky mají přírůstkový vektor ***h*** vytvořený jako násobek středové buňky ve směru x a y. Na tomto povrchu je možné určit směry anizotropie ve, kterých je variogram nejvíce informativní (viz. [3]).

Pro výpočty související s variogramem lze použít speciální program Variowin 2.2 [3] nebo procedur v jazyku MATLAB 5.3 vytvořených autory této práce.

3. Experimentální část

Technická aplikace chemicky pojené textilie obchodního názvu Perlan, například v elektrotechnickém průmyslu pro výrobu hydroizolačních pásek, je podmíněna zaručenou spolehlivostí v podélné pevnosti a tažnosti.

V upraveném stavu jsou u této netkané textilie požadovány zaručené hodnoty v elektrické průrazné pevnosti, nasákavosti a pevnosti v přetrhu. Všechny tyto vlastnosti souvisejí se stejnoměrností uspořádání vlákenných složek a pojiva.

Účelem je popis kolísání plošné hustoty této textilie. Plošná hustota z(x)=z(x,y) v místě x = (x,y) je definována jako hmotnost M(S) dělená plochou S =4dxdy elementárního čtverce tj. plochou příčného řezu objemového elementu o tloušťce odpovídající tloušťce textilie a příčných rozměrech x ± dx a y ± dy. Formálně je

$$z(x,y) = \lim_{S \to 0} \frac{M(S)}{S} = t * \rho(x,y)$$

kde ρ(x,y) je objemová hustota textilie v místě **x** = (x,y)

Vzorky pro gravimetrická měření byly odebrány ve tvaru čtverců rozměrů 100 x 100 mm. Tyto vorky byly rozděleny na rektangulární síť o velikosti cely 10 x 10 mm. Pro textilii o plošné hmotnosti 60 g/m^2 má cela plošného obsahu $S_j = 100\ mm^2$ hmotnost kolem 6 mg. Kontrola přesnosti přípravy cel, byla provedena na náhodném výběru 25 vzorků.. Relativní chyba velikosti cely se pohybovala od 0.88% do 1.22%. Hmotnost každé cely m_{ij} byla určena jako průměr z pěti vážení. Maximální relativní chyba vážení u vzorku 60 g/m^2 byla 1.606%. Hodnoty m_{ij} pro vzorek pojené textilie plošné hmotnosti 60 g m^{-2} jsou uvedeny v práci [4].

4. Výsledky a diskuse

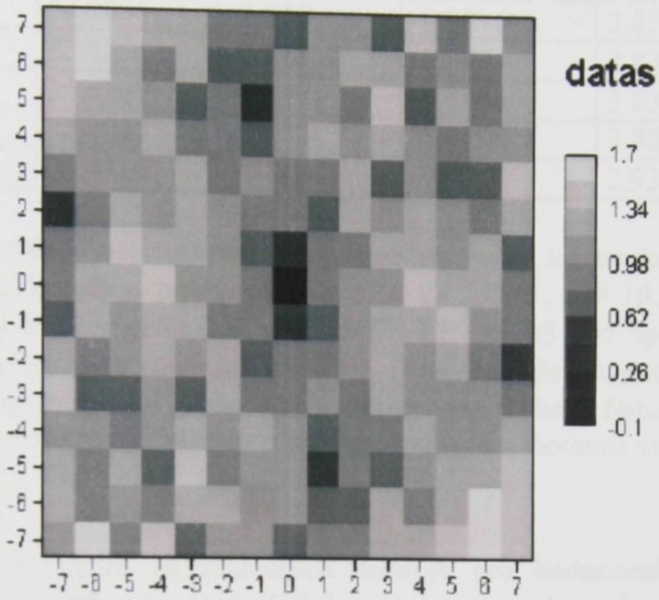
Vzhledem k tomu, že byla použita stejná velikost cel o ploše $S_j = 100\ mm^2$ je plošná hustota $z_{ij} = m_{ij} / S_j$ v [g m^{-2}] číselně rovna hodnotám v tab. 1. Základní statistické charakteristiky tohoto pole plošné hustoty jsou uvedeny v tab.1.

Tabulka 1. Základní statistické charakteristiky plošné hustoty

Počet hodnot	100	rozměr
Průměr	58.92	[g m^{-2}]
Směrodatná odchylka	5,12	[g m^{-2}]

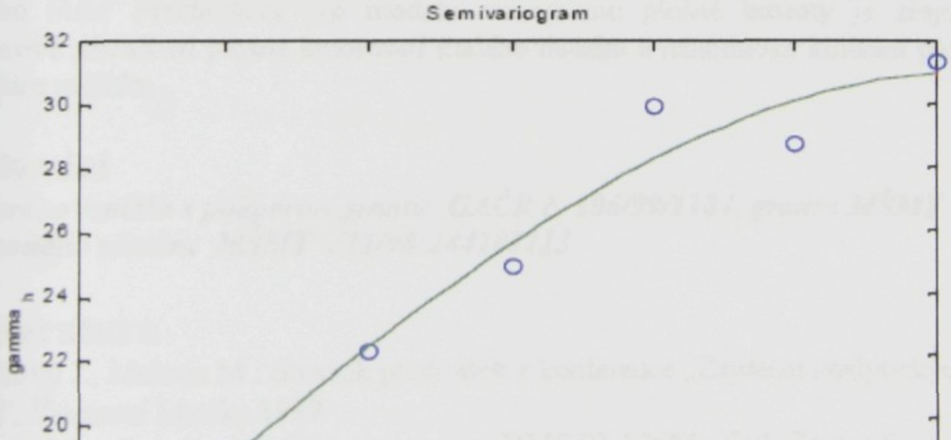
Variační koeficient	8.68	[%]

Variogramový povrch je ukázán na obr 1.



Obr. 1 Variogramový povrch

Je patrné, že z variogramového povrchu nelze stanovit preferenční směr. Všesměrový variogram je znázorněn na obr 2.



Obr 2. Všesměrový variogram

Je patrná diskontinuita v počátku (nugget efekt). Vypočtené hodnoty všesměrového variogramu, kovariance, korelogramu a madogramu jsou uvedeny v tab. 2 Rozptyl je zde roven c(0,0) = 25.937.

Tabulka 3. Všesměrové charakteristiky prostorové variability

Posun	Variogram	Covariance	Correlogram	Madogram
1	20.1198	5.1710	0.205	2.557
2	21.1538	2.096	0.0901	2.603
3	24.9066	-2.045	-0.0895	2.839
4	25.1356	-2.272	-0.0994	2.831
5	25.4189	-1.197	-0.0494	2.838
6	25.8043	-0.50	-0.0198	2.867
7	26.4319	1.180	0.0427	2.934

Hodnoty všesměrového variogramu byly použity pro konstrukci sférického modelu definovaného rov (21). Byly nalezeny odhady $c0 = 14.78013$, $c = 10.99973$ a $a = 4.642217$. Indikativní ukazatel kvality proložení vyšel IGF: 1.8986e-03 což spolu s grafem na obr 5 indikuje vhodnost sférického modelu (viz. [5]). Je zřejmé, že nugget má poměrně vysokou hodnotu, což indikuje nesplnění předpokladu stacionarity druhého řádu. Tento přechodový typ modelu ukazuje na prostorovou závislost malého dosahu a náhodnost ve větším měřítku [6].

5. Závěr

Variogram je jedním ze základních nástrojů pro hodnocení statistické variability náhodných polí. Hodí se při případy vyšších korelací mezi prvky pole. Pro regulární mřížky je možno použít směrového variogramu ve směru podélném, příčném a diagonálním nebo jejich kombinaci- všesměrový variogram. Parametrické modely umožňují vyjádření závislosti variogramu na velikosti a orientaci směrového vektoru. Programy pro vyjádření prostorové variability náhodných polí v jazyce MATLAB 5.3 jsou k dispozici u autorů této práce.

Ukázalo se, že pro zkoumanou netkanou textilii není splněn předpoklad stacionarity druhého řádu: Přechodový typ modelu variogramu plošné hustoty je zřejmě důsledkem prostorové závislostí plošné hmotnosti malého dosahu a náhodnosti kolísání plošné hmotnosti ve větším měřítku

i

Poděkování

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SPATIAL VARIATION OF NONWOVENS SURFACE DENSITY

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1. INTRODUCTION

The products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exists a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1,2]. Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation [4]. Basic on is direct measurement of local planar mass variation by weighting (gravimetric method). The extension of linear textiles uniformity based on the variation coefficient CV to the planar case is frequently used [2].
In this contribution the planar uniformity is described on the base of random field theory and spatial variation characteristics..

2. RANDOM FIELD OF PLANAR UNEVENNESS

The planar density $z(\mathbf{x})=z(x,y)$ describes sufficiently the planar uniformity or unevenness [2]. The quantity $z(x,y)$ in the point $\mathbf{x} = (x,y)$ is defined as limit of mass $M(S)$ divided by the area $S = 4dxdy$ of elementary rectangle i.e. the cross sectional area of volume element having thickness t (thickness of nonwoven) and perpendicular dimensions $x \pm dx$ and $y \pm dy$. Formally

$$z(x,y) = \lim_{S \to 0} \frac{M(S)}{S} = t * \rho(x,y) \tag{1}$$

where $\rho(x,y)$ is planar textile density in the point $\mathbf{x} = (x,y)$. Quantity $z(\mathbf{x})$ is random function of two variables called random field. This random field is fully described by the n variate probability density function

$$p_n(z_1, z_2 ... z_n) = P\{z_i \le z(\mathbf{x}_i) \le z_i + dz_i,\ \ i = 1..n\} \tag{2}$$

Homogeneous random field has property of invariance according to the translation.
The mean value $m(\mathbf{x}) = E(z)$ is defined as

$$E(z) = \int z\, p_1(z)\, dz \tag{3}$$

Variability of random field is characterized by the covariance function

$$C(\mathbf{x}_1, \mathbf{x}_2) = \iint (z_1 - E(z_1)(z_2 - E(z_2)\, p_2(z_1, z_2)\, dz_1\, dz_2 \tag{4}$$

For the case when point $\mathbf{x}_1$ and $\mathbf{x}_2$ are coincident is covariance function reduced to the *variance function* $D(x)$ defined as

$$D(\mathbf{x}) = E(z(\mathbf{x})^2) - (E(z(\mathbf{x})))^2 \tag{5}$$

Another measure of spatial variability is so called *variogram* or *semivariogram* defined as half of variance of the increment ($z(\mathbf{x_1})$ - $z(\mathbf{x_2})$)

$$\gamma(\mathbf{x}_1,\mathbf{x}_2) = 0.5 * D[z(\mathbf{x}_1) - z(\mathbf{x}_2)] \qquad (6)$$

For *homogeneous random field* is covariance function dependent on the distance between points $\mathbf{x_1} = (x_1, y_1)$ and $\mathbf{x_2} = (x_2, y_2)$ only. For this case is valid

$$C(\mathbf{x}_1,\mathbf{x}_2) = C(x_2 - x_1, y_2 - y_1)$$

For isotropic random field is covariance function invariant against rotation and mirroring . This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore

$$C(\mathbf{x}_1,\mathbf{x}_2) = R(d)$$

A random function $z(\mathbf{x})$ is said to be *second order stationary*, if

- the mean value exists and is independent on the location vector $\mathbf{x}$, i.e. $E(\mathbf{x}) = m$.
- for each pair of random variables $z(\mathbf{x})$ and $z(\mathbf{x} + \mathbf{h})$ is covariance dependent on the separation vector $\mathbf{h}$ only

$$C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x}+\mathbf{h})] - m^2 \qquad (7)$$

The stationarity of variance implies the stationarity of covariance

$$D(z(\mathbf{x})) = C(\mathbf{h} = 0) = C(0) \qquad (8)$$

and stationarity of variogram

$$\gamma(\mathbf{h}) = C(0) - C(\mathbf{h}) \qquad (9)$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation.
From eqn.(9) is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$. If $\gamma(0) = c_0 > 0$ then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h}) = const.$ for all $\mathbf{h}$ then the z(.) are uncorrelated in this direction.
The dependence of $\gamma(\mathbf{h})$ on $\mathbf{h}$ can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\begin{aligned} \gamma(h) &= c_0 + c[1.5(h/a) - 0.5(h/a)^3] \quad \text{for } 0 \le h \le a \\ \gamma(h) &= c_0 + c \quad \text{for } h > a \end{aligned} \qquad (10)$$

where h is the length of $\mathbf{h}$. The distributional properties of variogram and techniques for parameter estimation are discussed in the book [5].

If the spatial phenomenon is seen as being generated by the addition of several independent sources having similar spatial distributions, then the **z(x)** can be modeled by a multivariate ***Gaussian*** random function. Since the linear combination of multinormal vector is also normally distributed a check of this assumption is based on the verification that the difference [**z(x)** - **z(x+h)**] is normally distributed with man 0 and variance $2\gamma(\mathbf{h})$.

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of planar densities z($\mathbf{x_i}$) = z(k,j) of k,j th cell (k = 1...m, j = 1...n) of the rectangular net are used. The *sample directional variogram* function for chosen separation vector **h** is calculated according to the following formula

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}[z(x_i) - z(x_i + \mathbf{h})]^2 \qquad (11)$$

where N(**h**) is number of points in separation distances **h.** For regularly distributed points **x** are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° (**h** = c*[1,0]), 45° (**h** = c*[1,1]), and 90° (**h** = c*[1,0]) for lags c = 1,2,3... only. Averagings of variograms calculated in all directions leads to the *omnidirectional variogram*.

The sample mandrogram M(**h**) for a separation vector **h** is computed as

$$M(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}\left|z(\mathbf{x}_i) - z(\mathbf{x}_i + \mathbf{h})\right| \qquad (12)$$

If the z(**x**) is multivariate Gaussian, then the following relation is valid for all separation vectors **h**

$$\frac{\sqrt{\gamma(\mathbf{h})}}{M(\mathbf{h})} = \sqrt{\pi} \qquad (13)$$

This relation can be therefore used for quick evaluation of Gaussian distribution of z(**x**).
The sample *standardized variogram* for separation vector **h** is defined as

$$\gamma_s(h) = \frac{\gamma(\mathbf{h})}{\sigma_1\sigma_h} \qquad (14)$$

where

$$\sigma_1^2 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i)^2 - m_1^2 \text{ and } \quad m_1 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) \qquad (15)$$

and

$$\sigma_h^2 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h})^2 - m_h^2 \text{ and } \quad m_h = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h}) \qquad (16)$$

For an omnidirectional case is the *standardized variogram* directly related to the *correlogram* $\rho(\mathbf{h}) = 1 - \gamma(\mathbf{h})$. The sample covariance for separation vector **h** is calculated according to

$$C(\mathbf{h}) = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) * z(\mathbf{x}_i + \mathbf{h}) - m_1 * m_h \qquad (17)$$

For graphical exploration of spatial variation the *h-scatter-plot* and *variogram surface* are useful. On the h-scatter-plot the $z(\mathbf{x}_i)$ are plotted against $z(\mathbf{x}_i+\mathbf{h})$.For Gaussian distribution forms the h-scatter-plot the elliptical cloud around the diagonal line with higher density of points in the center of this cloud. A succession of h-scatter-plots calculated for increasing lags (values of **h**) provides check of stationarity. If successions of h-scatter-plots shows that the center of the clouds of pairs depart from diagonal line , the stationarity cannot be accepted.

Variogram surface is constructed as a set of variograms arranged to cells of regular grids starting from central one with zero separation vector (0,0). Every cell has separation vector **h** created as number of lags in x an y directions from central one. This surface identifies the directions of anisotropy i.e. preferential directions in which the directional variograms should be constructed.

For computation of these spatial measures the program Variowin 2.2 [4] and procedures written in MATLAB 5.3 have been used

3. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibers (VS) was prepared. Starting lap of planar weight 60 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding

The rectangular samples of dimensions 100 x 100 mm (area Aj = 100 mm^2 and weight 6 mg) were cut for further analysis [3].These samples were divided to the rectangular net having dimensions of individual cells 10 x 10 mm. Relative error of cell dimensions was in the interval from 0.88% to 1,22%. The weight m_{ij} of i,j th cell has been computed as mean from five parallel weightings. Maximal relative error of weighing was 1,606%.

4. RESULTS AND DISCUSSION

From the weights m_{ij} and cell area S_j = 100 mm^2 the surface densities $z_{ij} = m_{ij} / S_j$ v [g m^{-2}] have been computed. Basic statistical characteristics of resulted random field of surface density are given in the table 1

Table 1. Basic characteristics of surface density

Number of values	100	dimension
Mean	58.92	[g m^{-2}]
Standard deviation	5,12	[g m^{-2}]
Variation coefficient	8.68	[%]

The variogram surface is shown on the fig 1.

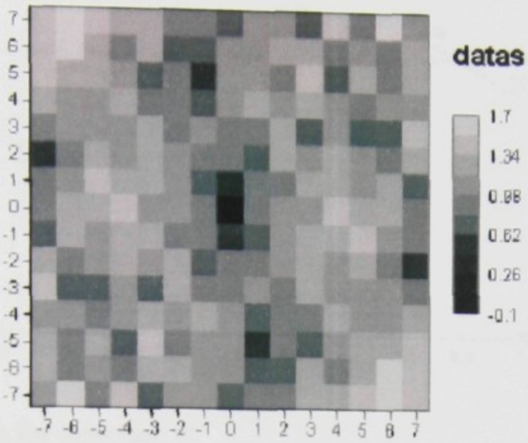

Fig. 1 Variogram surface

No preferential direction can be identified and therefore the directional variograms are constructed for all possible directions for rectangular net. The omnivariate directional variogram is shown on the fig 2., directional variogram for 0° is shown on the fig 3, directional variogram for 90° is shown on the fig 4 and directional variogram for 45° is shown on the fig 5. Dashed lines in these graphs are on the level of variance C(0) which cannot be exceeded for the case of second order stationarity. Numbers at individual points are number of data pairs used for variogram computation.

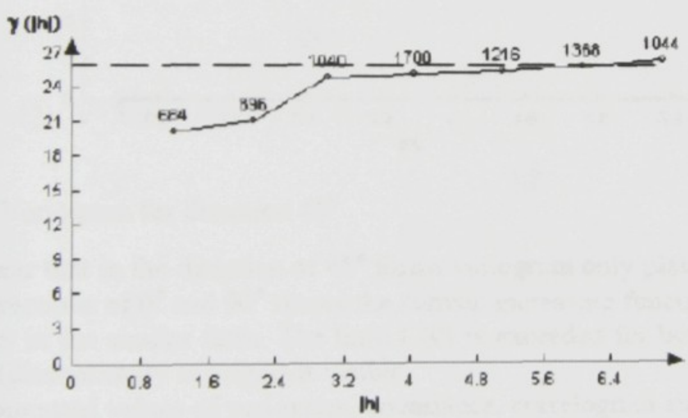

Fig 2. Omnidirectional variogram

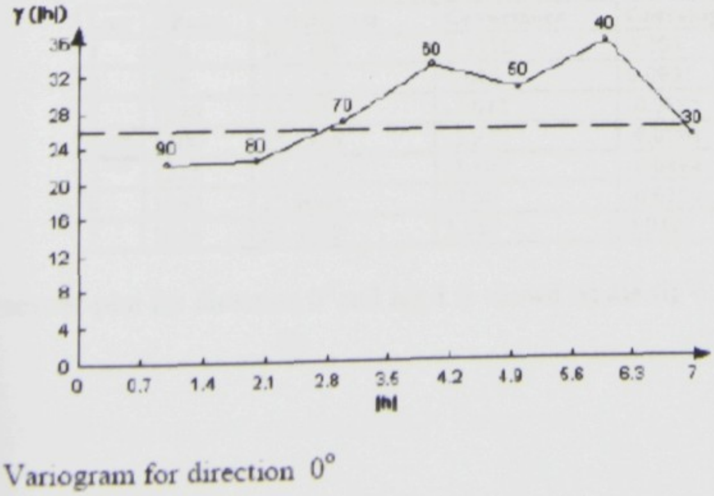

Fig 3. Variogram for direction 0°

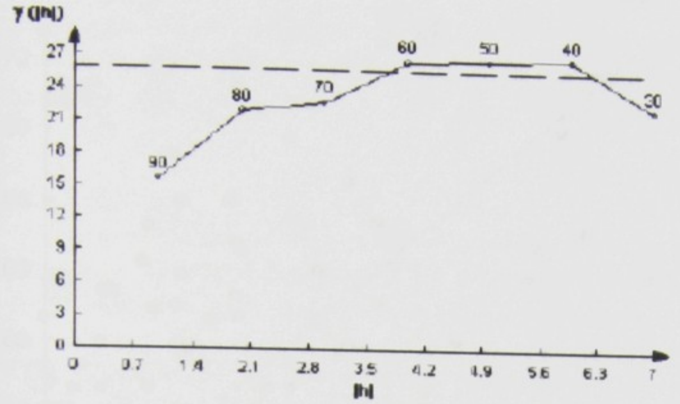

Fig 4. Variogram for direction 0°

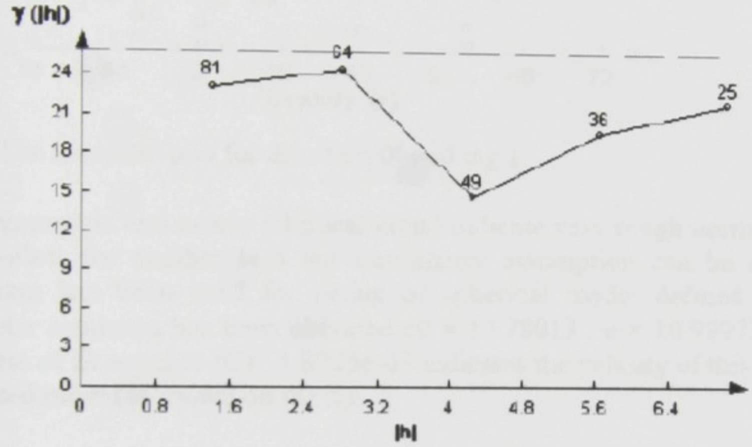

Fig 5. Variogram for direction 45°

It is clear that in the direction of 45° forms variogram only plateau (no correlation in this direction). The directions of 0° and 90° shows the convex increasing function and omnidirectional variogram is roughly in the similar form. The limit C(0) is exceeded for both 0° and 90° directions. The nugget effect (discontinuity at origin) is visible.
The computed values of variogram, covariance, correlogram and madogram for the omnidirectional case are in the table II. The corresponding variance C(0) = 25.937.

Table II. Spatial characteristics for omnidirectional case

Lag	NPairs	Variogram	Covariance	Correlogram	Madogram
1	684	20.1198	5.1710	0.205	2.557
2	896	21.1538	2.096	0.0901	2.603
3	1040	24.9066	-2.045	-0.0895	2.839
4	1700	25.1356	-2.272	-0.0994	2.831
5	1216	25.4189	-1.197	-0.0494	2.838
6	1368	25.8043	-0.50	-0.0198	2.867
7	1044	26.4319	1.180	0.0427	2.934

The h-scatter-plot for direction 0° and lag 1 is shown on the fig 6.

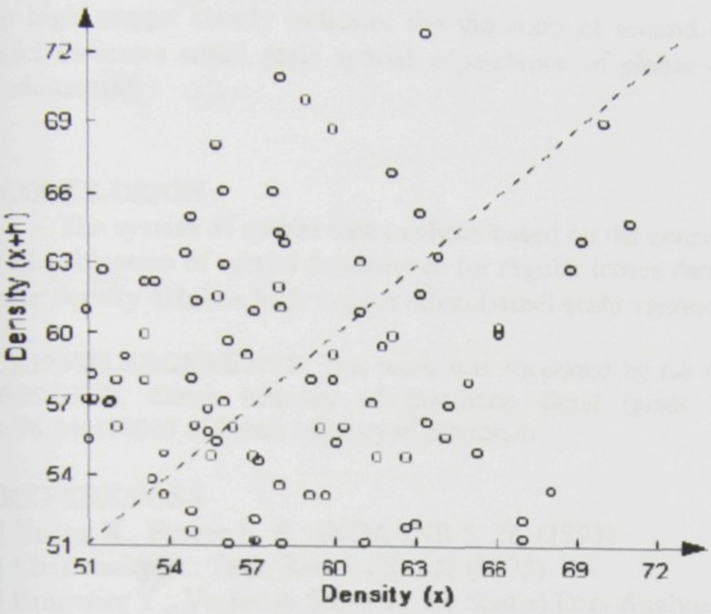

Fig.6. The h-scatter-plot for direction 0° and lag 1

Near symmetric and nearly elliptical cloud indicate very rough normality. From the similarity of h-scatter-plots for another lags the stationarity assumption can be accepted. The omnidirectional variogram has been used for fitting of spherical model defined by eqn. (10). The following parameter estimates has been obtained c0 = 14.78013 , c = 10.99973 and a = 4.642217. Indicative goodness of fit equal to IGF: 1.8986e-03 indicates the validity of this model (see[3]).
The fitted model is shown on the fig. 7.

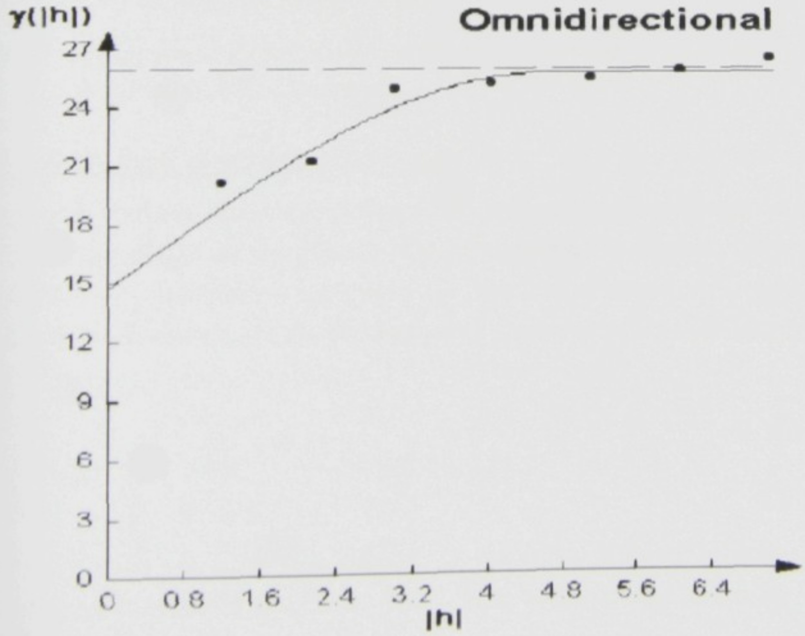

Fig 7. Spherical model for omnidirectional variogram

The high nugget clearly indicates the violation of second order stationarity. The transition type model indicates small scale spatial dependence of planar density and large scale independence (randomness).

5. CONCLUSION

The system of spatial data analysis based on the concept of variogram definition can be used for identification of spatial dependence for regular lattice data or planar unevenness evaluation. The planar density exhibits high nugget effect (small scale variations) but large scale randomness.

ACKNOWLEDGEMENTS: This work was supported by the Czech National Grant Agency (grant No. 106/99/0372), Czech Ministry of Education Grant (grant No. VS 97084) and research project J11/98:244100003 of Czech Ministry of Education

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Application of variogram for explanation of nonwovens surface density uniformity

Jiří Militký, Jitka Rubnerová, Václav Klička, Miroslav Brzezina

Dedicated to our friend Vladimír Kracík on the occasion of his 70^{th} birthday.

Abstract: The main results of random field characterization are presented. The applications of various indices for evaluation of spatial variation are discussed. These indices especially variogram are used for describing of nonwoven textiles uniformity.

Key words: Variogram, nonwovens, uniformity.

1. Introduction

The spatial or area variation of geometrical and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exists a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1,2]. Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation [4]. It is based on direct measurement of local planar mass variation by weighting (gravimetric method). We frequently use the extension of linear textiles uniformity based on the variation coefficient CV to the planar case, see [2].

In this contribution the planar uniformity is described on the base of random field theory and spatial variation characteristics.

2. Random field of planar unevenness

The planar density $z(\mathbf{x})=z(x,y)$ describes sufficiently the planar uniformity or unevenness [2]. The quantity $z(x,y)$ in the point $\mathbf{x} = (x,y)$ is defined as limit of mass M(S) divided by the area $S = 4dxdy$ of elementary rectangle i.e. the cross sectional area of volume element having thickness t (thickness of nonwoven) and perpendicular dimensions $x \pm dx$ and $y \pm dy$. Formally

$$z(x,y) = \lim_{S \to 0} \frac{M(S)}{S} = t * \rho(x,y), \qquad (1)$$

where $\rho(x,y)$ is planar textile density in the point $\mathbf{x} = (x,y)$. Quantity $z(\mathbf{x})$ is random function of two variables called random field. This random field is fully described by the n variate probability density function

$$p_n(z_1, z_2, ..z_n) = P\{z_i \le z(\mathbf{x}_i) \le z_i + dz_i,\ \ i = 1..n\}. \qquad (2)$$

Homogeneous random field has property of invariance according to the translation.
The mean value $m(\mathbf{x}) = E(z)$ is defined as

$$E(z) = \int z\, p_1(z)\, dz \tag{3}$$

Variability of random field is characterized by the covariance function

$$C(\mathbf{x}_1, \mathbf{x}_2) = \iint (z_1 - E(z_1))(z_2 - E(z_2))\, p_2(z_1, z_2)\, dz_1\, dz_2 . \tag{4}$$

For the case when points $\mathbf{x_1}$ and $\mathbf{x_2}$ are coincident is covariance function reduced to the *variance function* D(x) defined as

$$D(\mathbf{x}) = E(z(\mathbf{x})^2) - (E(z(\mathbf{x})))^2 . \tag{5}$$

Another measure of spatial variability is so called ***variogram*** or ***semivariogram*** defined as half of variance of the increment $(z(\mathbf{x_1}) - z(\mathbf{x_2}))$

$$\gamma(\mathbf{x}_1, \mathbf{x}_2) = 0.5 * D[z(\mathbf{x}_1) - z(\mathbf{x}_2)] \tag{6}$$

For *homogeneous random field* is covariance function dependent on the distance between points $\mathbf{x_1} = (x_1, y_1)$ and $\mathbf{x_2} = (x_2, y_2)$ only. For this case is valid

$$C(\mathbf{x}_1, \mathbf{x}_2) = C(x_2 - x_1, y_2 - y_1) .$$

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore

$$C(\mathbf{x}_1, \mathbf{x}_2) = R(d) .$$

A random function $z(\mathbf{x})$ is said to be ***second order stationary***, if

- the mean value exists and is independent on the location vector $\mathbf{x}$, i.e. $E(\mathbf{x}) = m$.
- for each pair of random variables $z(\mathbf{x})$ and $z(\mathbf{x} + \mathbf{h})$ is covariance dependent on the separation vector $\mathbf{h}$ only

$$C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x} + \mathbf{h})] - m^2 \tag{7}$$

The stationarity of variance implies the stationarity of covariance

$$D(z(\mathbf{x})) = C(\mathbf{h} = 0) = C(0) \tag{8}$$

and stationarity of variogram

$$\gamma(\mathbf{h}) = C(0) - C(\mathbf{h}) . \tag{9}$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation.

From equation (9) is clear that second order stationarity leads to the continuity at origin because $\gamma(0)=0$. If $\gamma(0)=c_0>0$ then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h})=const.$ for all **h** then the z(.) are uncorrelated in this direction.

The dependence of $\gamma(\mathbf{h})$ on **h** can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\begin{aligned}\gamma(h)&=c_0+c[1.5(h/a)-0.5(h/a)^3]\quad \text{for } 0\le h\le a\\ \gamma(h)&=c_0+c\quad \text{for } h>a\end{aligned}\tag{10}$$

where h is the length of **h.** The distributional properties of variogram and techniques for parameter estimation are discussed in the book [5].

If the spatial phenomenon is seen as being generated by the addition of several independent sources having similar spatial distributions, then the z(**x**) can be modeled by a multivariate ***Gaussian*** random function. Since the linear combination of multinormal vector is also normally distributed a check of this assumption is based on the verification that the difference [z(**x**) - z(**x**+**h**)] is normally distributed with man 0 and variance $2\gamma(\mathbf{h})$.

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of planar densities z($\mathbf{x}_i$) = z(k,j) of k,j th cell (k = 1...m, j = 1...n) of the rectangular net are used. The ***sample directional variogram*** function for chosen separation vector **h** is calculated according to the following formula

$$\gamma(\mathbf{h})=\frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}[z(x_i)-z(x_i+\mathbf{h})]^2\tag{11}$$

where N(**h**) is number of points in separation distances **h.** For regularly distributed points **x** are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° (**h** = c*[1,0]), 45° (**h** = c*[1,1]), and 90° (**h** = c*[1,0]) for lags c = 1,2,3... only. Averagings of variograms calculated in all directions leads to the *omnidirectional variogram*.

The sample mandrogram M(**h**) for a separation vector **h** is computed as

$$M(\mathbf{h})=\frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}\left|z(\mathbf{x}_i)-z(\mathbf{x}_i+\mathbf{h})\right|\tag{12}$$

If the z(**x**) is multivariate Gaussian, then the following relation is valid for all separation vectors **h**

$$\frac{\sqrt{\gamma(\mathbf{h})}}{M(\mathbf{h})}=\sqrt{\pi}\tag{13}$$

This relation can be therefore used for quick evaluation of Gaussian distribution of z(**x**).

The sample-standardized *variogram* for separation vector **h** is defined as

$$\gamma_s(h) = \frac{\gamma(\mathbf{h})}{\sigma_1 \sigma_h} \tag{14}$$

where

$$\sigma_1^2 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i)^2 - m_1^2 \text{ and } m_1 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) \tag{15}$$

and

$$\sigma_h^2 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h})^2 - m_h^2 \text{ and } m_h = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h}). \tag{16}$$

For an omnidirectional case is the *standardized variogram* directly related to the *correlogram* $\rho(\mathbf{h}) = 1 - \gamma(\mathbf{h})$. The sample covariance for separation vector **h** is calculated according to

$$C(\mathbf{h}) = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) * z(\mathbf{x}_i + \mathbf{h}) - m_1 * m_h \quad . \tag{17}$$

For graphical exploration of spatial variation the *h-scatter-plot* and *variogram surface* are useful. On the h-scatter-plot the $z(\mathbf{x_i})$ are plotted against $z(\mathbf{x_i}+\mathbf{h})$. For Gaussian distribution forms the h-scatter-plot the elliptical cloud around the diagonal line with higher density of points in the center of this cloud. A succession of h-scatter-plots calculated for increasing lags (values of **h**) provides check of stationarity. If successions of h-scatter-plots show that the center of the clouds of pairs depart from diagonal line, the stationarity cannot be accepted.
Variogram surface is constructed as a set of variograms arranged to cells of regular grids starting from central one with zero separation vector (0,0). Every cell has separation vector **h** created as number of lags in x and y directions from central one. This surface identifies the directions of anisotropy i.e. preferential directions in which the directional variograms should be constructed.

For computation of these spatial measures the program Variowin 2.2 [4] and procedures written in MATLAB 5.3 have been used

3. Experimental part

The chemically bonded (by the acrylate binder) nonwoven from viscose fibers (VS) was prepared. Starting lap of planar weight 60 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding.

The rectangular samples of dimensions 100 x 100 mm (area Aj = 100 mm^2 and weight 6 mg) were cut for further analysis [3].These samples were divided to the rectangular net having dimensions of individual cells 10 x 10 mm. Relative error of cell dimensions was in the interval from 0.88% to 1,22%. The weight m_{ij} of i,j th cell has been computed as mean from five parallel weightings. Maximal relative error of weighing was 1,606%.

4. Results and discussion

From the weights m_{ij} and cell area S_j= 100 mm^2 the surface densities $z_{ij} = m_{ij} / S_j$ v [g m^{-2}] have been computed. Basic statistical characteristics of resulted random field of surface density are given in the table 1.

Table I. Basic characteristics of surface density

Number of values	100	Dimension
Mean	58.92	[g m^{-2}]
Standard deviation	5,12	[g m^{-2}]
Variation coefficient	8.68	[%]

The variogram surface is shown on the fig 1.

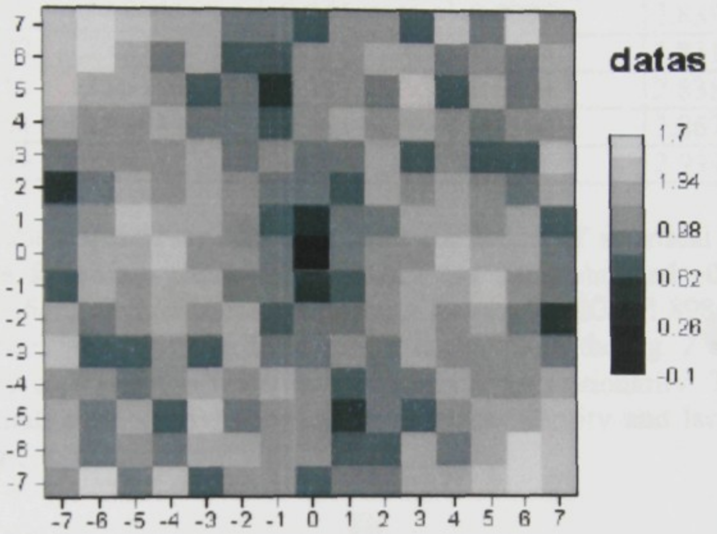

Fig. 1 Variogram surface

No preferential direction can be identified and therefore the directional variograms are constructed for all possible directions for rectangular net. The omnivariate directional variogram is shown on the fig 2.

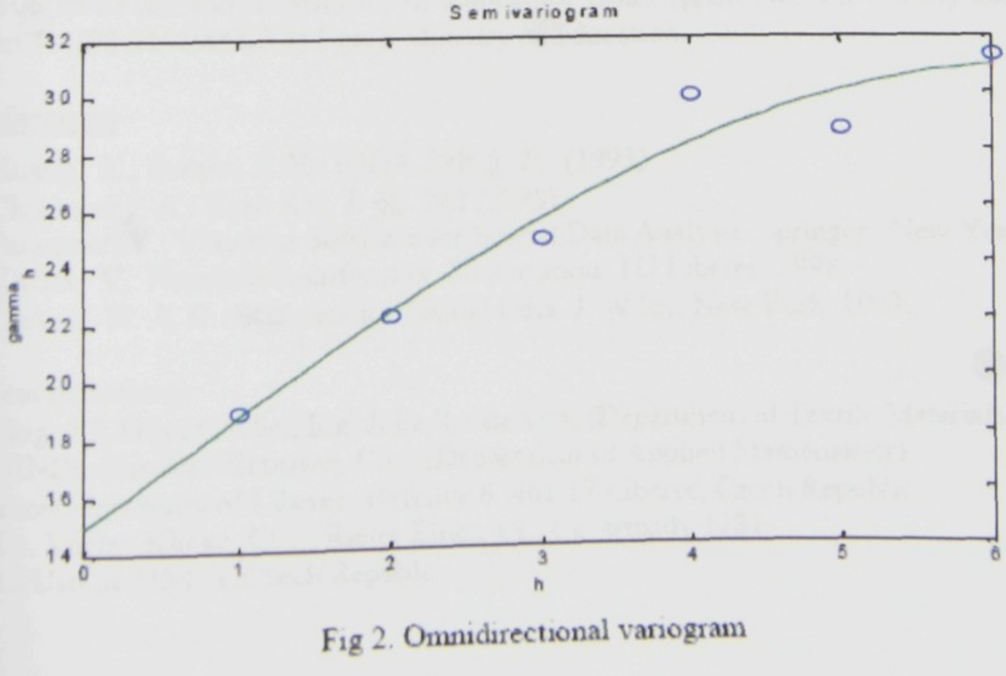

Fig 2. Omnidirectional variogram

The nugget effect (discontinuity at origin) is visible. The computed values of variogram, covariance, correlogram and madogram for the omnidirectional case are in the table II. The corresponding variance C(0) = 25.937.

Table II. Spatial characteristics for omnidirectional case

Lag	NPairs	Variogram	Covariance	Correlogram	Madogram
1	684	20.1198	5.1710	0.205	2.557
2	896	21.1538	2.096	0.0901	2.603
3	1040	24.9066	-2.045	-0.0895	2.839
4	1700	25.1356	-2.272	-0.0994	2.831
5	1216	25.4189	-1.197	-0.0494	2.838
6	1368	25.8043	-0.50	-0.0198	2.867
7	1044	26.4319	1.180	0.0427	2.934

The omnidirectional variogram has been used for fitting of spherical model defined by equation (10). The following parameter estimates has been obtained c0 = 14.78013, c = 10.99973 and a = 4.642217. Indicative goodness of fit equal to IGF: 1.8986e-03 indicates the validity of this model (see [3]). The fitted model is shown on the fig. 2 as solid curve. The high nugget clearly indicates the violation of second order stationarity. The transition type model indicates small-scale spatial dependence of planar density and large-scale independence (randomness) .

5. Conclusion

The system of spatial data analysis based on the concept of variogram definition can be used for identification of spatial dependence for regular lattice data or planar unevenness evaluation. The planar density exhibits high nugget effect (small scale variations) but large-scale randomness.

Acknowledgements: This work was supported by the Czech National Grant Agency (grant No. 106/99/0372), Czech Ministry of Education Grant (grant No. VS 97084) and research project J11/98:244100003 of Czech Ministry of Education.

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INDICATOR FUNCTION FOR CHARACTERIZATION OF NONWOVENS MASS SPATIAL CLUSTERINIG

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Abstract:
The main aim of this contribution is evaluation of local surface unevenness of nonwovens based on the data in the form of rectangular arrays (quadrat method). These data can be obtained from digital images where the variation of mass is characterizes by the variation of grey level or by direct measurement of local planar mass variation by weighting (gravimetric method). The evaluation of mass spatial clustering is based on the utilization of the indicator function

1. INTRODUCTION

The spatial variation of geometric and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties (Erickson, Baxter (1973)). There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens (Huang, Bresee (1993); Chhabra (2003); Klička (1998)). Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation of Klička (1998). In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity. Another possibility is to use some techniques based on the spatial pattern analysis as variance to mean ratio.

The main aim of this work is attempt to describe surface irregularity of nonwoven textile structure based on the so-called quadrat methods, where characteristic of quadrat is its weight. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats some characteristics as weight, mean optical transparency, mean relief etc. can be measured. Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.

For evaluation of mass irregularity the five kinds of methods are useful.

- **First one** is based on the computation of variation coefficient in selected directions (machine and cross direction)., and testing the significance of their differences (Cherkassky (1998)).
- **Second one** is based on the modelling of raw data arrays by the ANOVA (analysis of variance) type models and testing hypothesis about homogeneity in selected directions (Meloun, Militký, Forina (1992)).
- **Third one** is based on the analysis of random field. The moment characteristics of second order as spatial covariance and variogram are used for description of these fields. The fractal dimension characterizing random field complexity will be computed from variogram (Davies(1999)).
- **Fourth one** is based on the global and local spatial variation indices of Geary and Moran type (Cliff and Ord (1973)).

- **Fifth one** is based on the utilization of multivariate kurtoisis of indicator random variables (Johansson(2000))

There exist a lot of other characteristics as spatial descriptors of irregularity (Chhabra (2003)) suitable for special situations (point patterns).

This work is devoted to the use of indicator random variables (Johansson (2000)) for characterization of local no unevenness of chemically bonded lightweight nonwoven lap.

2. SPATIAL LATTICE PROCESSES

Spatial data are investigated on the specific domain *D*. Usually *D* is a subset of 2-dimensional space, but generally the *d* dimensional domain can be used and then $D \subset \Re^d$. The vector s contains information on the data location. Locations in *D* are denoted by the vector s. In 2-dimensional space, s have 2 components (x, y) containing the coordinates. At locations s, the values of some variable *z(s)* of interests (mass, density, thickness etc.) are obtained. The *Z*(s) is a random variable at each location. The general spatial model has the form $\{\mathbf{Z}(s) : s \in D\}$.

There exist three basic model types:

1: Geostatistical data. Here *D* is a continuous fixed subset of $\Re^d$; **Z**(s) is a random vector at location $s \in D$.

2: Lattice data. Here *D* is a fixed but countable subset of $\Re^d$ such as a grid some representation with nodes; **Z**(s) is a random vector at locations $s \in D$.

3: Point Patterns. Here *D* is a random subset of $\Re^d$ and is called a point process; if **Z**(s) is a random vector at location $s \in D$ then it is a *marked spatial point process*; if $\mathbf{Z}(s) \equiv 1$ so that it is a degenerate random variable, then only D is random and it is called a *spatial point process*.

For the quadrat method is quantity z(**x**) random function of two variables called random field. This random field is fully described by the *n* variate probability density function

$$p_n(z_1, z_2, .. z_n) = P\{z_i \le z(s_i) \le z_i + dz_i, \quad i = 1..n\}. \tag{1}$$

Homogeneous random field has property of invariance according to the translation. The mean value m(**x**) = E(z) is defined as

$$E(z) = \int z\, p_1(z)\, dz \tag{2}$$

Variability of random field is characterized by the covariance function

$$C(\mathbf{x}_1, \mathbf{x}_2) = \iint (z_1 - E(z_1)(z_2 - E(z_2))\, p_2(z_1, z_2)\, dz_1\, dz_2. \tag{3}$$

For the case when points $\mathbf{x}_1$ and $\mathbf{x}_2$ are coincident is covariance function reduced to the *variance function* D(**x**) defined as (Meloun, Militký, Forina (1992))

$$D(\mathbf{x}) = E(z(\mathbf{x})^2) - (E(z(\mathbf{x})))^2. \tag{4}$$

Another measure of spatial variability is so called *variogram* or *semivariogram* defined as half of variance of the increment ($z(\mathbf{x}_1) - z(\mathbf{x}_2)$)

$$\gamma(\mathbf{x}_1, \mathbf{x}_2) = 0.5 * D[z(\mathbf{x}_1) - z(\mathbf{x}_2)] \tag{5}$$

$$\gamma(\mathbf{h}) = \mathrm{Var}(Z(\mathbf{u}) - Z(\mathbf{u} + \mathbf{h})) = \mathrm{Var}(Z)\,(1 - \rho(\mathbf{h}))$$

For *homogeneous random field* is covariance function dependent on the distance between points

$\mathbf{x}_1 = (x_1, y_1)$ and $\mathbf{x}_2 = (x_2, y_2)$ only. For this case is $C(\mathbf{x}_1, \mathbf{x}_2) = C(x_2 - x_1, y_2 - y_1)$.

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore $C(\mathbf{x}_1, \mathbf{x}_2) = R(d)$. A random function z(**x**) is said to be *second order stationary*, if (Cressie (1993))

- the mean value exists and is independent on the location vector **x**, i.e. E(**x**) = m.
- for each pair of random variables z(**x**) and z(**x** + **h**) is covariance dependent on the separation vector **h** only $C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x}+\mathbf{h})] - m^2$

The stationarity of variance imply the stationarity of covariance and variogram

$$D(z(\mathbf{x})) = C(\mathbf{h} = 0) = C(0) \qquad \gamma(\mathbf{h}) = C(0) - C(\mathbf{h}). \tag{6}$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation. It is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$.

If $\gamma(0) = c_0 > 0$, then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h}) = const.$ for all **h** then the z(.) are uncorrelated in this direction.

The variogram or correlogram are *moments* of the *bivariate distribution* between properties at any two spatial locations. The bivariate distribution is a more complete measure of spatial dependency than the variogram

$$\mathrm{P}(Z(\mathrm{s}) \le z, Z(\mathrm{s}+\mathbf{h}) \le z') = F_2(\mathbf{h}, z, z') \tag{7}$$

While the variogram considers the overall spatial continuity between any two locations, the bi-variate distribution quantifies spatial continuity between specific classes of the property at any two locations. For example, the bivariate distribution allows quantifying the spatial correlation between the low property values (when z, z' is low) separately from the high (when z, z' is high) property values. The overall variogram $\gamma(\mathbf{h})$ measures the dissimilarity between all ranges of the data taken together. To quantify the bivariate distribution, one employs so-called *indicator random variables*

$$I(\mathrm{s}, z) = \begin{cases} 1 & \text{if } Z(\mathrm{s}) > Tp \\ 0 & \text{elsewhere} \end{cases} \tag{8}$$

It is possible to define multiple of these indicator variables for each threshold Tp. The indicator correlogram or variogram is related to the bivariate distribution.

3. MULTIVARIATE KURTOISIS

It is known that kurtosis is the 4 th normalized moment of a investigated property z distribution. Let $\boldsymbol{z}$ is n dimensional random vector having vector of mean values $\boldsymbol{m}$ and covariance matrix $\boldsymbol{C}$

$$\mathbf{C} = E\left[(\mathbf{z}-\mathbf{m})*(\mathbf{z}-\mathbf{m})^T\right] \tag{9}$$

The multidimensional kurtosis Kn is nonregular affine invariant measure of peakness defined by relation (Meloun, Militký and Forina (1992))

$$Kn = E\{[(\mathbf{z}-\mathbf{m})^T C^{-1}(\mathbf{z}-\mathbf{m})]^2\} \tag{10}$$

For univariate case is Kn equivalent to the standard coefficient of kurtosis (normalized fourth central moment). For n - variate normal distribution is kurtosis Kn = $n(n+2)$.

Let $\boldsymbol{zr}$ is reduced and centered random vector defined by relation

$$\mathbf{xr} = \mathbf{C}^{-1/2}(\mathbf{z} - \mathbf{m}) \tag{11}$$

The above-introduced multivariate kurtosis is then simply

$$Kn = E\left[(\|\mathbf{xr}\|)^4\right] \tag{12}$$

where $\|*\|$ is Euclidian norm. The sample estimate based on the sample (x_1, x_2 , x_N) where component are n variate vectors is equal to (Meloun, Militký and Forina (1992))

$$Kn = \frac{1}{N}\sum_{i=1}^{N}\{(x_i - m)^T * S^{-1} * (x_i - m)\}^2 \tag{13}$$

Sample mean vector $\boldsymbol{m}$ and covariance matrix $\boldsymbol{S}$ are defined by the usual manner

$$\mathbf{m} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{z}_i \qquad \mathrm{S} = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{z}_i - \mathbf{m})^T(\mathbf{z}_i - \mathbf{m}) \tag{14}$$

For the case when $N > n+1$ is matrix $\boldsymbol{S}$ almost surely nonsingular.

For the bivariate rectangular distribution is $Kn=5.6$ and for the discrete bivariate uniform distribution on the grid of size $(2n+1)x(2n+1)$ is valid

$$Kn = 5.6 - \frac{1.2}{n(n+1)} \tag{15}$$

In this case tends Kn to 5.6 if is the size of grid is sufficiently large. The kurtosis is generally sensitive to peakedness and peaked distributions have high values of Kn. In the bivariate case, peakedness can be considered as a spatial clustering of values. Therefore the surface homogeneity is characterized by $Kn=5.6$ and in the case of surface heterogeneity is Kn much higher. This property of bivariate kurtosis can be simply used for measuring the homogeneity of a given attribute (investigated property) on fabric surface. For continuous attributes it is only necessary to threshold individual values into binary ones (Johanssen (2000)).

The threshold operation (transformation to the binary values) is defined as

$$z(x,y) = 1 \quad \text{for} \quad r > Tp \quad \text{or} \quad z(x,y) = 0 \quad \text{elsewhere} \tag{16}$$

The value Tp determines the type of the outcomes 0 or 1. Spatial concentrations of outcomes of the same value are called clusters. In this binary case there are 0-valued and 1-valued clusters. For evaluation of Tp the selected quantiles can be simply used. The sample quantiles can be computed from order statistics $z_{(1)} < z_{(2)} < ... < z_{(D)}$ where $D=N*N$ is number of cells in grid. It can be shown that $z_{(i)}$ is rough estimate of sample quantile for probability (Meloun, Militký and Forina (1992))

$$\mathrm{P_i} = \frac{\mathrm{i}}{\mathrm{N}+1} \tag{17}$$

For obtaining of quantiles with prescribed probability (e.g. $P_i = 0.9$) the linear approximation can be used. The program NONVCOMP in MATLAB created for estimation of kurtosis based homogeneity evaluation computes Tp as sample based quantiles for probabilities 0.1, 0.2,..,0.9.

4. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibres (VS) was prepared. Starting lap of planar weight 30 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding. The rectangular samples of dimensions 100 x 100 mm were used for further analysis. Samples were cut to quadrats having dimensions 10 x 10 mm. Relative errors of quadrat dimensions were from 0.88% to 1.22%. For the case of mass density 60 g/m^2 has quadrat with area S_j =

$100\ mm^2$ weight around 6 mg. Quadrat mass m_{ij} was evaluated as mean from five measurements. Maximum relative error of weighting for samples having around 60 g/m^2 was 1.606%.

5. RESULTS AND DISCUSSION

The results are part of outputs from program NONVCOMP. The local mass variation of tested sample is visible from fig.1.

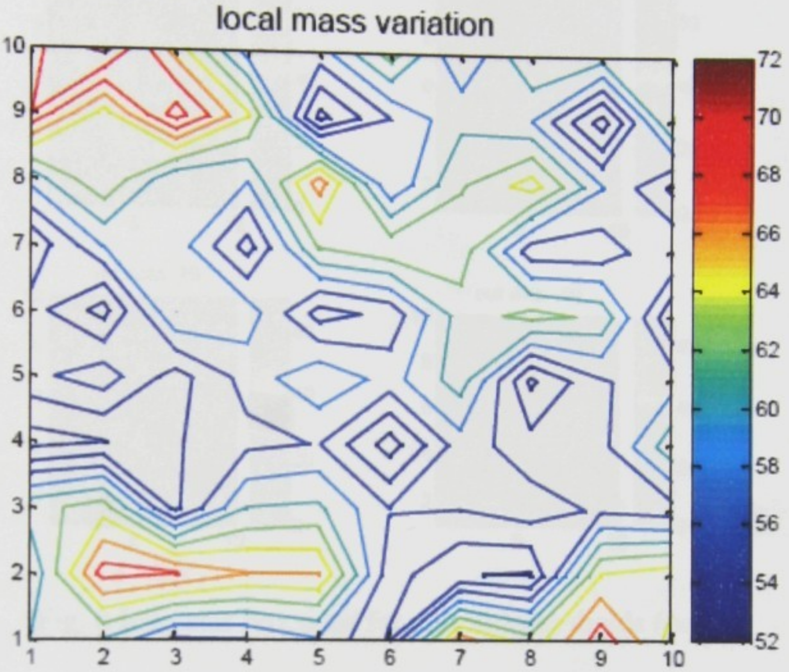

Fig. 1 Local mass variation contours

The kurtosis for various percentiles is shown on the fig. 2.

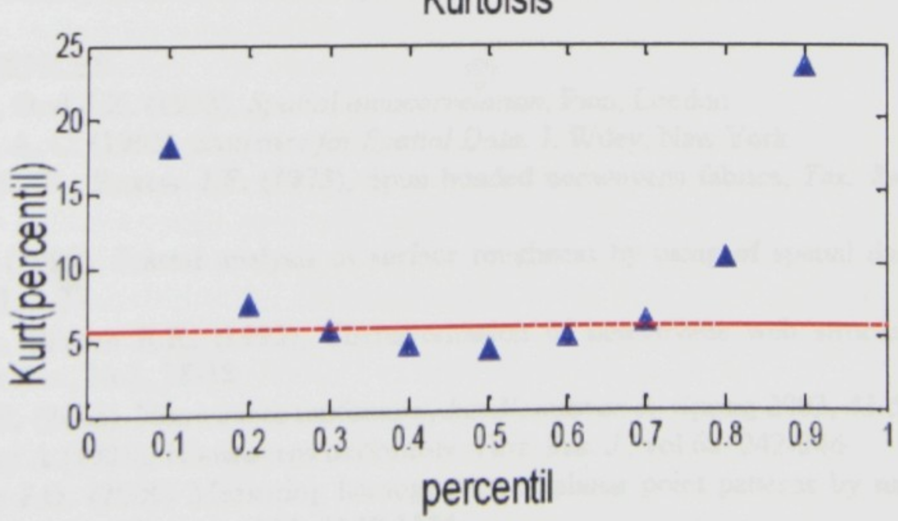

Fig.2 Kurtosis for various percentiles

It is clear that from $Tp = 0.7$ till $Tp = 0.7$ looks the distribution of "binarized" local mass as homogeneous. For lower and higher values the formation of spatial clusters is clearly indicated.
The indicator functions (see eqn. (8)) for selected Tp are shown on the fig. 3. It is visible that for higher Tp are identified local anomalies.

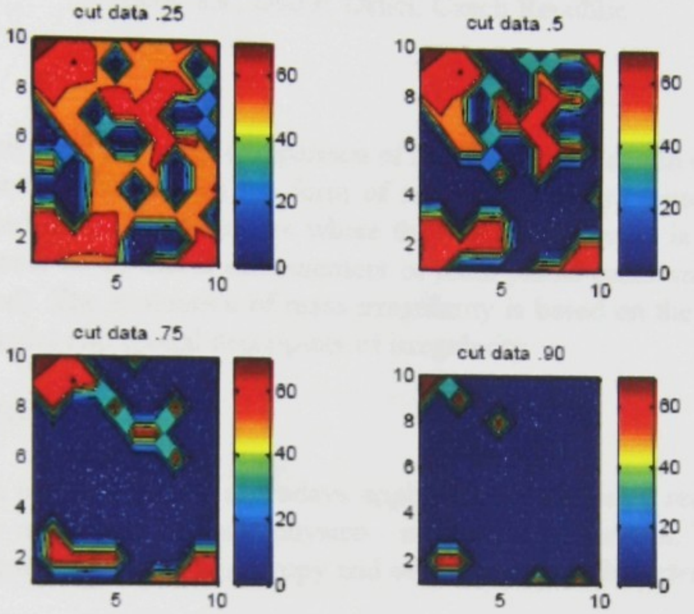

Fig. 8 Indicator functions for selected thresholds (cut)

6. CONCLUSION

The indicator function and multivariate kurtosis can be used for identification of spatial clusters for regular lattice data. Tested nonwoven exhibits higher complexity with local anomalies (clusters).

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SPATIAL STATISTICS AND MASS UNEVENESS OF NONWOVENS

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Abstract:
The main aim of this contribution is comparison of method for evaluation of surface uniformity of nonwovens based on the data in the form of rectangular arrays (quadrat method). These data can be obtained from digital images where the variation of mass is characterizes by the variation of grey level or by direct measurement of local planar mass variation by weighting (gravimetric method). The evaluation of mass irregularity is based on the variation coefficient model, ANOVA model and spatial descriptors of irregularity

1. INTRODUCTION

The products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exists a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1,2].
The spatial variation of geometric and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties (Erickson, Baxter (1973)). There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens (Huang, Bresee (1993); Chhabra (2003); Klička (1998)). Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation of Klička (1998). In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity. Another possibility is to use some techniques based on the spatial pattern analysis as variance to mean ratio.
The main aim of this work is attempt to describe surface irregularity of nonwoven textile structure based on the so-called quadrat methods, where characteristic of quadrat is its weight. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats some characteristics as weight, mean optical transparency, mean relief etc. can be measured. Direction X is equivalent to the <u>machine direction</u> (index i). In this direction are N quadrats. Direction y is equivalent to the <u>cross direction</u> (index j). In this direction are M quadrats.
For evaluation of mass irregularity the five kinds of methods are useful.

- **First one** is based on the computation of variation coefficient in selected directions (machine and cross direction)., and testing the significance of their differences (Cherkassky (1998)).
- **Second one** is based on the modelling of raw data arrays by the ANOVA (analysis of variance) type models and testing hypothesis about homogeneity in selected directions (Meloun, Militký, Forina (1992)).
- **Third one** is based on the analysis of random field. The moment characteristics of

second order as spatial covariance and variogram are used for description of these fields. The fractal dimension characterizing random field complexity will be computed from variogram (Davies (1999)).

- **Fourth one** is based on the global and local spatial variation indices of Geary and Moran type (Cliff and Ord (1973)).
- **Fifth one** is based on the utilization of multivariate kurtoisis of indicator random variables (Johansson (2000))

There exist a lot of other characteristics as spatial descriptors of irregularity (Chhabra (2003)) suitable for special situations (point patterns).

The comparison of proposed characteristics of uniformity is demonstrated on the example of chemically bonded lightweight nonwoven lap.

2. IRREGULARITY CHARACTERIZATION

Irregularity characterization is classically based on the coefficient of variation CV or derived statistics. For characterization of lattice data array the models based on the ANOVA principle are often used. For detailed description of irregularity field the second order characteristics as function of distance separation vector can be used as well. These characteristics can be compared with ideal models of nonwoven structures. The spatial autocorrelation enables to characterize organised patterns in data. Some simple indices can be obtained from indicator random variable, which is simply threshold of original spatial variable.

2.1 Spatial lattice processes

Spatial data are investigated on the specific domain *D*. Usually *D* is a subset of 2-dimensional space, but generally the *d* dimensional domain can be used and then $D \subset \Re^d$. The vector s contains information on the data location. Locations in *D* are denoted by the vector s. In 2-dimensional space, s has 2 components (x, y) containing the coordinates. At locations s, the values of some variable *z(s)* of interests (mass, density, thickness etc.) are obtained. The *Z*(s) is a random variable at each location. The general spatial model has the form $\{\mathbf{Z}(s) : s \in D\}$.

There exist three basic model types:

1: Geostatistical data. Here *D* is a continuous fixed subset of $\Re^d$; **Z**(s) is a random vector at location $s \in D$.

2: Lattice data. Here *D* is a fixed but countable subset of $\Re^d$ such as a grid some representation with nodes; **Z**(s) is a random vector at locations $s \in D$.

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$$p_n(z_1, z_2, ..z_n) = P\{z_i \le z(s_i) \le z_i + dz_i, \quad i = 1...n\}. \tag{1}$$

Homogeneous random field has property of invariance according to the translation. The mean value m(**z**) ~ E(z) is defined as

$$E(z) = \int z\, p_1(z)\, dz \tag{2}$$

Variability of random field is characterized by the covariance function

$$C(\mathbf{s}_1, \mathbf{s}_2) = \iint (z_1 - E(z_1))(z_2 - E(z_2))\, p_2(z_1, z_2)\, dz_1\, dz_2 . \tag{3}$$

For the case when points $\mathbf{x}_1$ and $\mathbf{x}_2$ are coincident is covariance function reduced to the *variance function* D(s) defined as (Meloun, Militký, Forina (1992))

$$D(\mathbf{s}) = E(z(\mathbf{s})^2) - (E(z(\mathbf{s})))^2 . \tag{4}$$

Another measure of spatial variability is so called *variogram* or *semivariogram* defined as half of variance of the increment $(z(\mathbf{s}_1) - z(\mathbf{s}_2))$

$$\gamma(\mathbf{s}_1, \mathbf{s}_2) = 0.5 * D[z(\mathbf{s}_1) - z(\mathbf{s}_2)] \tag{5}$$

$$\gamma(\mathbf{h}) = \mathrm{Var}(Z(\mathbf{u}) - Z(\mathbf{u} + \mathbf{h})) = \mathrm{Var}(Z)\,(1 - \rho(\mathbf{h}))$$

For *homogeneous random field* is covariance function dependent on the distance between points

$s_1 = (x_1, y_1)$ and $s_2 = (x_2, y_2)$ only. For this case is $C(\mathbf{s}_1, \mathbf{s}_2) = C(x_2 - x_1, y_2 - y_1)$.

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore $C(\mathbf{s}_1, \mathbf{s}_2) = R(d)$. A random function z(s) is said to be *second order stationary*, if (Cressie (1993))

- The mean value exists and is independent on the location vector s, i.e. E(s) = m.
- For each pair of random variables z(s) and z(s + **h**) is covariance dependent on the separation vector **h** only $\quad C(\mathbf{h}) = E[z(\mathbf{s}) * z(\mathbf{s} + \mathbf{h})] - m^2$

The stationarity of variance imply the stationarity of covariance and variogram

$$D(z(\mathbf{s})) = C(\mathbf{h} = 0) = C(0) \qquad \gamma(\mathbf{h}) = C(0) - C(\mathbf{h}) . \tag{6}$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation. It is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$.

If $\gamma(0) = c_0 > 0$, then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h}) = const.$ for all **h** then the z(.) are uncorrelated in this direction.

The dependence of $\gamma(\mathbf{h})$ on **h** can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\begin{aligned} \gamma(h) &= c_0 + c[1.5(h/a) - 0.5(h/a)^3] \quad \text{for } 0 \le h \le a \\ \gamma(h) &= c_0 + c \quad \text{for } h > a \end{aligned} \tag{7}$$

where h is the length of **h**. The distributional properties of variogram and techniques for parameter estimation are discussed in the book of Cressie (1993).

If the spatial phenomenon is seen as being generated by the addition of several independent sources having similar spatial distributions, then the z(**x**) can be modelled by a multivariate ***Gaussian*** random function. Since the linear combination of multinormal vector is also normally distributed a check of this assumption is based on the verification that the difference $[z(\mathbf{s}) - z(\mathbf{s}+\mathbf{h})]$ is normally distributed with man 0 and variance $2\gamma(\mathbf{h})$.

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of planar densities (or mass) $z(s_i) = z(k,j)$ of k,j th cell (k = 1...m, j = 1...n) of the rectangular net are used. The *sample directional variogram* function for chosen separation vector **h** is calculated according to the following formula

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} [z(\mathbf{s}_i) - z(\mathbf{s}_i + \mathbf{h})]^2 \tag{8}$$

where N(**h**) is number of points in separation distances **h**. For regularly distributed points s are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° (**h** = c*[1,0]), 45° (**h** = c*[1,1]), and 90° (**h** = c*[1,0]) for lags c = 1,2,3... only. Averaging of variograms calculated in all directions leads to the *omnidirectional variogram*.

The sample-standardized *variogram* for separation vector **h** is defined as

$$\gamma_s(h) = \frac{\gamma(\mathbf{h})}{\sigma_1 \sigma_h} \tag{9}$$

where

$$\sigma_1^2 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{s}_i)^2 - m_1^2 \text{ and } \quad m_1 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{s}_i) \tag{10}$$

and

$$\sigma_h^2 = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{s}_i + \mathbf{h})^2 - m_h^2 \text{ and } \quad m_h = \frac{1}{N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} z(\mathbf{s}_i + \mathbf{h}). \tag{11}$$

For an omnidirectional case is the *standardized variogram* directly related to the *correlogram* $\rho(\mathbf{h}) = 1 - \gamma(\mathbf{h})$.

For graphical exploration of spatial variation the *h-scatter-plot* and *variogram surface* are useful. On the h-scatter-plot the $z(s_i)$ are plotted against $z(s_i+\mathbf{h})$. For Gaussian distribution forms the h-scatter-plot the elliptical cloud around the diagonal line with higher density of points in the centre of this cloud. A succession of h-scatter-plots calculated for increasing lags (values of **h**) provides check of stationarity. If successions of h-scatter-plots show that the centre of the clouds of pairs depart from diagonal line, the stationarity cannot be accepted.

Variogram surface is constructed as a set of variograms arranged to cells of regular grids starting from central one with zero separation vector (0, 0). Every cell has separation vector **h** created as number of lags in x and y directions from central one. This surface identifies the directions of anisotropy i.e. preferential directions in which the directional variograms should be constructed.

For computation of these spatial measures the program Variowin 2.2 (Pannatier (1996)) and our program NONVCOMP written in MATLAB 7.0 can be used

The variogram or correlogram are *moments* of the *bivariate distribution* between properties at any two spatial locations. The bivariate distribution is a more complete measure of spatial dependency than the variogram

$$P(Z(\mathbf{s}) \le z, Z(\mathbf{s}+\mathbf{h}) \le z') = F_2(\mathbf{h}, z, z') \tag{12}$$

While the variogram considers the overall spatial continuity between any two locations, the bi-variate distribution quantifies spatial continuity between specific classes of the property at any two locations. For example, the bivariate distribution allows quantifying the spatial correlation between the low property values (when z, z' is low) separately from the high (when z, z' is high) property values. The overall variogram $\gamma(\mathbf{h})$ measures the dissimilarity between all ranges of the data taken together. To quantify the bivariate distribution, one employs so-called *indicator random variables*

$$I(\mathrm{s}, z) = \begin{cases} 1 & \text{if } Z(\mathrm{s}) > Tp \\ 0 & \text{elsewhere} \end{cases} \tag{13}$$

It is possible to define multiple of these indicator variables for each threshold Tp. The indicator correlogram or variogram is related to the bivariate distribution.

2.2 Analysis based on CV

Surface irregularity is classically described by the coefficient of variation (CV). This coefficient is traditionally used as the characteristics of unevenness.
According to the common definitions we can simply computed the overall mean, variance and coefficient of variation

$$m = \frac{1}{MN}\sum_i\sum_j(z_{ij}) \qquad s^2 = \frac{1}{MN}\sum_i\sum_j(z_{ij}-m)^2 \qquad CV = \frac{s}{m} \tag{14}$$

Here z_{ij} is selected characteristic of quadrats (here mass m_{ij}.). Direction X is equivalent to the <u>machine direction</u> (index i). In this direction are N quadrats. Direction y is equivalent to the <u>cross direction</u> (index j). In this direction are M quadrats.
The quantity CV is in fact external variation coefficient CB(F) between cell areas F^2.
Ideal value of CV for nonwovens of total weight W having Poisson distribution of random fibres of fineness T_V and density ρ_F is defined as (Militký (1998))

$$CV_N(P) = \frac{\sqrt[4]{\pi}}{\sqrt{2}}\sqrt[4]{\frac{T_V\rho_V}{W^2}}$$

The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{io} = \frac{1}{M}\sum_j z_{ij} \qquad\qquad m_{oj} = \frac{1}{N}\sum_j z_{ij}$$

Symbol „$_0$"*denotes* index used for summation *i.e.* m_{io} is mean value for i th position in the machine direction. For the <u>machine direction</u> (expansion of eqn.(14) by using of the m_{io}) the following relation results (Cherkassky (1998))

$$s^2 = s_L^2 + s_{HL}^2 \tag{15}$$

where the variance in the machine direction s_L^2 is

$$s_L^2 = \frac{1}{N}\sum_i(m_{io}-m)^2$$

and the variance in the transversal direction s_{HL}^2 is

$$s_{HL}^2 = \frac{1}{MN}\sum_i\sum_j(z_{ij}-m_{io})^2$$

For the <u>cross direction</u> is

$$s^2 = s_H^2 + s_{LH}^2 \tag{16}$$

where the variance in the cross-direction s_H^2 is

$$s_H^2 = \frac{1}{M}\sum_j (m_{oj} - m)^2$$

and the variance in the longitudinal direction s_{LH}^2 is

$$s_{LH}^2 = \frac{1}{MN}\sum_i\sum_j (z_{ij} - m_{oj})^2$$

The coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} are obtained by dividing the corresponding standard deviations by the mean m. These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals the variance of point estimates have to be computed (Meloun Militký and Forina (1992)). The rough formula of sample variation coefficient variance D(CV) has the form[2]

$$D(CV) = CV^2\left(\frac{n + CV^2(2n+1)}{2n(n-1)}\right)$$

where n = (N or M) is number of cells in the corresponding direction. Asymptotic 95 %th confidence interval for CVP is then defined as

$$CV \pm 2\sqrt{D(CV)} \tag{17}$$

The coefficients of variation are statistically different in the cases when corresponding confidence intervals are not intersecting. This analysis can be simply realized by using of program NONVCOMP in MATLAB.
The uniformity of mass distribution can be also characterized by index of dispersion.

$$I_d = \frac{s^2}{m} \tag{18}$$

Spatial randomness corresponds to the Poisson distribution. The null hypothesis of randomness can be tested by comparison of Id with quantiles of χ^2 distribution. It is possible to compute the limit M_L bellow the pattern is uniform and limit M_U above the pattern is clumped (Chhabra (2003)).

2.3 Analysis by the ANOVA

The differences between variability in machine and cross directions can be formally tested by the analysis of variance (ANOVA. The z_{ij} can be interpreted as realizations of random field on the discrete two-dimensional integer valued rectangular mesh (regular lattice). Let the z_{ij} are described by the following model (Meloun, Militký and Forina (1992)).

$$z_{ij} = \mu_{ij} + \varepsilon_{ij} \qquad \mu_{ij} = \mu + \alpha_i + \beta_j + c.\alpha_i.\beta_j \tag{19}$$

where μ_{ij} is true value in the ij cell, ε_{ij}, μ is total mean α_i are **effects in the cross direction**, β_j are **effects in the machine direction** and c is constant of Tukey one degree of freedom non - additivity (Meloun, Militký and Forina (1992)).
Uniformity in the machine direction is equal to validity of hypotheses $H_0 : \beta_j = 0, j = 1...M$
and uniformity in the cross direction is equal to validity of hypotheses $H_0 : \alpha_i = 0, i = 1...N$.
(Meloun, Militký and Forina (1992)).
Testing of these hypotheses can be realized by the ANOVA (model with a single observation per cell). For the ANOVA model the following constraints are imposed

$$\sum_i \alpha_i = 0,\ \sum_{j=1} \beta_j = 0,\ \sum_i \alpha_i \beta_j = 0,\ \sum_j \alpha_i \beta_j = 0$$

For the pure additive effects the interactions $\tau_{ij} = c.\alpha_i.\beta_j = 0$ and then

$$\hat{\alpha}_i = \frac{1}{M}\sum_j (z_{ij} - m) \qquad \text{and} \qquad \hat{\beta}_j = \frac{1}{N}\sum_i (z_{ij} - m)$$

where m is estimator of the total mean defined by the eqn.(2).
From residuals $\hat{e}_{ij} = z_{ij} - m - \hat{\alpha}_i - \hat{\beta}_j$ the parameter c can be simply estimated

$$c = \frac{\sum_i \sum_j \hat{e}_{ij}.\hat{\alpha}_i.\hat{\beta}_j}{\sum_i \sum_j \hat{\alpha}_i^2.\hat{\beta}_j^2} \tag{20}$$

For ANOVA testing the sum of squares due to machine direction (effects $\hat{\beta}_j$), cross direction (effects $\hat{\alpha}_i$) and due to interaction are computed and compared with total sum of squares $s * M * N$. Statistical tests based on the F-criterion may be performed (Meloun, Militký and Forina (1992)). According to the results of testing of the null hypothesis $H_0\ (\beta_j = 0 \text{ or } \alpha_i = 0)$ the statistical uniformity in the machine and cross direction can be accepted or not.
When eqn. (19) is considered as the special regression model, the diagonal elements of projection matrix have the same value (Meloun, Militký and Forina (1992))

$$H_{ii} = \frac{N + M - 1}{N.M}$$

Outlying cells may be then detected by the standardized residuals

$$e_{S_{ij}} = \frac{e_{ij}}{\sqrt{\sigma_R^2(1 - H_{ii})}}$$

where σ_R^2 is variance of error term estimated from residual sum of squares divided by corresponding degrees of freedom (NM-N-N). Roughly, if $e_{Sij} > 3$, the given cell is taken as an outlier. ANOVA analysis is a part of NONVCOMP program written in MATLAB.

2.4 Multivariate kurtoisis

It is known that kurtosis is the 4 th normalized moment of a investigated property z distribution. Let z is n dimensional random vector having vector of mean values $\mathbf{m}$ and covariance matrix $\mathbf{C}$

$$\mathbf{C} = E\left[(\mathbf{z} - \mathbf{m}) * (\mathbf{z} - \mathbf{m})^T\right] \tag{21}$$

The multidimensional kurtosis Kn is nonregular affine invariant measure of peakness defined by relation (Meloun, Militký and Forina (1992))

$$Kn = E\{[(\mathbf{z} - \mathbf{m})^T C^{-1} (\mathbf{z} - \mathbf{m})]^2\} \tag{22}$$

For univariate case is Kn equivalent to the standard coefficient of kurtosis (normalized fourth central moment). For n - variate normal distribution is kurtosis $Kn = n(n+2)$.
Let zr is reduced and centered random vector defined by relation

$$\mathbf{xr} = \mathbf{C}^{-1/2}(\mathbf{z} - \mathbf{m}) \tag{23}$$

The above-introduced multivariate kurtosis is then simply

$$Kn = E\left[(\|\mathbf{xr}\|)^4 \right] \tag{24}$$

where $\|\ast\|$ is Euclidian norm. The sample estimate based on the sample (z_1, z_2 , z_N) where component are n variate vectors is equal to (Meloun, Militký and Forina (1992))

$$Kn = \frac{1}{N} \sum_{i=1}^{N} \{(x_i - m)^T * S^{-1} * (x_i - m)\}^2 \tag{25}$$

Sample mean vector m and covariance matrix S are defined by the usual manner

$$\mathbf{m} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{z}_i \qquad \mathbf{S} = \frac{1}{N-1} \sum_{i=1}^{N} (\mathbf{z}_i - \mathbf{m})^T (\mathbf{z}_i - \mathbf{m}) \tag{26}$$

For the case when N > $n+1$ is matrix S almost surely nonsingular.
For the bivariate rectangular distribution is $Kn=5.6$ and for the discrete bivariate uniform distribution on the grid of size $(2n+1)x(2n+1)$ is valid [1]

$$Kn = 5.6 - \frac{1.2}{n(n+1)} \tag{27}$$

In this case tends Kn to 5.6 if is the size of grid is sufficiently large. The kurtosis is generally sensitive to peakedness and peaked distributions have high values of Kn. In the bivariate case, peakedness can be considered as a spatial clustering of values. Therefore the surface homogeneity is characterized by $Kn=5.6$ and in the case of surface heterogeneity is Kn much higher. This property of bivariate kurtosis can be simply used for measuring the homogeneity of a given attribute (investigated property) on fabric surface. For continuous attributes it is only necessary to threshold individual values into binary ones (Johanssen (2000)).
The threshold operation (transformation to the binary values) is defined as

$$z(x,y) = 1 \quad \text{for} \quad r > Tp \quad \text{or} \quad z(x,y) = 0 \quad \text{elsewhere} \tag{28}$$

The value Tp determines the type of the outcomes 0 or 1. Spatial concentrations of outcomes of the same value are called clusters. In this binary case there are 0-valued and 1-valued clusters. For evaluation of Tp the selected quantiles can be simply used. The sample quantiles can be computed from order statistics $z_{(1)} < z_{(2)} < \dots < z_{(D)}$ where $D=N*N$ is number of cells in grid. It can be shown that $z_{(i)}$ is rough estimate of sample quantile for probability (Meloun, Militký and Forina (1992))

$$P_i = \frac{i}{N+1} \tag{29}$$

For obtaining of quantiles with prescribed probability (e.g. $P_i = 0.9$) the linear approximation can be used. The program NONVCOMP in MATLAB created for estimation of kurtosis based homogeneity evaluation computes Tp as sample based quantiles for probabilities 0.1, 0.2,..,0.9.

2.5 Fractal dimension

A convenient way of characterizing the smoothness (uniformity) of an isotropic surfaces is Hausdorf or fractal dimension. If the surface is very smooth is fractal dimension equal to $D_p = 2$. For extremely rough surfaces is fractal dimension approaching to limit value $D_p = 3$. Let the random field $z(s)$ is stationary Gaussian and covariance function $C(h)$ is sufficiently smooth (Davies (1999)). The behavior of this function near the origin can be described by power type model

$$\gamma(h) = C(0) - C(h) \approx c|h|^{\alpha} \tag{30}$$

The value α always lies between 0 and 2 and equals (for Gaussian field) to 2 if $z(s)$ is differentiable. The value α is conventionally obtained through linear regression of the log-log transformation of eqn (30). Fractal dimension is computed from equation (Davies (1999))

$$D = d + 1 - \alpha / 2 \tag{31}$$

where $d=2$ for surface and $d=1$ for curve .The extent to which the fractal index of a line transects of a random field vary with orientation is particularly limited. Even in the case where the fractal dimensions of line transect samples can assume different values in different directions, the fractal dimension of surface $z(s)$ is 1 plus the higher of the fractal dimensions of line transect sections. For the rectangular mesh the direction of rows, columns and diagonal direction are sufficient.

For computation of fractal dimension D the program NONVCOMP in MATLAB has been written

2.5 Spatial autocorrelation

For characterization of the random field non-homogeneity or patterns in investigated properties (local concentration, clustering etc.) the spatial autocorrelation could be used (Cliff and Ord (1973)).

The spatial autocorrelation deals simultaneously with both location and attribute information. Most measures of spatial autocorrelation can be recast as a (normalized) cross-product statistic that indexes the degree of relation between corresponding entries from two matrices - one specifying the spatial connections among a set of n locations, and the other reflecting a very explicit definition of similarity between the set of values on some variable z realized over locations (Sawada(2000)).

In spatial autocorrelation analysis some measure of contiguity is required. Contiguity has a rather broad definition depending on the research question; however, most analyses in spatial autocorrelation adhere to a common definition of neighborhood relations. Namely, neighborhood relations for regular net of points (raster format) are defined as either **rooks case** (B), **bishops case** (A) or **queens (kings) case** (C). These are rather simple and intuitive as their names suggest (Figure 1).

X		X		X		X	X	X
	O		X	O	X	X	O	X
X		X		X		X	X	X
	A			B			C	

Fig. 1: Different definitions of contiguity

The connectivity (spatial weight) matrix W contains elements $W_{ij} = 1$, if i-th and j-th cell are neighborhood or $W_{ij} = 0$ if i-th and j-th cell are far each other.

Let value $Z_k = z(_{i,j})$ for $k = i + m*(j-1)$ are arranged columnwise. The Geary autocorrelation index is defined by relation (Cliff and Ord(1973))

$$c = \frac{N-1}{2*\sum_i \sum_j W_{ij}} * \frac{\sum_i \sum_j W_{ij} * (Z_i - Z_j)^2}{\sum_i (Z_i - Zm)^2} \quad (32)$$

where Zm is arithmetic mean of all cells. The statistics c is defined in the range from 0 to 2. Negative spatial autocorrelation is for $c > 1$ and positive spatial autocorrelation is for $c < 1$. Mean value (spatial randomness) is equal to $E(c) = 1$. Variance $D(c)$ based on the approximate normality is defined as

$$D(c) = \frac{(N-1)*(2*S_1 + S_2) - 4*S_0^2}{S_0^2 * 2*(N+1)} \quad (33)$$

Individual symbols in eqn. (33) are defined as

$$S_0 = \sum_i \sum_j W_{ij} \quad S_1 = \frac{1}{2}\sum_i \sum_j (W_{ij} + W_{ji})^2 \quad S_2 = \sum_i (W_{i\bullet} + W_{\bullet i})^2$$

Symbol $W_{i\bullet}$ denotes i-th row and $W_{\bullet i}$ denotes i-th column of matrix W. Random variable

$$Z(c) = \frac{c-1}{\sqrt{D(c)}}$$

has approximately standardized normal distribution. If absolute value $abs(Z(c)) \geq 2$ the significant autocorrelation occurs

Very interesting are local measures of spatial dependence. The aim is often the detection of clusters, whose purpose is to identify „hot spots" (extremely outlying points or locations having sufficiently unusual local behavior), without any preconceptions about their locations.

For the detection of clusters the statistics $G_i(d)$ introduced by (Ord and Getis (1995)) are useful. The statistic $G_i(d)$ is defined as

$$G_i(d) = \frac{\sum_j w_{ij}(d) * z_j}{\sum_j z_j} \quad j \neq i \quad (34)$$

where $w_{ij}(d)$ is a symmetric one/zero spatial weight matrix with ones for all links defined as being within distance d of a given i, all other links are zero including the link of point i to itself. The d argument is here dropped when only a single distance is under consideration. The sum of the weights is written as

$$W_i = \sum_{j \neq i} w_{ij}(d) \quad (35)$$

When we set

$$\bar{z}(i) = \frac{\sum_j z_j}{(n-1)} \qquad s^2(i) = \frac{\sum_j z_j^2}{(n-1)} - [\bar{z}(i)]^2 \quad (36)$$

it may be shown that

$$D(G_i) = \frac{W_i(n-1-W_i) * s^2(i)}{(n-1)^2(n-2) * \bar{z}^2(i)} \quad (37)$$

It was shown that if $E(G_i)$ is bounded away from 0 and from 1, then the permutations distribution of G_i under Ho approaches normality. The statistics G_i can be redefined as a standard variable by taking the statistic minus its expectation, $E[G_i] = W_i/(n-1)$ divided by the square root of its variance; at the same time the requirement on weights to be binary could be allowed.

Moran´s global spatial autocorrelation statistic can be written as

$$I(d) = \frac{\sum_i (Z_i - Zm) \sum_j w_{ij} (Z_j - Zm)}{W * s^2} - \frac{n}{W} \tag{38}$$

3. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibres (VS) was prepared. Starting lap of planar weight 30 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding. The rectangular samples of dimensions 100 x 100 mm were used for further analysis. Samples were cut to quadrats having dimensions 10 x 10 mm. Relative errors of quadrat dimensions were from 0.88% to 1.22%. For the case of mass density 60 g/m^2 has quadrat with area $S_j = 100\ mm^2$ weight around 6 mg. Quadrat mass m_{ij} was evaluated as mean from five measurements. Maximum relative error of weighting for samples having around 60 g/m^2 was 1.606%.

4. RESULTS AND DISCUSSION

The results are part of outputs from program NONVCOMP. The local mass variation of tested sample is visible from fig.2.

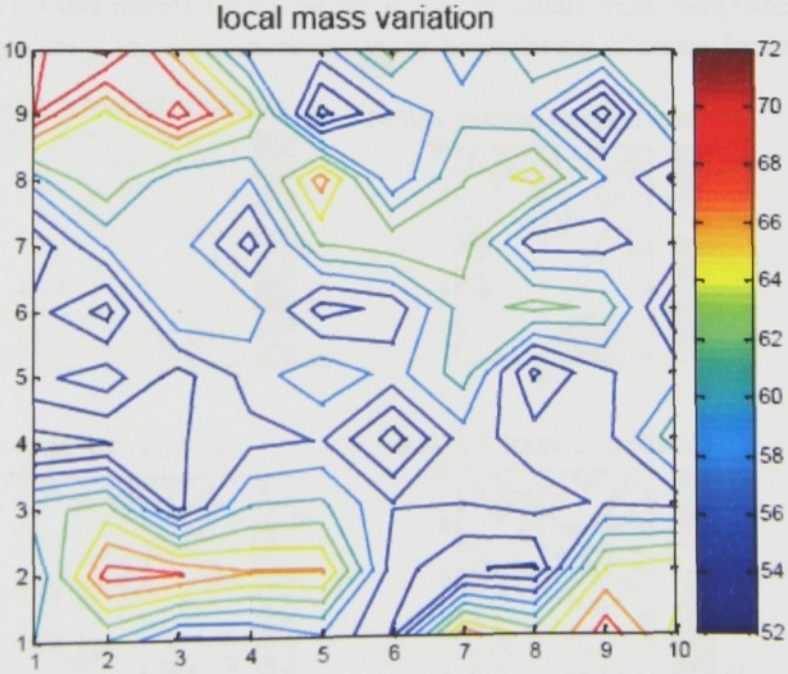

Fig. 2 Local mass variation contours

For deeper investigation of anomalous regions the moving windows were used. Principle is division the study area to the several local neighborhoods of equal size (moving windows) and within each local window the mean and variance are computed. The dimension of moving windows can be gradually changed to obtain good identification of local anomalies. The plot of local means and variances are given in fig.3. The row mean and variances are shown a well.

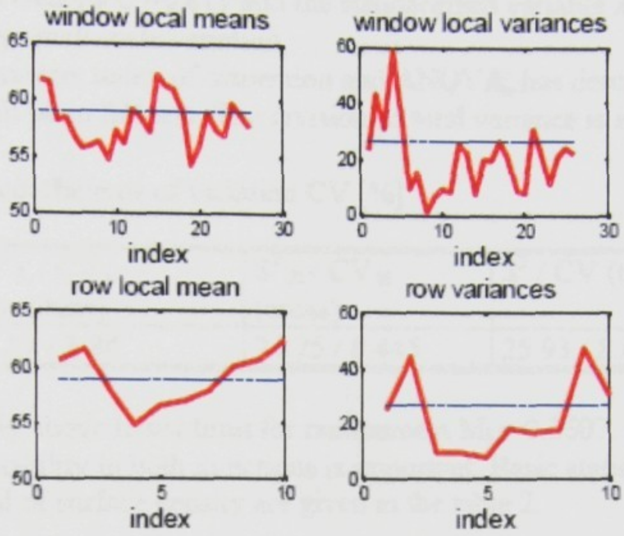

Fig. 3 Local statistics characterizing stability of mean and variance

There are visible some departures from constancy of mean and variance (stationarity). Deeper analysis of local anomalies is based on the investigation of residuals. Simple parametric model is based on the ANOVA model without interaction $z_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij}$. The residuals and squared residuals for this model are on the fig. 4. The residuals were computed from total mean m, row means m_{io} and column means m_{oj} or by replacing of means by medians.

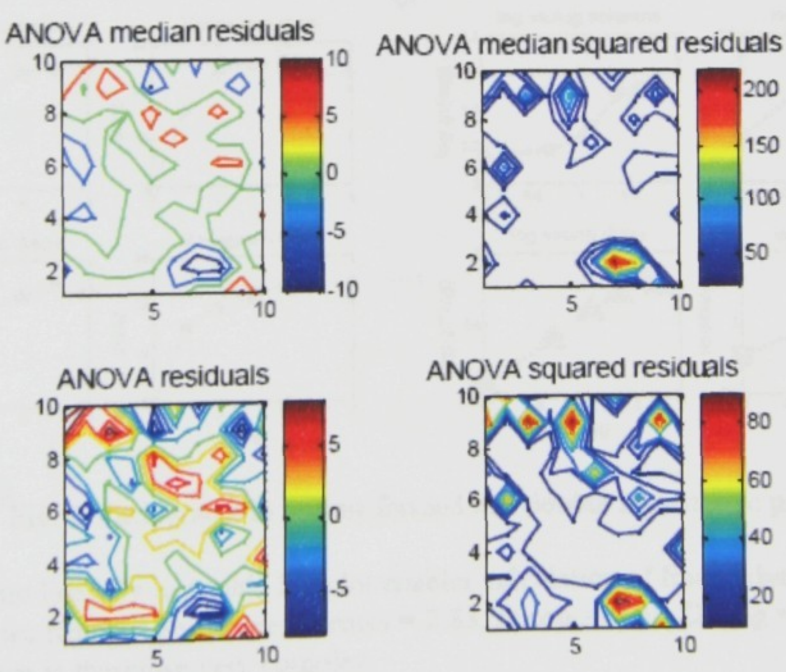

Fig. 4 Residuals and squared residuals for ANOVA model

The local "hot spots" (anomalies) are here clearly visible.
The median ANOVA residuals were used for computation of Geary spatial autocorrelation coefficient. The bad case was Bishops arrangement with following results:

Geary's C =0.982 and the standardized variable Z(c) =0.199. The residuals are therefore spatially uncorrelated and in data are the long scale variations mainly. For original data and Bishops arrangement is Geary's C =0.819 and the standardized variable Z(c) =20.39. These data exhibits very strong small scale variation.
The division of total variance, index of dispersion and ANOVA, has described mass variation. Details about results will be in full text. The division of total variance is in the table I.

Table 1 Variances and coefficients of variation CV [%]

Characteristics	S^2_L / CV_L (machine)	S^2_H / CV_H (cross)	S^2 / CV (total)
weight	1.17 / 1.84	24.75 / 8.445	25.93 / 8.64

The I_d = 0.444 is slightly above lower limit for randomness M_L= 0.3607. ANOVA analysis leads to results that variability in both directions is important. Basic statistical characteristics of resulted random field of surface density are given in the table 2.

Table 2 Basic characteristics of surface density

Number of values	100	Dimension
Mean	58.92	[g m^{-2}]
Standard deviation	5,12	[g m^{-2}]
Variation coefficient	8.64	[%]

The variogram is machine direction, cross direction, diagonal direction and omni-variogram are shown on the fig. 5 in the untransformed and log /log form

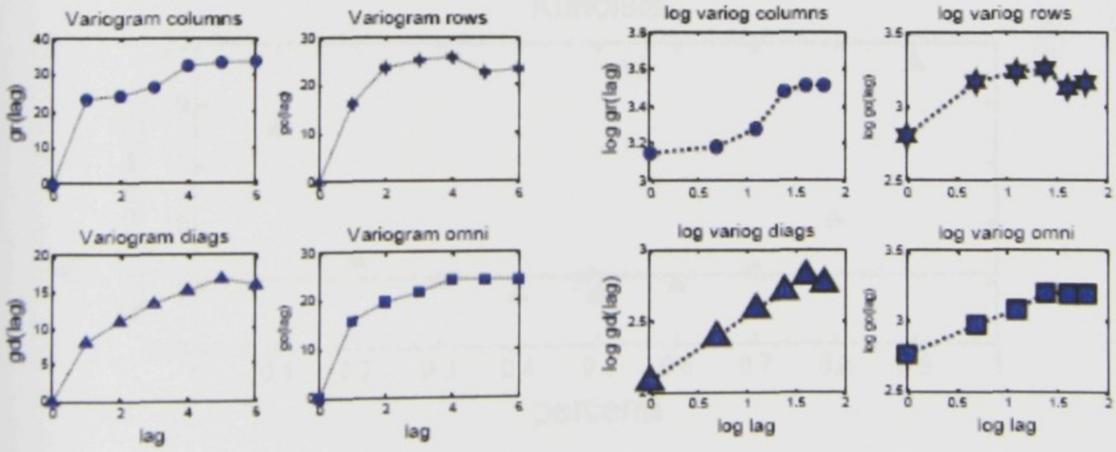

Fig. 5 Variograms in untransformed and double logarithmic plot

The approximate linearity in double log plot enables calculation of fractal dimension. The least squares estimates from all points are: D rows = 2.83, D cols = 2.91, D diag = 2.79, D omni = 2.86. The surface is therefore very complex.
The spherical model for omni-variogram (see eqn. (7)) is shown on the fig. 6. By using of nonlinear least squares the following results were obtained:
Sum of squares due to regression on x1 = 74.72
Sum of squares added by x2 = 3.93
Total sum of squares = 83.03

Co (Nugget) = 14.04
C+Co (Sill) = 29.28
a = 4.642217.

Due to high nugget effect the stationarity of data cannot be accepted.

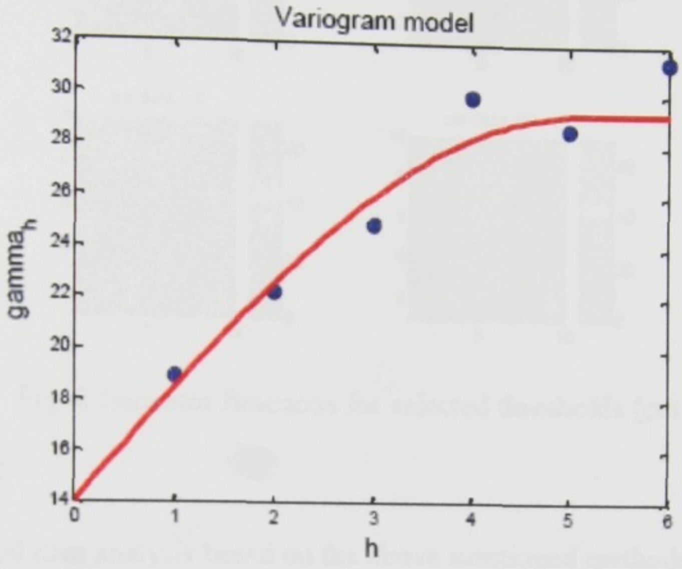

Fig 6. Spherical model for omnivariogram

The kurtosis for various percentiles is shown on the fig. 7.

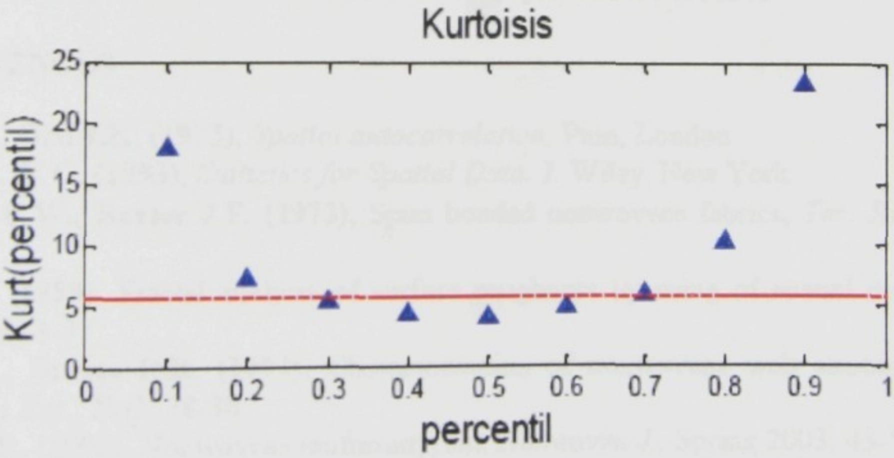

Fig.7 Kurtosis for various percentiles

It is clear that from *Tp = 0.7* till *Tp = 0.7* looks the distribution of "binarized" local mass as homogeneous. For lower and higher values the formation of spatial clusters is clearly indicated.

The indicator functions (see eqn. (13)) for selected *Tp* are shown on the fig. 8. It is visible that for higher *Tp* are identified local anomalies.

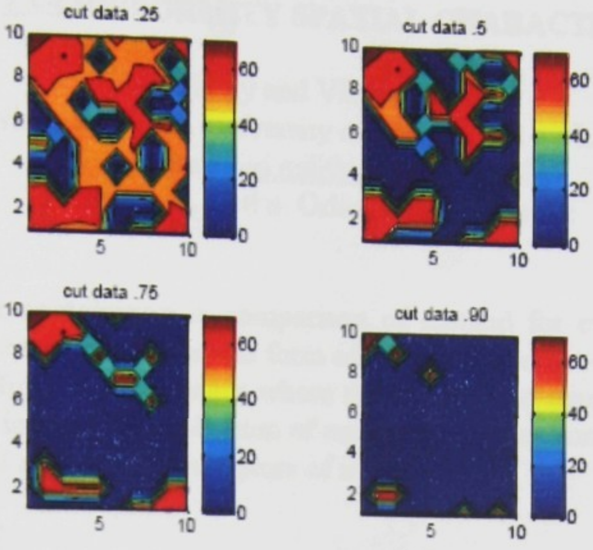

Fig. 8 Indicator functions for selected thresholds (cut)

5. CONCLUSION

The system of spatial data analysis based on the above mentioned methods can be used for identification of spatial dependence for regular lattice data or planar unevenness evaluation. Tested nonwoven exhibits large-scale variation and higher complexity with local anomalies.

ACKNOWLEDGEMENTS: This work was supported by the research project "Textile Centre" of Czech Ministry of Education LN00B090 and project 1M4674788501

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NONWOVENS UNIFORMITY SPATIAL CHARACTERIZATION

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Abstract:
The main aim of this contribution is comparison of method for evaluation of nonwovens surface uniformity based on the data in the form of rectangular arrays (quadrat method). These data can be obtained from digital images where the variation of mass is characterizes by the variation of grey level image. The evaluation of uniformity is based on the variation coefficient model, ANOVA model and spatial descriptors of irregularity.

1. INTRODUCTION

The products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exists a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1,2].

The spatial variation of geometric and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties (Erickson, Baxter (1973)). There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens (Huang, Bresee (1993); Chhabra (2003); Klička (1998)). Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation of Klička (1998). In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity. Another possibility is to use some techniques based on the spatial pattern analysis as variance to mean ratio.

The main aim of this work is attempt to describe surface irregularity of nonwoven textile structure based on the so-called quadrat method, where characteristic of quadrat is mean value of grey level. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats the mean optical transparency (grey level) is evaluated. Direction X is equivalent to the <u>machine direction</u> (index i). In this direction are N quadrats. Direction y is equivalent to the <u>cross direction</u> (index j). In this direction are M quadrats.

For evaluation of uniformity the five kinds of methods are useful.

- **First one** is based on the computation of variation coefficient in selected directions (machine and cross direction), and testing the significance of their differences (Cherkassky (1998)).
- **Second one** is based on the modelling of data arrays by the ANOVA (analysis of variance) type models and testing hypothesis about homogeneity in selected directions (Meloun, Militký, Forina (1992)).
- **Third one** is based on the analysis of random field. The moment characteristics of second order as spatial covariance and variogram are used for description of these fields. The fractal dimension characterizing random field complexity can be computed directly from variogram (Davies (1999)).

- **Fourth one** is based on the global and local spatial variation indices of Geary and Moran type (Cliff and Ord (1973)).
- **Fifth one** is based on the utilization of multivariate kurtoisis of indicator random variables (Johansson(2000))

There exist a lot of other characteristics as spatial descriptors of irregularity (Chhabra (2003)) suitable for special situations (point patterns).
The aim of this work is comparison of some characteristics of uniformity on the example of spun bonded lightweight nonwoven lap.

2. IRREGULARITY CHARACTERIZATION

Irregularity characterization is classically based on the coefficient of variation CV or derived statistics. For characterization of lattice data array the models based on the ANOVA principle are often used. For detailed description of irregularity field the second order characteristics as function of distance separation vector can be used as well. These characteristics can be compared with ideal models of nonwoven structures. Some simple indices can be obtained from indicator random variable, which is simply threshold of original spatial variable.

2.1 Spatial lattice processes

Spatial data are investigated on the specific domain D. Usually D is a subset of 2-dimensional space, but generally the d dimensional domain can be used and then $D \subset \Re^d$. The vector s contains information on the data location. Locations in D are denoted by the vector s. In 2-dimensional space, s has 2 components (x, y) containing the coordinates. At locations s, the values of some variable *z(s)* of interests (grey level, mass, density, thickness etc.) are obtained. The Z(s) is a random variable at each location. The general spatial model has the form $\{\mathbf{Z}(s) : s \in D\}$.

There exist three basic model types:

1: Geostatistical data. Here D is a continuous fixed subset of $\Re^d$; $\mathbf{Z}$(s) is a random vector at location $s \in D$.

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For the quadrat method is quantity z(**x**) random function of two variables called random field. This random field is fully described by the n variate probability density function

$$p_n(z_1, z_2, .. z_n) = P\{z_i \le z(s_i) \le z_i + dz_i, \quad i = 1...n\}. \tag{1}$$

Homogeneous random field has property of invariance according to the translation. The mean value m(**x**) = E(z) is defined as

$$E(z) = \int z \, p_1(z) \, dz \tag{2}$$

Variability of random field is characterized by the covariance function

$$C(\mathbf{x}_1, \mathbf{x}_2) = \iint (z_1 - E(z_1)(z_2 - E(z_2)) \, p_2(z_1, z_2) \, dz_1 \, dz_2. \tag{3}$$

For the case when points $\mathbf{x}_1$ and $\mathbf{x}_2$ are coincident is covariance function reduced to the *variance function* D(x) defined as (Meloun, Militký, Forina (1992))

$$D(\mathbf{x}) = E(z(\mathbf{x})^2) - (E(z(\mathbf{x})))^2 . \tag{4}$$

Another measure of spatial variability is so called *variogram* or *semivariogram* defined as half of variance of the increment ($z(\mathbf{x}_1) - z(\mathbf{x}_2)$)

$$\gamma(\mathbf{x}_1, \mathbf{x}_2) = 0.5 * D[z(\mathbf{x}_1) - z(\mathbf{x}_2)] \quad . \tag{5}$$

$$\gamma(\mathbf{h}) = \mathrm{Var}(Z(\mathbf{u}) - Z(\mathbf{u} + \mathbf{h})) = \mathrm{Var}(Z)\,(1 - \rho(\mathbf{h}))$$

For *homogeneous random field* is covariance function dependent on the distance between points

$\mathbf{x}_1 = (x_1, y_1)$ and $\mathbf{x}_2 = (x_2, y_2)$ only. For this case is $C(\mathbf{x}_1, \mathbf{x}_2) = C(x_2 - x_1, y_2 - y_1)$.

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $\mathrm{d} = \sqrt{(\mathrm{x}_2 - \mathrm{x}_1)^2 + (\mathrm{y}_2 - \mathrm{y}_1)^2}$ and therefore

$C(\mathbf{x}_1, \mathbf{x}_2) = R(d)$. A random function $z(\mathbf{x})$ is said to be *second order stationary*, if (Cressie (1993))

- the mean value exists and is independent on the location vector $\mathbf{x}$, i.e. $E(\mathbf{x}) = m$.
- for each pair of random variables $z(\mathbf{x})$ and $z(\mathbf{x} + \mathbf{h})$ is covariance dependent on the separation vector $\mathbf{h}$ only $\qquad C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x} + \mathbf{h})] - m^2$

The stationarity of variance imply the stationarity of covariance and variogram

$$D(z(\mathbf{x})) = C(\mathbf{h} = 0) = C(0) \qquad \gamma(\mathbf{h}) = C(0) - C(\mathbf{h}) . \tag{6}$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation. It is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$.

If $\gamma(0) = c_0 > 0$, then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h}) = const.$ for all $\mathbf{h}$ then the z(.) are uncorrelated in this direction.

The dependence of $\gamma(\mathbf{h})$ on $\mathbf{h}$ can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\begin{aligned} &\gamma(h) = c_0 + c[1.5(h/a) - 0.5(h/a)^3] \quad \text{for } 0 \le h \le a \\ &\gamma(h) = c_0 + c \quad \text{for } h > a \end{aligned} \tag{7}$$

where h is the length of $\mathbf{h}$. The distributional properties of variogram and techniques for parameter estimation are discussed in the book of Cressie (1993).

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of uniformity (grey level, planar densities or mass) $z(\mathbf{x}_i) = z(k,j)$ of k, j th cell ($k = 1...m$, $j = 1...n$) of the rectangular net are used. The *sample directional variogram* function for chosen separation vector $\mathbf{h}$ is calculated according to the following formula

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} [z(x_i) - z(x_i + \mathbf{h})]^2 \tag{8}$$

where $N(\mathbf{h})$ is number of points in separation distances $\mathbf{h}$. For regularly distributed points $\mathbf{x}$ are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° ($\mathbf{h}$ = c*[1,0]), 45° ($\mathbf{h}$ = c*[1,1]), and 90° ($\mathbf{h}$ = c*[1,0]) for lags c = 1,2,3...only. Averaging of variograms calculated in all directions leads to the *omnidirectional variogram*. For computation of these spatial measures the program NONWP written in MATLAB 7.04 was created.

2.2 Analysis based on CV

Surface uniformity is classically described by the coefficient of variation (CV). This coefficient is traditionally used as the characteristics of unevenness.

According to the common definitions we can simply computed the overall mean, variance and coefficient of variation

$$m = \frac{1}{MN}\sum_i\sum_j (z_{ij}) \qquad s^2 = \frac{1}{MN}\sum_i\sum_j (z_{ij} - m)^2 \qquad CV = \frac{s}{m} \qquad (9)$$

Here z_{ij} is selected characteristic of quadrats (here mean grey level m_{ij}.). Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.

The quantity CV is in fact external variation coefficient CB(F) between cell areas F^2.

Ideal value of CV for nonwoven of total weight W having Poisson distribution of random fibres of fineness T_V and density ρ_V is defined as (Militký (1998))

$$CV_N(P) = \frac{\sqrt[4]{\pi}}{\sqrt{2}}\sqrt[4]{\frac{T_V \rho_V}{W^2}}$$

The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{io} = \frac{1}{M}\sum_j z_{ij} \qquad m_{oj} = \frac{1}{N}\sum_j z_{ij}$$

Symbol „o"*denotes* index used for summation *i.e.* m_{io} is mean value for i th position in the machine direction. For the machine direction (expansion of eqn.(14) by using of the m_{io}) the following relation results (Cherkassky (1998))

$$s^2 = s_L^2 + s_{HL}^2 \qquad (10)$$

where the variance in the machine direction s_L^2 is

$$s_L^2 = \frac{1}{N}\sum_i (m_{io} - m)^2$$

and the variance in the transversal direction s_{HL}^2 is

$$s_{HL}^2 = \frac{1}{MN}\sum_i\sum_j (z_{ij} - m_{io})^2$$

For the cross direction is

$$s^2 = s_H^2 + s_{LH}^2 \qquad (11)$$

where the variance in the cross-direction s_H^2 is

$$s_H^2 = \frac{1}{M}\sum_j (m_{oj} - m)^2$$

and the variance in the longitudinal direction s_{LH}^2 is

$$s_{LH}^2 = \frac{1}{MN}\sum_i\sum_j (z_{ij} - m_{oj})^2$$

The coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} are obtained by dividing the corresponding standard deviations by the mean m. These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals the variance of point estimates have to be computed (Meloun Militký and Forina (1992)).

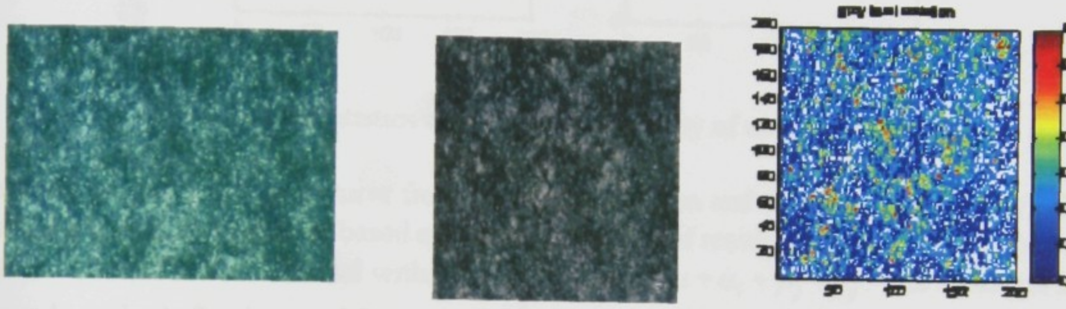
The uniformity of mass distribution can be also characterized by index of dispersion.

$$I_d = \frac{s^2}{m} \tag{12}$$

Spatial randomness corresponds to the Poisson distribution. The null hypothesis of randomness can be tested by comparison of Id with quantiles of χ^2 distribution. It is possible to compute the limit M_L bellow the pattern is uniform and limit M_U above the pattern is clumped (Chhabra (2003)).

3. EXPERIMENTAL PART

The spun bonded nonwoven image (see fig. 1a) was used for uniformity evaluation. The quadrat size 2x2 pixels was selected. Corresponding modified image is on the fig. 1b and mean grey levels in quadrats is on the fig. 1c. These data were used for characterization of uniformity. The influence of quadrat size on the corresponding areal CV was investigated by using of program NONWCV.



a b c

Fig. 1 Raw image (a), quadrats 2x2 image (b) and mean grey levels in quadrats (c)

4. RESULTS AND DISCUSSION

The results are part of outputs from program NONWP. The dependence of CV on the quadrat area size (program NONWCV) is given on the fig 2

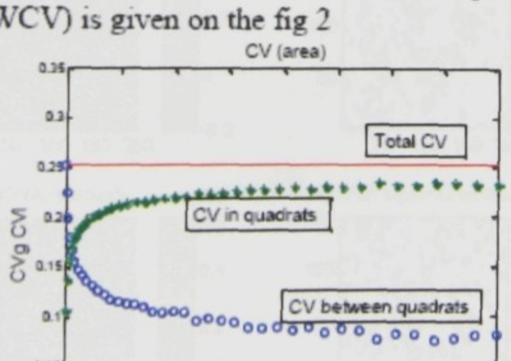


Fig. 2 Dependence of CV on quadrat size

For deeper investigation of non uniformity the moving windows were used. Principle is division the study area to the several local neighborhoods of equal size (moving windows) and within each local window the mean and variance are computed. The dimension of moving windows can be gradually changed to obtain good identification of local anomalies. The plot of local means and variances are given in fig.3. The row mean and variances are shown as well.

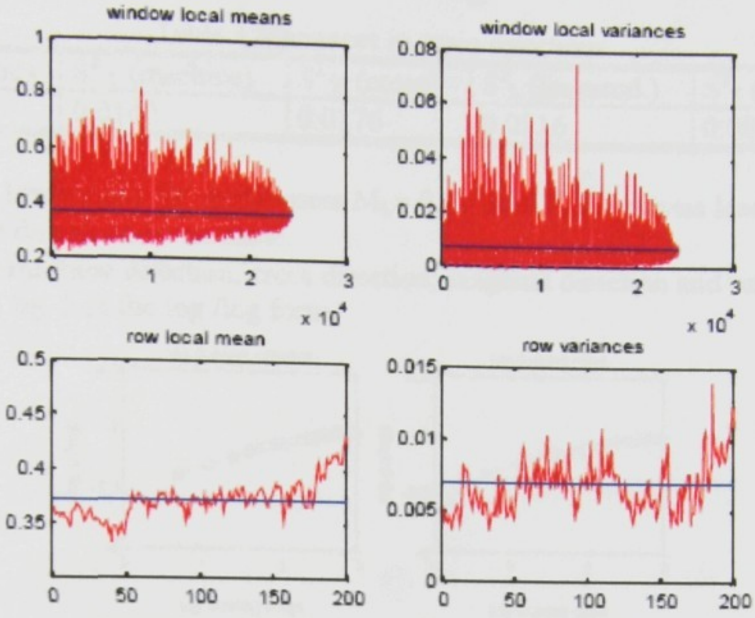


Fig. 3 Local statistics characterizing stability of mean and variance

There are visible some departures from constancy of mean and variance (stationarity). Deeper analysis of local anomalies is based on the investigation of residuals. Simple parametric model is based on the ANOVA model without interaction $z_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij}$. The residuals and squared residuals for this model are on the fig. 4. The residuals were computed from total mean m, row means m_{io} and column means m_{oj} or by replacing of means by medians.

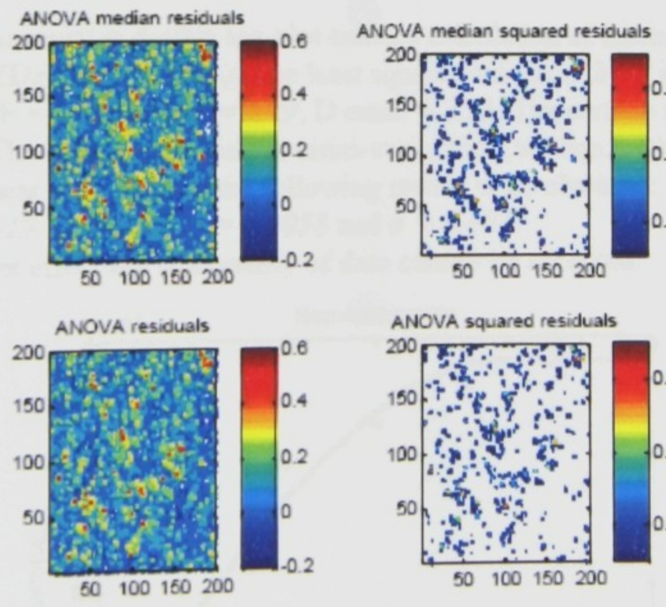


Fig. 4 Residuals and squared residuals for ANOVA model

The local "hot spots" (anomalies) are here clearly visible.
The division of total variance and index of dispersion can characterize uniformity. The division of total variance is in the table 1.

Table 1 Variances in main directions

Characteristics	$S^2{}_L$ (machine)	$S^2{}_H$ (cross)	S^2_L (longitud.)	S^2_T (transvers.)
Grey level	0.0142	0.0176	0.0816	0.0823

The $I_d = 0.018$ is lower limit for randomness $M_L = 0.81$. ANOVA analysis leads to results that variability in both directions is the same.

The variogram is machine direction, cross direction; diagonal direction and omni-variogram are shown on the fig. 5 in the log /log form

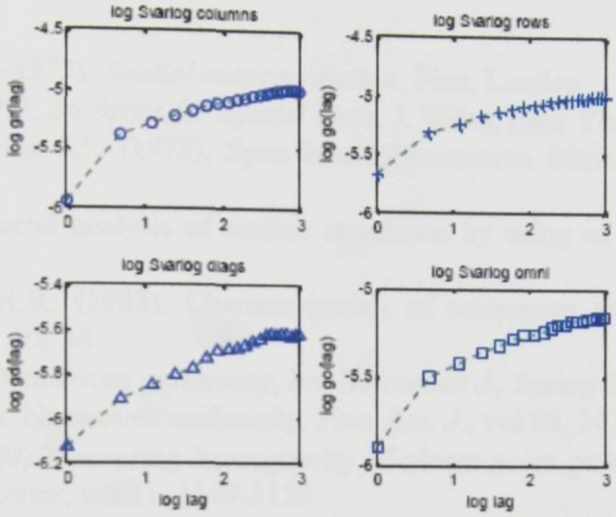
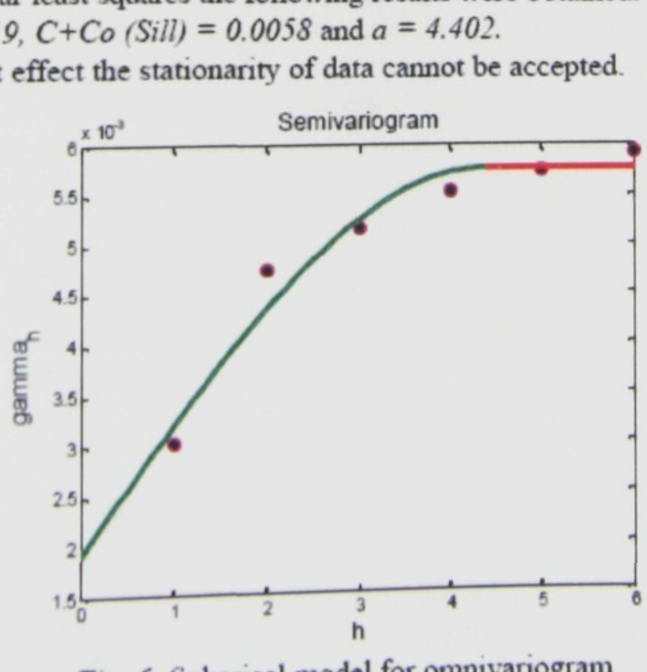


Fig. 5 Variograms in double logarithmic plot

The approximate linearity in double log plot enables calculation of fractal dimension from straight line slope (Davies S. (1999)). The least squares estimates from initial points are: D rows = 2.24, D cols = 2.16, D diag = 2.29, D omni = 2.22. The surface is therefore only slightly complex. The spherical model for omni-variogram (see eqn. (7)) is shown on the fig. 6. By using of nonlinear least squares the following results were obtained:

Co (Nugget) = 0.019, C+Co (Sill) = 0.0058 and *a = 4.402*.

Due to high nugget effect the stationarity of data cannot be accepted.



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NONWOVENS UNIFORMITY CHARACTERIZATION BY SURFACE VARIATION FUNCTION

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Abstract:
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For the quadrat method is quantity z($\mathbf{x}$) random function of two variables called random field. This random field is fully described by the n variate probability density function

$$p_n(z_1, z_2, .. z_n) = P\{z_i \le z(s_i) \le z_i + dz_i, \quad i = 1..n\}. \tag{1}$$

Homogeneous random field has property of invariance according to the translation. The mean value m($\mathbf{x}$) = E(z) is defined as

$$E(z) = \int z \; p_1(z) \, dz \tag{2}$$

Variability of random field is characterized by the covariance function

$$C(\mathbf{x}_1, \mathbf{x}_2) = \iint (z_1 - E(z_1)(z_2 - E(z_2) \; p_2(z_1, z_2) \, dz_1 \, dz_2 . \tag{3}$$

For the case when points $\mathbf{x}_1$ and $\mathbf{x}_2$ are coincident is covariance function reduced to the *variance function* D($\mathbf{x}$) defined as (Meloun, Militký, Forina (1992))

$$D(\mathbf{x}) = E(z(\mathbf{x})^2) - (E(z(\mathbf{x})))^2 . \qquad (4)$$

Another measure of spatial variability is so called *variogram* or *semivariogram* defined as half of variance of the increment $(z(\mathbf{x}_1) - z(\mathbf{x}_2))$

$$\gamma(\mathbf{x}_1, \mathbf{x}_2) = 0.5 * D[z(\mathbf{x}_1) - z(\mathbf{x}_2)] \qquad (5)$$

$$\gamma(\mathbf{h}) = \mathrm{Var}(Z(\mathbf{u}) - Z(\mathbf{u} + \mathbf{h})) = \mathrm{Var}(Z)\,(1 - \rho(\mathbf{h}))$$

For *homogeneous random field* is covariance function dependent on the distance between points

$\mathbf{x}_1 = (x_1, y_1)$ and $\mathbf{x}_2 = (x_2, y_2)$ only. For this case is $C(\mathbf{x}_1, \mathbf{x}_2) = C(x_2 - x_1, y_2 - y_1)$.

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore $C(\mathbf{x}_1, \mathbf{x}_2) = R(d)$. A random function $z(\mathbf{x})$ is said to be *second order stationary*, if (Cressie (1993))

- the mean value exists and is independent on the location vector $\mathbf{x}$, i.e. $E(\mathbf{x}) = m$.
- for each pair of random variables $z(\mathbf{x})$ and $z(\mathbf{x} + \mathbf{h})$ is covariance dependent on the separation vector $\mathbf{h}$ only $\quad C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x} + \mathbf{h})] - m^2$

The stationarity of variance imply the stationarity of covariance and variogram

$$D(z(\mathbf{x})) = C(\mathbf{h} = 0) = C(0) \qquad \gamma(\mathbf{h}) = C(0) - C(\mathbf{h}) . \qquad (6)$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation. It is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$.

If $\gamma(0) = c_0 > 0$, then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h}) = const.$ for all $\mathbf{h}$ then the z(.) are uncorrelated in this direction.

The dependence of $\gamma(\mathbf{h})$ on $\mathbf{h}$ can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\begin{aligned} &\gamma(h) = c_0 + c[1.5(h/a) - 0.5(h/a)^3] \ \text{ for } 0 \le h \le a \\ &\gamma(h) = c_0 + c \ \text{ for } h > a \end{aligned} \qquad (7)$$

where h is the length of $\mathbf{h}$. The distributional properties of variogram and techniques for parameter estimation are discussed in the book of Cressie (1993).

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of uniformity (grey level, planar densities or mass) $z(\mathbf{x}_i) = z(k,j)$ of k, j th cell ($k = 1...m$, $j = 1...n$) of the rectangular net are used. The *sample directional variogram* function for chosen separation vector $\mathbf{h}$ is calculated according to the following formula

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} [z(x_i) - z(x_i + \mathbf{h})]^2 \qquad (8)$$

where $N(\mathbf{h})$ is number of points in separation distances $\mathbf{h}$. For regularly distributed points $\mathbf{x}$ are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° ($\mathbf{h} = c*[1,0]$), 45° ($\mathbf{h} = c*[1,1]$), and 90° ($\mathbf{h} = c*[1,0]$) for lags $c = 1,2,3...$only. Averaging of variograms calculated in all directions leads to the *omnidirectional variogram*. For computation of these spatial measures the program NONWP written in MATLAB 7.04 was created.

2.2 Analysis based on CV

Surface uniformity is classically described by the coefficient of variation (CV). This coefficient is traditionally used as the characteristics of unevenness.

According to the common definitions we can simply computed the overall mean, variance and coefficient of variation

$$m=\frac{1}{MN}\sum_i\sum_j(z_{ij}) \qquad s^2=\frac{1}{MN}\sum_i\sum_j(z_{ij}-m)^2 \qquad CV=\frac{s}{m} \tag{9}$$

Here z_{ij} is selected characteristic of quadrats (here mean grey level m_{ij}.). Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.

The quantity CV is in fact external variation coefficient CB(F) between cell areas F^2.

Ideal value of CV for nonwovens of total weight W having Poisson distribution of random fibres of fineness T_V and density ρ_V is defined as (Militký (1998))

$$CV_N(P)=\frac{\sqrt[4]{\pi}}{\sqrt{2}}\sqrt[4]{\frac{T_V\rho_V}{W^2}}$$

The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{io}=\frac{1}{M}\sum_j z_{ij} \qquad m_{oj}=\frac{1}{N}\sum_j z_{ij}$$

Symbol „o"*denotes* index used for summation *i.e.* m_{io} is mean value for i th position in the machine direction. For the machine direction (expansion of eqn.(14) by using of the m_{io}) the following relation results (Cherkassky (1998))

$$s^2=s_L^2+s_{HL}^2 \tag{10}$$

where the variance in the machine direction s_L^2 is

$$s_L^2=\frac{1}{N}\sum_i(m_{io}-m)^2$$

and the variance in the transversal direction s_{HL}^2 is

$$s_{HL}^2=\frac{1}{MN}\sum_i\sum_j(z_{ij}-m_{io})^2$$

For the cross direction is

$$s^2=s_H^2+s_{LH}^2 \tag{11}$$

where the variance in the cross-direction s_H^2 is

$$s_H^2=\frac{1}{M}\sum_j(m_{oj}-m)^2$$

and the variance in the longitudinal direction s_{LH}^2 is

$$s_{LH}^2=\frac{1}{MN}\sum_i\sum_j(z_{ij}-m_{oj})^2$$

The coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} are obtained by dividing the corresponding standard deviations by the mean m. These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals the variance of point estimates have to be computed (Meloun Militký and Forina (1992)).

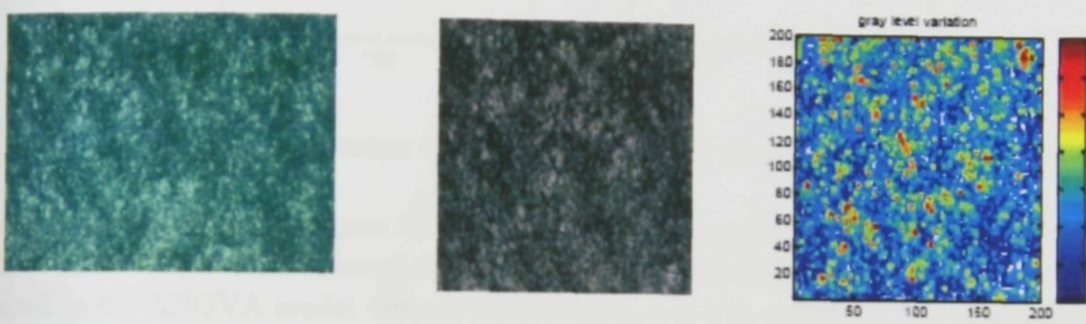
The uniformity of mass distribution can be also characterized by index of dispersion.

$$I_d = \frac{s^2}{m} \tag{12}$$

Spatial randomness corresponds to the Poisson distribution. The null hypothesis of randomness can be tested by comparison of Id with quantiles of χ^2 distribution. It is possible to compute the limit M_L bellow the pattern is uniform and limit M_U above the pattern is clumped (Chhabra (2003)).

3. EXPERIMENTAL PART

The spun bonded nonwoven image (see fig. 1a) was used for uniformity evaluation. The quadrat size 2x2 pixels was selected. Corresponding modified image is on the fig. 1b and mean grey levels in quadrats is on the fig. 1c. These data were used for characterization of uniformity. The influence of quadrat size on the corresponding areal CV was investigated by using of program NONWCV.



a b c

Fig. 1 Raw image (a), quadrats 2x2 image (b) and mean grey levels in quadrats (c)

4. RESULTS AND DISCUSSION

The results are part of outputs from program NONWP. The dependence of CV on the quadrat area size (program NONWCV) is given on the fig 2

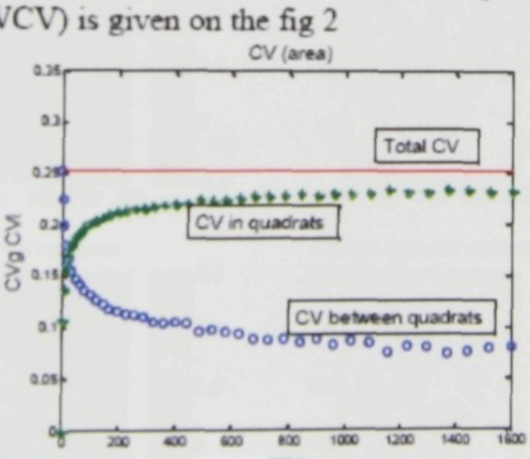


Fig. 2 Dependence of CV on quadrat size

For deeper investigation of nonuniformity the moving windows were used. Principle is division the study area to the several local neighborhoods of equal size (moving windows) and within each local window the mean and variance are computed. The dimension of moving windows can be gradually changed to obtain good identification of local anomalies. The plot of local means and variances are given in fig.3. The row mean and variances are shown as well.

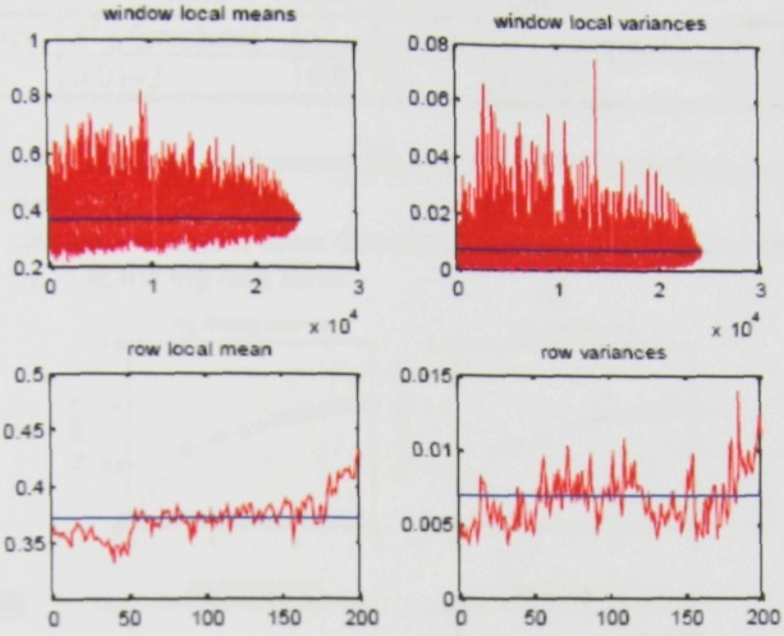


Fig. 3 Local statistics characterizing stability of mean and variance

There are visible some departures from constancy of mean and variance (stationarity). Deeper analysis of local anomalies is based on the investigation of residuals. Simple parametric model is based on the ANOVA model without interaction $z_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij}$. The residuals and squared residuals for this model are on the fig. 4. The residuals were computed from total mean m, row means m_{io} and column means m_{oj} or by replacing of means by medians.

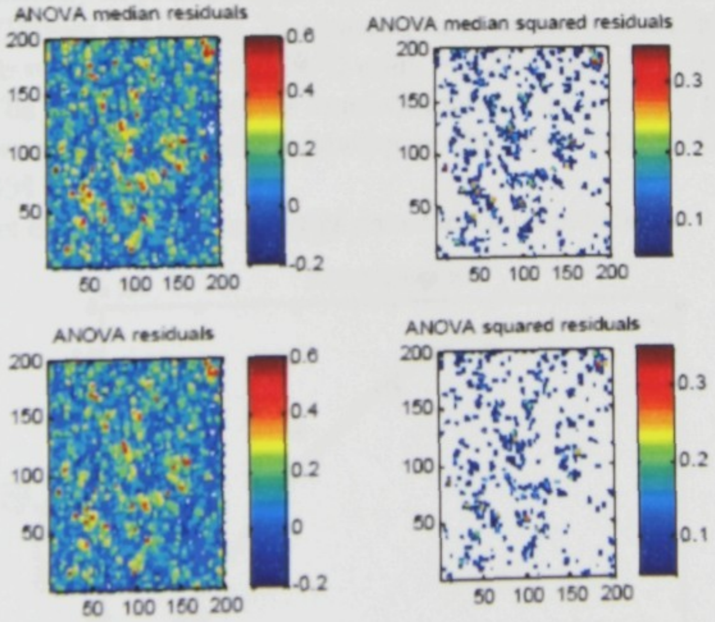


Fig. 4 Residuals and squared residuals for ANOVA model

The local "hot spots" (anomalies) are here clearly visible.
The division of total variance and index of dispersion can characterize uniformity. The division of total variance is in the table 1.

Table 1 Variances in main directions

Characteristics	S^2_L (machine)	S^2_H (cross)	S^2_L (longitud.)	S^2_T (transvers.)
Grey level	0.0142	0.0176	0.0816	0.0823

The $I_d = 0.018$ is lower limit for randomness $M_L= 0.81$. ANOVA analysis leads to results that variability in both directions is the same.

The variogram is machine direction, cross direction; diagonal direction and omni-variogram are shown on the fig. 5 in the log /log form

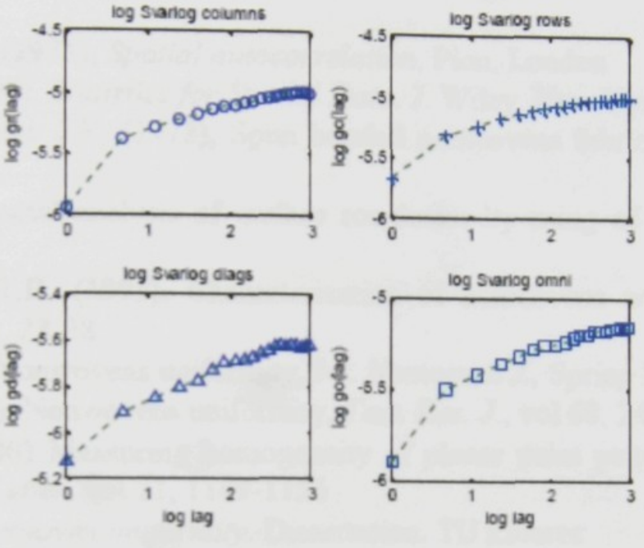


Fig. 5 Variograms in double logarithmic plot

The approximate linearity in double log plot enables calculation of fractal dimension from straight line slope (Davies S. (1999)). The least squares estimates from initial points are: D rows = 2.24, D cols = 2.16, D diag = 2.29, D omni = 2.22. The surface is therefore only slightly complex. The spherical model for omni-variogram (see eqn. (7)) is shown on the fig. 6. By using of nonlinear least squares the following results were obtained: Co (Nugget) = 0.0 19, C+Co (Sill) = 0.0058 and a = 4.402.

Due to high nugget effect the stationarity of data cannot be accepted.

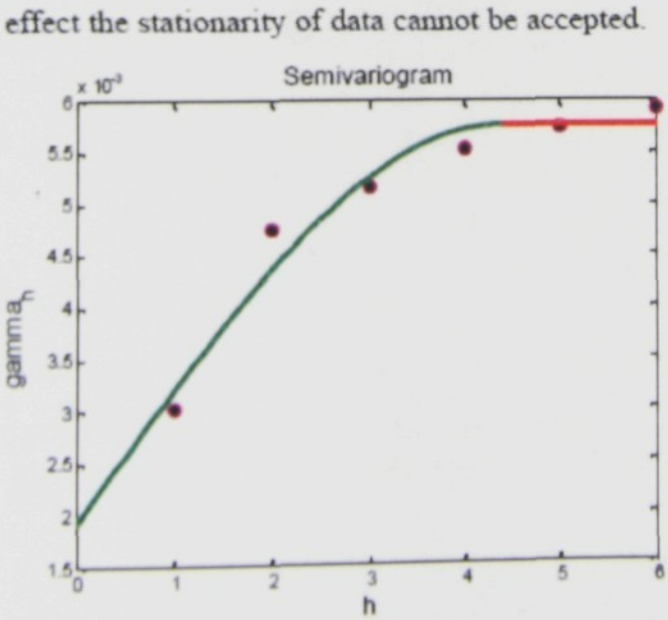


Fig. 6. Spherical model for omnivariogram

5. CONCLUSION

The system of data analysis based on the above mentioned methods can be used for identification of spatial dependence for regular lattice data or planar unevenness evaluation. Tested nonwovens exhibits large-scale variation and slight complexity.

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CHARACTERIZATION OF TEXTILES MASS VARIATION IN PLANE

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Abstract

Mass irregularity is one of the important characteristics of textile structures. This characteristic is closely connected to the variation function for appearance, transparency, reflectivity, and thickness and to the properties as e.g. air permeability. The main aim of this work is attempt to describe surface irregularity of nonwoven textile structure based on the so-called quadrat methods, where characteristic of quadrat is its weight. The evaluation of mass irregularity is based on the variation coefficient model, ANOVA model and spatial descriptors of irregularity.

Key Words, Nonwovens characterization, variation coefficient, ANOVA, spatial uniformity,

1. INTRODUCTION

The spatial variation of geometric and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties (Erickson, Baxter (1973)). There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens (Huang, Bresee (1993); Chhabra (2003); Klička (1998)). Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation of Klička (1998). In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity. Another possibility is to use some techniques based on the spatial pattern analysis as variance to mean ratio.
The main aim of this work is attempt to describe surface irregularity of nonwoven textile structure based on the so-called quadrat methods, where characteristic of quadrat is its weight. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats some characteristics as weight, mean optical transparency, mean relief etc. can be measured. Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.
The evaluation of mass irregularity is based on the variation coefficient model (Cherkassky (1998)), ANOVA model (Meloun, Militký, Forina (1992)) and spatial descriptors of irregularity (Chhabra (2003); Cressie (1993)).

2. SURFACE IRREGULARITY CHARACTERIZATION

Surface irregularity characterization is classically based on the coefficient of variation CV or derived statistics of the second order. For detailed description of irregularity field the second order characteristics as function of distance separation vector can be used as well. These characteristics can be compared with pure randomness or ideal models of nonwoven structures.

2.1 Unevenness random field

The planar density z(**x**)=z(x,y) describes sufficiently the planar uniformity or unevenness (Cherkassky (1998)). The quantity z(x,y) in the point **x** = (x,y) is defined as limit of mass M(S) divided by the area S = 4dxdy of elementary rectangle i.e. the cross sectional area of volume element having thickness t (thickness of nonwoven) and perpendicular dimensions x ± dx and y ± dy. Formally

$$z\,(x,y) = \lim_{S \to 0} \frac{M\,(S)}{S} = t * \rho\,(x,y), \tag{1}$$

where ρ(x,y) is volume textile density in the point **x** = (x,y). For the case of constant area S is variation of z(**x**) the same as variation of local mass M(**x**). Quantity z(**x**) is random function of two variables called random field. This random field is fully described by the *n* variate probability density function

$$p_n(z_1, z_2, .. z_n) = P\{z_i \le z(\mathbf{x_i}) \le z_i + dz_i,\; i = 1..n\}. \tag{2}$$

Homogeneous random field has property of invariance according to the translation. The mean value m(**x**) = E(z) is defined as

$$E(z) = \int z\, p_1(z)\, dz \tag{3}$$

Variability of random field is characterized by the covariance function

$$C\,(\mathbf{x_1}, \mathbf{x_2}) = \iint (z_1 - E(z_1)(z_2 - E(z_2)\, p_2(z_1, z_2)\, dz_1\, dz_2. \tag{4}$$

For the case when points $\mathbf{x_1}$ and $\mathbf{x_2}$ are coincident is covariance function reduced to the *variance function* D(x) defined as (Meloun, Militký, Forina (1992))

$$D(\mathbf{x}) = E(z(\mathbf{x})^2) - (E(z(\mathbf{x})))^2. \tag{5}$$

Another measure of spatial variability is so called *variogram* or *semivariogram* defined as half of variance of the increment $(z(\mathbf{x_1}) - z(\mathbf{x_2}))$

$$\gamma(\mathbf{x_1}, \mathbf{x_2}) = 0.5 * D[z(\mathbf{x_1}) - z(\mathbf{x_2})] \tag{6}$$

For *homogeneous random field* is covariance function dependent on the distance between points $\mathbf{x_1} = (x_1, y_1)$ and $\mathbf{x_2} = (x_2, y_2)$ only. For this case is $C\,(\mathbf{x_1}, \mathbf{x_2}) = C\,(x_2 - x_1, y_2 - y_1)$.

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore $C\,(\mathbf{x_1}, \mathbf{x_2}) = R\,(d)$.

A random function z(**x**) is said to be *second order stationary*, if (Cressie (1993))

- the mean value exists and is independent on the location vector **x**, i.e. E(**x**) = m.
- for each pair of random variables z(**x**) and z(**x** + **h**) is covariance dependent on the separation vector **h** only $C(\mathbf{h}) = E[z(\mathbf{x}) * z(\mathbf{x} + \mathbf{h})] - m^2$

The stationarity of variance imply the stationarity of covariance and variogram

$$D(z(\mathbf{x})) = C(\mathbf{h} = 0) = C(0) \qquad \gamma(\mathbf{h}) = C(0) - C(\mathbf{h}). \tag{8}$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation. It is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$.

If $\gamma(0) = c_0 > 0$, then c_0 is called as nugget effect (small scale variations cause discontinuity at origin).

If $\gamma(\mathbf{h}) = const.$ for all **h** then the z(.) are uncorrelated in this direction.

The dependence of $\gamma(\mathbf{h})$ on **h** can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\gamma(h) = c_0 + c[1.5(h/a) - 0.5(h/a)^3] \quad \text{for } 0 \le h \le a$$
$$\gamma(h) = c_0 + c \quad \text{for } h > a \tag{9}$$

where *h* is the length of **h**. The distributional properties of variogram and techniques for parameter estimation are discussed in the book of Cressie (1993).

If the spatial phenomenon is seen as being generated by the addition of several independent sources having similar spatial distributions, then the z(**x**) can be modeled by a multivariate ***Gaussian*** random function. Since the linear combination of multinormal vector is also normally distributed a check of this assumption is based on the verification that the difference [z(**x**) - z(**x**+**h**)] is normally distributed with man 0 and variance $2\gamma(\mathbf{h})$.

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of planar densities (or mass) z(**x**$_i$) = z(k,j) of k,j th cell (k = 1...m, j = 1...n) of the rectangular net are used. The *sample directional variogram* function for chosen separation vector **h** is calculated according to the following formula

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})}[z(x_i) - z(x_i + \mathbf{h})]^2 \tag{10}$$

where N(**h**) is number of points in separation distances **h.** For regularly distributed points **x** are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° (**h** = c*[1,0]), 45° (**h** = c*[1,1]), and 90° (**h** = c*[1,0]) for lags c = 1,2,3... only. Averagings of variograms calculated in all directions leads to the *omnidirectional variogram*.
The sample-standardized *variogram* for separation vector **h** is defined as

$$\gamma_s(h) = \frac{\gamma(\mathbf{h})}{\sigma_1\sigma_h} \tag{11}$$

where

$$\sigma_1^2 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i)^2 - m_1^2 \text{ and } \quad m_1 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i) \tag{12}$$

and

$$\sigma_h^2 = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h})^2 - m_h^2 \text{ and } \quad m_h = \frac{1}{N(\mathbf{h})}\sum_{i=1}^{N(\mathbf{h})} z(\mathbf{x}_i + \mathbf{h}). \tag{13}$$

For an omnidirectional case is the *standardized variogram* directly related to the *correlogram* $\rho(\mathbf{h}) = 1 - \gamma(\mathbf{h})$.

For graphical exploration of spatial variation the *h-scatter-plot* and *variogram surface* are useful. On the h-scatter-plot the z(**x**$_i$) are plotted against z(**x**$_i$+**h**). For Gaussian distribution forms the h-scatter-plot the elliptical cloud around the diagonal line with higher density of points in the center of this cloud. A succession of h-scatter-plots calculated for increasing lags (values of **h**) provides check of stationarity. If successions of h-scatter-plots show that the center of the clouds of pairs depart from diagonal line, the stationarity cannot be accepted.
Variogram surface is constructed as a set of variograms arranged to cells of regular grids starting from central one with zero separation vector (0, 0). Every cell has separation vector **h** created as number of lags in x and y directions from central one. This surface identifies the directions of anisotropy i.e. preferential directions in which the directional variograms should be constructed.
For computation of these spatial measures the program Variowin 2.2 (Pannatier (1996)) and own procedures written in MATLAB 7.0 have been used

2.2 Analysis based on CV

Surface irregularity is classically described by the coefficient of variation (CV). This coefficient is traditionally used as the characteristics of unevenness. According to the common definitions we can simply computed the overall mean, variance and coefficient of variation

$$m = \frac{1}{MN}\sum_i\sum_j(P_{ij}) \qquad s^2 = \frac{1}{MN}\sum_i\sum_j(P_{ij} - m)^2 \qquad CV = \frac{s}{m} \tag{14}$$

Here P_{ij} is selected characteristic of quadrats (here mass m_{ij}). Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.
The quantity CV is in fact external variation coefficient CB(F) between cell areas F^2.
Ideal value of CV for nonwovens of total weight W having Poisson distribution of random fibres of

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The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

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Symbol „o"*denotes* index used for summation *i.e.* m_{io} is mean value for i th position in the machine direction. For the <u>machine direction</u> (expansion of s^2 by using of the m_{io}) the following relation results (Cherkassky (1998))

$$s^2 = s_L^2 + s_{HL}^2$$

where s_L^2 is the variance in the machine direction

$$s_L^2 = \frac{1}{N} \sum_i (m_{io} - m)^2 \tag{15}$$

and the variance in the transversal direction and s_{HL}^2 is

$$s_{HL}^2 = \frac{1}{MN} \sum_i \sum_j (P_{ij} - m_{io})^2 \tag{16}$$

For the <u>cross direction</u> is

$$s^2 = s_H^2 + s_{LH}^2 \tag{17}$$

where s_H^2 is the variance in the cross-direction

$$s_H^2 = \frac{1}{M} \sum_j (m_{oj} - m)^2 \tag{18}$$

and s_{LH}^2 is the variance in the longitudinal direction.

$$s_{LH}^2 = \frac{1}{MN} \sum_i \sum_j (P_{ij} - m_{oj})^2 \tag{19}$$

The coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} are obtained by dividing the corresponding standard deviations by the mean *m*. These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals the variance of point estimates have to be computed (Meloun Militký and Forina (1992)).
The uniformity of mass distribution can be also characterized by index of dispersion.

$$I_d = \frac{s^2}{m} \tag{18}$$

Spatial randomness corresponds to the Poisson distribution. The null hypothesis of randomness can be tested by comparison of Id with quantiles of χ^2 distribution. It is possible to compute the limit M_L bellow the pattern is uniform and limit M_U above the pattern is clumped (Chhabra (2003)).

2.3 Analysis by the ANOVA

The differences between variability in machine and cross directions can be formally tested by the analysis of variance (ANOVA. The P_{ij} can be interpreted as discrete presentations of random field on the discrete two dimensional integer valued rectangular mesh Let the P_{ij} are described by the following model

$$P_{ij} = \mu_{ij} + \varepsilon_{ij} \qquad \mu_{ij} = \mu + \alpha_i + \beta_j + c.\alpha_i.\beta_j$$

where μ_{ij} is true value in the ij cell, ε_{ij}, μ is total mean α_i are **effects in the cross direction**, β_j are **effects in the machine direction** and *c* is constant of Tukey one degree of freedom non - additivity. (Meloun, Militký and Forina (1992)).
Uniformity in the machine direction is equal to validity of hypotheses $H_0 : \beta_j = 0, j = 1...M$

and uniformity in the cross direction is equal to validity of hypotheses $H_0: \alpha_i = 0, i = 1...N$. Testing of these hypotheses can be realized by the ANOVA (model with a single observation per cell). This procedure is in details described in book of Meloun, Militký and Forina (1992).

3. EXPERIMENTAL PART

The chemically bonded (by the acrylate binder) nonwoven from viscose fibres (VS) was prepared. Starting lap of planar weight 30 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding. The rectangular samples of dimensions 100 x 100 mm were used for further analysis. Samples were cut to quadrats having dimensions 10 x 10 mm. Relative error of quadrat dimensions were from 0.88% to 1.22%. For the case of mass density 60 g/m^2 has quadrat with area $S_j = 100\ mm^2$ weight around 6 mg. Quadrat mass m_{ij} was evaluated as mean from five measurements. Maximum relative error of weighting for samples having around 60 g/m^2 was 1.606%.

4. RESULTS AND DISCUSSION

The division of total variance, index of dispersion and ANOVA, has described mass variation. Details about results will be in full text. The division of total variance is in the table I.

Table 1 Variances and coefficients of variation CV [%]

Characteristics	S^2_L / CV_L (machine)	S^2_H / CV_H (cross)	S^2 / CV (total)
weight	1.17 / 1.84	24.75 / 8.445	25.93 / 8.64

The I_d = 0.444 is slightly above lower limit for randomness M_L= 0.3607. ANOVA analysis leads to results that variability in both directions is important.

Basic statistical characteristics of resulted random field of surface density are given in the table 2.

Table 2 Basic characteristics of surface density

Number of values	100	Dimension
Mean	58.92	[g m^{-2}]
Standard deviation	5,12	[g m^{-2}]
Variation coefficient	8.64	[%]

The variogram surface is shown on the fig 1a and local variation of mass is shown on fig 1b.

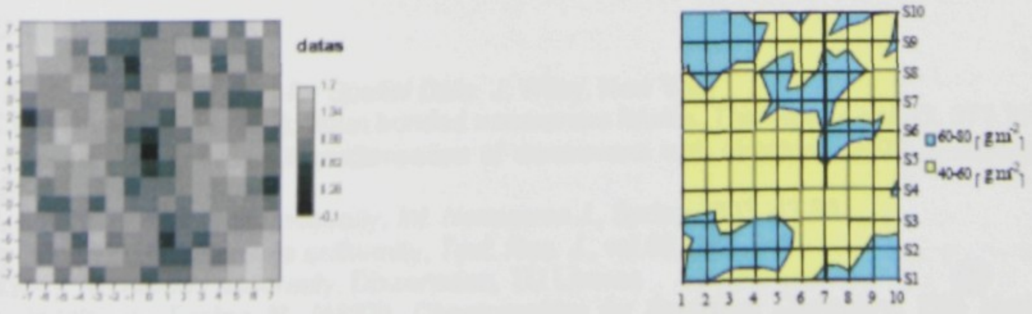

Fig. 1 a) Variogram surface, b) local mass variation

No preferential direction can be identified and therefore the directional variograms are constructed for all possible directions for rectangular net. The omnivariate directional variogram is shown on the fig 2.

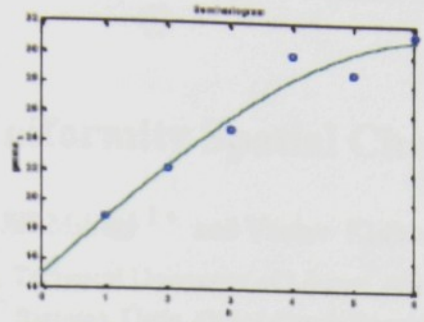

Fig 2. Omnidirectional variogram

The nugget effect (discontinuity at origin) is visible. The corresponding variance C(0) = 25.937. The omnidirectional variogram has been used for fitting of spherical model defined by equation (9). The following parameter estimates has been obtained c0 = 14.78013, c = 10.99973 and a = 4.642217. Indicative goodness of fit equal to IGF: 1.8986e-03 indicates the validity of this model (see [3]). The fitted model is shown on the fig. 2 as solid curve. The high nugget clearly indicates the violation of second order stationarity. The h-scatter-plot for direction 0° and lag 1 is shown on the fig 3.

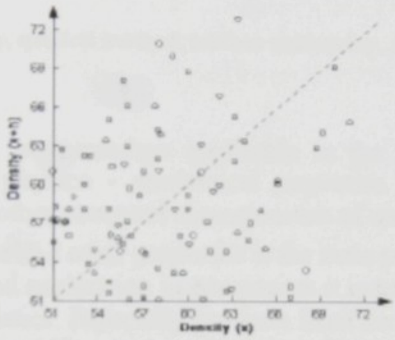

Fig.3 The h-scatter-plot for direction 0° and lag 1

Near symmetric and nearly elliptical cloud indicate very rough normality. From the similarity of h-scatter-plots for another lags the stationarity assumption can be accepted.

5. CONCLUSION

The system of spatial data analysis based on the concept of CV and variogram definition can be used for identification of spatial dependence for regular lattice data or planar unevenness evaluation. Tested nonwoven exhibits small scale variation and large-scale randomness.

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Nonwovens Uniformity Spatial Characterization *

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Abstract. The main aim of this contribution is comparison of method for evaluation of nonwovens surface uniformity based on the data in the form of rectangular arrays (quadrat method). These data can be obtained from digital images where the variation of mass is characterizes by the variation of grey level image. The evaluation of uniformity is based on the variation coefficient model, ANOVA model and spatial descriptors of irregularity

Keywords: spatial heterogeneity, quadrat method, surface uniformity, ANOVA, spatial descriptors

1. Introduction

The products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens (see [5] and [6]).

The spatial variation of geometric and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties [3]. There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens (see [5]; [6]; [9]). Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation [9]. In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity. Another possibility is to use some techniques based on the spatial pattern analysis as variance to mean ratio.

The main aim of this work is attempt to describe surface irregularity of nonwoven textile structure based on the so-called quadrat method, where characteristic of quadrat is mean value of grey level. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats the mean optical transparency (grey level) is evaluated. Direction x is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.

For evaluation of uniformity the five kinds of methods are useful.

First one is based on the computation of variation coefficient in selected directions (machine and cross direction), and testing the significance of their differences [7].

Second one is based on the modelling of data arrays by the ANOVA (analysis of variance) type models and testing hypothesis about homogeneity in selected directions [10].

Third one is based on the analysis of random field. The moment characteristics of second order as spatial covariance and variogram are used for description of these fields. The fractal dimension characterizing random field complexity can be computed directly from variogram [4].

Fourth one is based on the global and local spatial variation indices of Geary and Moran type [1].

Fifth one is based on the utilization of multivariate kurtosis of indicator random variables [8]

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There exist a lot of other characteristics as spatial descriptors of irregularity [6] suitable for special situations (point patterns).

The aim of this work is comparison of some characteristics of uniformity on the example of spun bonded lightweight nonwoven lap.

2. Irregularity characterization

Irregularity characterization is classically based on the coefficient of variation CV or derived statistics. For characterization of lattice data array the models based on the ANOVA principle are often used. For detailed description of irregularity field the second order characteristics as function of distance separation vector can be used as well. These characteristics can be compared with ideal models of nonwoven structures. Some simple indices can be obtained from indicator random variable, which is simply threshold of original spatial variable.

2.1. Spatial lattice processes

Spatial data are investigated on the specific domain D. Usually D is a subset of two-dimensional space, but generally the d dimensional domain can be used and then $D \subset \Re^d$. The vector s contains information on the data location. In two-dimensional space, s has 2 components (x, y) containing the coordinates. At locations s, the values of some variable z(s) of interests (grey level, mass, density, thickness etc.) are obtained. The z(s) is a random variable at each location. The general spatial model has the form $\{z(s) : s \in D\}$.

There exist three basic model types:

1: Geostatistical data. Here D is a continuous fixed subset of $\Re^d$; z(s) is a random vector at location $s \in D$.

2: Lattice data. Here D is a fixed but countable subset of $\Re^d$ such as a grid some representation with nodes; z(s) is a random vector at locations $s \in D$.

3: Point Patterns. Here D is a random subset of $\Re^d$ and is called a point process; if z(s) is a random vector at location $s \in D$ then it is a marked spatial point process; if $z(s) \equiv 1$ so that it is a degenerate random variable, then only D is random and it is called a spatial point process.

For the quadrat method is quantity z(s) random function of two variables called random field. This random field is fully described by the n variate probability density function

$$p_n(z_1, z_2, ...z_n) = P\{z_i \le z(s_i) \le z_i + dz_i, \quad i = 1...n\} \tag{1}$$

Homogeneous random field has property of invariance according to the translation. The mean value E(z) is defined as

$$E(z) = \int z \, p_1(z) \, dz \tag{2}$$

Variability of random field is characterized by the covariance function

$$C\ (\mathbf{s}_1, \mathbf{s}_2) = E((z_1 - E(z_1))(z_2 - E(z_2))) . \tag{3}$$

For the case when points s_1 and s_2 are coincident is covariance function reduced to the variance function D(s) defined as [10]

$$D(\mathbf{s}) = E(z(\mathbf{s})^2) - (E(z(\mathbf{s})))^2 . \tag{4}$$

Another measure of spatial variability is so called variogram or semivariogram defined as half of variance of the increment $(z(s_1) - z(s_2))$

$$\gamma(\mathbf{s}_1, \mathbf{s}_2) = 0.5 * D[z(\mathbf{s}_1) - z(\mathbf{s}_2)] = \mathrm{Var}(z(\mathbf{u}) - z(\mathbf{u} + \mathbf{h})) = \mathrm{Var}(z)\,(1 - \rho(\mathbf{h})) \tag{5}$$

For homogeneous random field is covariance function dependent on the distance between points

$s_1 = (x_1, y_1)$ and $s_2 = (x_2, y_2)$ only. For this case is $C\ (\mathbf{s}_1, \mathbf{s}_2) = C\ (x_2 - x_1, y_2 - y_1)$.

For isotropic random field is covariance function invariant against rotation and mirroring. This function is then dependent on the length $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ and therefore $C\ (\mathbf{s}_1, \mathbf{s}_2) = R\ (d)$. A random function z(s) is said to be second order stationary, if [2]

- the mean value exists and is independent on the location vector x, i.e. E(z) = m.
- for each pair of random variables z(s) and z(s + **h**) is covariance dependent on the separation vector *h* only $C(\mathbf{h}) = E[z(\mathbf{s}) * z(\mathbf{s}+\mathbf{h})] - m^2$

The stationarity of variance imply the stationarity of covariance and variogram

$$D(z) = C(\mathbf{h}=0) = C(0) \qquad \gamma(\mathbf{h}) = C(0) - C(\mathbf{h}). \tag{6}$$

The second order stationarity implies that the covariance and variogram are the equivalent tools for characterization of spatial correlation. It is clear that second order stationarity leads to the continuity at origin because $\gamma(0) = 0$.

If $\gamma(0) = c_0 > 0$, then c_0 is called as nugget effect (small scale variations cause discontinuity at origin). If $\gamma(\mathbf{h}) = const.$ for all h then the z(.) are uncorrelated in this direction.

The dependence of $\gamma(\mathbf{h})$ on *h* can be expressed by the various parametrical models. Very often it is suitable to use the spherical model expressed in the form

$$\gamma(h) = c_0 + c[1.5(h/a) - 0.5(h/a)^3] \quad \text{for } 0 \le h \le a \quad \text{or } \gamma(h) = c_0 + c \quad \text{for } h > a \tag{7}$$

where h is the length of *h*. The distributional properties of variogram and techniques for parameter estimation are discussed in the book of [2].

For computation of sample estimators of above defined measures of spatial continuity the experimentally determined values of uniformity (grey level, planar densities or mass) z(s$_i$) = z(k,j) of k, j th cell (k = 1...m, j = 1...n) of the rectangular net are used. The sample directional variogram function for chosen separation vector *h* is calculated according to the following formula

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{i=1}^{N(\mathbf{h})} [z(\mathbf{s}_i) - z(\mathbf{s}_i + \mathbf{h})]^2 \tag{8}$$

where N(h) is number of points in separation distances h. For regularly distributed points s are the separation distances multiples of distance between cells of net. Therefore it is possible to compute characteristics for directions 0° (*h* = c*[1,0]), 45° (*h* = c*[1,1]), and 90° (*h* = c*[1,0]) for lags c = 1,2,3...only. Averaging of variograms calculated in all directions leads to the omnidirectional variogram. For computation of these spatial measures the program NONWP written in MATLAB 7.04 was created.

2.2. Analysis based on CV

Surface uniformity is classically described by the coefficient of variation (CV). This coefficient is traditionally used as the characteristics of unevenness.

According to the common definitions we can simply computed the overall mean, variance and coefficient of variation

$$m = \frac{1}{MN}\sum_i \sum_j (z_{ij}) \qquad s^2 = \frac{1}{MN}\sum_i \sum_j (z_{ij} - m)^2 \qquad CV = \frac{s}{m} \tag{9}$$

Here z_{ij} is selected characteristic of quadrats (here mean grey level m_{ij}.). Direction x is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.

The quantity CV is in fact external variation coefficient CB(F) between cell areas F.

Ideal value of CV for nonwoven of total weight W having Poisson distribution of random fibres of fineness TV and density ρ_T is defined as [11]

$$CV_N(P) = \frac{\sqrt[4]{\pi}}{\sqrt{2}} \sqrt[4]{\frac{T_V \rho_V}{W^2}}$$

The total variance s2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{i0} = \frac{1}{M}\sum_j z_{ij} \qquad m_{0j} = \frac{1}{N}\sum_j z_{ij}$$

Symbol „0“ denotes index used for summation i.e. m_{i0} is mean value for i th position in the machine direction. For the machine direction (expansion of eqn.(14) by using of the m_{io}) the following relation results [7]

$$s^2 = s_L^2 + s_{HL}^2 \tag{10}$$

where the variance in the machine direction s_L^2 is

$$s_L^2 = \frac{1}{N}\sum_i (m_{io} - m)^2$$

and the variance in the transversal direction s_{HL}^2 is

$$s_{HL}^2 = \frac{1}{MN}\sum_i \sum_j (z_{ij} - m_{io})^2$$

For the cross direction is

$$s^2 = s_H^2 + s_{LH}^2 \tag{11}$$

where the variance in the cross-direction s_H^2 is

$$s_H^2 = \frac{1}{M}\sum_j (m_{oj} - m)^2$$

and the variance in the longitudinal direction s_{LH}^2 is

$$s_{LH}^2 = \frac{1}{MN}\sum_i \sum_j (z_{ij} - m_{oj})^2$$

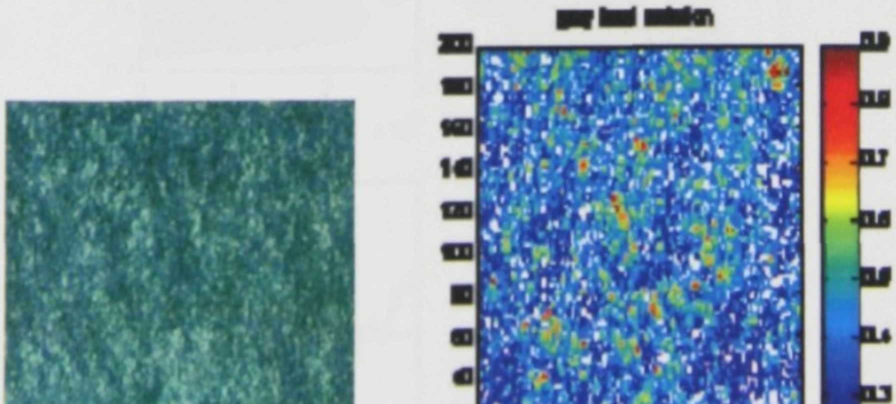
The coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} are obtained by dividing the corresponding standard deviations by the mean value m. These coefficients are from statistical point of view the point estimates of population variation coefficients CV_{PL}, CV_{PH}, etc. For creation of confidence intervals the variance of point estimates have to be computed [10].

The uniformity of mass distribution can be also characterized by index of dispersion.

$$I_d = \frac{s^2}{m} \tag{12}$$

Spatial randomness corresponds to the Poisson distribution. The null hypothesis of randomness can be tested by comparison of Id with quantiles of χ^2 distribution. It is possible to compute the limit ML bellow the pattern is uniform and limit MU above the pattern is clumped [6].

3. Experimental part



a b

Fig. 1 Raw image (a) and mean grey levels in quadrats (b)

Journal of Information and Computing Science, 2 (2007) 2, pp 85-92

The spun bonded nonwoven image (see fig. 1a) was used for uniformity evaluation. The starting quadrat size 2x2 pixels was selected. This size was expanded by averaging. Mean grey levels in quadrats of starting size is shown on the fig. 1b. These data were used for characterization of uniformity. The influence of quadrat size (expanded starting size) on the corresponding areal CV was investigated by using of program NONWCV.

4. Results and discussion

The results are part of outputs from program NONWP. The dependence of CV on the quadrat area size (program NONWCV) is given on the fig 2

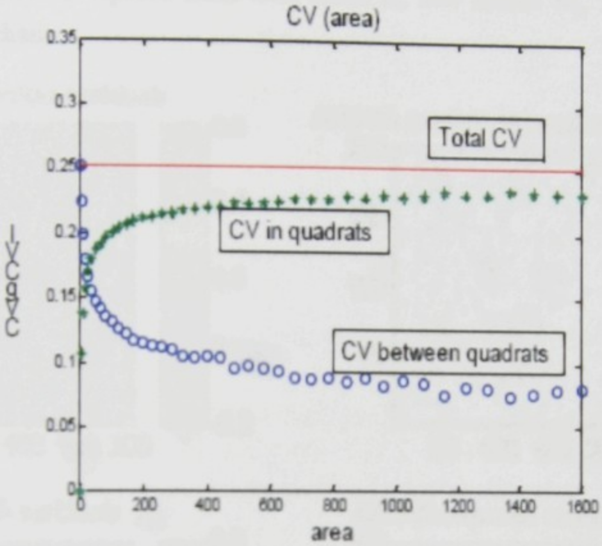


Fig. 2 Dependence of CV on quadrat size

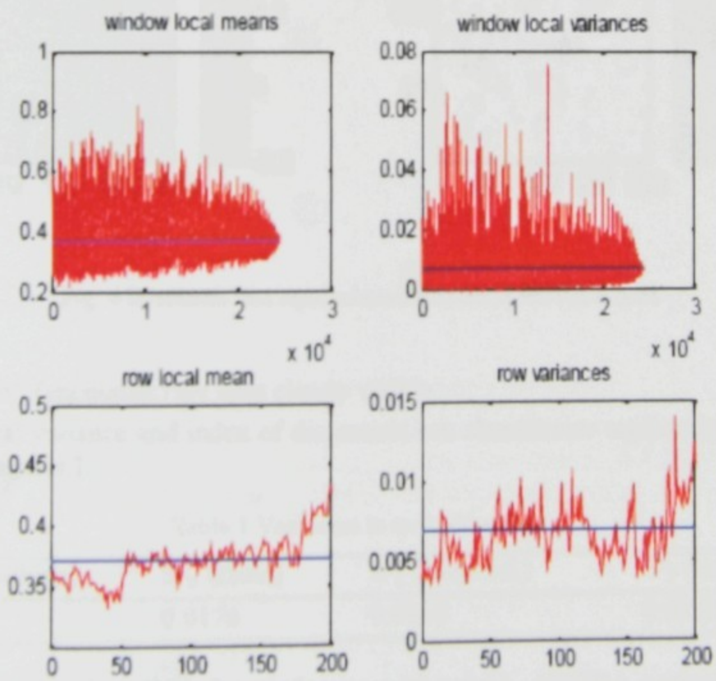


Fig. 3 Local statistics characterizing stability of mean and variance

For deeper investigation of non uniformity the moving windows were used. Principle is division the study area to the several local neighborhoods of equal size (moving windows) and within each local window the mean and variance are computed. The dimension of moving windows can be gradually changed to obtain good identification of local anomalies. The plot of local means and variances are given in fig. 3. The row mean and variances are shown as well.

There are visible some departures from constancy of mean and variance (stationarity). Deeper analysis of local anomalies is based on the investigation of residuals. Simple parametric model is based on the ANOVA model without interaction $z_{ij} = \mu + \alpha_i + \beta_j + \varepsilon_{ij}$. The residuals and squared residuals for this model are on the fig. 4. The residuals were computed from total mean m, row means m_{io} and column means m_{oj} or by replacing of means by medians.

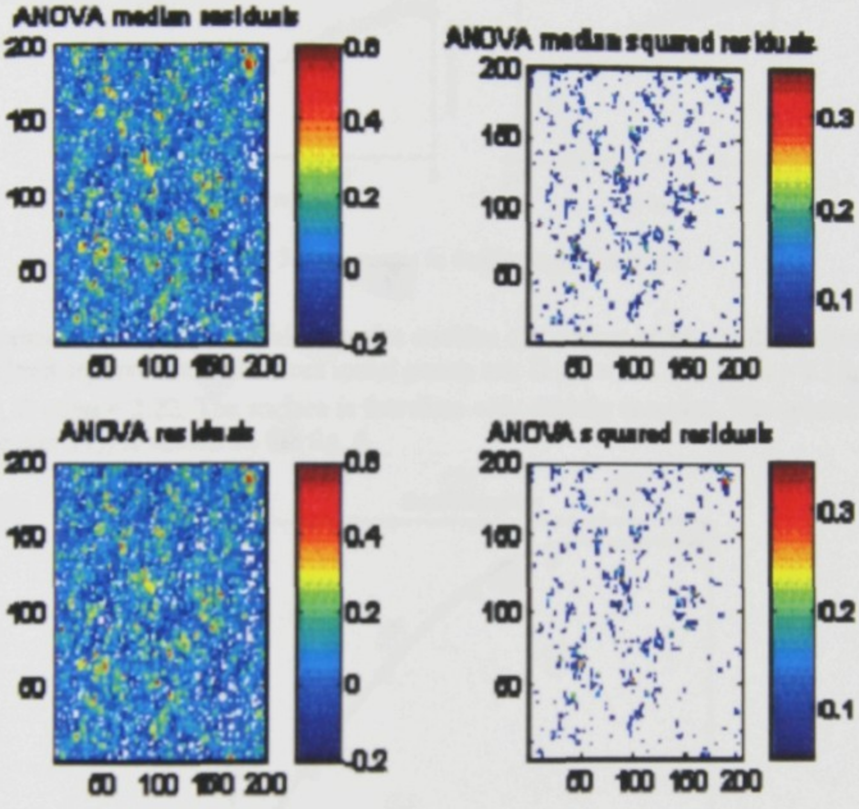


Fig. 4 Residuals and squared residuals for ANOVA model

The local "hot spots" (anomalies) are here clearly visible.

The division of total variance and index of dispersion can characterize uniformity. The division of total variance is given in the table 1.

Table 1 Variances in main directions

S^2_L (machine)	S^2_H (cross)	S^2_L (longitud.)	S^2_T (transvers.)
0.0142	0.0176	0.0816	0.0823

The I_d = 0.018 is lower than limit for randomness M_L= 0.81. ANOVA analysis leads to results that variability in both directions is not significantly different.

The variogram is machine direction, cross direction; diagonal direction and omni-variogram are shown on the fig. 5 in the log /log form

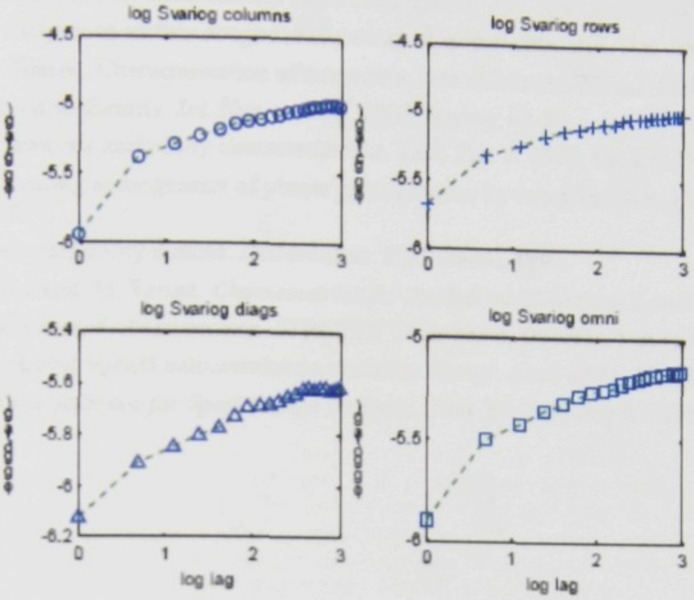


Fig. 5 Variograms in double logarithmic plot

The approximate linearity in double log plot enables calculation of fractal dimension from straight line slope [4]. The least squares estimates from initial points are: D rows = 2.24, D cols = 2.16,
D diag = 2.29, D omni = 2.22. The surface is therefore only slightly complex. The spherical model for omni-variogram (see eqn. (7)) is shown on the fig. 6.

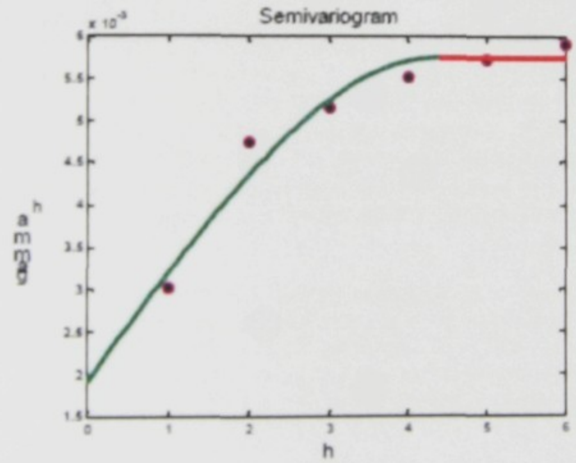


Fig. 6. Spherical model for omnivariogram

By using of nonlinear least squares the following results were obtained: *Co (Nugget) = 0.019*, *C+Co (Sill) = 0.0058* and *a = 4.402*. Due to high nugget effect the stationarity of data cannot be accepted.

5. Conclusion

The system of data analysis based on the above mentioned methods can be used for identification of spatial dependence for regular lattice data or planar unevenness evaluation. Tested nonwoven exhibits large-scale variation and slight complexity.

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SOME TOOLS FOR NONWOVENS UNIFORMITY DESCRIPTION

Jiří MILITKY & Václav KLICKA

Abstract: *Products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens. In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats the mean optical transparency (grey level) is evaluated. Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats. These data are obtained from digital images, where the variation of mass is characterized by the variation of grey level. The surface variation function can be combined with some techniques based on the image multiresolution (modification od Gaussian pyramid principle) for suppression of high frequency variations. The main aim of this contribution is a creation of surface variation function combined with image multiresolution for evaluation of nonwovens surface uniformity.*

Keywords: *Uniformity of nonwovens; Gaussian pyramid, quadrat method; surface variation function.*

1. Introduction

The products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exists a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1,2].

The spatial variation of geometric and other properties is the main peculiarity of textile products. For the purpose of design, quality control and application in composites it is necessary to have tools for expressing this variability by suitable characteristics. Especially products from nonwovens are nowadays applicable in the fields requiring relative high mass uniformity or uniformity of basic physico - mechanical properties. There exist a lot of methods for description of planar anisotropy and other structural characteristics of nonwovens [1-4]. Selected methods of continuous and discontinuous measurement of planar uniformity of nonwovens are described in the dissertation of Klička [4]. In parallel to the description of unevenness of linear textile structures by the length variation function, there can be constructed surface variation function for textile fabrics. The surface variation function can be easily used for description of unevenness or uniformity. Another possibility is to use some techniques based on the spatial pattern analysis as variance to mean ratio.

The main aim of this work is an attempt to describe a surface irregularity of nonwoven textile structure based on the so-called quadrat method, where characteristic of quadrat is a mean value of grey level. Principle is to divide sample to the rectangular net of cells named quadrats. In these quadrats the mean optical transparency (grey level) is evaluated. Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j). In this direction are M quadrats.

For evaluation of uniformity the five kinds of methods are useful.

- First one is based on the computation of variation coefficient in selected directions (machine and cross direction), and testing the significance of their differences (Cherkassky [3]).
- Second one is based on the modelling of data arrays by the ANOVA (analysis of variance) type models and testing hypothesis about homogeneity in selected directions (see book of Meloun, Militký, Forina [5]).
- Third one is based on the analysis of random field. The moment characteristics of second order as spatial covariance and variogram are used for description of these fields. The fractal dimension characterizing random field complexity can be computed directly from variogram [9].
- Fourth one is based on the global and local spatial variation indices of Geary and Moran type [8].
- Fifth one is based on the utilization of multivariate kurtoisis of indicator random variables [7].

There exist a lot of other characteristics as spatial descriptors of irregularity which, can be used in special situations (point patterns) [2].

The aim of this work is a creation of surface variation function combined with the image multiresolution (multiscale characterization) for evaluation of lightweight nonwoven lap surface uniformity.

2. Irregularity characterization

Irregularity characterization is classically based on the coefficient of variation CV or derived statistics. For characterization of lattice data array the models based on the ANOVA principle are often used. These characteristics can be compared with ideal models of nonwoven structures. For suppression of high frequency variations the modified Gaussian pyramid multiresolution technique can be applied.

2.1 Modified Gaussian pyramid

Gaussian pyramid is a filter based technique for decomposition of images into information at multiple scales, for extraction of typical features and for attenuation of noise component. Sometimes, it is useful to have a multiscale representation of an image. The small resolution image allows us to study the low-frequency information, while the large resolution image retains the high-frequency gradients. Constructing a Gaussian pyramid is generally a recursive process. Given any image, the next-most-coarse image is created by blurring (convolving with a Gaussian) the previous image, and downsampling that by half with nearest-neighbor interpolation. Thus, we start with the fine resolution image, and create the next-most coarse, and so on, until we have coarsest image (use the number of levels that gives the best results) [10].

The Gaussian pyramid is also technique for removing image correlation which combines features of predictive and transform methods. The predicted value for each pixel is computed as a local weighted average, using a unimodal Gaussian-like (or related trimodal) weighting function centered on the pixel itself.

The first step in pyramid creation is to low-pass filter the original image g_0 to obtain image g_1. The g_1 is a "reduced" version of g_0 in that both resolution and sample density are decreased. In a similar way we form g_2 as a reduced version of g_1 and so on. Filtering is performed by a procedure equivalent to a convolution with one of a family of local, symmetric weighting functions. An important member of this family resembles the Gaussian probability distribution, so the sequence of images g_0, g_1,..., g_n is called the Gaussian pyramid.

Suppose the image is represented initially by the array g_0, which contains C columns and R rows of pixels. Each pixel represents the light intensity at the corresponding image point by an integer I between 0 and K - 1. This image becomes the bottom or zero level of the Gaussian pyramid. Pyramid level 1contains image g_1, which is a low-pass filtered (reduced) version of g_0. Each value within level 1 is computed as a weighted average of values in level 0 within a 5-by-5 window. Each value within level 2, representing g_2, is then obtained from values within level 1 by applying the same pattern of weights. A graphical representation of this process in one dimension is given in Figure 1.

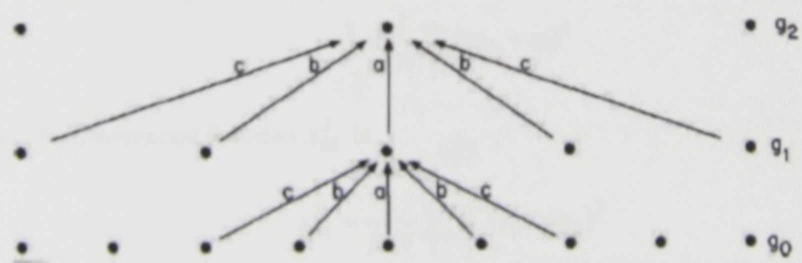


Figure 1: Gaussian pyramid creation sequence

The size of the weighting function is not critical. Usually is selected the 5-by-5 pattern, because it provides adequate filtering at a low computational cost. The level-to-level averaging process is performed by the function REDUCE. The function EXPAND is the reverse of REDUCE. Its effect is to expand an reduced array obtained after application of REDUCE function into a original size array by interpolating new node values between the given values. Thus, EXPAND applied to array g_l of the Gaussian pyramid would yield an array g_l, which is the same size as g_{l-1} [10]. Standard Gaussian pyramid in MATLAB is sequence of REDUCE function followed by sequence of EXPAND function. The resolution is progressively reduced (at the l th level is number of pixels 2^{N-l}, where 2^N is number of pixels in original image). Modified Gaussian pyramid is based on the subsequent repeating of REDUCE EXPAND functions.

2.2 Analysis based on CV

Surface uniformity is classically described by the coefficient of variation (CV). This coefficient is traditionally used as the characteristics of unevenness [5].

According to the common definitions we can simply computed the overall mean, variance and coefficient of variation

$$m = \frac{1}{MN}\sum_i \sum_j (z_{ij}) \qquad s^2 = \frac{1}{MN}\sum_i \sum_j (z_{ij} - m)^2 \qquad CVg(F) = \frac{s}{m}$$

Here z_{ij} is selected characteristic of quadrats (here mean grey level m_{ij}). Direction X is equivalent to the machine direction (index i). In this direction are N quadrats. Direction y is equivalent to the cross direction (index j).The quantity CVg(F) is in fact external variation coefficient between quadrat areas F. In this direction are M quadrats. The quadrat area is denoted as *F*. Replacing the z_{ij} by the pixel values, i.e. quadrats, having the lowest possible area 1 pixel the total variance CV can be computed. The mean variance CVI(F) within quadrats of area F is then simply computed as

$$CVI(F) = \sqrt{CV^2 - CVg^2(F)}$$

Ideal value of CV for nonwovens of total weight W having Poisson distribution of random fibres of fineness T_V and density ρ_V is defined as [6]

$$CV_N(P) = \frac{\sqrt[4]{\pi}}{\sqrt{2}}\sqrt[4]{\frac{T_V \rho_V}{W^2}}$$

The total variance s^2 can be divided to the two terms by using of means in the machine direction and cross direction

$$m_{i0} = \frac{1}{M}\sum_j z_{ij} \qquad m_{0j} = \frac{1}{N}\sum_j z_{ij}$$

Symbol „0"*denotes* index used for summation *i.e.* m_{i0} is mean value for i th position in the machine direction. For the machine direction the following relation results (Cherkassky [3])

$$s^2 = s_L^2 + s_{HL}^2$$

where the variance in the machine direction s_L^2 is

$$s_L^2 = \frac{1}{N}\sum_i (m_{i0} - m)^2$$

and the variance in the transversal direction s_{HL}^2 is

$$s_{HL}^2 = \frac{1}{MN}\sum_i \sum_j (z_{ij} - m_{i0})^2$$

For the cross direction is

$$s^2 = s_H^2 + s_{LH}^2$$

where the variance in the cross-direction s_H^2 is

$$s_H^2 = \frac{1}{M}\sum_j (m_{0j} - m)^2$$

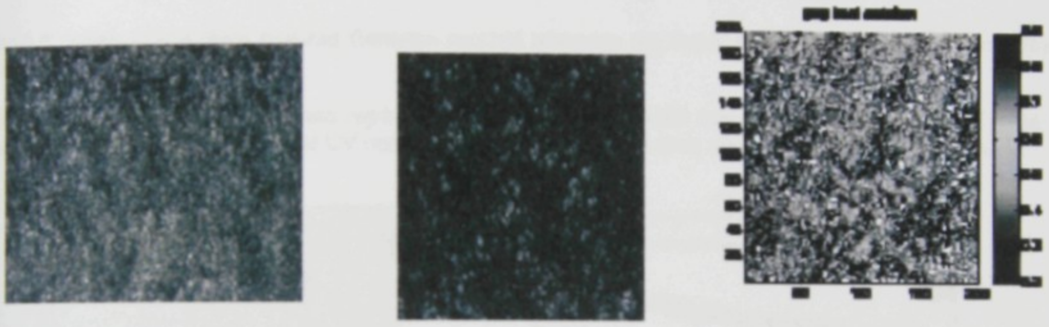
and the variance in the longitudinal direction s_{LH}^2 is

$$s_{LH}^2 = \frac{1}{MN}\sum_i \sum_j (z_{ij} - m_{0j})^2$$

The coefficients of variation CV_L, CV_{HL}, CV_H and CV_{LH} are obtained by dividing the corresponding standard deviations by the mean *m*. These coefficients are from statistical point of view the point estimates of population variation coefficients CVP_L, CVP_H, etc. For creation of confidence intervals the variance of point estimates have to be computed [5].

3. Experimental part

The chemically bonded (by the acrylate binder) nonwovens from viscose fibres (VS) was prepared. Starting lap of planar weight 30 g m^{-2} was created on the pneumatic web former. The lap consists of two types of viscose fibers mixed in the weight ratio 67/33 (VS 3,1 dtex/60 mm and 1,6 dtex/40mm). Binding acrylate (relative amount 20 %) was applied by padding.The original nonwovens image (see fig. 1a) was used for evaluation of surface variation components computed by quadrat method combined with modified Gaussian pyramid. The results of quadrat smoothing for quadrat size 2x2 pixels is shown on the fig. 1b and mean grey levels in quadrats is on the fig. 1c. The original image (fig. 1a) was used for characterization of surface variation and combination with Gaussian pyramid multiresolution. The influence of quadrat size on the corresponding areal CV was investigated by using of program NONWSV.

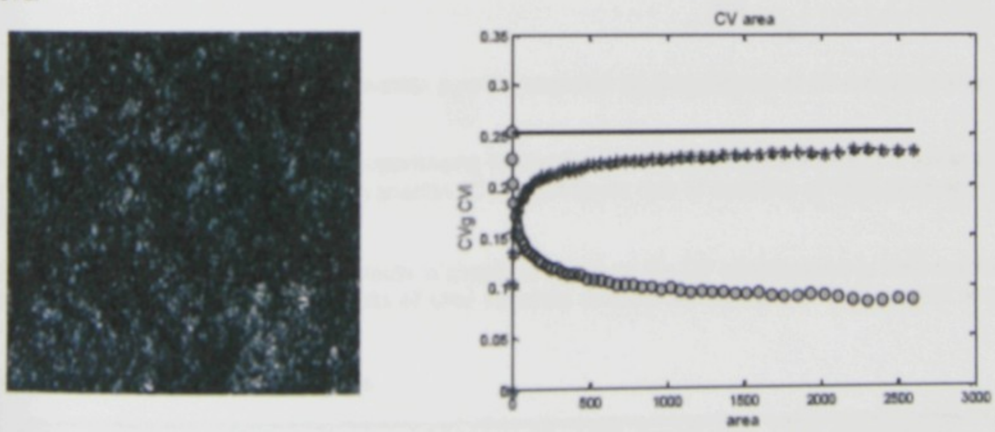


a b c

Figure 2: Raw image (a), quadrats 2x2 image (b) and mean grey levels in quadrats (c)

4. Results and discussion

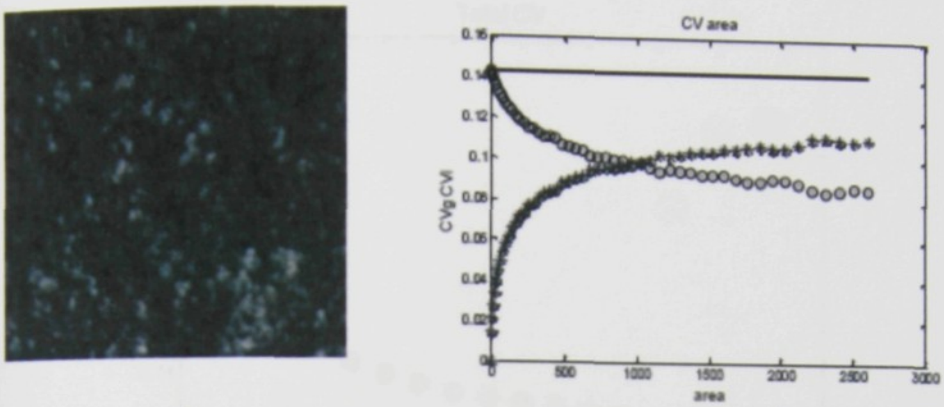
The original image transformed into gray scale is on the Figure 3a. The corresponding dependence of CV components on the quadrat area size (program NONWSV) is shown on the Figure 3b
First level



a b

Figure 3: Raw image in gray scale (a), Dependence of CV components on quadrat area

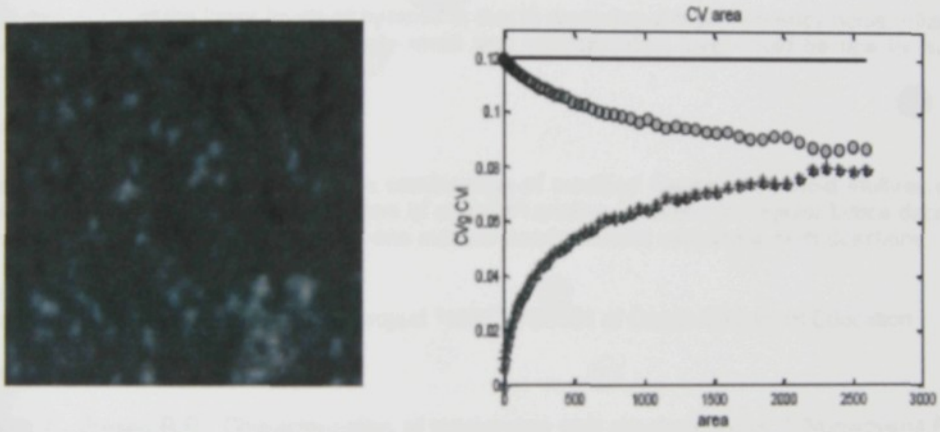
The lower resolution image after 6 times repeating of REDUCE, EXPAND sequence is shown on the Figure 4a. The corresponding dependence of CV components on the quadrat area size is shown on the Figure 4b



a b

Figure 4: Image after 6 times modified Gaussian pyramid sequence (a), Dependence of CV components on quadrat area (b)

The resolution image after 17 times repeating of REDUCE, EXPAND sequence is shown on the Figure 5a. The corresponding dependence of CV components on the quadrat area size is shown on the Figure 5b.



a b

Figure 5: Image after 17 times modified Gaussian pyramid sequence (a), Dependence of CV components on quadrat area (b)

It is visible that the lower resolution is suppressing higher frequency variations and result is lower total CV, lower rate of drop of between quadrats variation (CVg) and lower rate of increase of inter-quadrats variation (CVI).

For each level of modified Gaussin pyramids is simple to compute the CV contributions in both machine and cross directions. In the Table1 are results of total variance division for the case of 2x2 quadrat smoothing (see. Figure 1b)

Table 1: Variances in the main directions

Characteristics	S2 L (machine)	S2 H (cross)	S2L (longitudial)	S2T (transversal)
Grey level	0.0142	0.0176	0.0816	0.0823

ANOVA analysis leads to results that variability in both directions is the same.

It is illustrative to visualize the effect of the repeating the REDUCE EXPAND cycle (modified Gaussian pyramid levels) on the total variation CV (see. Figure 6).

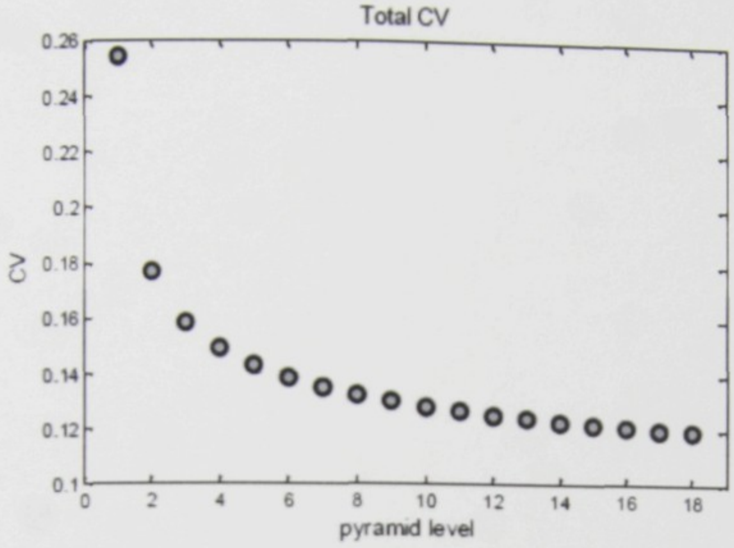


Figure 6: Dependence of total CV on the modified Gaussian pyramide level

The high drop of CV at the lower levels of pyramid is due to removing of high frequency noise. After reaching of suitable level is the drop of CV relatively small and corresponding level could be use for subsequent analysis by quadrat method.

5. Conclusion

The system of data analysis based on the combination of modified Gaussian pyramid multiresolution and quadrat method can be used for identification of surface variation functions for regular lattice data or planar unevenness evaluation. The tested nonwovens exhibits nearly uniform variation in both directions.

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