

DWT Based Face Recognition Using PNN and SVM

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Abstract

Face recognition is one of the commonly used biometric methods for automatic identification. In this paper, DWT based face recognition system is performed using PNN and SVM. Firstly, photos of the faces were detected by the method of Viola Jones. For the feature extraction DWT and for the classification PNN and SVM are used separately. The results of both methods are compared with tables according to performance percentage and process times. The results of the implementations indicate that PNN method gives better performance than SVM method.

Keywords: Face recognition, Discrete Wavelet Transform, Probabilistic Neural Network, Support Vector Machine.

1. 1. Introduction

Now a days, face recognition as a biometric identification method has rapidly gained a big importance and become a research topic. Face recognition has many advantages concerning to other biometric methods. For example, taking samples from a person for recognition is more simple than the other methods. There are some requirements like direct looking at the scanning device for iris or retina scanning or one must hold his or her finger for a while to give his or her fingerprints on the device [1]. However, for the face recognition it is enough to get a suitable photo of a person from right angle and distance. In addition the data that used in face recognition is more readable and understandable [2]. In practice, false alarms in security systems that use face recognition can be also controlled visually by officials. This control is almost impossible for other approaches. Another advantage of face recognition systems is forming a data base is much more easier than the other methods.

Many studies have been presented in the field of face recognition. Özdemir has used involved wavelet transform to recognize a person's face image from pictures taken in front [3]. Gümüş, conducted for the eigenfaces method the size of the eigenfaces space, the number of neurons in the hidden layer of the neural network and error change in training and have examined the effects of the Support Vector Machines in recognition performance [3]. In the study presented by

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Sağiroğlu and Özkaya using only fingerprints of people to estimate their faces towards new and intelligent system based on artificial neural networks are introduced [3]. Yang and Liu presented their work about expanded color image discriminant model [4].

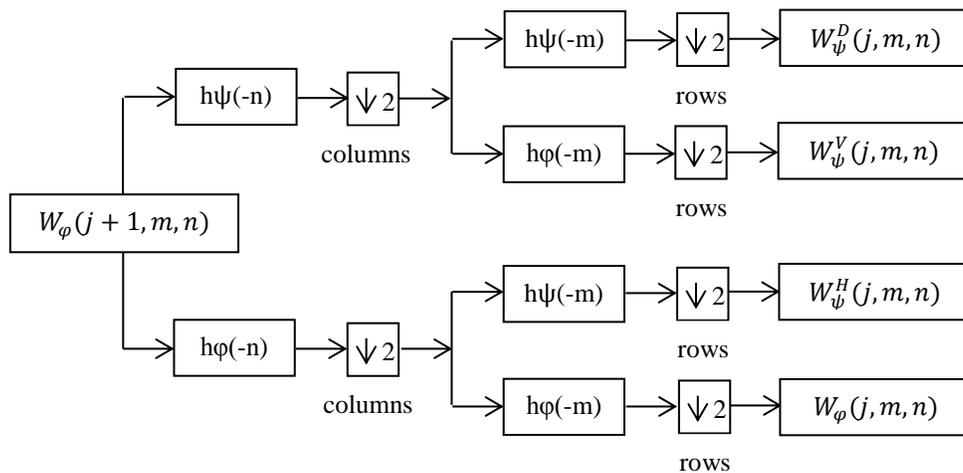
In this paper, a face recognition algorithm based on DWT using PNN and SVM classifiers is presented. Whereby, recognition of human face is provided quickly with the computer. In this way, ensuring ease in many areas, also access to personal information with face recognition by security systems are intended to become easier. Also, the success performance of the used methods are evaluated and compared. The rest of the article is organized as follows: In the second part (section) details of the proposed methods have been described. Face recognition process and its evaluation will be described in the third part. Finally, in the fourth part the results obtained from the study will be described.

2. The Methods

2.1. Discrete Wavelet Transform

Taking the wavelet transform of a function is done by dividing into different resolutions of wavelet coefficients and determining wavelet coefficients. For this operation, a function called mother wavelet is subjected to a correlation with the function which is wanted to transform in a different time and width. So corresponding wavelet coefficients are obtained.

Two dimensional wavelet transform applies low and high pass filter to an image repetitively. Each filtering provides obtaining low-resolution part and detail parts of image at different resolutions. This process can be maintained to the image has one pixel (Figure 1). Variables $W_\varphi, W_\psi^H, W_\psi^D, W_\psi^V$ are low, vertical, diagonal and horizontal wavelet coefficients of an image at j th resolution.



a)

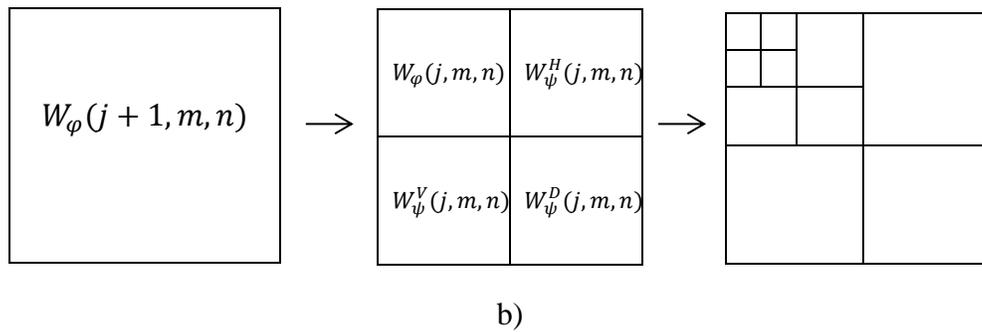


Figure 1. The two-dimensional fast wavelet transform: (a) the analysis filter bank; (b) the resulting decomposition.

2.2. Probabilistic Neural Network

Probabilistic Neural Network (PNN) is well-known as the Bayesian-Parzen classifier technique. Consider a pattern vector x with m dimensions that belongs to one of two categories K_1 and K_2 . Let $F_1(x)$ and $F_2(x)$ be the probability density functions (pdf) for the classification categories K_1 and K_2 , respectively. From Bayes' decision rule, x belongs to K_1 if

$$F_1(x)/F_2(x) > L_1P_2/L_2P_1 \quad (1)$$

conversely, x belongs to K_2 , where L_1 is the loss or cost function associated with misclassifying the vector as belonging to category K_1 while it belongs to category K_2 , L_2 is the loss function associated with misclassifying the vector as belonging to category K_2 while it belongs to category K_1 , P_1 is the prior probability of occurrence of category K_1 , and P_2 is the prior probability of occurrence of category K_2 . If $F_1(x)$, $F_2(x)$, L_1 and L_2 are known, then the vector x can be identified with maximum probability to which class it belongs [6]. In many situations, the loss functions and the prior probabilities are equal. Hence using the Parzen the estimation of the probability density functions for the classification categories is [7]:

$$F(x) = 1/(2\pi)^{m/2} \sigma^m n \sum_{i=1}^n \exp[-(x - x_i)^T(x - x_i)/2\sigma^2] \quad (2)$$

where n is the number of training patterns, m is the input space dimension, i is the pattern number, and σ is an adjustable smoothing parameter.

2.3. Support Vector Machines

We first explain the basics of Support Vector Machines (SVMs) for binary classification. Then we discuss how this technique can be extended to deal with general multi-class classification problems [8].

2.3.1. Binary classification

SVMs belong to the class of maximum margin classifiers. They perform pattern recognition between two classes by finding a decision surface that has maximum distance to the closest points in the training set which are termed support vectors. We start with a training set of points $x_i \in n, i=1, 2, \dots, N$ where each point x_i belongs to one of two classes identified by the label $y_i = \{-1, 1\}$. Assuming linearly separable data, the goal of maximum margin classification is to separate the two classes by a hyperplane such that the distance to the support vectors is maximized. This hyperplane is called the optimal separating hyperplane (OSH) (Figure 2). The OSH has the form:

$$f(x) = \sum_{i=1}^l \alpha_i y_i x_i \cdot x + b \quad (3)$$

The coefficients α_i and the b in Eq. (3) are the solutions of a quadratic programming problem. Classification of a new data point x is performed by computing the sign of the right-hand side of Eq. (3). In the following the equation given below:

$$d(x) = \sum_{i=1}^l \alpha_i y_i x_i \cdot x + b / \left\| \sum_{i=1}^l \alpha_i y_i x_i \right\| \quad (4)$$

will be used to perform multi-class classification. The sign of d is the classification result for x , and $|d|$ is the distance from x to the hyperplane. Intuitively, the farther away a point is from the decision surface, i.e., the larger $|d|$, the more reliable the classification result.

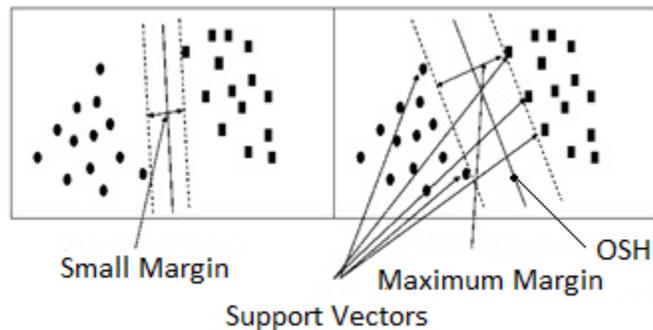


Figure 2. Optimal Separating Hyperplane in case of Maximum Margin.

2.3.2. Multi-class classification

There are a number of strategies for solving q -class problems with binary SVM classifiers. Popular are the one-vs-all and the pairwise approach: (i) In the one-vs-all approach q SVMs are trained. Each of the SVMs separates a single class from all remaining classes; (ii) In the pairwise

approach $q(q-1)/2$ machines are trained. Each SVM separates a pair of classes. We opted for one-vs-all.

3. Face Recognition Process

In this section application process and results are presented. For application ORL face database is used. We use 200 face images acquired of 40 individual (5 images per individual). 140 images are used for training and 60 images are used for testing. Flowchart of the face recognition system is shown in Figure 3.

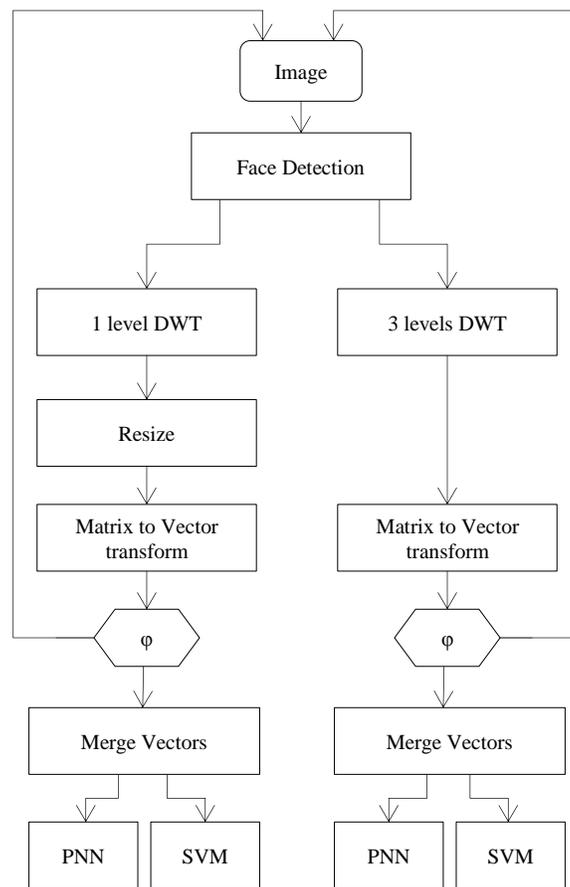


Figure 3. Flowchart of the face recognition system.

Firstly a face image of a person is given to the system as input. The faces are detected by Viola-Jones face detector and cropped [9]. Then 1 level DWT and 3 levels DWT are used separately for feature extraction. Low frequency regions of DWT results are used. The resizing operations are implemented after 1 level DWT. These operations are shown in Table 1.

Face image matrixes obtained from DWT and resizing are converted to vectors (length of vector: a). Then, the feature vectors are merged as a matrix. The dimension of matrix is $140 \times a$ for training and $60 \times a$ for testing. a is varied according to resizing of image. PNN and SVM classifiers are used for classification. The matrix is used as input of PNN and SVM. After some experiments it is acquired that PNN gives better performance than SVM. The process times and recognition rates for two method are shown in Table 2 and Table 3.

Table 1. The facial image of persons after implementing Viola-Jones algorithm, cropping, 1 level DWT, resizing, 3 levels DWT.

Methods \ Persons	1. person		2. person	
	1. image of 1. person	2. image of 1. person	1. image of 2. person	2. image of 2. person
Images after Viola-Jones algorithm				
Images after cropping				
Images after 1 level DWT				
Images after resizing				
Images after 3 levels DWT				

Table 2. PNN and SVM performances after 1 level DWT.

1 level DWT		PNN	SVM
No resize	$m=40, n=38$	% 85	68.333
		$t[\text{sec}]$ 0.7150	1.4565
Resize	$m=20, n=19$	% 83.333	71.666
		$t[\text{sec}]$ 0.0825	0.8081
Resize	$m=10, n=10$	% 78.333	70
		$t[\text{sec}]$ 0.0541	0.7531

Table 3. PNN and SVM performances after 3 levels DWT.

3 levels DWT	PNN	SVM
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No resize	$m=11, n=10$	%	83.3333	70
		$t[\text{sec}]$	0.6394	0.9205

4. Conclusions

In this paper, DWT based face recognition system has been developed using PNN and SVM classifiers. Performances of both classifiers are compared and results are shown in tables. Different tests are implemented using 1 level DWT and 3 levels DWT. Resizing operations are used after 1 level DWT. In summary some conclusions are obtained. While the recognition rates after 3 levels DWT are the same as the recognition rates after 1 level DWT, more processing time is required. So it is determined that implementing resizing after 1 level DWT is more advantageous according to implementing 3 levels DWT. In addition, PNN classifier is performed higher success at lower time according to SVM. While the image gets smaller, the performances and processing times of PNN get lower. SVM is more stable even though image gets smaller.

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