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Automatic Classification of Woven Fabrics using Multi-class Support Vector Machine

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ABSTRACT

This paper proposes the recognition and classification of three mean woven fabrics, twill, satin and plain. The proposed classifier is based on the texture analysis of woven fabric images for the recognition.

In the pattern recognition phase, three methods are tested and compared: Gabor wavelet, Local Binary Pattern operators (LBP) and gray-level co-occurrence matrices (GLCM).

Taking advantage of the difference between the woven fabric textures, we adopt a technique which is based on the texture of the images in the pattern recognition phase. For the classification phase we used a support vector machine (SVM) which we have proven is a suitable classifier for this type of problem.

The experimental results show that some of the studied methods are more compatible with this classification problem than others. Although it is the oldest method, GLCM always remains accurate (97.2 %).The fusion of the Gabor wavelet and GLCM give the best result (98%), but the GLCM have the better running time.

Keywords: Recognition, Classification, Woven Fabric, Feature Extraction, LBP, GLCM, Gabor wavelet, SVM

1. Introduction

In the textile industry, the identification of a weave pattern is usually manual which requires considerable human efforts. This difficult operation requires a long time which is not beneficial for the industry. That is why it is highly desirable to develop an automatic recognition system for fabric patterns.

Image processing has proved to be an efficient method for analyzing fabric structures, and fabric weave pattern recognition by image analyzing has been studied since the mid 1980s. These methods are based on the properties of the Fourier spectrum. This fabric texture research has been used for recognition of woven fabric texture (Bugao, 1996; Ravandi & Toriumi, 1995), and analysis of the fuzz and pills on the surface of knitted fabric (Jensen & Carstensen, 2002).

Another identification method uses warp and weft floats to determine the weave patterns (Boong & Ji, 2003; Huang, Liu & Yu, 2000; Kang, Kin & Choi, 1999).

Here in the step, the principal is to locate warp and weft crossed areas by analyzing the gray value changes in both horizontal and vertical directions. In the second step, we use these geometric area shapes to determine warp or weft floats.

However, due to the differences in yarn material, count, and density, different fabrics have diverse geometric shapes for warp and weft floats, hence making the recognition a difficult mission.

On the other hand, the texture analysis has already

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been applied on some related items for fabric recognition. However, it is still unable to recognize all types of fabrics and textures through computer vision. Therefore, in the present study, we will compare three methods Gabor wavelet filter, local binary pattern operators (LBP) and gray-level co-occurrence matrices (GLCM) to recognize the characterization of the texture of woven fabrics.

We consider that the SVM classifier is a powerful tool to be used in this case (Burges, 1998).

Many other classifiers used such as the back propagation neural network and learning vector quantification networks (LVQ) (Ben, Nasri & Tourki, 2005; Boong & Ji, 2003; Chung-Feng & Cheng-Chih, 2006), show weaknesses especially for classification during time.

2. Feature Extraction and Texture Classification

Texture is one of the most important features used in an image. In this section, we describe the three methods widely used in the feature extraction:

- Gabor wavelet.
- LBP.
- GLCM.

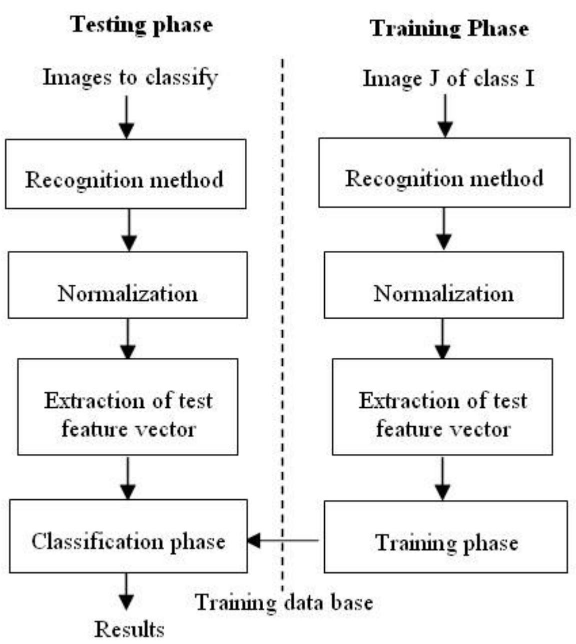

Fig. 1. Texture classification algorithm

The texture classification phase needs two feature vectors. The train feature vector is obtained by applying one of the recognition methods. With the same method we calculate the test feature vectors for each sample. This work is elaborated according to the algorithm presented in Figure 1.

2.1 Feature Extraction Based on Gabor Wavelet Method

The texture features are extracted using the Gabor filter bank as in (Manjunath & Ma, 1996).

A 2D Gabor function *g(x, y)* and its Fourier transform *G(u,v)* can be written as:

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right]+2\pi jW_x\right] \qquad (1)$$

and

$$G(u,v) = exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \qquad (2)$$

where, $\sigma_u = \frac{1}{2}\pi\sigma_x$ and $\sigma_v = \frac{1}{2}\pi\sigma_y$.

A class of self-similar functions, referred as the Gabor wavelet is discussed below.

Let *g(x, y)* be the mother Gabor wavelet, then this self similar filter dictionary can be obtained by appropriate dilation and rotations of one of *g(x, y)* through the generating function:

$$g_{mn}(x,y) = a^{-m}g(x,y), a > 1 \qquad (3)$$

$$x' = a^{-m}(x\cos\theta + y\sin\theta) \qquad (4)$$

$$y' = a^{-m}(-x\sin\theta + y\cos\theta) \qquad (5)$$

where, $\theta = \frac{n\pi}{K}$ and k is the total number of orientations. In multi-resolution decomposition the number of scales is equal to the number of stages (Manjunath & Ma, 1996).

The texture features are calculated with the Gabor filter bank while varying the two parameters scales and orientations (S, O). The mean and standard deviation of each filtered images are calculated and taken as a feature vector.

2.2 Feature Extraction Based on LBP Method

The original LBP operator, introduced by Ojala et al. (Ojala, Pietikäinen, & Mäenpää, 2002), is a powerful means of texture description. The operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor (Figure 2).

			Threshold			Weights		
5	9	1	1	1	0	1	2	4
4	4	6	1		1	128		8
7	2	3	1	0	0	64	32	16

Fig. 2. The basic LBP operator

Later the operator was extended to use neighbourhoods of different sizes (Ojala, Pietikäinen, & Mäenpää, 2002).

Using the circular neighbourhood's interpolation of the pixel values allows any radius and number of pixels in the neighbourhood. Another extension to the original operator uses so called uniform patterns. A LBP is called uniform if it contains at most, two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular.

A: histogram of labeled image $M(x, y)$ can be defined as:

$$H_i = \sum_{x,y} I\{M(x,y) = i\}, i = 0, \ldots, n-1, \quad (6)$$

In which n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1, A \text{ is true} \\ 0, A \text{ is false} \end{cases} \quad (7)$$

This histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image. With this histogram and while varying the two parameters of the circular neighbourhood *(R, P)*; P sampling points on a circle of radius R, we formed the feature vector, which is used as the input vector for the classification process.

2.3 Feature Extraction Based on GLCM Method

The third method studied in this paper is based on the GLCM. A GLCM (Davis, Clearman & J.K, 1981; Gotilieb & Kreyszig, 1990; Haralick, Shanmugam & Dinstein, 1973) extracts the texture measured from an image.

Two parameters affect the calculation of the co-occurrence matrix; D, the distance between two pixels, and θ, the position angle between two pixels (p,q) and (j,k). There are four directions for the position angle: the horizontal position $\theta = 0°$, right diagonal position direction $\theta = 45°$, vertical direction $\theta = 90°$ and the diagonal direction $\theta = 135°$ (Figure 3). We have defined the offset parameter, offset= [0 D, -D D,-D 0, -D –D].

It affects considerably in the GLCM features vector.

There is another important parameter that affects the GLCM features vector. It is the number of gray levels (*Numlevels*) in the GLCM, it determines the size of the GLCM, and we note that this parameter is very influencing in the classification results.

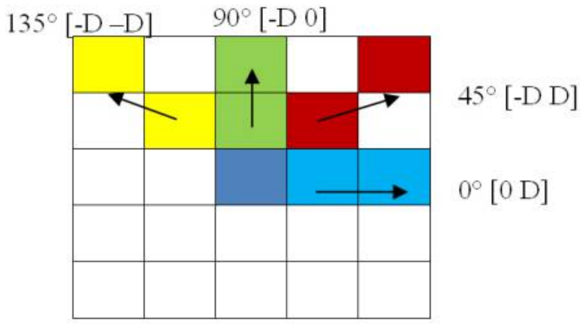

Fig. 3. Texture of an image with offset varying in distance and orientation

All values of the co-occurrence matrix M need to be normalized. This step is very important because otherwise the results will not be in our ambition.

After normalization, the co-occurrence matrix, C_{mn} can be expressed as:

$$C_{mn} = \frac{M_{mn}}{\sum_{m=0}^{N}\sum_{n=0}^{N} M_{mn}} \tag{8}$$

In order to estimate the similarity between different GLCM Haralick (Haralick, Shanmugam & Dinstein, 1973) proposed 14 statistical features to represent the characterizations of the image. We will be satisfied with 4 descriptive parameters. Assuming that C_{mn} are the normalized matrices, the 4 features are expressed as (Haralick, Shanmugam & Dinstein, 1973) below:

Angular Second Moment:

$$ASM = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} C_{mn}^{2} \tag{9}$$

Contrast:

$$CON = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} (m-n)^2 . C_{mn} \tag{10}$$

Entropy (or Correlation):

$$COR = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} \frac{(1-\mu_x)(1-\mu_y)}{\sigma_x \sigma_y} C_{mn} \tag{11}$$

with

$$\mu_x = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} mC_{mn}$$

$$\mu_y = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} nC_{mn}$$

$$\sigma_x = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} (1-\mu_x)^2 C_{mn}$$

$$\sigma_y = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} (1-\mu_y)^2 C_{mn}$$

Homogeneity:

$$ENT = \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} \frac{C_{mn}}{1+|m-n|} \tag{12}$$

Where (m, n) are the coordinates of the co-occurrence matrix space, C (m, n) is the element of the m and n coordinates, and $(N \times N)$ is the dimension of the digital image.

Taking advantage of the periodicity of the woven fabric images by the 4 parameters contrast, homogeneity, Angular Second Moment and correlation (Figure 5), we have used this point to extract the input feature vectors and used in the corresponding algorithm and classifying of the woven fabric.

3. Classification

For a supervised classification, machine learning and pattern recognition consist of the extraction of regularity or some sort of structure from a collection of data. Neural network (NN) and Bayesian classifiers are typical examples for learning such organization from the given data observations. A support vector machine (SVM) is a relatively new classifier and based on strong foundations from the broad area of statistical learning theory (Vapnik, 1998).

Since its inception in the early 90s, it has found applications in a wide range of pattern recognition problems. In practice, the SVM has become a suitable classifier for several real-world classification problems. The advantage of the SVM comes from its capability of generalizing (predicting the unseen or unknown samples with a good degree of accuracy) compared to many traditional classifiers. On the other hand, it offers several advantages which are typically not found in other classifiers:

- Computationally much less intensive (in comparison to NN).
- Good performance in higher dimensional spaces (a factor which limits many efficient classifiers).
- Lack of training data is often not a severe problem.
- Based on minimizing an estimate of test error rather than the training error (structural risk minimization).
- Robust with noisy data (noise can severely degrade the performance of NN).
- Does not suffer so much from the curse of dimensionality and prevents over fitting.

The main aim of such a classifier is to obtain a function *f*(*x*), which determines the decision boundary or hyperplane. This hyperplane optimally separates two classes of input data points (Figure 4). The margin *M* is the distance from the hyperplane to the closest point for both classes of data points.

The classifier positions the decision boundary by using a maximal margin among all possible hyper planes. In order to maximize the margin *M*, $||w||$ has to minimize the subject with conditions given below,

$$min\frac{||w||^2}{2} \text{ s.t. } \forall n, y_n(\langle w.x_n\rangle + b) \geq 1 \qquad (9)$$

where *n* is the number of input data of SVM, *w* is a vector defining the boundary, x_n is the input data point, and *b* is a scalar threshold value.

To obtain the optimal hyper plane of SVM *f(x)* is written:

$$\mathrm{f(x)} = \sum_{n=1}^{t} y_n a_n \langle x_n.x\rangle + b \qquad (10)$$

x_n is a support vector having non-zero Lagrange multiplier (a_n).

a_n is a Lagrange multiplier and must be $a_n \geq 0$

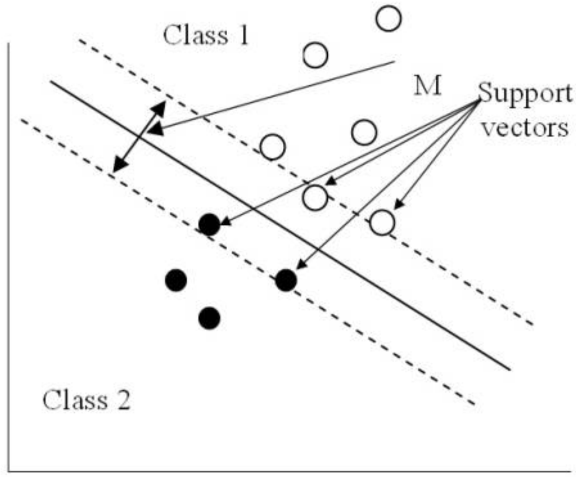

Fig. 4. Optimal separation hyperplane of SVM.

There are many types of multi-class classifiers. Some of them are called one against one and the others are called one against all. One against all trains *k* classifiers (*k* is the number of classes). In that case the classifier tries to separate class *i* from the rest. In contrast, one against one needs to construct one classifier for two arbitrary classes, i.e. *k(k-1)/2* classifiers all together. Then the two-class classifiers evaluate the input data and vote on their classes.

We have chosen to work with the *simpleSVM* Matlab toolbox (Gaëlle Loosli) as it seems to be a simple and effective algorithm.

4. Experimental Results and Interpretation

A database consisting of three types of woven fabric; plain, twill and satin was used. The image was acquired with a flat bed scanner and saved as a gray scale .bmp image. The resolution was kept between 300 and 600 dpi. Figure 6 shows a sample of this database. We have used 3 classes. Each class contains 180 images. For the training phase we have used 20 images per class and 160 samples per class for the test phase. For all of the experiences, samples are chosen randomly from each class. Table 1 shows the percentages of correctly classified samples of all the test samples.

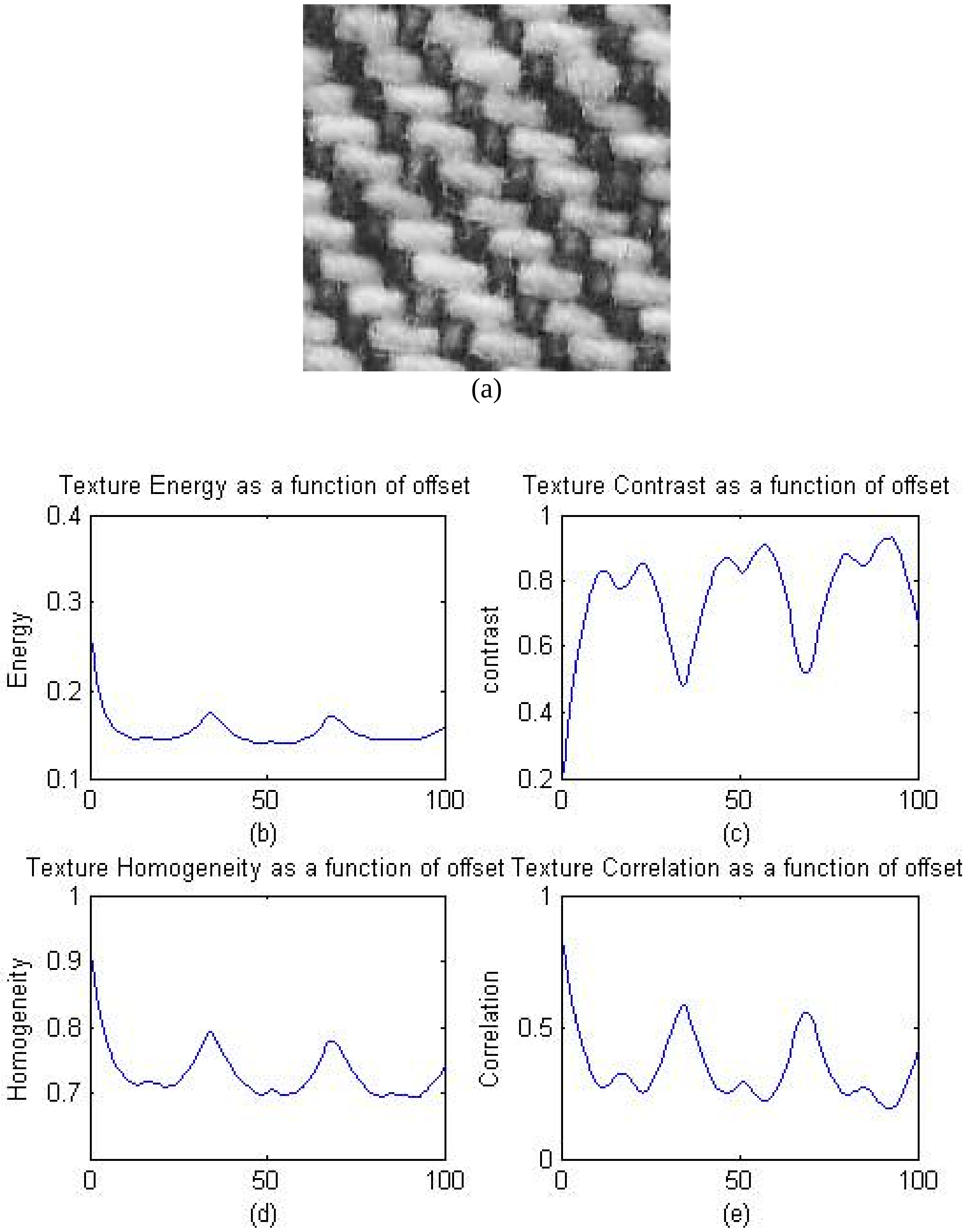

Fig. 5. (a) Original twill woven fabric image;(b) Texture Angular Second Moment (energy) as a function of offset; (c) Texture contrast as a function of offset; (d) Texture homogeneity as a function of offset; (e) Texture correlation as a function of offset. (Offset = [0 100]).

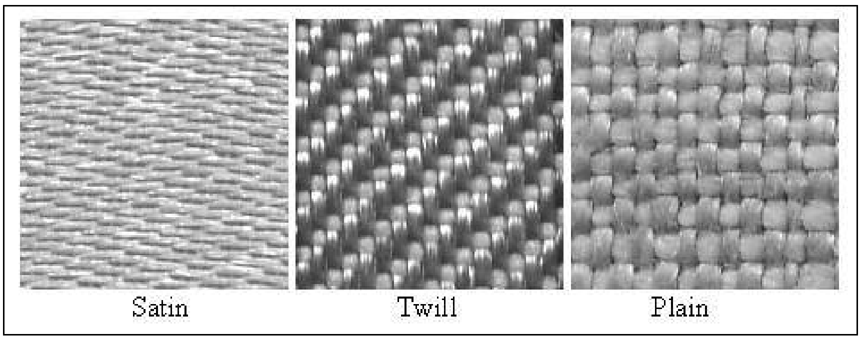

Fig. 6. Woven fabric patterns

Table 1. Classification accuracy with different methods.

Method	LBP			Gabor Wavelet			GLCM				Gabor +GLCM	Gabor +LBP	GLCM+ LBP
	(1,8)	(2,8)	(2, 16)	(3, 4)	(3, 6)	(3, 8)	(2, 16)	(3, 64)	(15, 10)	(20, 10)	(3,4)+(2,8)	(3,4)+(2,8)	(2,8)+(2,8)
Satin	90,2	91,4	89,1	93,6	96,1	94,6	95	93,2	96,2	95,7	98,3	93,4	96,2
Twill	90	90,6	86,9	90	96,3	97,4	90	91,9	95,3	96,3	98,1	93,4	94,4
Plain	98,2	97,3	90,4	98,5	97,5	98,8	96,3	98,8	100	98,8	98,2	97,4	97,5
Average	**92,8**	**93,1**	**88,8**	**94,0**	**96,6**	**96,9**	**93,8**	**94,6**	**97,2**	**96,9**	**98,2**	**94,7**	**96,0**
Running time	32,2	31,5	369	295	356	508,4	102,5	151,8	605,4	786,2	420	293,2	235,1
Number of feature vector	36	36	4116	24	36	48	32	48	240	320	56	60	68

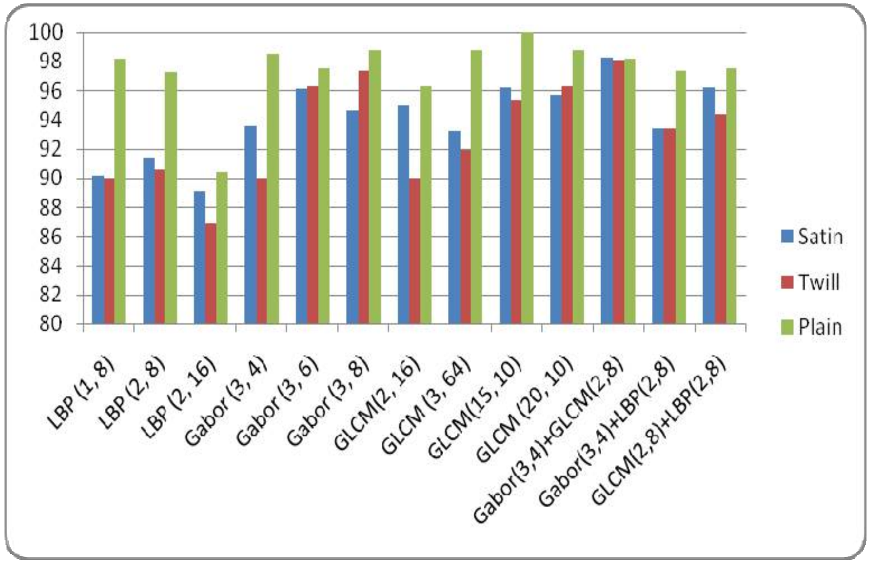

Fig. 7. Classification accuracy of the three woven fabric with different methods

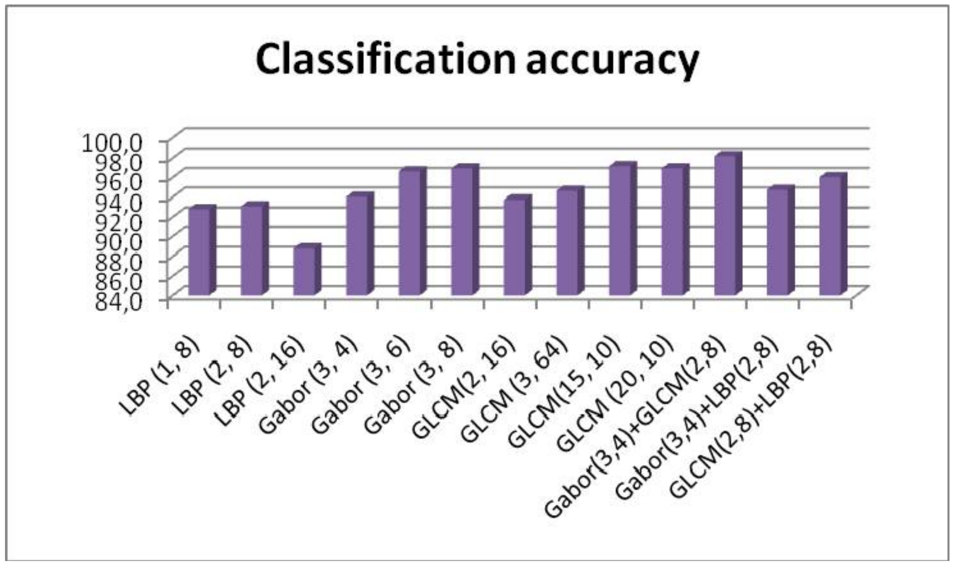

Fig. 8. Classification accuracy with different methods

With the GLCM method, we calculated the percentage of the successful classified images. When varying the two parameters (*offset* and *Numlevels*) the best averages (97.2%) are estimated with the couple (15, 10), offset=[0 1, -1 1, -1 0,-1 -1, 0 2, -2 2, -2 0,-2 -2,…-15 15] and *Numlevels*=10, the running time is 605,4 seconds and the feature vector is composed of 240 elements.

The application of the LBP method and the variation of its two parameters (*R, P*) lead to comparable results around 93.1 %. The best ones are obtained with the couple (2, 8) in a running time equal to 31.5 seconds and 36 elements. The accuracy of this method is less than that of the GLCM.

Varying the two parameters (*S, O*), of the Gabor wavelet method, we obtained the best results of 96.9% with the couple (3, 8) estimated at 508.4 seconds. When we increase the two parameters the results debase and the running time increases. It is worse than the other methods.

We note that with the fusion of Gabor+GLCM provide the best result of 98.2%. The Gabor wavelet method gives a good result but with bad running time.

According to Figure 7, the different methods lead to similar percentages of recognition (between 88% and 98%) which explain the utility of these methods in the texture classification problems. Then we note that the plain is the easiest woven fabric to classify and satin is the most difficult woven fabric to classify.

Figure 8 illustrates that the percentages of the recognition of the different woven fabrics of the Gabor wavelet and GLCM methods are better than those provided by the LBP method even though GLCM seems to be an old and forgotten method. Nevertheless, to have good results with this method we should optimize the two parameters that affect it (*offset*, *Numlevels*).

Concerning the running time of the algorithm, the GLCM and LBP give the best results compared to the Gabor wavelet.

Finally, it was interesting to study the fusion of the different proposed methods. The fusion of the Gabor wavelet+GLCM leads to an accuracy of 98% whereas the fusion GLCM+LBP leads to 96%. The best accuracy is obtained with the first fusion with 420 seconds of running time.

5. Conclusion

We have dealt with the problem of pattern recognition and classification of the images in the textile field and in particular, pattern recognition of woven fabric satin, twill and plain. We have adopted a technique which is based on the texture of the images in the pattern recognition phase. This gives us a feature extraction vector which is the input vector for our algorithm.

In this algorithm, we have used the SVM to classify, which corresponds best to this type of problem. It is better then the NN classifiers, such as the LVQ (Chung-Feng & Cheng-Chih, 2006).

Several tests have been carried out. Table 1 includes the most significant results. The three methods show good classification accuracy, but the Gabor wavelet remains the best.

By comparing these results with others which have already dealt with this problem (Chung-Feng & Cheng-Chih, 2006), we notice an improvement of performance, due to the optimization of the parameters which affect the results, and especially to the use of the SVM classifier.

Although it is the oldest method, GLCM always remains accurate for this type of problem. The fusion of the method can bring improvements in classification performance (98%) but with respect to the running time of the algorithm, the GLCM and LBP give the best results in comparison to the Gabor wavelet.

REFERENCES

[1] Ben Salem, Y., Nasri, S. & Tourki, R. 2005, 'Classification of Tissues by neural network'; *12th IEEE International Conference Electronics Circuits, and systems, ICECS 2005*, Gammarth, Tunisia.

[2] Boong, S.J. & Ji H.B. 2003, 'Automatic recognition of woven fabric patterns by an artificial neural network', *Textile Res. J.*, vol. 73, no. 7, pp. 645-650.

[3] Bugao, X. 1996, 'Identification fabric Structures with fast Fourier Transform Techniques', *Textile Res. J.*, vol. 66, no. 8, pp. 496-506.

[4] Burges, C.J.C. 1998, 'A tutorial on support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery', vol 2, no. 2, pp. 1-47.

[5] Chung-Feng, J.K. & Cheng-chih, T. 2006, 'Automatic Recognition of Fabric Nature by Using the Approach of Texture Analysis'; *Textile Res. J.* vol. 76, no. 5, pp. 375-382.

[6] Davis, L.S. & M. Clearman, & J.K. 1981, 'Aggarwal. An empirical evaluation of generalized co-occurrence matrices'; *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 3, no. 2, pp. 214–221.

[7] Gaëlle Loosli, Toolbox SimpleSVM cumentation, http://cbio.ensmp.fr/sirene/documentationSimpleSVM.pdf.

[8] Gotlieb, C.C. & Kreyszig, H.E. 1990, 'Texture descriptors based on co-occurrence matrices', *Comput. Vision Graph. Image Process.* vol. 51, no. 1, pp. 70–86.

[9] Haralick, R.M., K. Shanmugam, & I. Dinstein. 1973, 'Textural features for image classification', *IEEE Trans. Sys. Man. Cybern*, vol. 3, no. 6, pp. 610–621.

[10] Huang, C.C., Liu, S.C. & Yu, W. H. 2000, 'Woven Fabric Analysis by Image Processing, Part I: identification of weave patterns', *Textile Res. J.*, vol. 70, no. 6, pp. 481-485.

[11] Jensen, K.L. & Carstensen, J.M. 2002, 'Fuzz and Pills Evaluated on Knitted Textiles by image Analysis', *Textile Res. J.*, vol. 72, no. 1, pp. 34-38.

[12] Kang, T.J., Kin, S.M. & Choi, S.H. 1999, 'Automatic recognition of fabric weave patterns by digital image analysis', *Textile Res. J.*, vol. 69, no. 2, pp. 77-83.

[13] Manjunath, B.S. & Ma, W.Y. 1996, 'Texture features for browsing and retrieval of image data', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 8, pp. 837–842.

[14] Ojala, T., M. Pietikäinen & T. Mäenpää. 2002, 'Multiresolution gray-scale and rotation invariant texture classification with local binary patterns', *IEEE Transactions on Pattern Analysis and Machine Intelligence.*, vol. 24, no. 7, pp. 971-986 July.

[15] Ravandi, S.A.H. & Toriumi, K. 1995, 'Fourier Transform Analysis of Plain Weave Fabric Appearance', *Textile Res. J.*, vol. 65, no. 11, pp. 676-683.

[16] Vapnik, V. 1998, 'Statistical Learning Theory', Wiley, New York.

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2. Anindya Ghosh, Tarit Guha, R. B. Bhar. 2013. Classification of yarn interlacement pattern in fabrics using least square support vector machines. *Fibers and Polymers* **14**:7, 1215-1219. [CrossRef]