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AUTOMATIC CHARACTERIZATION OF NEEDLEPUNCHED FELTS BY CONTENT BASED IMAGE RETRIEVAL - CBIR

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Abstract: *The needled felts whose fibrous bats had been gotten by the classic carding process give us fabrics in which staple fibres follow a marked preferential direction of the machine workflow. This direction is named, as machine direction, main direction or MD and the perpendicular direction is known as cross direction or CD. In consequence of this fibre deposition, the mechanical properties of these products are different when submitted to longitudinal or transversal loads, with a much higher strength in the CD direction and a greater elongation in the MD direction. However, some technical applications of the nonwoven industry, such as filters, geotextiles, and some felts for the automotive industry demands equal mechanical properties along all their directions, particularly, an even MD:CD ratio. In order to introduce additional control in the production system and to achieve a final fabric with the desired behaviour, we envisioned an an automatic system for the pre-needling web drafting control. The management of the pre-needled felts drafting operation was made by an automatic inspection system based upon textural descriptors and content-based image retrieval, which assured optimal drafting conditions to attain a quasi-isotropic fiber distribution and an even MD:CD ratio. Our findings have shown that the comparison between collected images and reference images of the same product stored in the database - for the same feature vector and metric distance – is an excellent tool for the remote and continuous supervising of needlepunched felts quality.*

Key words: *Nonwovens, Needlepunched, Texture Analysis, Content Based Image Retrieval, Isotropy, MD:CD Ratio,*

1. INTRODUCTION

The fibre geometrical arrangement in a needled felt is primarily defined by the basic fibre web structure proceeding from the bat forming system. This special fibre arrangement should be understood as a three-dimensional system; however, this kind of analysis is very complex, and for the time being impossible. To create the opportunity of studying those materials, we will admit our felt structure with a neglectable thickness allowing a three-dimensional system to become a two-dimensional planar structure. The needled felts whose fibrous bats had been gotten by the classic carding process give us fabrics in which staple fibres follow a marked preferential direction of the machine workflow [1,2]. This direction is named, as machine direction, main direction or MD. The perpendicular direction is designed as cross direction or CD. In consequence of this fibre deposition, the mechanical properties of these products are different when we applied longitudinal or transversal loads, with a much higher strength in the CD direction and a greater elongation in the MD direction.

Some technical applications of the nonwoven industry, such as filters, geotextiles, and some felts for the automotive industry requires equal mechanical properties along all their directions, particularly, an even MD:CD ratio. This need, compels us to introduce some modification in the production system to achieve a final fabric with the desired behaviour [3,4].

2. IMAGE AND TEXTURE ANALYSIS

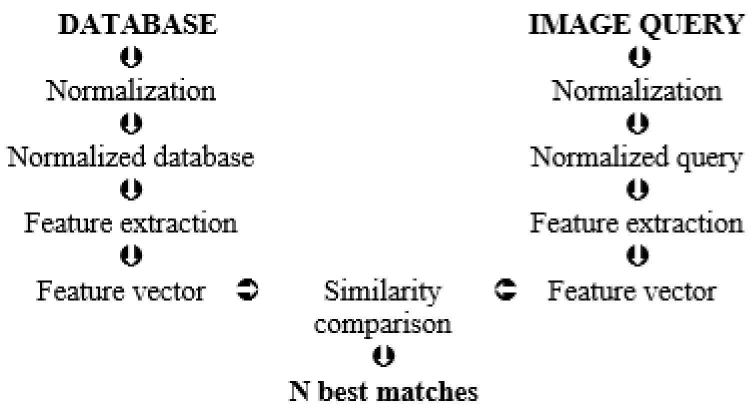
Image analysis deals with images and can be summarized as a set of techniques that convert object images in numbers and prepares this data to be processed by computer methods [5]. Texture analysis, is an essential concept of image analysis that deals with primitives or elements called texels, and this mean a contiguous set of pixels with some regional property or pattern. A texture feature is a numerical value, extracted from an object image, that gives us some information about the variation of grey levels distribution and variation on an image. Normally, texture feature is independent from his location, orientation, size and glow of the analysed object, as referred by Castelman K.N. (1996). From a statistical point of view, image textures are complicated pictorial patterns that can be defined by statistical models, in way to characterize these same patterns. According to Haralick et all [6], we have several approaches to measure and characterize image texture, that can be summarized in eight main techniques:

① - Autocorrelation function;
② - Optical transforms;
③ - Numerical transforms;
④ - Edge and contour detection;
⑤ - Structural analysis;
⑥ - Spatial grey level dependence method – Co-Occurrence matrixes method
⑦ - Run length method of grey levels;
⑧ - Autoregressive models.

According to the consulted bibliography, we found a prevalence of texture discrimination by the co-occurrence matrixes method in multiple researches works abroad many different fields. This technique gives us a high dimensional texture description and can be used for directly measure statistical distances between different textures. For this reason, we based our feature extraction on this methodology. This method places to evidence the space relations between the grey levels. Thus, as the grey levels are a function of the mass per unit area, we can accede to a characterization of the web structure. The probability of spatial grey level co-occurrence is a second order density probability, which can be defined by a matrix of relative frequencies *f(i,j)* with which two neighbouring pixels separated by a distance d on θ direction, occur on the image, one with grey level *i*, and the grey level *j*. Hence, for an image with N_G grey levels, the probability density functions can be written under the form of four squared matrices N_G X N_G for the 0º,45º,90º e 135º directions. Haralick, Shanmungan and Dienstein proposed 14 measures of textural features derived from the co-occurrence matrices, each one representing certain image properties. The textural descriptors selected and used in this research work were: First order entropy; Second order entropy; Energy or angular second moment; Homogeneity or inverse difference moment; Contrast and Correlation.

3. CONTENT BASED IMAGE RETRIEVAL

Content based image retrieval (CBIR) is a set of techniques which use visual content (pictorial content) to search images from an image database according to user interest [7]. In this work, instead of the exact matching, our system calculates the visual similarities between the query image and pattern images on a database. For this purpose, we used the Euclidian distance method, so as to get the distance between query image *i* and image *j* on the database, because each individual dimension is independent and have equal importance [8]. This metric is also widely spread and commonly used in image retrieval [9,10]. The image database consists of 4080 (256x256 sized 8 bit long) grey level images from standard pre-needled nonwoven and integrating, for each one of them, a feature vector with the textural descriptors based on first and second order statistics, and also their mechanical properties. For all and each acquired image on the experimental development, a feature vector is determined, and similarity comparison is made in accordance with the following schematic representation:



With this process, on a near future, we will be able to elaborate detailed quality reports for each felted roll produced, with the spatial localization, length and severity of the defects in accordance to a defined scale.

4. EXPERIMENTAL DEVELOPMENT

The experimental setup developed in this research work was comprised by the following elements:

1 – A Cosmatex nonwoven laboratorial line composed by a feeding/opener loader, card, cross-lapper and pre-needling/needling apparatus.

2 – An image analysis system composed by a Frame grabber DT3155 from Data Translation inc; 2 CCD_s Cohu model 2652-2000; Lenz system from Cosmicar – pentax; Monochromatic video monitor model TM923B from JVC, 1 PC for the drafting operation control and 1 PC for image acquisition and processing.

3 – A specifically devised pre-needled drafting prototype, conceived with 4 drafting zones between 5 drafting sets of cylinders and equipped with two CCD_s, one at the beginning of the process and another one at the end.

Ten experimental dynamometric tests for both axes (longitudinal and transverse directions), where made according to the following flow:

1 – Image acquisition of the dynamometric tests for both axes;
2 – Image pre-processing;
3 – Feature extraction;
4 – Similarity comparison;
5 – Data collecting and conclusions;

5. RESULTS

The obtained results are condensed in the following table and graphical representations.

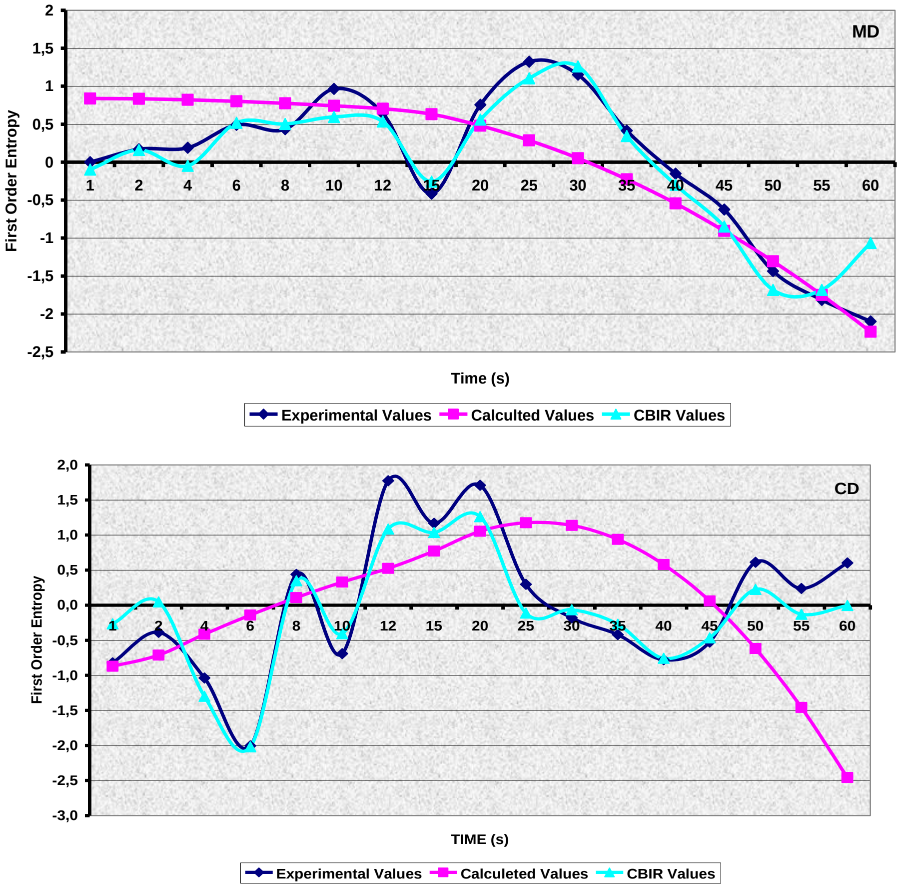
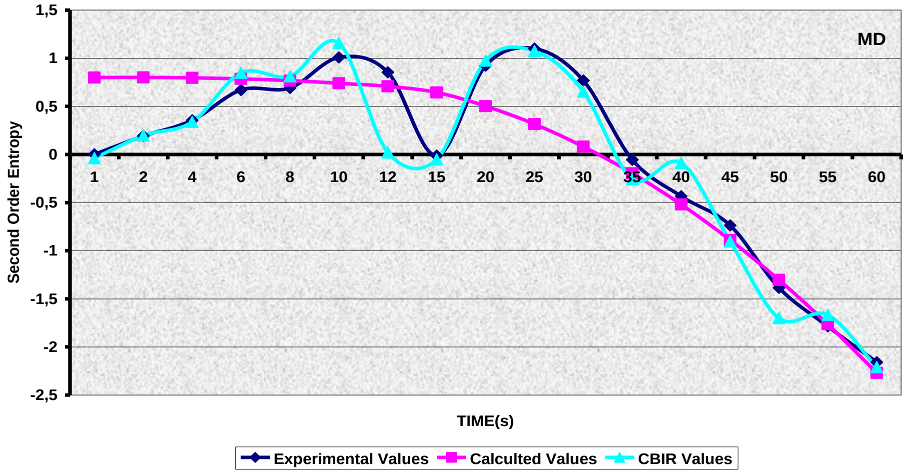


Fig1: *Graphical representation of first order entropy with all the studied models and for both axes.*



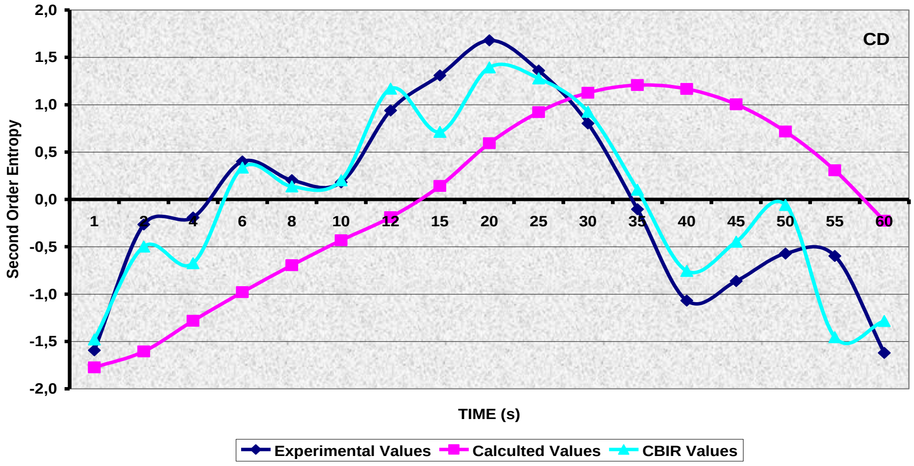


Fig2: *Graphical representation of the average second order entropy with all the studied models and for both axes.*

Table 1 *– Correlation coefficients for all the studied models and or both axes.*

CORRELATION	EXPERIMENTAL VALUES X CALCULATED VALUES		EXPERIMENTAL VALUES X C.B.I.R. VALUES		C.B.I.R. VALUES X CALCULATED VALUES	
DIRECTION	**MD**	**CD**	**MD**	**CD**	**MD**	**CD**
Average First Order Entropy	0,8138	0,1385	0,9835	0,9431	0,7413	0,2104
Average Second Order Entropy	0,9037	0,2238	0,8828	0,9274	0,9684	0,3549
Average Energy	0,9244	0,4937	0,9656	0,9273	0,9278	0,6334
Average Contrast	0,5693	0,7436	0,9379	0,8789	0,4683	0,5427
Average Correlation	0,8908	0,9543	0,9387	0,8268	0,7806	0,8666
Average Homogeneity	0,8983	0,7642	0,9372	0,9664	0,9281	0,7610
Mechanical Strength	0,9997	0,9998	0,9855	0,9490	0,9860	0,9508

6. CONCLUSIONS

The comparison between collected images gathered with the new experimental tests and reference images of the same product in the database, for the same feature vector and metric distance, showed that, for all evaluated textural descriptor, CBIR method presents the higher correlation coefficients for both studied directions. All the textural descriptors exhibited greater proximity between experimental values and CBIR values than, comparatively, experimental values and calculated values for both studied directions. The calculated values and the experimental values are very similar. This may be due to imposed limitations of the carried out experimental set. However, CBIR method showed no significant deviations for this parameter and equal sensitivity. With this experimental framework and based on the collected information it is possible to affirm that the proposed technological solution based on CBIR methodology as great potential as a tool for quality control of the nonwoven pre-needled drafting process. It is particularly relevant the capabilities of queries formularization based on total or partial evaluated textural features associated with the main mechanical properties, which allows remote and continuous monotoring of production lines.

REFERENCES

[1] Mário F.N., “Novo Método de Controlo na Produção de Têxteis Técnicos”, XX Seminário da APETT, Famalicão, 1999;

[2] Belino N.J.R., “Optimização de um sistema automático de controlo da isotropia de mantos pré-agulhados por análise de textura e recuperação de imagem baseada em conteúdo, PhD Thesis, UBI, 2006

[3] Tsai, P.P., “Theoretical and Experimental Investigation on the Relationship Between the Nonwoven Structure and the Web Properties”, International Nonwovens Journal, Nº4. pp. 33-36,2002

[4] Hearle, J.W.S., Stevenson, P.J. “A Study of needled Fabrics, Part III: “The Anisotropy of Nonwoven Fabrics”, Textile Research Journal, nº11, pp. 877-888, 1963

[5] Schalkoff, R., “Digital Image Processing and Computer Vision”, John Wiley & Sons, Inc., 1989

[6] Haralick, R M., Shanmungam, K., Dinstein, I., “Textural Features for Image Classification”, IEEE, Vol. 3, Nº. 6, pp. 610-621, 1973

[7] Baraldi, A., Parmigianni, F., “An Investigation of Textural Characteristics Associated with Grey-Level Co-occurrence Matrix Statistical Parameters”, IEEE, Vol. 33, Nº. 2, pp. 195-199, 1995

[8] Moura, D. et Al., “Recuperação de Imagem Baseada em Conteúdo”, Anais do IV Workshop de Tratamento de Imagem, NPDI/UFMG, pp. 101-109, 2003

[9] Aksoy, S., Textural Features for Image Database Retrieval”, Msc Thesis, Seattle, Washington University, 1998

[10] Mitchel, O.R., Myers, C.R., Boyne, W., “A Maximum Measure for Image Texture Analysis”, IEEE, Vol. 2, pp. 408-414, 1977.