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CWT and Fisherface for Human Face Recognition

Abbas Hussien Miry
Electrical Engineering Dept.
AL-MustansiriyahUniversity

ABSTRACT
Recognition of face is a good authentication and verification tool of people, has a great interest in our live. One of its important algorithms is eigenface which has been used widely; it has limitations such as poor discriminatory power, to solve this problem fisherface is used which attempt the distance between is maximum classes and the distance inside class is minimum, but it suitable for small data . Complex Wavelet Transform (CWT) is used to get import information of image and input it to fisherface. It uses dual-tree wavelet filters to obtain the imaginary and real to obtain shift invariance and different direction. This combination improved the accuracy of face recognition. Fisherface makes the best representation of the data entry while CWT is decomposing the training image with various rotated image recognition. Finally, the performance is compared to the proposed method with other methods, and gives better identification accuracy .

Keywords
Eigenface, Fisherface, complex wavelet.

1. INTRODUCTION
Biometrics recognition refers to the analyzing body parts of human for the security. More than one identity verification used in the application in the real world system is unimodal. It depends on the evidence of a single source of information for authentication. Identification data is becoming more popular now for one day, due to security requirements in the existing community in the field of information, commercial, military and business, e-commerce and other [1].

The facial recognition is always active research area and there is a wide range of applications such as gender classification, and verification of identity ... etc.With of the past few decades, and there are implemented to identify the faces of many of the algorithms. The big challenge is how to prove the value of facial features so that a computer is capable of facial recognition, in light of the range of features. Investigations by many researchers over the past several years indicate that the use of certain facial characteristics of humans to identify faces. And more than required to progress quickly and efficiently recognize the faces of the pictures [2].

The algorithm Eigen faces longtime mainstay in the field of facial recognition due to high image dimensions of the face. While providing minimal reconstruction error, and Eigen face based on the conversion of the de-emphasize an area of high-frequency information, and reduce the effectiveness of the information available to rating [3].Process to reduce the dimensions are an essential stage in face recognition tasks where high-dimensional data to a large extent. Eigenface is used to reduce the dimensions of the image area. Admission is performed to give a new image in the subspace spanned from the faces of Eigen and then assess the face by comparing its position in the face space with the positions of well-known individuals. While trying to reduce the dimensions of the space it can remove the necessary information to determine things within this space [3].

The drawback of Eignface is sensitivity to the large variation in facial expression and lighting due it maximizes the scatter between all classes. Fisherface can solve this problem by maximizing the scatter between different classes and minimize the scatter inside scatter.

The fisherface face recognition uses the analysis of the PCA and to develop a matrix of subspace projection, minimizing variation within each class, yet still maximizing class separation [4].

Linear Discriminate Analysis (LDA) attempts of the difference between the data classes. Power of LDA will be shown in face recognition technology, it exceeds the limit of the PCA by apply the linear discriminate criterion .this criterion is trying to increase the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within class scatter matrix of the projected samples. LDA collect data of the same class and isolate data of different classes [5].

There was a revived interest in the application of wavelet techniques to solve a lot of problems of the real world. One example is the image retrieval database and facial recognition. Appropriate wavelet transform can lead to a strong representation to capture large facial features while maintaining a minimum level of computational complexity [6].

In recent several work study face recognition and developed different methods [7-8].our work develop the previous work and attempt to show the powerful of fisherface recognition by comparing it with eignfac.

2. COMPLEX WAVELET
Complex Wavelet is using dual trees of filters to produce complex wavelet coefficients real and imaginary separately. Although each tree is downsampled output by collecting the output of the two trees during the reconstruction, the components of the signal can be borrowed suppressed and shift invariance can achieved [9].

A.Shift Invariance

The banks of multiple filter channels with LPF analysis and synthesis filters are shown in figure 1. For the input signal, the analysis of Bank followed by down-sampling gives the low-pass and high-pass coefficients. LF part and HF part is the output filtered along with upsampling. Output is the sum of these elements signal [9].

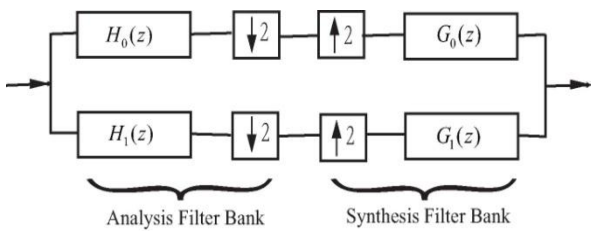

Figure 1: DWT Filter Bank

$C^{l}(n^2) = 0.5((U(n) H0(n) + U(-n) H0(-n)$ (1)

$D^{l}(n^2) = 0.5((U(n) H1(n) + U(-n) H1(-n))$ (2)

$Y(n) = U_1(n) + U_h(n)$ (3)

Where,

$Ul(n) = C^1(n^2)\ Go(n)=0.5 ((U(n) H0(n) G_o(n) + U(-z) H0(-n) G_o(z))$ (4)

$Uh(n)=D^1(n^2)\quad G1(n)=0.5((U(n)H1(n)G1(n)+U(-n)H1(-n) G_1(n))$ (5)

This decomposition does not become fixed because of the conditions in the U(-n) of the equation 4 and 5 that are offered by the shorthand operators. If the transfer of the input signals, for example $n^{-l}U(n)$, and the application of filter banks results in the following decomposition

$n^{-l}U(n) = \tilde{U}_l(n) + \tilde{U}_h(n)$
(6)

For an input $n^{-l}U(n)$ it become:

$C^l(n^2)=0.5(n^{-l}U(n)HO(n) + (-n^{-l})U(-n)H_O(-n)$ (7)

And

$\tilde{U}_l(n) = 0.5\ (U(n)\ HO(n)\ G_o(n) - U(-n)\ H_O(-n)\ G_o(-n))$ (8)

With same producer, for the part of high-pass, If n^{-l} substituted in (4). From this computing it can be seen that the reliance shift caused as containing U(-n), and where the meandering. It cannot be achieved one access to the transformation decomposition fixed by adding a candidate to see banks with figure 1

Turning inputs $n^{-l}U$ (n) and later taking the average lowpass, branches and banks Bass candidate as shown in Figure 2 [9].

Another option is to add a filter bank with shifted inputs z^{-l} $H_0(n)$, n^{-l} $H_1(n)$ and synthesis filters $nG_0(n)$, $nG_1(n)$ and the average of the lowpass and the highpass branches of both filter banks is taken. To indicate the first filter bank (a) Second indicators (b) then this procedure involves the following degradability:

$U(n) = U_l(n) + U_h(z)$ (9)

where for lowpass channels of tree a and tree b have

$U_l(n) = 0.5(Ca^l (n^2) G_{0a}(n) + Cb^l (n^2) G_{0b}(n))$

$= 0.5\ U(n)\ H_0(n)\ G_0(n)$ (10)

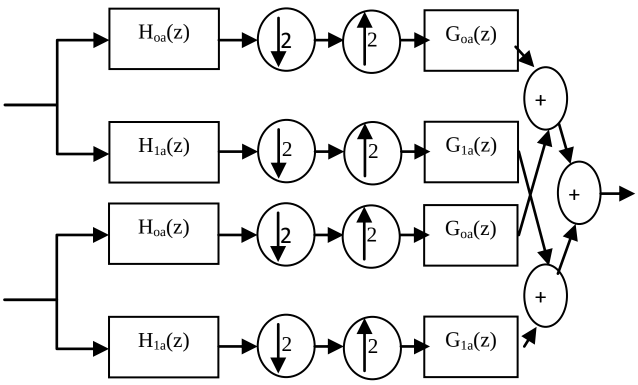

Figure 2: First level CWT.

Likewise for the high-pass part. It has disappeared in the long meandering containing U(-n) in U_l and decomposition becomes a constant shift in reality. Using the same principle for the design of the decomposition constant transformation candidate, he suggested Kingsbury CWT constructed where "double" two banks candidate parallel tree and outputs are grouped. Full output filters bank structure analysis in Figure 2. complex tree of signal U (n) is implemented [9].

B. Directional Selectivity

Ordinary DWT gives information about the orientation of three pixels where trends and complex wavelet gives information about the six orientation pixels trends. Figure 3: Trends orientation in the complex wavelet, there are six sub-bands that give information about the image details. Directed filters subband six in the corners of ± 15, ±45, ± 75 degrees as shown in figure.3 [6].

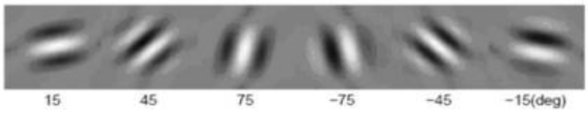

Figure 3: Complex filter response trends show complex wavelets

3. FISHERFACE

Fisherface is a specific method of class, which it was trying to form scatter to make them more reliable in the classification. Choose this method to make the ratio of the between class scatter to within class scatter as large as possible. Where between classes scatter is:

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T \tag{11}$$

withinclass scatter

$$S_w = \sum_{i=1}^{c} \sum_{X_K \in X_i} N_i(\mu_i - \mu)(\mu_i - \mu)^T \tag{12}$$

Where $\mu\mu$ is the average image of Xi , Ni is the number of images in class i $Wopt$ which is best projection is chosen as the matrix with the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples [11] , i.e.,

$$W_{opt} = \arg \max_{W} \frac{|W^T S_B W|}{|W^T S_W W|} \tag{13}$$

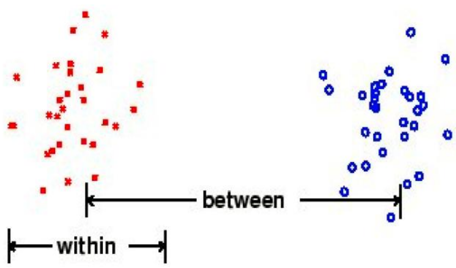

Figure.4 class separation in LDA

4. PROPOSED METHOD

Feature was developed fisherface with complex wavelet to overcome the limitations of the fisherface, the Euclidean distance is used for the implementation of the classification. The proposed method consists of two phases, the training phase extraction feature; the stage was conducted in recognition to identify the portraits of the unknown. Step training includes a feature extraction training images. Feature extraction image determines the basis of representational images in the area of interest. Later, the recognition step translates the face of unknown, according to a representational basis, that has been identified in step training. Figure 5 show the flow chart of proposed method.

5. EXPERIMENTAL RESULT

To test the efficiency of proposed method several data base is used, at training phase some of image are taken to build a data base while the reaming are used in test phase ,the proposed method is compared with standard method of face recognition eigenface .The experimental results presented by the method of identifying the human face have been building a program to recognize faces using MATLAB2013a. It was chosen this environment because it supports image processing easily. Table 1 show that the identification for a combination the complex wavelets with fisherface and the proposed method of database accuracy (figure 5 and 6). The performance index for the Recognition Accuracy is given by:

Recognition Accuracy= (No. of correct classified/Total number of image) x 100 % (14)

The database which used in this work is:

1) (ORL) [12]
2) Georgia Tech database **[**13**]**
3) Czech Technical University **[**14**]**
4) Aberdeen [15]

Table1. Comparison result in termRecognition accuracy

Database	Recognition accuracy (%)	
	Eigenface	Fisherface
ORL	93.8 %	94.3 %
Georgia	91.4 %	92.5 %
Czech	94.1 %	94.6 %
Aberdeen	92 %	92.3 %

6. CONCLUSION

In this work, facial recognition using fisherface and complex wavelet has been used to be accurate recognition with different database is used for test the proposed method. Complex wavelet is applied, which greatly reduces the dimension of the image by maintaining visually important components of the image with efficient data representation fisherface and it compared with eigenface. From result it can be concluded that, database (Czech): all method has high recognition due to small variation in test image while database (Georgia) has lower recognition due to high variation between training and test image ,table 1 prove the powerful of complex wavelet in recognition with different dada base used in this work.

7. REFERENCES

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8. APPENDIX

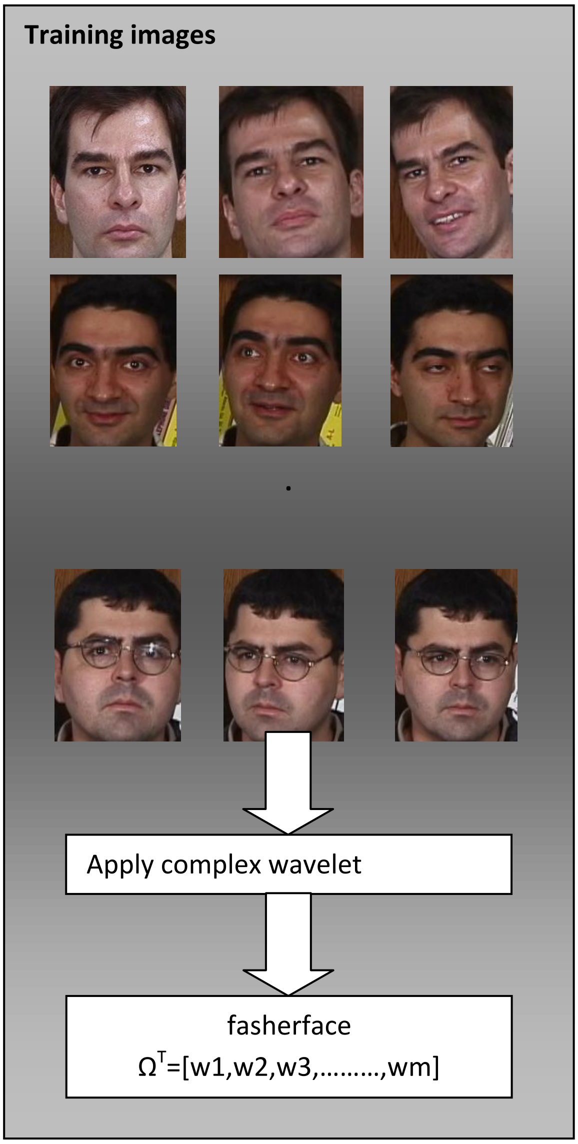

Figure .5 Training stage

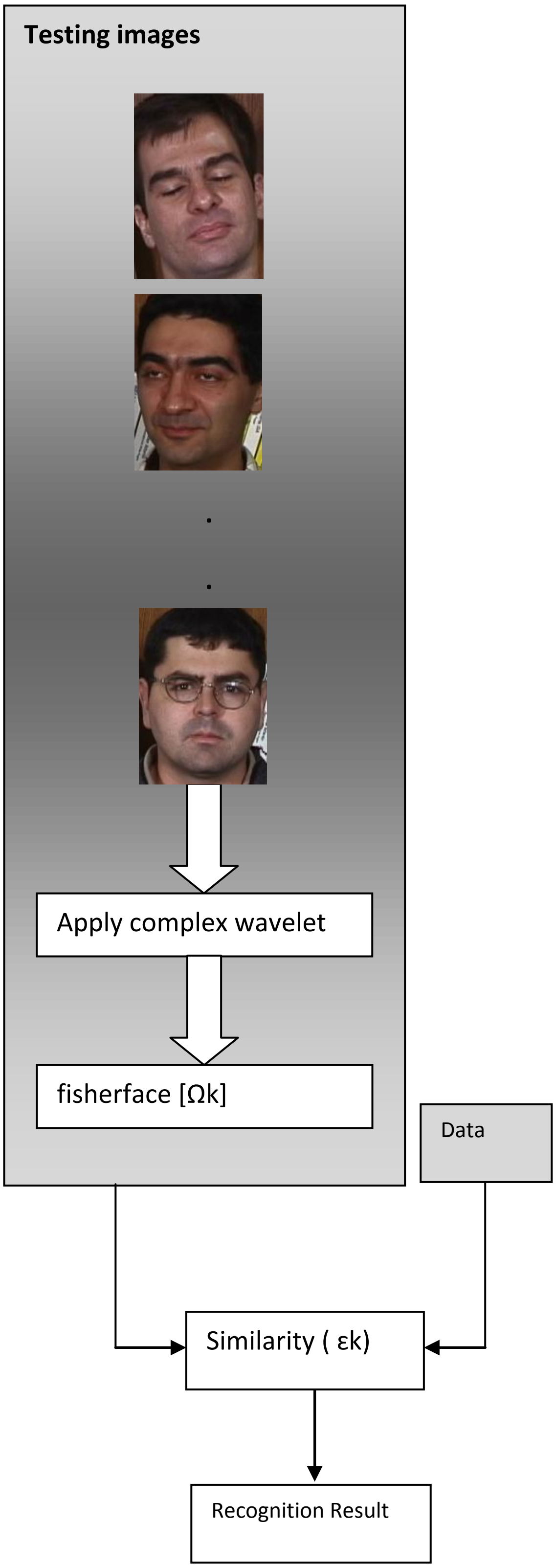

Figure .6 Recognition stage