Pattern Recognition of Woven Fabric Using Texture Analysis Approach

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ABSTRACT: *Computer vision plays a crucial role in pattern recognition. In this study we propose pattern recognition for textures analysis. In this work we deal with the pattern recognition and classification of the images in the textile field and in particular, pattern recognition of woven fabric satin, twill and plain. We made experimentation and compared the results with others which have already dealt with this problem, we notice an improvement of performance, due to the optimization of the parameters.*

1. Introduction

In textile industry, the identification of a weave pattern is usually manual which requires considerable human efforts. This difficult operation requires a long time. That is why it is highly desirable to develop an automatic recognition system for fabric patterns.

The science of computer vision and specially Image processing has proved to be an efficient method of analyzing fabric structures, and fabric weave pattern recognition by image analysis has been studied since middle of the 1980s. The main methods are based on the properties of the Fourier spectrum. This fabric texture research has been used for recognition of woven fabric texture [11, 6], and analysis of the fuzz and pills on the surface of knitted fabric [1]. Another identification method uses warp and weft floats to determine the weave patterns [5, 7, 8]. The purpose, in a first step, 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 and density, different fabrics have diverse geometric shapes for warp and weft floats, hence making the recognition a difficult mission.

The techniques used in a texture analysis are discussed in four categories: statistical approach, structural approach, filters based methods and model based approach with a detailed list of references to some recent works.

Texture analysis has already 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 use the three most famous methods:

filter of Gabor and wavelet, local binary pattern operators (LBP) and gray-level cooccurrence matrices (GLCM) to recognize the characterization of the texture of woven fabrics. They are compared to determine the most accurate and suitable one in such problems.

2. Used Methods

2.1 LBP Method
The LBP operator was first introduced as a complementary measure for local contrast of an image [4, 10]. The first incarnation of the operator has worked with the 8 neighbors of a pixel, using the center pixel value as a threshold. LBP code for a neighborhood was produced by multiplying a threshold values with weights given to the corresponding pixels. As can be seen in figure 1, the LBP is by definition invariant to changes in gray level. It was complemented by a measure of orthogonal local contrast. (Figure 2). shows how the contrast measure was derived. The average gray levels below the central pixel are subcontracted to one of the gray levels above the central pixel. Dimensional distributions of LBP and local measures of contrast were used as devices for measuring. The operator was called LBP / c and good rates of discrimination were reported with textures selected from Brodatz photographic album [2, 10].

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

Example : LBP = 1 + 16 + 32 + 64 + 128 = 141

Figure 1. The basic LBP operator

T is the texture in a local neighborhood of a gray level image joint distribution of gray levels of (P +1) pixels in an image (P > 0):

$$T = t (g_c, g_0, ..., g_{P-1})$$

Where g_c is the gray level of the pixel that occupies the center in a circular neighborhood, and g_p (0,..., P-1) corresponds to the values of gray level equidistant from P and a circle of radius R.

The algorithm based on this method provides a vector of variable size depending on device parameters. It is the characteristic of each image and represents the input vector for the classifier.

For example the case of armor images, we notice that the three weaves have three different histograms.

2.2 GLCM Method
The statistical gray level co-occurrence (LMA) was first described by Haralick [3], and is actively developed until today. A set of matrices of gray level co-occurrence (GLCM) is constructed.

Two parameters affect the calculation of the GLCM matrix: the distance D between two pixels, and the position angle θ between two pixels. There are four directions for the angle θ: the horizontal θ = 0°, the right diagonal direction for θ = 45°, the vertical direction where θ = 90° and the left diagonal direction where θ = 135° (Figure 3).

The GLCM matrix consist on measuring a joint probability into a pair of pixels by calculating the frequency of occurrence of two
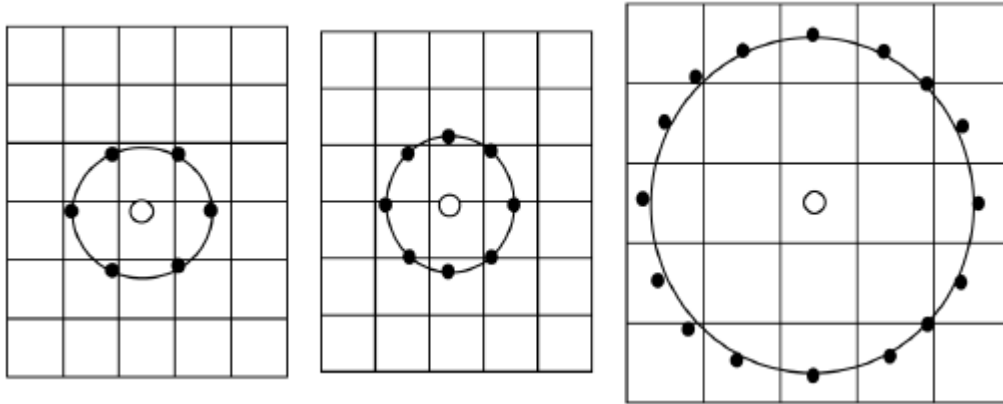
Figure 2. Three circular neighborhoods: (R = 1, P = 6), (R = 1, P = 8), (R = 2, P = 16)

simultaneous levels of gray at the ends of a given vector U = (D, θ).Assuming that g (x) is the pixel value x in a neighborhood of the specified pixel (i, j), the GLCM corresponds to the 2D histogram pair [g (x), g (x + U)] on this neighborhood.

We define the offset parameter that significantly affects the device GLCM vector, offset = [0 D, - DD-D 0 - D-D]. In practice the GLCM can be calculated in all possible orientations for a fixed D.
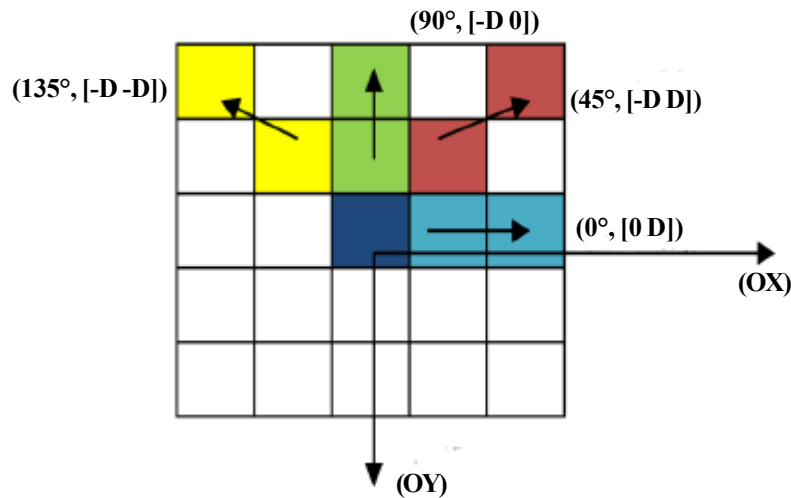
Figure 3. Variation of D and θ parameters of GLCM method

There is another important parameter that affects the device GLCM vector, the number of gray level in the GLCM (Numlevels). It determines the size of the GLCM, and we note that this parameter influences the classification results significantly.

After calculating the matrix of co-occurrence M_{mn} size $N \times N$, we must normalize this matrix. It was found that this step affects the classification results.

Thus the co-occurrence matrix can be expressed:

$$C_{mn} = \frac{M_{mn}}{\sum_0^N \sum_0^M M_{mn}} \qquad (1)$$

Haralick[3] presented 14 measures extracted from the GLCM statistics that can provide information on the homogeneity of an image, its contrast, or linearity, etc.

In this study, we chose four effective measures extracted from the GLCM: energy, entropy (or correlation), homogeneity and

contrast.

If (m, n) are the coordinates of an element of co-occurrence matrix, C (m, n) is the value of this element and $(N \times N)$ dimension of the digital image is processed, then we can write the following relations: [3]

Energy (Angular Second Moment):

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

Contrast:

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

Entropy(or Correlation):

$$COR = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} \frac{(1-\mu_x)(1-\mu_y)}{\sigma_x \, \sigma_y} C_{mn} \tag{3}$$

With

$$\mu_x = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} m C_{mn} \quad and \quad \mu_y = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} n C_{mn} \tag{4}$$

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

$$Homogenety : \; ENT = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} \frac{C_{mn}}{1+|m-n|} \tag{5}$$

We noted that the 4 measurement parameters provide periodic graphs and each type of armor gives us a different chart (Figure 4). By leveraging this point we extracted input vectors of our classifier and we got some interesting results.

2.3 Filter of Gabor and wavelet Method
Gabor filters are band pass filters. Their general form follows from the multiplication of a Gaussian function shaped envelope with a complex sinusoidal function.

The 2D Gabor function is written:

$$g(x, y) = \left(\frac{1}{2\pi\sigma_x \sigma_y}\right) exp\left[-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right] + 2\pi j W_x \right] \tag{6}$$

And its Fourier transforms:

$$G(u, v) = exp\left\{ -\frac{1}{2}\left[\frac{(u-w)^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right]\right\} \tag{7}$$

with

$$\sigma_u = \frac{1}{2}\pi\sigma_x, \quad \sigma_y = \frac{1}{2}\pi\sigma_y.$$

and

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

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

With $\theta = \frac{n\pi}{K}$ is the orientation of the Gaussian lobe and k is the total number of directions. The standard deviation σ of the Gaussian determines the width of the window around the pixel center of the convolution. The parameter λ is the wavelength at which $\frac{1}{\lambda}$ is the spatial frequency in the image. φ is the phase shift. The actual detection of texture is to marry the image with a bank of Gabor filters parameterized by λ, θ, φ and S (scale) (Figure 5).

(a)

(b)
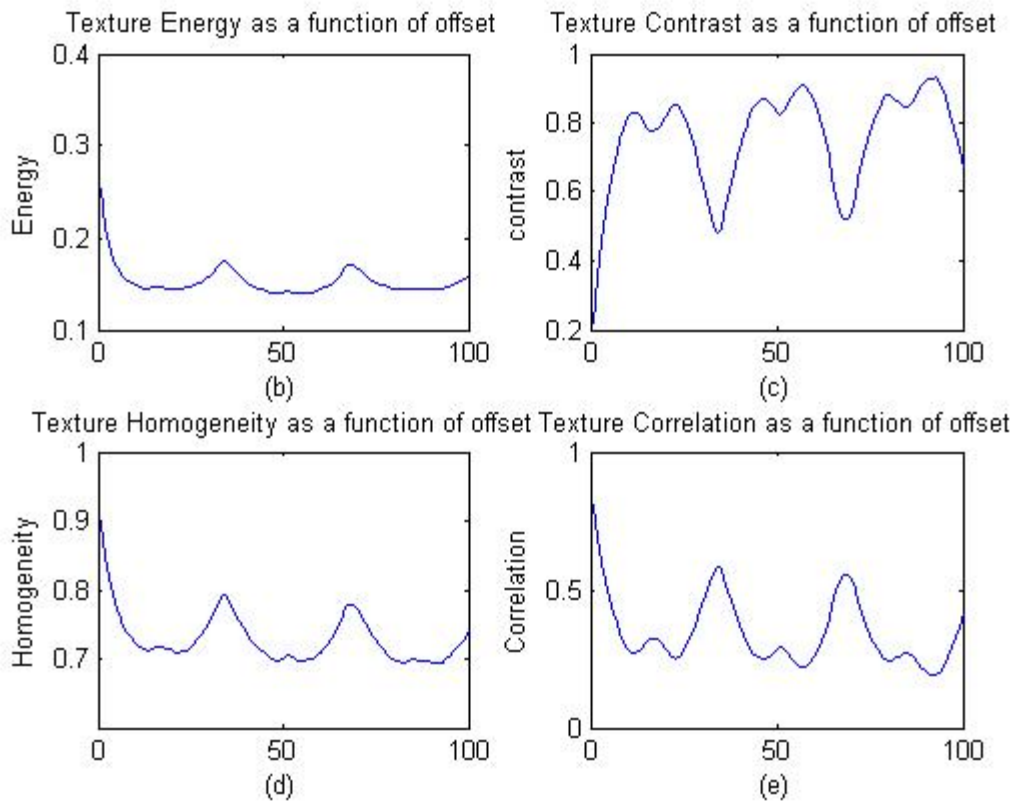
(c)

(d)

(e)
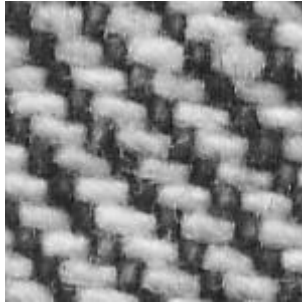
Figure 4. (a) Original twill woven fabric image;(b) Texture Angular Second Moment (energy) as a function of offset; (c) Texture contrast as a function of offset; (d) Texture homogeneity as a function of offset; (e) Texture correlation as a function of offset. (Offset = [0 100]).

Figure 5. A bank of Gabor filter oriented respectively 0°, 45° and 90°

This method provides a Feature vector variable size depending on the parameters, which has the feature for each image. It will be seen as input vector for the classifier.

3. Algorithm and Classification

In the proposed methodology, the classification is the second step. It can assign to each data a class (a class picture in our case), and consolidating similar data in the same class.

In terms of action, the act of classifying an object corresponds to a decision on the basis of one or more rules. This tool is called classifier. There are two families of classifiers: supervised classifiers and unsupervised classifiers, the SVM is a supervised one.

The classification of a large data stream, as in our case an image base is a serious problem that cannot be solved with non-conventional classifiers. Thus, we have demonstrated that support vector machines (SVM) tools are suitable for such applications.

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 vector for each sample. This work is elaborated according to the algorithm presented in Figure 6.
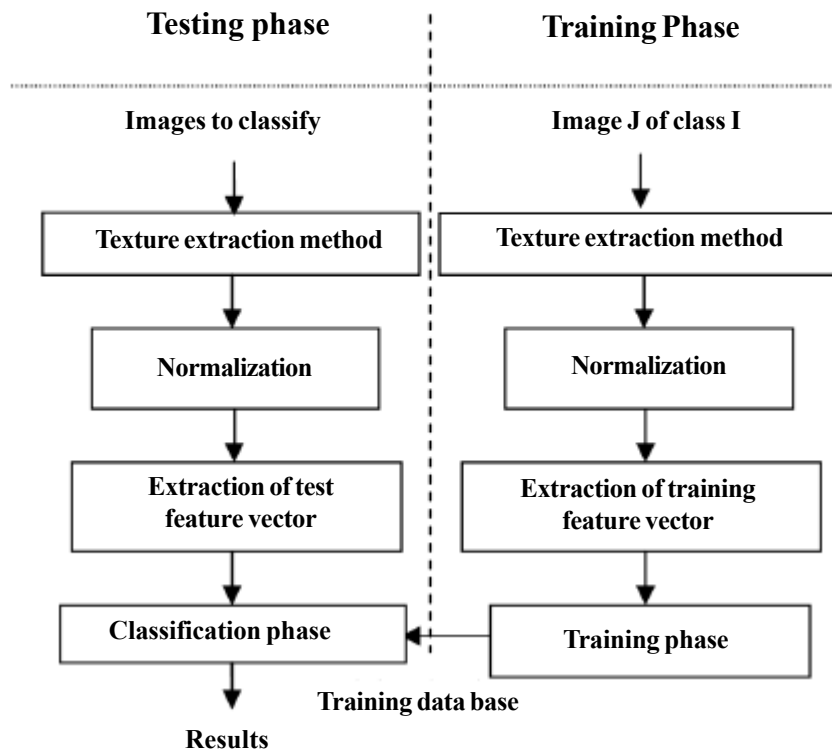
Figure 6. Texture classification algorithm

4. SVM Method

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 7). 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 hyperplanes. In order to maximize the margin M, $\| w \|$ has to minimize the subject with conditions given below,

$$min \ \frac{||w||^2}{2} \ \text{s.t.} \ \forall \ n, \ y_n \left((w, \ x_n) + b \right) \geq 1 \qquad (8)$$

Where n is the number of SVM input data, 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 SVM hyperplane $f(x)$ is written:

$$f(x) = \sum_{n=1}^{t} y_n \ a_n (x_n, \ x) + b \qquad (9)$$

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

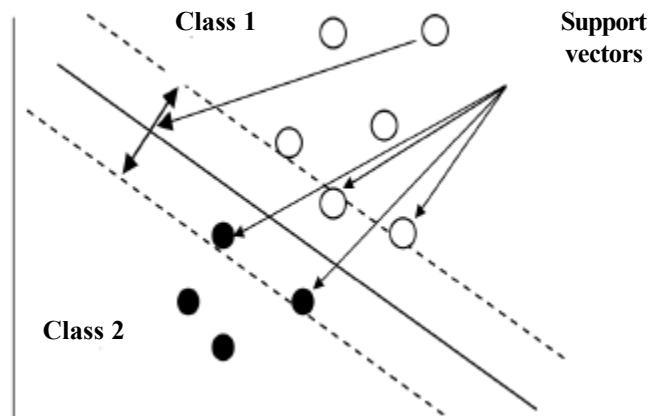a_n is a Lagrange multiplier and must be $a_n \geq 0$

Figure 7. 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 [8] since it seems to be a simple and effective algorithm.

5. Data Base

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. 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.

6. Results and Interpretation

We consider two criteria to assess the pattern recognition methods textures. The average classification is the first criterion (Figure 8), it represented an average success rate of classification obtained between the three tissues namely the plain, the satin and the twill. The second criterion is the time taken to achieve this success rate of classification; it was called the execution time as shown in Figure 9.

In addition, for each recognition method, we vary the parameters for all possible values for each parameter, keeping only the significant values.
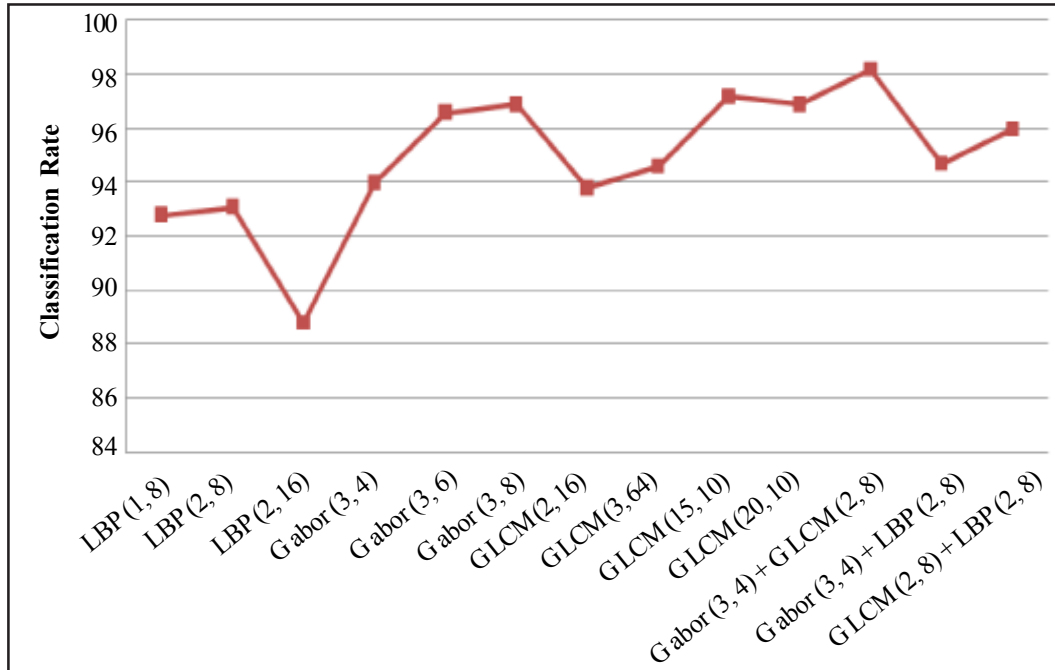
Figure 8. Classification rate of three types of woven fabrics with different methods and different parameters
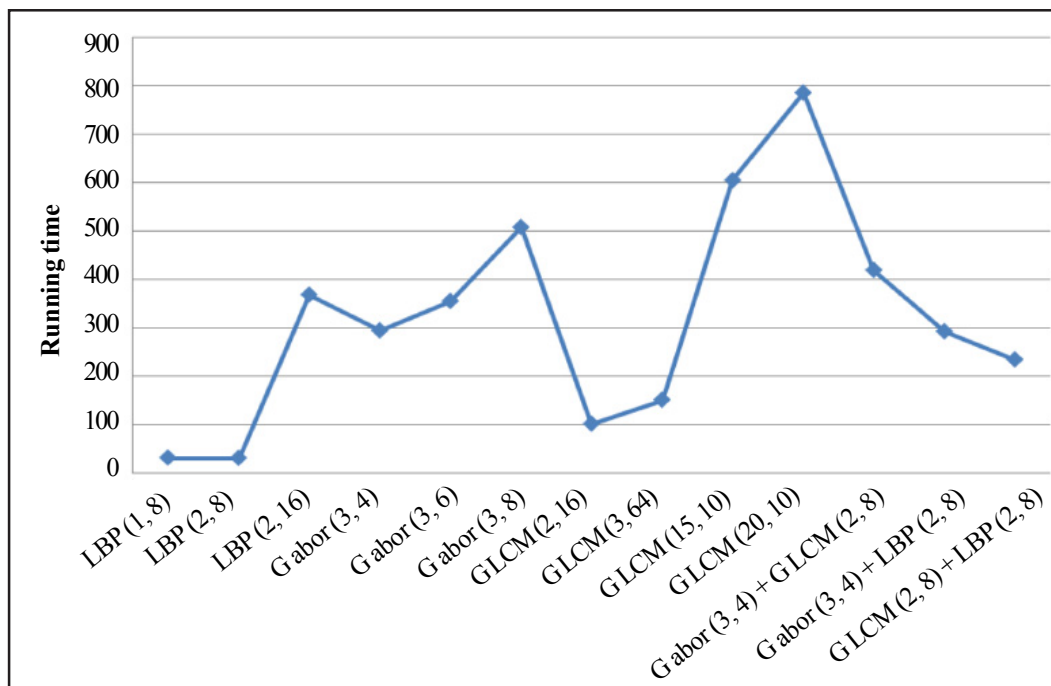

Figure 9. Running time for each method by varying the parameters

For the GLCM method, we vary both offset and Numlevels and for the LBP method we vary the pair (R, P) R: radius of the circle and P: the number of pixels in this circle. For the filter of Gabor and wavelet method we vary the pair (S, O): scale and orientation.

From these results we find that in all cases, the offset that gives the best results consists of $\theta = 0^o$ and D = 50. The measure of homogeneity gives the best results that can reach 100% and energy gives the worst 60%. The required time for image classification is about 47 images per second. This time is interesting, especially for industrial applications in real time.

With the GLCM method, we calculated the classification rate by changing both offset and Numlevels. The best result (97.2%) is obtained with couples (15, 10) that is to say, offset = [0 1 -1 1, -10, -1, -1, 0 2 - 2 2, -2 0, -2 -2 ... -15 15] and Numlevels = 10, the execution time is 605.4 seconds and the vector of device is constituted of 240 elements.

The application of the LBP method and the variation of two parameters (R, P) lead to results close to 93.1%. The best results are obtained with the pairs (2, 8) with a running time equal to 31.5 seconds and with a vector device of 36 elements. The percentage of this method is lower than the GLCM.

By changing the two parameters (S, O) of the filter of Gabor and wavelet, we obtained results of 96.9% with couples (3, 8) we obtain a running time of 508.4 seconds. When we increase both parameters, those results demean and the execution time increases. It is less interesting than other methods.

We note that with the merger of GLCM + Gabor we get the best result of 98.2%. The filter of Gabor and wavelet method gives also good results (96.9%) but with a longer running time (508.4 seconds).

The different methods lead to percentages between 88%and 98%, which advocates the choice of these three methods for texture classification problems. We also note that the plain is the easiest to classify as the satin weave is the most difficult to classify.

For the GLCM method, we must choose the two parameters that affect it (offset and Numlevels) to get better results and that by varying the two parameters and see the results of classification rate and execution time. Regarding the execution time of the algorithm, the LBP and GLCM offer better results compared to the filter and filter of Gabor and wavelet.

6. 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.

Several tests have been carried out. Figure 8 includes the most significant results. The three methods show good classification accuracy, but the filter of Gabor and wavelet method remains the best.

By comparing these results with others which have already dealt with this problem [5], 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 filter of Gabor and wavelet.

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