A COMPARATIVE STUDY OF TEXTURE ANALYSIS ALGORITHMS IN TEXTILE INSPECTION APPLICATIONS

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ABSTRACT

Nowadays, quality control is an important problem for fabric manufacturers. Typically these operations have been carried out by humans operators. However, this method has numerous drawbacks such as low precision, performance and effectiveness. Therefore, automatic inspection systems have increased substantially in the last decade. This work evaluates the performance of some texture measures in textile defect detection applications. For classification a method based on leaving-one-out is used. Our study has been carried out using a large database of samples to take into account a wide spectrum of fabrics and multiple defects of different nature reported by specialized works and publications. A ranking with the effectiveness of best algorithms is presented for every type of fabric. In addition, the computation time of algorithms is compared.

1. INTRODUCTION

Quality inspection of textile products is an important problem for fabric manufacturers. Currently, quality control tasks are mostly carried out by human operators because of the flexibility of the human visual system. However these methods have numerous drawbacks and automatic inspection is usually desirable because of its superior reliability, effectiveness and performance [1].

Numerous methods have been designed to solve particular texture inspection tasks: wood, paper, leather and metallic surfaces to mention just a few. In the same way, other measures related to texture properties have been proposed for the automatic inspection of specific fabrics: woven fabrics, cotton fabrics, dyed fabrics, etc…[2][3], however, due to the wide spectrum of textile products and defects [4] there is no unique solution. This work evaluates both the performance of some texture measures which have been successfully used in various applications and of some promising new approaches proposed recently. Our study has been carried out using a large database of samples to take into account a wide spectrum of fabrics and multiple defects of different nature reported in specialized works and publications[5],[6]. The best results for every type of fabric are presented. In addition, the computations complexities of algorithms are compared by the output achieved using a PC-based implementation.

2. TEXTURE MEASURES AND CLASSIFICATION ALGORITHMS

2.1. First order statistics (FOH)

These are statistical measures on the histogram of grey level probabilities of the texture: *K moments (Mk), Energy (En), Entropy(En), Skewness(Sk) and Kurtosis (Kr).* These measures were used as features for classification.

2.2. Second order statistics (SOH)

These statistics are based on grey level coocurrence matrix GLCM [7].. The coocurrence $P_{q,d}(i,j)$ of an image is a function that expresses the relative frequency of pairs of pixels with grey values i and j, and at distance d along angular direction q. GLCM will be a square matrix of side equal to the number of grey levels. A large number of textural features derived from the matrix have been proposed starting with the original fourteen features described by Haralick, however, only some of these are in general use: *Energy (En), Entropy (Et) , Maximum Probability (Mp) , K moments (Mk), K Inv. moments(Imk), Cluster Shade(Cs), Clust. Prominence(Cp) and Haralick's Correlation (Hc).* The mentioned measures were computed for four angles (0º, 45º, 90º and 135º) using d=1,2, to form the feature vector.

2.3. Sum and difference histograms (SMH, DFH)

Similar to the coocurrence matrix, they depend on the displacements d_x and d_y , and are computed as the histograms of the sum and difference of all pixels d_x and d_y apart [8]. Similar features to coocurrence can be extracted combining sum and difference histograms. The parameters used were d=1,2.

Additionally, the probability distribution of DFH can be used for texture classification [9]. This way, DIFFX and DIFFY are histograms of absolute grey level differences between neighboring pixels computed in horizontal and vertical directions, respectively, while DIFF2 accumulates absolute differences in vertical and horizontal and DIFF4 in all four principal directions respectively, in a single histogram. The four histograms were used as features for classification.

2.4. Fractal dimension measures(FD)

The underlying assumption for the use of the fractal dimension for texture classification is that images are self similar. Then FD can be defined as

$$FD= \log (N_r)/\log(r^{-1})$$

Where N_r is the number of nonoverlaping copies of a set similar to the original set , scaled down by a ratio r. FD can be approximated determining the slope of the least-squares linear fit of $\log(N_r)$ vs $\log(r^{-1})$. The differencial box-counting method outlined in [10] was used to compute the FD.

A second feature is based on multifractals, which are used for self-similar distributions exhibiting nonisotropic and inhomogeneous scaling properties. Let k and l be the minimum and maximum gray level in the image centered at position (i,j), let $n_r(i,j)=l-k+1$, and let $P_r=(n_r / N_r)$; then the multifractal , FD_2 is defined by

$$FD_2= \lim_{r\to\infty} \frac{\log \sum_{i,j} P_r^2}{\log r}$$

The linear regression yields an estimate of FD_2. FD and FD_2 were used to form the feature vector.

2.5. Morphologic coefficient and Box counting (CM, BC)

The original image is divided on several grey level planes and the morphologic properties of every plane are measured. This was made by counting the number of nonoverlaping copies of a square set (structuring element) that cover (Box counting) or semi-cover (Morphologic coefficient) [11], the plane. The features used were the MC and BC of every plane and the dimension of the structuring element.

2.6. Geometric measures (GEO)

The features computed were area, perimeter and compactness [12].

2.7. Edge density (EDG)

The image was pre-processed using an edge detection filter (Laplacian, Sobel, Prewitt, etc…), then several parameters were computed for every sub-window: mean, variance, density of edge pixels, maximum and minimum edge level [12].

2.8 Laws' texture measures (LAW)

Each sub-window is convolved with nine different Laws' masks [13]. Then the energy is computed as the sum of the squares or absolute values of the nine filtered images. The feature vector was formed with the nine energy values. The Laws filters used was: E5L5, E5R5, L5R5, L5E5, R5E5, R5L5, E5E5, L5L5 and R5R5.

2.9 Thresholding (TH)

Several thresholding methods [14] were used to segment the default areas: Iterative selection thresholding, Minimum error thresholding, and Pun entropy. Subwindow classification is straightforward once the minimum area acceptable for the blobs derived from the thresholding has been determined.

3. EXPERIMENTS AND DISCUSSION

Two different types of image sets were used in the experiments: in the first experiment a set was formed with sample images from the TILDA textile defect image database created at the University of Freiburg, Germany; in the second, a database was created with images taken from defective fabrics from Drape-Cotti company, a Spanish textile manufacturer. Algorithms were applied on 32x32 pixels sub-windows with G=256, 32, 16 grey levels.

Every sample was classified in turn using the other samples as models, and the leave-one-out approach was applied. The sample was assigned the label of the model using the *K-nearest neighbour* (*K=3*) or *thresholding* method depending on the features. The metric used was the Euclidean distance for classification based on vectors of features, and Kullback's cross-entropy for classification based on feature distribution. Finally the effectiveness was calculated using the formula (1). Take notice that only the number of defective sub-windows was taking into account to calculate the effectiveness.

E=(nº_defective_windows_detected – nº_ false_positive)/ nº _defective_windows; (1)

In the first experiment we tried to get a ranking of all the proposed algorithms, depending on their ability to detect defective sub-windows correctly regardless of the different kind of fabric. The results are shown in Table 1. The results are not very promising for implementing an accurate detection system, however their unreliability is due to the high variance (greater than 10% in all cases). We can conclude that if only one method is used for all fabric classes, the reliability of the system will be very poor.

In the second experiment all the samples were manually classified, depending on the type of fabric, in the following classes: *Uniform Dyed fabric (UDF)*, fabrics dyed with a uniform colour, *Non Uniform Dyed Fabric (NUDF)*, for fabrics that present some type of stamp, *Interwoven Fabric (IF)*, fabrics with visible interweave, *Plush fabric (PF)*, fabrics that present a shaggy texture, and finally *Embroidered Fabrics (EF)* . About forty different textures were analysed.

Table 1. Effectiveness ranking with TILDA data base.

Method	Mean	Variance
FOH	73,23	13,69
SOH	73,14	12,23
SMH	68,67	10,04
DFH	65,88	10,93
FD	62,22	12,80
CM	73,99	12,62
GEO	72,87	14,22
EDG	68,36	10,34
LAW	70,08	11,80

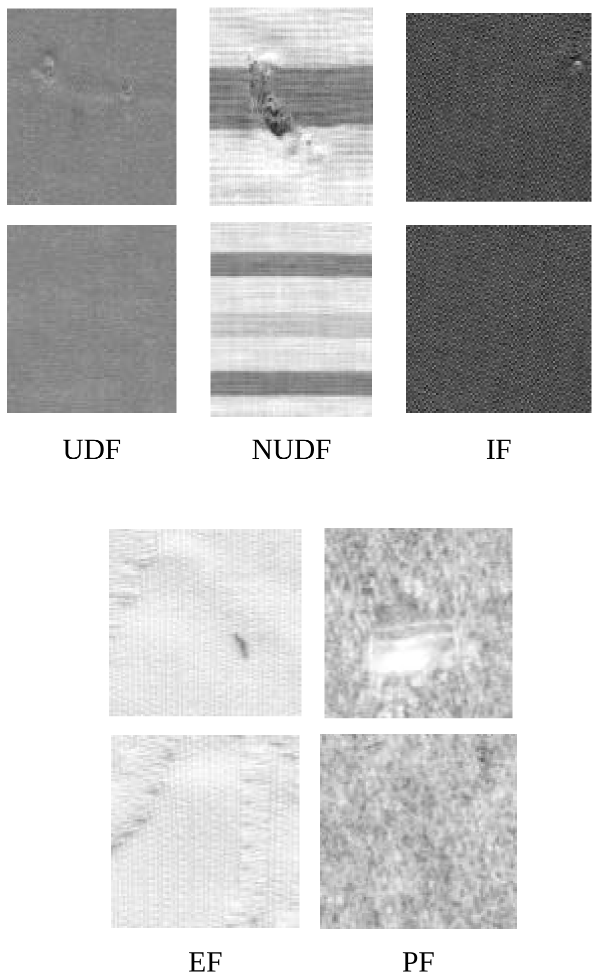

Fig 1. Samples of different fabrics and defects

In the same way the defects were classified using ASTM committee (D3990-93 standard) [4]and the ITS catalogue [5] terminology. About fifty different faults were processed. Fig 1 shows some defective and non defective samples used in the experiments. All the fabrics were scanned with 300ppp resolution, the minimum size of the defective area encountered was 7,5mm and the maximum 67mm.

In order to estimate the importance of the intensity information for the classification of the defects, a first test was performed on the samples previously grey-scaled normalized. In the majority of the cases the faults disappeared after the equalization of the histogram and the results shows a very poor effectiveness for all the algorithms behind 50%. Only for the cases where the fault is a very defined structural defect without a significant variation of the grey scale, some algorithms shows an acceptable performance.

In the second test Table 2 gives the classification rates of the best algorithms for every type of fabric. The algorithm effectiveness in detecting default windows was measured using formula (1). As a means of comparison, we contrast the classification results using all the features of one method and those using various feature subsets. The subsets were made by taking at random individual features or couples of features. Only the three bests algorithms are given. The experiment shows that more accurate results can be achieved when algorithms are applied taking the nature of the fabric into account.

Finally, Table 3 gives a measure of the algorithm complexity. All algorithms were implemented using MMX-optimized software libraries (Matrox MIL) on a PentiumIII based workstation. Computation times were obtained for processing images of 512x512 pixels (256 sub-windows of 32x32 pixels).

Table 2. Effectiveness ranking depending on kind of fabric

Type of Fabr	*First*		*Second*		*Third*	
	Meth	*Efec*	*Meth*	*Efec*	*Meth.*	*Efec*
IF	EDG	87,98	SOH	80,96	FOH	80,73
UDF	EDG GEO	86,80	FOH	85,36	TH	84,82
NUDF	EDG GEO	100	SMH CM	97,56	BC TH	92,31
PF	FD	92,30	BC GEO	87,82	FOH	84,67
EF	SOH CM	100	EDG	91,94	BC	91,16

Comparing tables 2 and 3 we can see a trade-off between effectiveness and computation time for every class of textile. In this way, depending on the speed and accuracy requirements of the target application, it is possible to choose the most suitable algorithm. E.G. FD is the most accurate method for working with plush fabric but its computation time could be very high for specific applications; on the other hand, using BC it is possible to set more demanding time requirements while preserving an acceptable effectiveness rate.

Table 3. Computation times

Method	*FOH*	*SOH*	*SMH*	*DFH*
t (msg)	14,56	2374,03	75,64	114,07
Method	*FD*	*CM*	*TH*	*FD*
t (msg)	340,98	50,38	5,30	340,98
Method	*BC*	*GEOM*	*EDG*	*LAW*
t (msg)	50,38	14,74	120,2	100,35

5. CONCLUSIONS

In this work, various texture analysis methods have been studied for the automatic defect inspection of textile fabrics. The experiments have shown that one-method based systems are unreliable due to the different nature of fabrics. A more specific study has been carried out on five classes of textiles in order to determine the best methods. The results show that there is not a winner between the algorithms and hence to implement a flexible inspection system several methods must be taken into account.

On the other hand a test of algorithm complexity has been carried out by estimating the computation time in the analysis of standard images. This measure has been realized using the most common tools in the implementation of vision systems (PC-based workstation and MMX-optimised libraries). Hence, the results give a real point of view of the real-time possibilities of every method with the actual technology.

Combining both tables can be observed a trade-off between effectiveness and computation time that allow us to select the most suitable algorithms regarding speed and reliability, in order to satisfy a wide spectrum of inspection systems.

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5. REFERENCES

[1] T.S. Newman. A survey of automated visual inspection. Computer vision and image understanding 61(2): 231-262, 1995.

[2] J.G. Campbell. Linear flaw detection in woven textiles using model-based clustering. Pattern Recognition Letters 18:1539-1548, 1997.

[3] Y.J. Han. White Speck Detection on Dyed Fabric Using Image Análisis. The Journal of Cotton Science 2:91-98, 1998.

[4] American Society for Testing and Materials. Standard terminology related to fabric defects. D3990-93. 1993.

[5] Catalogue of types of fabric defects in grey goods. International Textile Service Ltd. (ITS), Schieren, Suiza. 1989.

[6] TILDA , textile defect image database. University of Freiburg, Germany.

[7] R.M. Haralick, L.Saphiro. Computer and Robot Vision. Vol I. Addison-Wesley, New York, 1992.

[8] M. Unser. Sum and difference histograms for texture Classification. IEEE Trans. on Pattern Analysis and Machine Intelligenci. 8(1),1986.

[9] T. Ojala, M. Pietikäinen and D. Harwood. A comparative study of texture measures with classification based on feature distributions. Pattern Recognition 29(1):51-59, 1996.

[10] N. Sakar, B.B. Chauduri. An efficient differential box-counting approach to compute fractal dimension of image. *IEEE Trans. Sys. Man and Cybernetics*. 1(1994) 115-120.

[11] F. Ibarra Pico, S. Cuenca Asensi, J.M. Carcía Chamizo. Feature Extraction with an Associative Neural Network and its Application in Industrial Quality Control. Intl. Conf. On artificial and natural neural networks. Alicante, Spain 1999.

[12] J.R. Parker. Algorithms for image processing and computer vision. John Wiley & Sons. 1997.

[13] K.I. Laws. Rapid texture identification. SPIE Image Processing for missile guidance. 376-380. 1980.