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Dual Tree Complex Wavelet Transform for Face Recognition Using PCA Algorithm

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***Abstract*— In this paper the suitability of Dual Tree Complex Wavelet Transform for Face Recognition is studied. In contrast to the discrete wavelet transform (DWT), the design of Dual Tree Complex Wavelet Transform poses good directional properties for diagonal features and is rugged to shift Invariance. These features of DT-CWT motivated to study their suitability for Face Feature Extraction and Recognition, as the features of face are oriented in different directions. In this work the image is decomposed using DT-CWT to produce eight complex sub-bands and the features are extracted from the magnitude of low frequency band (*LL*) using Principal Component analysis (PCA). ORL database is used, as the database consists of variation in pose and expression. Recognition rate achieved on ORL database using DT-CWT is satisfactory.**

Keywords-Dual Tree Complex Wavelet Transform, PCA, and Euclidian Classifier.

I. INTRODUCTION

Biometrics comprises methods for unambiguously recognizing individuals based upon physical and behavioral attributes. Face recognition is one of the biometric systems that takes image or video of a person and compares it with images in database to grant access to secure areas. Many researchers showed that the features extracted from face images aid in designing robust security/authentication systems. Successful face recognition system [1] is proposed utilizing Eigen face approach. This method is conventional, considers frontal and clear faces for implementing the system, but in real time faces may not be frontal and device intrinsic capture (illumination variation) properties pose difficulties in the process of detection. Thus in security and other computer vision applications, pose and variation in illuminations plays a critical role.

Conventional Face feature extraction suffers mainly from

a) Pose variation,
b) Expression variation ,
c) Resolution variation and
d) Illumination problems

In this paper pose problem is addressed using Complex Wavelets [9-10][13] and PCA to extract Multiscale features towards secure Face Recognition system.

To aid the process of recognition, nearest neighborhood classifier [16] is used; this method finds an image to the class whose features are closest to it with respect to the Euclidean norm.

This work uses Dual tree Complex wavelet [15] transform mainly to reduce the computation complexity. In the ORL face database [7] all the images are of size 112x92, we worked on approximation details of first level decomposition using DT-CWT. The size in first level decomposition reduces to 56x46.

Figure.1. Different poses of a subject from ORL face database.

Principal Component Analysis (PCA) is used to extract features [1, 2, 3]. Eigenface approach is used for low dimensional representation of faces by applying Principal Component Analysis (PCA). The system functions by projecting face images onto a feature space that spans the significant variations among known face images. The significant features are known as “eigenfaces” because they are eigenvectors (principal components) [1].

The performance of the proposed algorithm is verified on available databases on the internet, such as ORL face database [7]. ORL face database consists of 400 images of 40 individuals; each subject has 10 images in different poses. Sample images of the database shown in Fig.1.

This paper is organized into six sections. In section II we discussed Dual Tree Complex Wavelet Transform, in section III Feature Extraction and classifier, in section IV proposed face recognition system, in section V, Experimental results and conclusion in the last section.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

The drawbacks in DWT can be eliminated by using an expansive wavelet transform in place of a critically-sampled one. (An expansive transform is one that converts an N-point signal into M coefficients with M > N). DT-CWT provides N multi scales, can be implemented using separable efficient Filter Banks as shown in Fig.2.

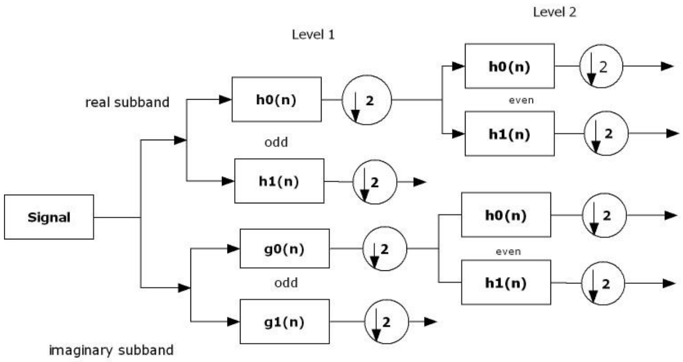

Figure.2. DT- CWT working principle for 1D signal

Here two sets of Filter banks are used, consists of low pass and high pass filters. Down sample the input signal by 2 through a filter of H(z) transfer function and again through G(z) filter. The filters should be Hilbert transform pairs

$$y_g(t) = \mathrm{H}\{y_{\mathrm{h}}(t)\} \qquad (1)$$

The filters in the upper and lower DWTs should not be the same, the filters used in the first stage of the dual-tree complex DWT [4] should be different from the filters used in the remaining stages. The sub band signals of the upper DWT can be interpreted as the real part of a complex wavelet transform, and sub band signals of the lower DWT can be interpreted as the imaginary part. Equivalently, for specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. Then designed, the dual-tree complex DWT is nearly *shift-invariant* and *strong directional* in contrast with the critically-sampled DWT. The designed filter complex wavelet should be analytic and it is

$$\psi_c(t) := \psi_h(t) + j\psi_g(t) \qquad (2)$$

The wavelet coefficients w are stored as a cell array. For j = 1..J, k = 1..2, d = 1..3, w{j}{k}{d} are the wavelet coefficients produced at scale j with an orientation d. The dual-tree complex DWT outperforms well compared to the critically-sampled DWT for applications like image de-noising and enhancement.

DT-CWT for image provides six (d=1…..6) directional high frequency sub bands and two (d=1, 2) low frequency sub bands as shown in fig 3.

The 2-D wavelet is defined as

$$y(x,y) = y(x)y(y) \qquad (3)$$

where $y(x)$ is complex analytic wavelet, given as

$$y(x) = y_r(x) + jy_i(y) \qquad (4)$$

similarly

$$y(x,y) = y_r(x)y_r(y) - y_i(x)y_i(y) + j\left[y_r(x)y_i(y) + y_i(x)y_r(y)\right]$$

ψ_r is real and even and $j\psi_i$ is imaginary and odd.

The complex-wavelet coefficient is defined as

$$d_c(k,l) = d_r(k,l) + jd_i(k,l) \qquad (6)$$

And its magnitude is

$$|d_c(k,l)| = \sqrt{|d_r(k,l)|^2 + |d_i(k,l)|^2} \qquad (7)$$

When $|d_c(k,l)| > 0$

And phase is given as

$$d_c(k,l) = \arctan q \qquad (8)$$

Where $\theta = \dfrac{d_i(k,l)}{d_c(k,l)}$

Key features of DT-CWT are

1. Better directionality
2. Anti- aliasing effect
3. Good shift-invariant
4. Geometry of the image features retained from phase
5. Better robustness for smooth varying
6. Low computation compared with DWT, 3 times that of maximally decimated DWT.

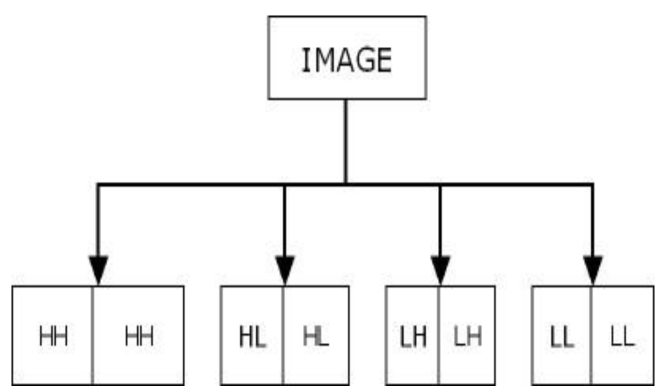

Figure.3. Decomposition of DT-CWT for 2D image

III. Feature Extraction and Classifier

A. *Principal Component Analysis*

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Let's suppose we have M vectors of size N (= rows of image $\times$ columns of image) representing a set of sampled images. p_j's represent the pixel values.

$$x_i = [p_1 : : : p_N]^T \, ; \, i = 1, ... , M$$

The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image.

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i \qquad (9)$$

And let w_i be defined as mean centered image

$$w_i = x_i - m$$

Our goal is to find a set of e_i's which have the largest possible projection onto each of the w_i's. We wish to find a set of M orthonormal vectors e_i for which the quantity

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M} (e_i^T w_n)^2 \qquad (10)$$

is maximized with the orthonormality constraint

$$e_l^T e_k = \delta_{lk}$$

It has been shown that the e_i's and λ_i's are given by the eigenvectors and eigenvalues of the covariance matrix

$$C = WW^T \qquad (11)$$

where W is a matrix composed of the column vectors w_i placed side by side. The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigenvalues. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first5% to 10% of the dimensions. A facial image can be projected onto M' (□ M) dimensions by computing $\Omega = [v_1, v_2 , , , V_{M'}]^T$

B. *Classifier*

In this work we have used nearest neighborhood classifier [16] to recognize the image. This classifier comes under minimum distance classifiers. It is also called as Euclidean classifier. In this method the minimum the distance from test feature vectors to train feature vectors the correct the image is. If Xi, Yj represents test and train image features then

$$\left\|X_i - Y_i\right\| \equiv \sqrt{\left(X_i - Y_i\right)^T \left(X_i - Y_i\right)} < \left\|X_i - Y_j\right\| \quad (12)$$

*Where‖. ‖ represents Euclidean norm

Because of its simplicity, it finds an image to the class whose features are closest to it with respect to the Euclidean norm.

IV. Proposed Algorithm

The first aspect of this work is to use Dual Tree Complex Wavelet transform [9, 10, 13] where multiscale analysis and extraction of features oriented in different directions are possible. The decomposition level of the wavelet transform is decided by the imagery details which we need. In this work first level decomposition is satisfactory to preserve the details. The Second and important aspect of this work is to extract the features from *mag*(LL) using PCA.

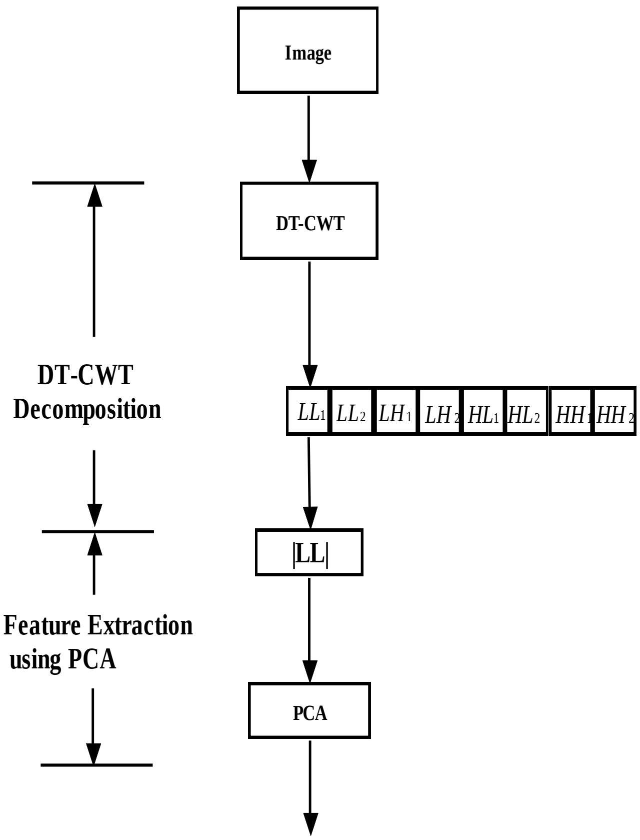

Figure.4. DT-CWT Feature Extraction (Proposed Algorithm)

The general procedure of the proposed technique is as follows. As a first step we will take a test image and form a database of training images excluding test image. As next step Approximation details of all images in database including test image are calculated using DT-CWT. The approximation coefficients of first level decomposition are complex numbers. Then we formed new database with magnitudes of these complex numbers.

Now the |*LL*| is processed using PCA to extract the features. Fig.4. shows all the steps of the proposed algorithm and feature Extraction.

Third aspect of this work, which is the decision making step to find suitable image. After extracting features for all train images and test image, nearest neighborhood classifier is used to recognize the correct image from database. Face recognition system with proposed algorithm is rugged to pose variation is shown in Fig.5.

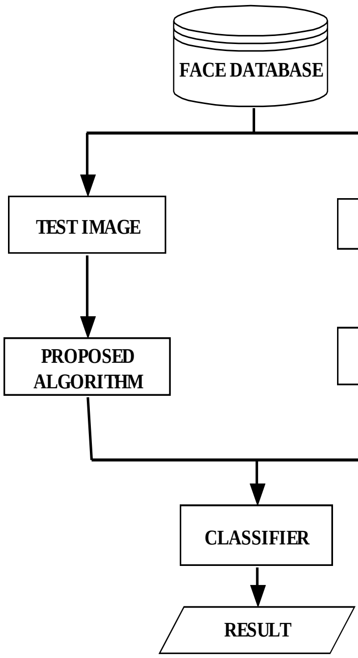

Figure.5. Block diagram of face recognition system

V. Experimental Results

A. Database

In this work experimentation is carried on ORL face database [7]. The database consists of 400 images of 40 individuals in 10 different poses. Sample images from ORL database are shown in below figure.6.

Figure.6. ORL Face Database

B. Expermental Results

In this paper Complex Wavelet is used to decompose the image in to eight sub-bands. The eight sub-bands produced are oriented in Horizontal, Vertical, Diagonal directions and are complex in nature. Of all the sub-bands the emphasis in this work is on *LL* band as the histogram of this band is similar to original image. Principal Component Analysis is used to extract the features from the magnitude of LL. Euclidean classifier is used to aid face recognition which can speed up the recognition process.

Experimentation is carried on openly available challenging face database. The recognition rate is evaluated varying the no. of features and the corresponding recognition rate is tabulated in Table.1. and in Fig.7. The max recognition rate reported in this work is 93.25 using 100 features.

FEATURES	**DATABASE NAME**	**RECOGNITION RATE (%)**
1	ORL	15.75
3	ORL	62.00
5	ORL	81.75
10	ORL	90.25
20	ORL	91.75
50	ORL	93.00
100	**ORL**	**93.25**

Table 1: Recognition Rate using proposed Method on ORL face database.

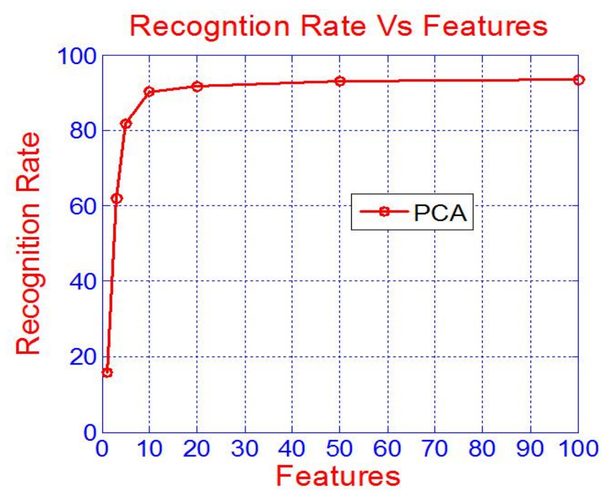

Figure.7. Recognition Rate vs. Features for ORL face database

VI. Conclusion

To ameliorate the Face recognition task in this work Complex Wavelets are utilized in contrast to DWT. Complex wavelet decomposition of image resulted in eight sub-bands and the feature extraction is carried on LL band using principal component analysis. Maximum Recognition rate reported is 93.5 using 100 features extracted from LL band.

Future work aims at extracting features from the other seven bands to utilize all the sub-bands features in improving the face recognition.

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