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Pose Invariant Face Recognition using DT-CWT Partitioning and KPCA

By K. Punnam Chandar & Dr. T. Satyasavithri
Kakatiya University, India

Abstract- In this paper the suitability of Dual Tree Complex Wavelet Transform for pose invariant Face Recognition is studied and a feature extraction frame work is proposed. This proposed framework will aid in design of Face Recognition system to address the challenging issue like Pose Variation. In contrast to the discrete wavelet Transform (DWT) the design of Dual Tree Complex Wavelet Transform is rugged to shift Invariance and poses good directional properties. These features of DT-CWT motivated to study their suitability for Face Feature Extraction, as the features of face are oriented in different directions. In this proposed frame work the Image is decomposed using DT-CWT and the features are extracted from low frequency band using Kernel Principal Component analysis (KPCA). To show the performance, the proposed method is tested on ORL Database. Satisfactory results are obtained using proposed method compared to existing state of art.

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Pose Invariant Face Recognition using DT-CWT Partitioning and KPCA

K. Punnam Chandar α & Dr. T. Satyasavithri σ

Abstract- In this paper the suitability of Dual Tree Complex Wavelet Transform for pose invariant Face Recognition is studied and a feature extraction frame work is proposed. This proposed framework will aid in design of Face Recognition system to address the challenging issue like Pose Variation. In contrast to the discrete wavelet Transform (DWT) the design of Dual Tree Complex Wavelet Transform is rugged to shift Invariance and poses good directional properties. These features of DT-CWT motivated to study their suitability for Face Feature Extraction, as the features of face are oriented in different directions. In this proposed frame work the Image is decomposed using DT-CWT and the features are extracted from low frequency band using Kernel Principal Component analysis (KPCA). To show the performance, the proposed method is tested on ORL Database. Satisfactory results are obtained using proposed method compared to existing state of art.

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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 and expression variation ,
b. Resolution variation and
c. Illumination problems

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

Author α: Asst. Professor, Dept. Of ECE, University College of Engineering (KU), Warangal-15, INDIA.
e-mail: k_punnam@kakatiya.ac.in

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 112 X92, we worked on approximation details of first level decomposition using DT-CWT. The size in first level decomposition reduces to 56 X46.

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

In this paper we used Kernel Principal Component Analysis (KPCA) as feature extraction method [1, 2, 3]. For comparing results 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.

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 & discussions, and conclusion in the last section.

II. Dual Tree Compex Wavelet Transform

The defects 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.

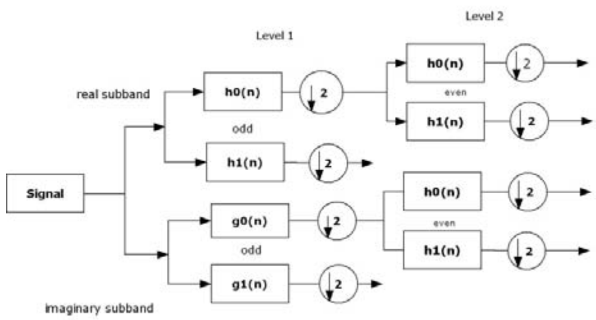

Figure 2 : Dual Tree Complex Wavelet Transform working principle for 1D signal

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

$$y_g(t) = \mathrm{H}\{y_h(t)\} \tag{1}$$

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

$$\psi_c(t) := \psi_h(t) + j\psi_g(t) \tag{2}$$

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 5.

The 2-D wavelet is defined as

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

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

$$y(x) = y_r(x) + jy_i(y) \tag{4}$$

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 is imaginary and odd.

The complex-wavelet coefficient is defined as

$$d_c(k,l) = d_r(k,l) + jd_i(k,l) \tag{6}$$

And its magnitude is

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

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

And phase is given as

$$d_c(k,l) = \arctan q \tag{8}$$

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

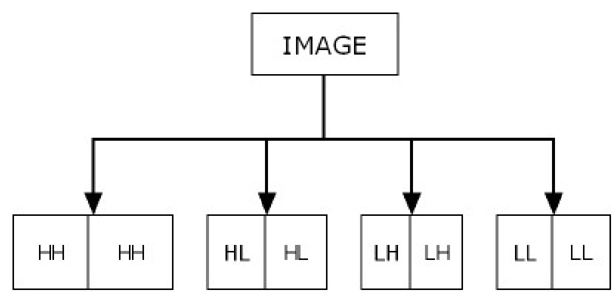

Figure 3 : Decomposition of DT-CWT for 2D image

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.

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 × columns of image) representing a set of sampled images. *pj*'s represent the pixel values.

xi = [p1 : : : pN]T ; i = 1, ... , M

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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 *ei*'s which have the largest possible projection onto each of the *wi*'s. We wish to find a set of M orthonormal vectors ei 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 or thonormality constraint

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

It has been shown that the *ei*'s and ¸*λi*'s are given by the eigenvectors and eigen values of the covariance matrix

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

where *W* is a matrix composed of the column vectors *wi* 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 Ω = *[v1, v2 , , , VM']T*

b) Kernel Principle Component Analysis

Kernel Principal Component Analysis is another technique used for dimensionality reduction when the data lie on the non-linear manifold .In KPCA data X are first mapped into a high dimensional space F via non linear mapping Φ [3]. Assuming that the mapped data are centered, i.e., $\sum_{i=1}^{M}\Phi(x_i) = 0$, where is M the number of input data (the centering method in F can be found in [10] and [13]). Kernel PCA diagonalizes the estimate of the covariance matrix of the mapped data $\Phi(x_i)$ defined as,

$$F = \frac{1}{M}\sum_{i=1}^{M}\Phi(x_i).\Phi(x_i) \; .$$

Polynomial, Exponential and Sigmoid functions are most widely used non linear functions. In this paper we considered only polynomial functions. If the new data set is 'K'. PCA is now performed in this K.

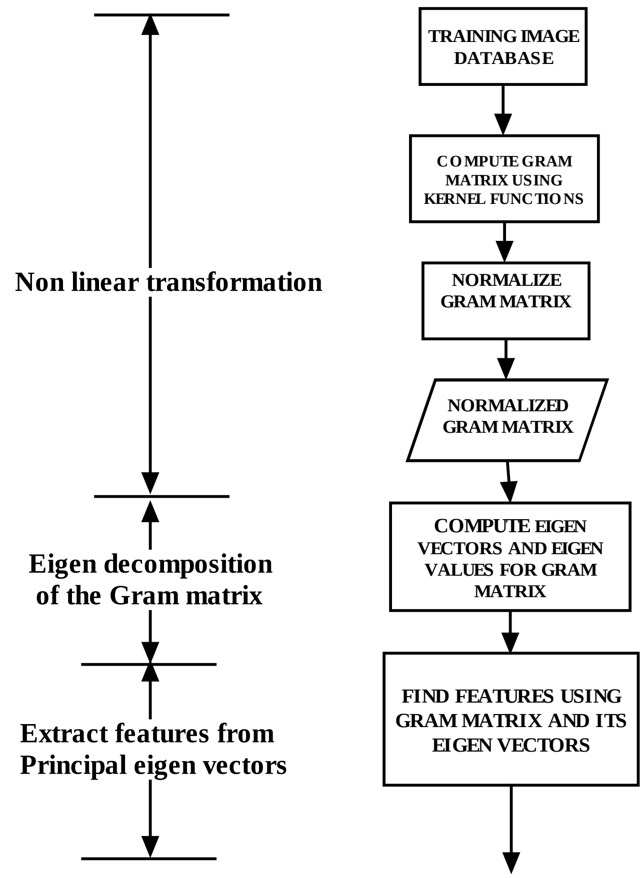

Figure 4 : Feature extraction using KPCA

Typical kernel functions are

(a) The radial basis function (RBF), defined as

$$K(x, y) = \exp\left(\frac{\|x-y\|^2}{P_0^2}\right) \qquad (4)$$

Where P0 is a user-defined parameter that specifies the rate of decay of k(x, y) toward zero, as y moves away from x and

(b) The polynomial function, defined as

$$K(x, y) = \left(x^T y + P_1\right)^{P2} \qquad (5)$$

Where P1and P2 are user defined parameters. The following Table.1 gives the effect of kernel parameters on recognition rate for given number of features.

We used (1, 2) as kernel parameters P_1, P_2 for polynomial kernel function. In the paper [3] by Kwang in Kim et.al they used (1, 4) as kernel parameters. Any P2 from 1 to 4 is considerable.

c) 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

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

*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 Face Recognition System

First aspect of this work is to use Dual Tree Complex Wavelet transform [9, 10, 13] where multiscale analysis is 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 the LL_{NEW} using KPCA.

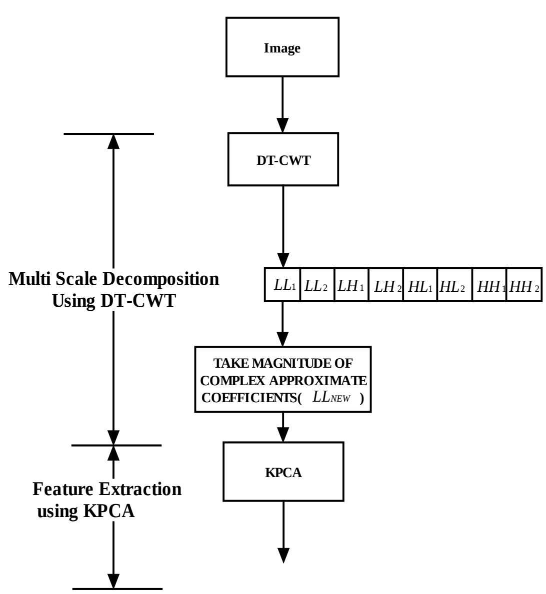

Figure 5 : DT-CWT Multiscale Feature Extraction (Proposed Algorithm)

The general procedure of the proposed technique is as follows. As a first step we divide database into testing and training database. Each database consists of 200 images of 40 subjects and 5 different poses. As next step Approximation details of all train 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 LL_{NEW} with magnitudes of these complex numbers.

Now the LL_{NEW} is processed using KPCA to extract the features Fig.2 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 rugged to pose variation is shown in Fig.7.

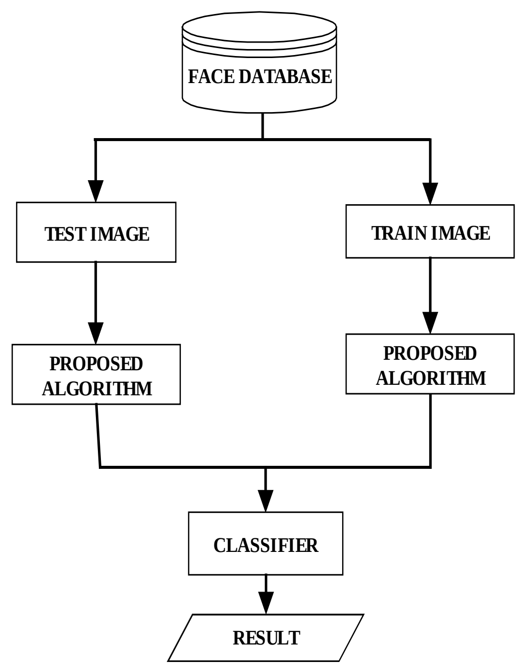

Figure 6 : Block diagram of face recognition system

V. Experimental Results & Discussions

a) Database

In this work experimentation is carried ORL face databases [7]. The ORL database consists of 400 images of 40 individuals in different poses. Sample images from ORL database are shown in below figure.7, ,Which shows 10 different poses of 5 subjects.

Figure 7 : ORL Face Database

b) Experimental Results

For evaluating the performance of the proposed algorithm we have used ORL database. Recognition rate was calculated on this database and results are shown in Table 1. The Results are also plotted in figure 7.It is observed from figure that as the number of features increasing the recognition rate is also increasing.

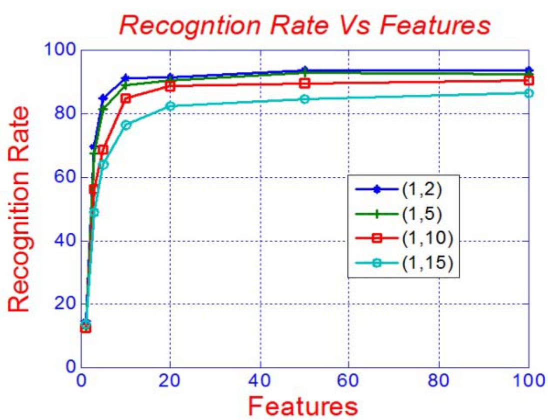

Figure 8 : Recognition Rate vs. Features for ORL face database

Table 1 : Recognition Rate Calculation On ORL Database using DT-CWT and KPCA

Recognition Rate Calculation by Using Various Kernel Parameters					
Features	*Database*	*(1, 2)*	*(1, 5)*	*(1, 10)*	*(1 , 15)*
1	ORL	14.5	12.5	12.5	13.5
3	ORL	69.5	67.5	56.0	49.0
5	ORL	85.0	81.5	68.5	64.0
10	ORL	91.0	89.0	85.0	76.5
20	ORL	91.5	90.5	88.5	82.5
50	ORL	93.5	93.0	89.5	84.5
100	ORL	93.5	92.5	90.5	86.5

VI. Conclussion

In this paper we proposed a novel approach for face recognition for pose variant case by extracting the multi scale features by using DT-CWT, KPCA, the algorithm follows top-down approach which process the image data in each level. In next step, the wavelet decomposition is applied to the entire database to reduce memory occupation. Here only the Low frequency information is used in the identification of the face and the mapping from input space of data to high dimensionality feature space is done by KPCA method along with nearest-neighbor distance classifier which can speed up the recognition process.

Experimentation is carried on openly available challenging face database. The experimental results show that as the feature space increases, the performance increases but the same time computational cost of the algorithm increases. The recognition rate is improved on ORL database. We are working out to find best suitable classifier to enhance the performance again, which is our future work remains.

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