The effect of wavelet transform for fabric defect classification

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ABSTRACT – REZUMAT

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An automatic control system during fabric production improves production quality. For this reason, the number of automatic systems developed is increasing day by day. These systems use different methods, different data sets, and different approaches. We investigate the effects of wavelet transform using four different feature sets (wavelet-based Principal Component Analysis, wavelet-based Gray Level Co-occurrence Matrix, Principal Component Analysis and Gray Level Co-occurrence Matrix). The methods of K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) are used as classifiers. Experiments have been carried out for six different fabric defects (fly, dirty warp, tight-loose warp, fibrous weft, rub mark and weft stack) on 57 images. The experimental results performed show that wavelet-based PCA (Principal Component Analysis) and KNN have been optimal methods for achieving the highest success rate. We have achieved a 92.9825% accuracy rate by using them.

Keywords: *defect classification, fabric defect, textile, wavelet transform, woven fabric*

Influența transformării wavelet pentru clasificarea defectelor țesăturii

Un sistem de control automat în timpul producției de țesături îmbunătățește calitatea produselor. Din acest motiv, numărul sistemelor automate dezvoltate crește pe zi ce trece. Aceste sisteme folosesc metode diferite, seturi de date diferite și abordări diferite. Investigăm influența transformării wavelet folosind patru seturi de caracteristici diferite (analiza wavelet a componentelor principale, matricea de co-ocurență la nivel de gri wavelet, analiza componentelor principale și matricea de co-ocurență la nivel de gri). Metodele K-Nearest Neighbor (KNN) și Support Vector Machine (SVM) sunt utilizate ca clasificatori. Au fost efectuate experimente pentru șase defecte diferite ale țesăturii (scame, urzeală murdară, urzeală strânsă-largă, bătătură fibroasă, semn de frecare și tasarea bătăturii) pe 57 de imagini. Rezultatele experimentale efectuate arată că PCA wavelet (Analiza componentelor principale) și KNN au fost metode optime pentru a obține cea mai mare rată de succes. Am obținut o rată de precizie de 92,9825% prin utilizarea acestora.

Cuvinte-cheie: *clasificarea defectelor, defect de țesătură, material textil, transformare wavelet, țesătură*

INTRODUCTION

Defects occurring during fabric production constitute 85% of the defects encountered in the clothing industry [1]. 130 different fabric defects are included in ISO standards [2]. The reasons for these defects can be caused by raw materials, machinery or human [3]. It is difficult and costly to find 130 types of fabric defects with manpower during textile production.

According to the study of Ala and İkiz [4], the defects of broken warp, stopping mark, and warp stack are the most common defects in the textile industry. Broken warp constitutes 48.02% of the defect in their study. The ratios of stopping mark and warp stack are 15.32% and 8.69%, respectively.

Studies have been started to automate the control process based on manpower. Thus, higher success is achieved with less cost through automatic systems. However, the systems developed are still not sufficient. There are some shortcomings of the fabric defect detection (FDD) systems. There are two known databases, Parvis [5] and TILDA [6] existing in the area of automatic fabric defect control. The Parvis database is private, and the TILDA database is not free. Since there is no public and free database for fabrics, it is seen that the authors have used the datasets they have created themselves in the studies. So, they cannot be compared to each other and the effectiveness of the developed systems are discussed [7]. Other disadvantages of this shortcoming are that studies have been carried out for an insufficient amount of data and a small number of defect types. Another shortcoming is that a lot of studies have been tested on only off-line images. It decreases the applicability of the studies in real life.

Different types of wavelet transform have been used in the studies since the emergence of the idea of automating the detection of fabric defects. Wavelet-based systems have been reviewed in this study [8–19]. It is seen that hybrid studies have developed to ensure robustness when a wavelet transform is used. Features are extracted using four scale dyadic wavelet decomposition [8]. Then, these features are classified using a neural network. They emphasize that the method developed has less time complexity than the other methods through the fastness of the wavelet transform. An algorithm has been developed using wavelet theory and co-occurrence matrix in the study of Latif-Amet et al. [9]. Classification is carried out with the success of up to 90.78%. Hu and Tsai use a backpropagation neural network after selecting the best wavelet packet bases [10]. Zhi et al. develop a method with adaptive wavelet design [11]. They suggest that adaptive wavelet is better compared to orthogonal wavelet transform. Yang et al. have compared six different methods based on wavelet transform [12]. Discriminative feature extraction using adaptive wavelet has been the best method among others. It achieves the classification with an accuracy rate of 95.8%. Ngan et al. have developed the WGIS (wavelet preprocessed golden image subtraction) method [13]. The success rate is 96.7%. Gabor wavelets have been used for feature extraction, and PCA is used to reduce the dimension of features extracted in the study of Basturk et al. [14]. Jianli and Baoqi classify the defects using both textural features and geometric features [15]. Kang et al. use the combination of wavelet transform and neural network as in the study of Jianli and Baoqi [16]. It is stated that the system developed is not sufficient for smaller fabric defects. Sakhare et al. compare the performances of six approaches (statistical approach, morphological approach, Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Wavelet Transform, and Gabor Filter) [17]. Input images are divided into four parts. The defected part is identified using the mean of these parts. First, it is investigated whether the defect is a hole or not. Second, the other types of defects are investigated for classification if the defect is not a hole. Tests have been performed to classify four different types of defects in the study. According to the experiments, the best performance has been obtained using FFT. In addition to that, the second most successful method has been DCT. Hanbay et al. use the methods of co-HOG (Co-occurrence Histograms of Oriented Gradients), wavelet transform and grey-level co-occurrence matrix to extract the features [18]. They use an artificial neural network to train the system in their study. When using the wavelet transform, defects are classified with a 90% success rate. Also, it is seen that the cost has decreased considerably. Kure et al. investigate homogeneity in fabric images [19]. They use local neighbourhood analysis to measure homogeneity.

A comparison between wavelet transform, gabor transform and the system developed has been made. According to the experiments, the cross-validation accuracy of the system is higher than the others (96.40%).

In this study, it is aimed to automate the process of detection and classification of fabric defects. The defects of fly, dirty warp, tight-loose warp, fibrous weft, rub mark and weft stack have been tried to classify. It has been investigated how wavelet transform affects the results. Different feature extraction methods (Principal Component Analysis and Gray Level Co-occurrence Matrix) have been tested. Besides, the performances of the K-Nearest Neighbor and Support Vector Machine have been compared. This paper is organized as: in the second section, we provide information about the methods we use in our study. The proposed system and experimental results are given in the third section. Finally, the fourth section presents conclusions.

BACKGROUND

The information about the methods has been provided in this section. Two-dimensional discrete wavelet transform has been used before feature extraction. The methods of principal component analysis and grey level co-occurrence matrix have been used as feature extraction methods, and their performances of them have been compared. The methods of K-Nearest Neighbor and Support Vector Machine have been used for the classification process of the extracted features.

The two-dimensional discrete wavelet transform (2D-DWT)

The 2D-DWT is a commonly used technique in image processing. Images are transformed from the spatial domain into the frequency domain through the 2D-DWT [20]. By using it, one scaling function ($\varphi(x,y)$) and three wavelet functions ($\Psi_H(x,y)$, $\Psi_V(x,y)$, $\Psi_D(x,y)$) can be obtained. $\varphi(x,y)$ is calculated as in equation 1. $\Psi_H(x,y)$, $\Psi_V(x,y)$, $\Psi_D(x,y)$ are the horizontal, vertical, and diagonal wavelet functions, respectively (equations 2, 3, 4).

$$\varphi(x,y) = \varphi(x)\varphi(y) \tag{1}$$

$$\Psi_H(x,y) = \Psi(x)\varphi(y) \tag{2}$$

$$\Psi_V(x,y) = \varphi(x)\Psi(y) \tag{3}$$

$$\Psi_D(x,y) = \Psi(x)\Psi(y) \tag{4}$$

The decomposition steps for images are given in figure 1. 3N + 1 different frequency bands are obtained with decomposition at the N level [21].

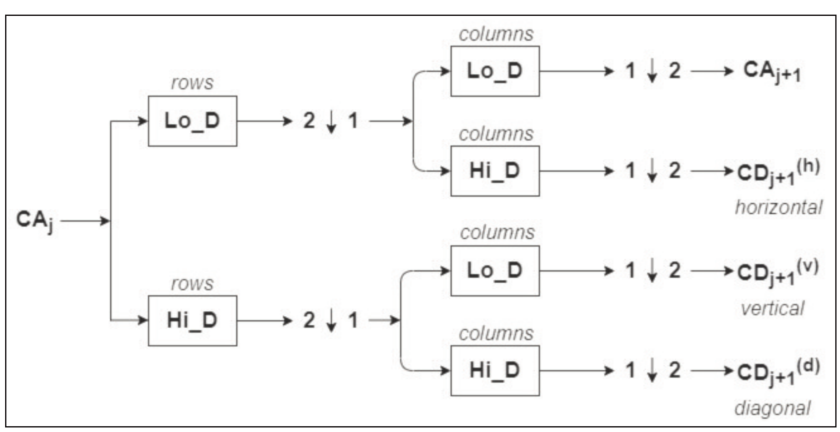

Fig. 1. 2D-DWT [21]

Feature extraction methods

Different textures can be found by revealing the texture characteristics [22]. In this study, texture characteristics have been extracted using the methods of Principal Component Analysis, and Gray Level Co-occurrence matrix.

The Principal Component Analysis (PCA)

PCA is a statistical method widely used in areas such as face recognition, image compression, and pattern recognition [23]. Using the PCA, many variables are converted into a small number of variables that are unrelated to each other. The small number of variables obtained is called the basic components of the data.

The steps for applying the PCA to a dataset are as follows:

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Step 1. Preparation of the data set
Step 2. Calculating the average
Step 3. Subtraction the average from each
        element in the data set
Step 4. Calculation of covariance matrix C
Step 5. Calculation of Eigenvalues λ and
        eigenvectors V of C
Step 6. Creation of new reduced data set
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Suppose, X is a dataset. x_i is the i^{th} element in the dataset X ($i = 1, \ldots, M$). Average of all elements in the dataset X is calculated. Then, the calculated average is subtracted from each element. Thus, the normalized data set X' is achieved. Covariance matrix C is calculated using the elements in X' and their transposes. After calculating λ and V, a new data set is obtained using V and X'.

The Gray Level Co-occurrence Matrix (GLCM)

The GLCM [24] is based on the studies of statistical measures. A matrix of the pixels in the image is created using it [25]. The differences between the grey values of any two pixels are compared in the matrix. The created matrix can be calculated at different angles and different distance values. The features of the image are extracted from it.

The equation of GLCM is given in equation 5. $f(x,y)$ is the matrix of image. H indicates the height of the image. W indicates the width of the image. θ is inter-pixel orientation. $d = (d_x, d_y)$ is the distance between the pixels. Current pixel in the image with grey level i and neighbour pixel with grey level j are checked in GLCM [26].

$$P_{i,j}(d,\theta) = \sum_{x=0}^{H-1} \sum_{y=0}^{W-1} \begin{cases} 1, \text{ if } \; f(x,y) = i \;\text{ and } \\ \qquad f(x+d_x, y+d_y) = j \\ 0, \text{ otherwise} \end{cases} \tag{5}$$

In this study, four features (contrast, correlation, energy, homogeneity) have been extracted using the GLCM. M is an input image in gray level space with matrix form. Local variations in M is calculated using the equation 6. Linear dependency in M is calculated using the equation 7. σ is a standard deviation, and mean μ is calculated (equation 8). The values of energy and homogeneity in M are calculated as in equation 9 and 10, respectively.

$$Contrast = \sum_{i,j} |i-j|^2 M(i,j) \tag{6}$$

$$Correlation = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j) M(i,j)}{\sigma_i \sigma_j} \tag{7}$$

$$\mu_i = \sum_{i,j=0}^{N-1} i M(i,j), \;\; \mu_j = \sum_{i,j=0}^{N-1} j M(i,j) \tag{8}$$

$$Energy = \sum_{i,j} M(i,j)^2 \tag{9}$$

$$Homogeneity = \sum_{i,j} \frac{M(i,j)}{1+|i-j|} \tag{10}$$

Classification algorithms

K-Nearest Neighbor (KNN)

The KNN is the most known supervised learning algorithm. In this algorithm, it is tried to find out the class of the test element based on the training set.

The first step is finding K nearest neighbors. There are more than one metrics that can be used to find distances between the elements. The metrics of Minkowski (equation 11), Euclidean (equation 12), and Manhattan (equation 13) are among the most known metrics. $x = (x_1, x_2, \ldots, x_n)$ and $y = (y_1, y_2, \ldots, y_n)$ are two elements. Euclidean distance and Manhattan distance are the customized version of the Minkowski distance for p=2 and p=1, respectively.

$$d_{Minkowski}(x,y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{1/p} \tag{11}$$

$$d_{Euclidean}(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{12}$$

$$d_{Manhattan}(x,y) = \sum_{i=1}^{n} |x_i - y_i| \tag{13}$$

Then, the test element is assigned to the class which is most frequent for K nearest neighbors.

Support Vector Machine (SVM)

The SVM is a supervised learning algorithm like KNN. The basics of SVM are based on statistical learning theory. It was developed by Vapnik for the problems of pattern recognition and classification [27]. The purpose of SVM is to find the hyperplane that can optimally distinguish two classes from each other. The optimal hyperplane is the farthest plane to the nearest data points of the classes.

SVM has been designed primarily for the problem of classification of two-class and linear data, and then it has been developed for the classification of multi-class and nonlinear data.

PROPOSED SYSTEM AND EXPERIMENTS

Experimental tests have been performed on 57 images belonging to six different fabric defects presented in the study of Kısaoğlu [28]. Some of these images have been obtained by applying data augmentation methods. The defects we try to classify are fly, dirty warp, tight-loose warp, fibrous weft, rub mark and weft stack. The purpose of this study is to assign the image included to the system to the class it belongs to. There are seven different classes. One of these classes is for non-defected fabric

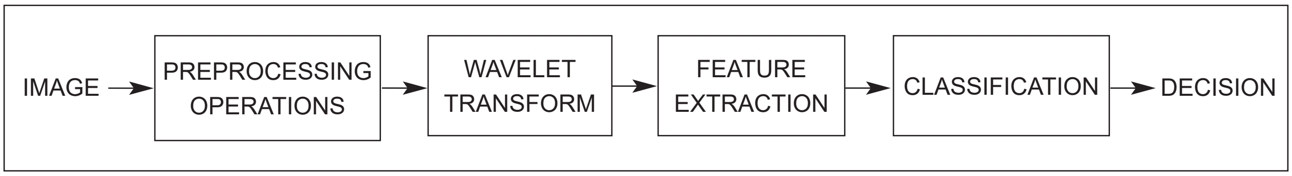

Fig. 2. The steps of Fs1 and Fs2

images. The remaining six classes are for six different types of defects. All tests were implemented using MATLAB2019a on a personal computer (Intel (R) Core (TM) i7-6700HQ CPU @2.60 GHz).

After preprocessing of images, feature extraction is made from these images. In this study, four different feature sets have been used for the classification process (Fs1, Fs2, Fs3, Fs4). The properties of them are given in table 1. The Fs1 has been created using PCA of wavelet energies. The Fs2 has been created using GLCM of wavelet energies. PCA has been used for extracting the features for the Fs3. GLCM has been used for extracting the features for the Fs4. Then, a classification method is applied to the features extracted. The classification methods of KNN and SVM have been used to classify the fabric images. The basic steps for these feature sets are given in figures 2 and 3.

In PCA, the number of parameters was changed between 5 and 17, and the results were examined. It was seen that the best results were obtained when the first 13 parameters were used. Since it shows the highest accuracy, the first 13 parameters have been selected for the PCA method. Then, these parameters have been introduced to the classifier.

Table 1

THE PROPERTIES OF FEATURE SETS			
Parameter	**Wavelet-based**	**PCA**	**GLCM**
Fs1	X	X	
Fs2	X		X
Fs3		X	
Fs4			X

The accuracy rates calculated in this section have been found using 10-fold cross-validation (CV). The accuracy rate is calculated using the values of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) (equation 14). Table 2 shows the values of TP, TN, FP, FN for a two-class data set (defected and non-defected). If there is a defect in the fabric sample and the classification method is classified as defected, the number of these samples gives the *TP* value. If non-defected samples are classified as non-defected, the number of these samples gives *TN.* The number of defected fabric samples classified as non-defected determines the *FN* value. The number of non-defected fabric samples classified as defected determines the *FP* value.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{14}$$

Table 2

PERFORMANCE OF THE SYSTEM		
Parameter	**Classified as Defected**	**Classified as Non-defected**
Defected	TP	FN
Non-defected	FP	TN

Accuracy rates for four different feature sets are given in table 3. KNN is the most successful classifier in all feature sets. The average accuracy rate of KNN is 88.1579%, and the average accuracy rate of SVM is 81.1404%. Fs1 has been the feature set with the highest accuracy rate. When PCA is used as a feature extraction method, Fs1 has been more successful (92.9825%, 89.4737%) than Fs3 (89.4737%, 78.9474%) for both classifiers (KNN and SVM). When GLCM is used, fs4 has given more successful results (87.7193%, 82.4561%) than fs2 (82.4561%,

Table 3

ACCURACY RATES OF THE FEATURE SETS (USING CV)			
Parameter	**KNN (%)**	**SVM (%)**	**Average (%)**
Fs1	92.9825	89.4737	91.2281
Fs2	82.4561	73.6842	78.0702
Fs3	89.4737	78.9474	84.2106
Fs4	87.7193	82.4561	85.0877
Average	88.1579	81.1404	-

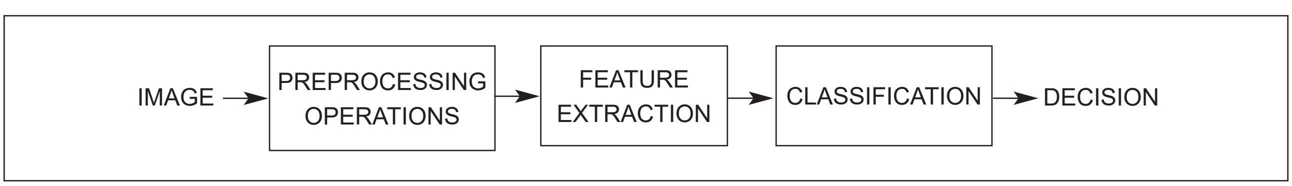

Fig. 3. The steps of Fs3 and Fs4

73.6842%). Among the feature sets, the most successful set has been fs1, while the most unsuccessful set has been fs2. The PCA is a feature extraction method that gives more successful results compared to the GLCM (table 4).

Table 4

ACCURACY RATES OF THE PCA AND GLCM (USING CV)			
Parameter	**KNN (%)**	**SVM (%)**	**Average (%)**
PCA	91.2281	84.2106	87.7194
GLCM	85.0877	78.0702	81.5790

Additionally, execution times for four different feature sets have been investigated (table 5). When the wavelet transform is used, the execution time increases. The average execution times of KNN and SVM are 1.3878 seconds and 9.798 seconds, respectively. The accuracy rates with the execution times of these sets are drawn in figure 4. As seen in the figure, KNN has been the best method in terms of accuracy rate and execution time.

Table 5

EXECUTION TIMES		
Parameter	**KNN (sec.)**	**SVM (sec.)**
Fs1	2.211	9.768
Fs2	1.072	13.434
Fs3	1.362	7.890
Fs4	0.906	8.100
Average	1.3878	9.798

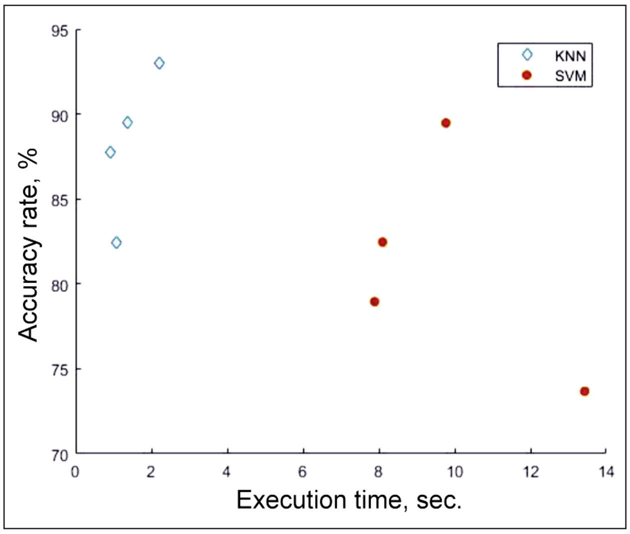

Fig. 4. Accuracy vs. Execution time

CONCLUSIONS

Four different feature sets and two different classifiers (KNN and SVM) have been used for the classification of six fabric defects (fly, dirty warp, tight-loose warp, fibrous weft, rub mark and weft stack). The feature sets used are based on PCA (Fs1, Fs3) and GLCM (Fs2, Fs4). The effect of wavelet transform on feature extraction methods has been investigated. According to the experiments on 57 images, wavelet-based PCA (Fs1) gives the highest average accuracy rate (91.2281%). GLCM method does not work well with wavelet transform for the data set, considering the accuracy rates of the feature sets. It has the lowest average accuracy rate (78.0702%).

The classifier method which has the highest accuracy rate among the two classification methods used is KNN (88.1579%). It provides the classification with the highest accuracy both when wavelet transform is used and is not used.

It is concluded that KNN results in a higher accuracy rate in less time when execution times are investigated. The execution time when using SVM is about seven times the execution time of KNN (for our samples).

In this study, which was carried out to detect and classify fabric defects, which reduced the quality of the fabric, the defect classification accuracy rate has been up to 93%. While a trained staff in the field of quality control can detect only 70% of fabric defects [29], the defects are detected and classified in our study with a success rate of 92.9825%. Hence, this system improves production quality.

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