FACE RECOGNITION USING STATIONARY WAVELET AND NEURAL NETWORK +

Ahkam K. Naji *

Abstract:

In this paper, Face recognition system are analyzed and classified based on a new approach, Stationary Wavelet and Neural Network (NN). In this method, the resulting coefficients were computed by the proposed stationary wavelet transform for single-level decomposition. The low pass sub bands of the upper left corner are considered in the proposed method as a resemblance and a smaller version of the original image. The NN of low coefficients is obtained. This method gave an excellent result for a database of 400 different images which indicate that the suggested algorithm is an excellent tool to process the database of standard pose of image. The algorithm is implemented using MATLAB programming languages version R2011a.

Keywords: Face Recognition, Stationary Wavelet Transform (SWT), Neural Network.

التعرف على الوجه باستخدام الشبكة العصبية والمويجة المستقرة

أحكام كامل ناجي

المستخلص :

في هذا البحث يحلل ويصنف نظام التعرف على الوجه اعتمادا على طريقة جديدة وهي الشبكة العصبية والمويجة المستقرة. في هذه الطريقة ناتج المعاملات احصلها من الشبكة المويجية المستقرة بعد مستوى واحد من التحليل. وسوف ناخذ الصورة في الركن الاعلى الايسر لاستخدامها في طريقتنا والتي تعتبر صورة مصغرة ومشابهة للصورة الاصلية. وبعدها طبقت الشبكة العصبية على هذه المعاملات التي تم الحصول عليها. وهذه الطريقة تعطي نتائج جيدة لقاعدة بيانات متكونة من 400 صورة مختلفة والتي تشير الى ان الخوارزمية المقترحة هي اداة ممتازة لمعالجة قاعدة بيانات الوقفة القياسية للصور. وهذه الخوارزمية تطبق باستخدام لغة الماتلاب النسخة R2011a .

1. Introduction :

SECURITY is the one of the main concern in today's world. Whether it is the field of telecommunication, information, network, data security, airport or home security, national security or human security, there are various techniques for the security. Biometric is one of the modes of it. Face recognition is one of the various biometric techniques used in identifying human's. Biometrics use physical and behavioral properties of the human. All biometric systems need some records in database against which they can search for matches. The requirement for reliable personal identification in

+ Received on 10/6/2013 , Accepted on 19/1/2014

*Assistant Lecturer / Electrical and Electronic Technical College

computerized access control has resulted in an increased interest in biometrics. Biometrics being investigated includes fingerprints, speech, signature dynamics and face recognition [1]. Face plays a primary role in identifying the person and also face is the more easily rememberable part of the human. As thousands of faces can be recognized in lifetime, this skill is very robust because a person can be identified even after so many years with different aging, different lightening conditions and viewing conditions [2]. Face recognition is one of the highly used biometric techniques [3] as shown in figure (1).

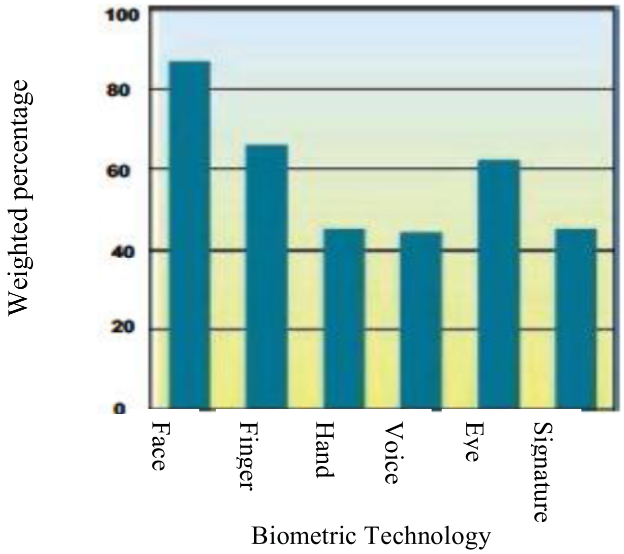

Figure (1): Comparison of biometric techniques [3].

Researchers are trying to implement robust face recognition systems, similar to the human recognition capabilities under various conditions, for security and multimedia information access applications where the identification of the object is necessary. The task of machine recognition of humans is becoming increasingly difficult and complex as the conditions/constrains and the sample size are growing. Face recognition has received substantial attention from researchers in biometrics, pattern recognition, and computer vision communities [4].

Many research works has been done over the past few decades into developing reliable face recognition techniques. Luo, et al. (2005) [5] proposed a new scheme for human face recognition using wavelet transform combined with Support Vector Machine (SVM) as well as clustering method, Gandhe, et al.(2007) [6] proposed different methods of face recognition namely Principal Component Analysis, and Discrete Wavelet Transform Cascaded with Principal Component Analysis. Face recognition appears to offer several advantages over other biometric methods. Almost all these technologies require some voluntary action by the user. However, face recognition can be done passively without any explicit action or participation on the part of the user since face images can be acquired from a distance by a camera [7].

In this paper Stationary Wavelet Transform (SWT) will be used in the recognition process to minimize the size of the data base. Since left direction poses equal to the right direction poses, and as it is a translation invariant, so it has the same data, so we can delete some images that have such direction in poses, so the size of the database will reduce.

2. Stationary Wavelet Transform :

The Stationary Wavelet Transform (SWT) was proposed by Nason and Silverman [8], which is redundant, shift invariant, and it gives a denser approximation to the continuous wavelet transform than the approximation provided by the orthogonal wavelet transform, it is also called undecimated wavelet transform.

The Discrete Wavelet Transform (DWT) lacks translation invariance, while the SWT expands the amount of data by over-representing signals in the wavelet domain. The two main discrete wavelet methods are known generally as the DWT and the SWT. Both methods use a father wavelet, Ψ which can be translated and dilated according to equation (1) [9-11].

$$\Psi a,b(x)=a^{-1/2}\Psi((x-b)/a) \tag{1}$$

Where $(a,b)\in R$ and $a\neq 0$; a is called the scaling or dilation factor and b is called the translation factor. In most practical applications it is necessary to place limits on the values of a and b. A common choice is $a=2^{-j}$ and $b=2^{-j}k$, where j and k are integers. The resulting equation is [12],

$$\Psi j,k(x)= 2^{j/2}\Psi(2^{j}x-k) \tag{2}$$

Equations (3,4) describe the DWT decomposition process. The broad scale, or approximation, coefficients a_j^{DWT} are convolved separately with g_0 and h_0 and the result is down-sampled by two. This process splits the a_j^{DWT} frequency information roughly in half, partitioning it into a set of fine scale, or detail coefficients d_{j+1}^{DWT} and a coarser set of approximation coefficients a_{j+1}^{DWT}. This procedure can be iteratively continued until the desired level of decomposition, j= J, is obtained [9,10].

$$a_{j+1}^{DWT}(k)=\sum_n h_i(n-2k)a_j^{DWT}(k) \tag{3}$$

$$d_{j+1}^{DWT}(k)=\sum_n g_i(n-2k)a_j^{DWT}(k) \tag{4}$$

Dyadically down-sampling the approximation and detail coefficients from f(n) leads to a completely different set of DWT coefficients than down-sampling the coefficients from its shifted version, f(n+1). Similarly, choosing to retain the odd wavelet coefficients during the dyadic down-sampling will result in a different outcome than retaining the even wavelet coefficients [10, 11]. As a result of the shift variability of the DWT, several authors have used translation invariant decomposition techniques, such as the continuous wavelet transform or stationary wavelet transform (SWT).

In contrast to the DWT, the SWT up-samples the decomposition filters by inserting zeros between every other filter coefficient and, consequently, avoids the translational variance problem caused by decimation [13]. The absence of a decimator leads to a full rate decomposition. Each sub band contains the same number of samples as the input [14]. Therefore, the SWT uses a set of level-dependent decomposition filters, h_i and g_i, which are the h_0 and g_0 filters with 2^j-1 zeros between each discrete filter coefficient. The SWT approximation and detail coefficients can then be computed using (3) and (4).

$$a_{j+1}^{SWT}(k) = \sum_n h_i\,(n-k)\,a_j^{SWT}(k) \tag{5}$$

$$d_{j+1}^{SWT}(k) = \sum_n g_i\,(n-k)\,a_j^{SWT}(k) \tag{6}$$

Inserting zeros between the filter coefficients allows the SWT to analyze every possible shift of the signal while the effective sample rate at each wavelet level remains unchanged. In the frequency domain, up-sampling acts to halve the corner frequency of both the low-pass and high-pass decomposition filters, resulting in the same bandwidth decomposition as is found in the DWT. The result is a redundant, or over-complete, set of detail and approximation coefficients. The drawbacks of the SWT algorithm include its increased computational complexity and the increased number of wavelet coefficients it generates [10].

The 2D Stationary Wavelet Transform (SWT) is based on the idea of no decimation [15, 16]. It applies the Discrete Wavelet Transform (DWT) and omits both down-sampling in the forward and up-sampling in the inverse transform.

More precisely, it applies the transform at each point of the image and saves the detail coefficients and uses the low frequency information at each level. The SWT decomposition scheme is illustrated in figure (2) where C^i, G^i, H^i are a source image, low-pass filter and high-pass filter, respectively. The SWT algorithm is very simple and is close to the DWT one.

More precisely, for level 1, all the decimated DWT for a given signal can be obtained by convolving the signal with the appropriate filters as in the DWT case but without down sampling. Then the approximation and detail coefficients at level 1 are both of size N, which is the signal length. The general step j convolves the approximation coefficients at level j-1, with up sampled versions of the appropriate original filters, to produce the approximation and detail coefficients at level-j.

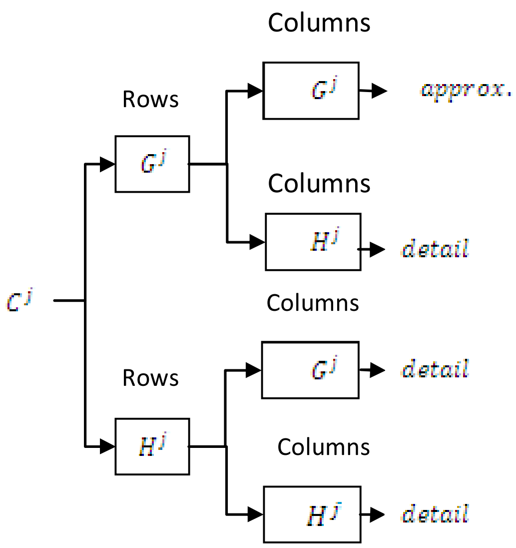

Figure (2): SWT decomposition scheme [13].

3. Gabor Wavelet Neural Network :

Gabor Wavelet Neural Network (GWNN) can be described as a perception with Gabor-node function as a preprocess unit for extraction feature. Network includes two parts: the first part of the feature extraction layer and the follow-up classification part of the structure.

There are K nodes in input layer $\emptyset_{ik}$, k =1,2....K , where $\emptyset_{ik}$ expresses that the Kth node of the Gabor basal function related to i group target signal vector.

$\emptyset_{ik}$,k =1,2....K can be defined the absolute value of inner-product of the basal function vector $g_k = g(u_k, d_k, f_k)$ and objectives vector, as shown in equation (7).

$$\emptyset_{ik} = |< g_k . x_i >| = | \int \frac{1}{\sqrt{d_k}} g * (\frac{t-u_k}{d_k}) e^{-jf_k t} x_i(t) dt| \quad (7)$$

Describe the correlation between K node basis function $g_k = g(u_k, d_k, f_k)$and the i signal $x_i(t)$.

Gabor node shown in (8) [17]:

$$g_k = g(\frac{t-u_k}{d_k}) e^{jf_k t} \quad (8)$$

Component basal function cluster, which is deformation of Gabor basal function g(t) , can be adjusted in the course of the training network. u_k is time-lapse parameter, d_k is scaling parameters, andf_k describe the frequency modulation parameters. These variable parameters should be relative to Gabor transform function. The exciting function of the hidden layer is the Sigmoid function. The structure diagram of Gabor wavelet network is as Figure (3):

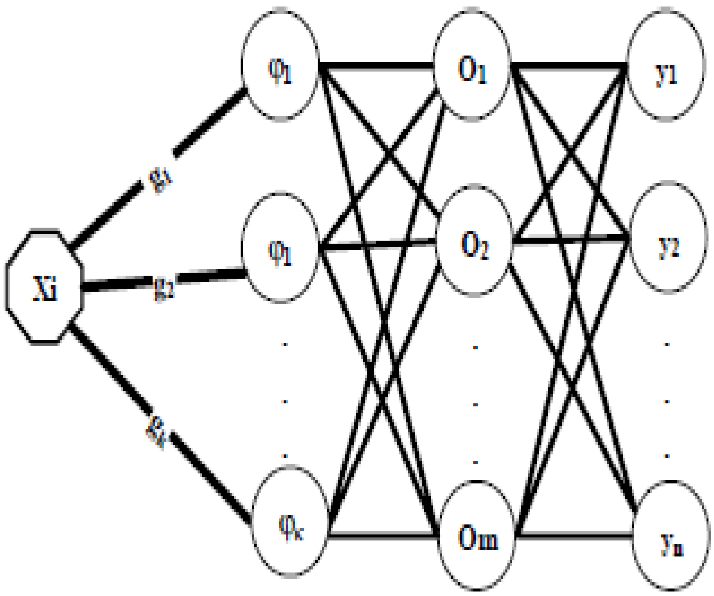

Figure (3): Structure diagram of Gabor wavelet network [17].

Here the method of improved steepest descent algorithm is adopted. In order to get the minimal sum of square errors between expectation output vector and the practical output of the input target vector. In the study stage, the weight coefficients w of the hidden layer and the output layer, and the parameters of Gabor basal function all need to be adjusted adaptable namely. Objective function is set as following in (9) (or also known as the cost function):

$$E(\theta)=\frac{1}{2}E\{[g_{\theta}(x)-y]^2\} \qquad (9)$$

Where, θ is vector contain the parameters of w_i,d, u, £;$g_{\theta}(x)$ the network output is defined by parameters for the vector θ. These parameters of θ is adjusted along the negative direction of the gradient by the steepest descent method in every iterative step of the training stage until the objective function convergence. Then they obtained Gabor atomic nodes are the optimal time- frequency - scale space for all the given training samples. Gabor basal function which decision-making by the parameters are most reliable for next classification. Optimizated scale and translation parameters of the standards Wavelet transform (θ vector), complete the effect to feature extraction and classification, improve the classification efficiency as well as removing redundant.

4. The Proposed Face Recognition System Block Diagram :

The general structure of the proposed face recognition system is shown in Figure (5). Function of each block is clarified below:

- **Test Image:** images are taken to the face of the person to see whether it is in the data base or not.
- **Feature Extraction:** SWT is used to split the images into four sub image at low resolution, but in the same dimension of the original images, not like the scalar wavelet, where the images is quadratic of the original images as shown in Figure (4).

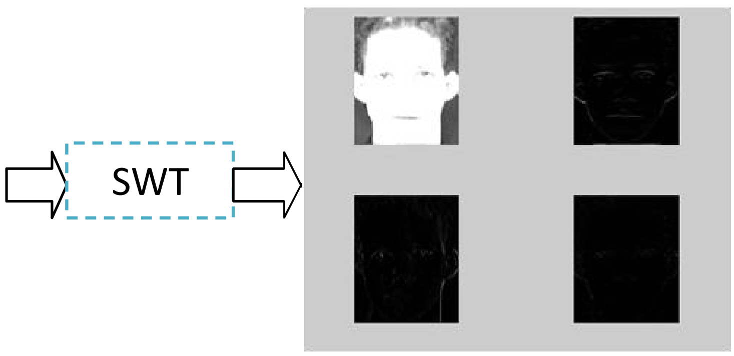

Figure (4): SWT applied on the image.

- **Classifier:** The Gabor wavelet network has been used here, where a comparison is made between the test image and images in the database.

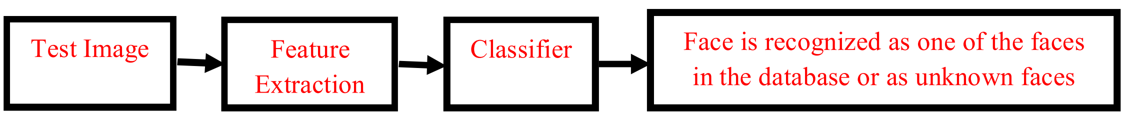

Figure (5): The Proposed Face Recognition System Block Diagram.

5. Experiments on Olivetti Research Laboratories (ORL) Face Database :

Ten different images for each of the 40 distinct subjects were used, for some subjects; the images were taken at different times, varying the lighting condition, facial expressions (open / closed eyes, smiling / not smiling)and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side tilting and rotation of up to about 20 degrees. There is some variation in scale of up to about 10%. Thumbnails of all of the images are shown in figure (6). The images are gray scale with a resolution of 92*112 [18].

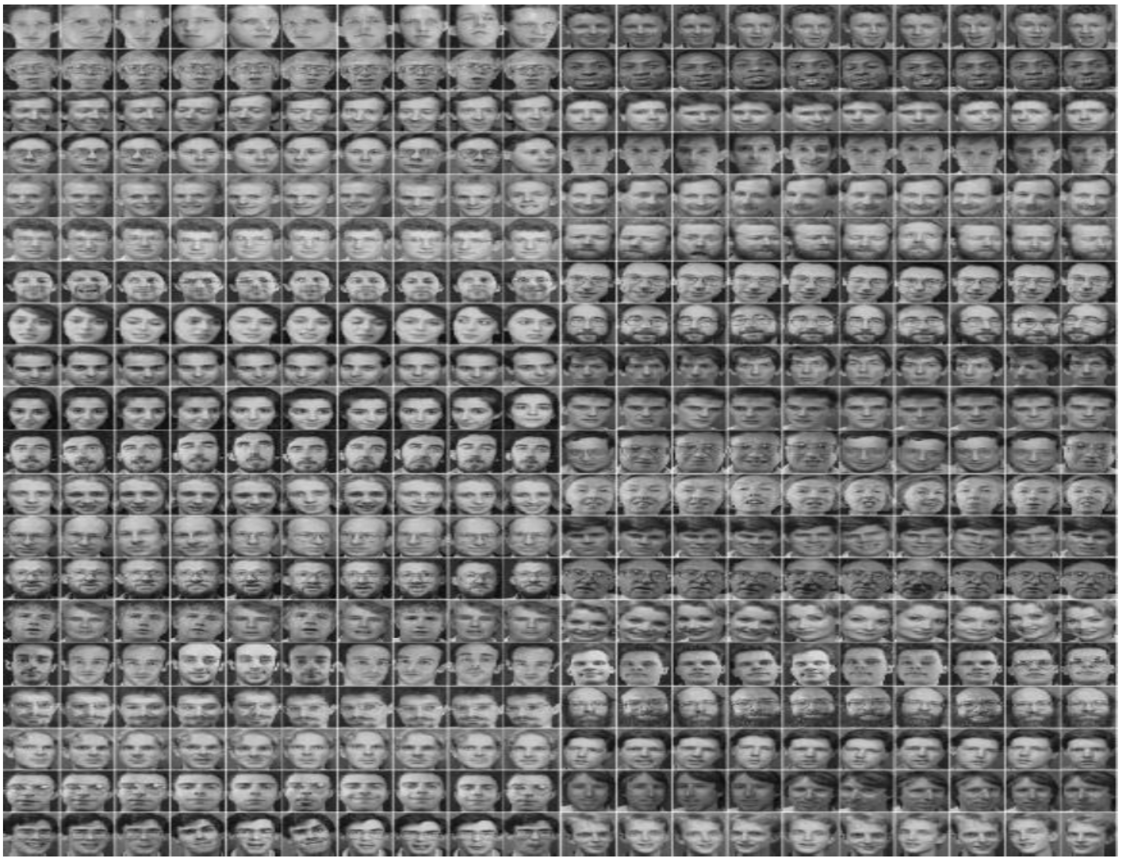

Figure (6): The ORL face database. There are 10 images each of the 40 subjects [18]

6. Experimental Results :

Results of Different Kind of Training and Test Images

From the results, a comparison is made between two methods namely DWT and SWT.

A. Using Different Number of Training and Test Images:

Since there are 10 images per individual in the generalized database the effect of different number of training and test image combinations is tested.

From the tests results in Table (I), it can be seen that when increasing the number of the training images the recognition rate increase, so using 5 training images and 5 testing images for each individual gives better results; hence, the rest of the tests are conducted using 5 training and 5 test images per individual.

$$\text{Recognition Rate} = \text{Success rate} = \frac{\text{No.of images correctly recognized}}{\text{Total No.of images in the dataset}} \times 100\ \%.$$

This result is obtained by using the SWT with GWNN, while the result using the discrete wavelet transform is shown in table (II).

Table (1): The success Rates Using Different Number of Training and Test Images Using SWT.

Total Number of Images	Number of Training Images (Per Subject)	Number of Test Images (Per Subject)	Recognition Rate (%)
400	2	8	64.75
400	3	7	78.78
400	4	6	88.46
400	5	5	95.65

Table (2): The Success Rates Using Different Number of Training and Test Images using the DWT.

Total Number Of images	Number of training images (per subject)	Number of Test images (per subject)	Recognition rate (%)
400	2	8	61.26
400	3	7	73.78
400	4	6	81.67
400	5	5	90.55

B. Changing the Training and Test Image Combination:

In the second part of the experiments, the effect of changing the images of each individual used in the training and testing stage in a rotating manner has been studied.
From the tests results in Table (III), it can be easily observed that the success rate changes with respect to the utilized sets of training and testing images. Best result that can be achieved is 98.5 % when the combination of training samples is 6,7,8,9,10.

Table (3): The success Rates Using Different Number of Training and Test Images.

Total Number of Images	Images Used in Training	Images Used in Testing	Recognition Rate (%)
400	1,3,5,7,9	2,4,6,8,10	92.66
400	1,2,3,4,5	6,7,8,9,10	95.65
400	6,7,8,9,10	1,2,3,4,5	98.58

7. Conclusion :

The face recognition performance has been systematically evaluated by using the "The Database of Faces" (formerly "The ORL Database of Faces"). In face recognition, there is a need to spatial information in the image to improve recognition rate. The stationary wavelets transform, gives the spatial and frequency information of the images at the same time. In this research, stationary wavelet were used to improve the face recognition performance. Experiment results show that this method achieves higher recognition rate.

The above system is trained and tested using MATLAB R2011a. For checking the correctness of proposed technique, ORL database was used, which consists of 40 subjects with 10 images per subject, with a total of 40 × 10 = 400 images. Out of 400 images, 200 images were used for training and remaining 200 used for testing purposes.

And it has been seen that as the number of training images (per subject) increases, the recognition rate increases. Where table (I) is the recognition rate using SWT, while table (II) is by using DWT. It can be seen that using 5 training images and 5 testing images for each individual results with better results, so in table (III) it has been shown that the recognition rate changes with changing the style of images distribution.

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