Pose Invariant Face Recognition using DT-CWT Partitioning and KPCA

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Abstract

In this paper the suitability of Dual Tree Complex Wavelet Transform for pose invariant FaceIn 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.

Index terms— dual tree complex wavelet transform, KPCA, and euclidian classifier.

1 Introduction

iometrics 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.

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. 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. 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.

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( ) : ( ) ( ) c h g t t j t ? ? ? = +**(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?.. ? is real and even and is imaginary and odd.

The complex-wavelet coefficient is defined as(,) (,) (,) c r i d k l d k l jd k l = + (6)

And its magnitude is The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image.1 1 M i i m x M = = ? (9)

And let i w be defined as mean centered imagei i w x 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

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.

2 A facial image can be projected onto M' (? M) dimensions by computing ? = [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 ? [3]. Assuming that the mapped data are centered, i.e., , 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 i ( ) x ? defined as, i i 1

3 ( ). ( )

M i F x x M = = ? ? ? .

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.

4 COMPUTE EIGEN

5 VECTORS AND EIGEN VALUES FOR GRAM MATRIX TRAINING IMAGE DATABASE FIND FEATURES USING GRAM MATRIX AND ITS EIGEN VECTORS

6 Extract features from

K(x, y)= 2 2 0 exp (4) x y P ? ? ? ? ? ? ? ? ? ?

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 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.

7 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 ( ) ( )T i i i i i i i j X Y X Y X Y X Y ? ? ? ? < ?**(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.

8 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 NEW LL using KPCA. 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. **??**. 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 **??**.It is observed from figure that as the number of features increasing the recognition rate is also increasing. VI.

9 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. [1] [2] [3] [4]

1

Figure 1: Figure 1 :

2

Figure 2: Figure 2 :

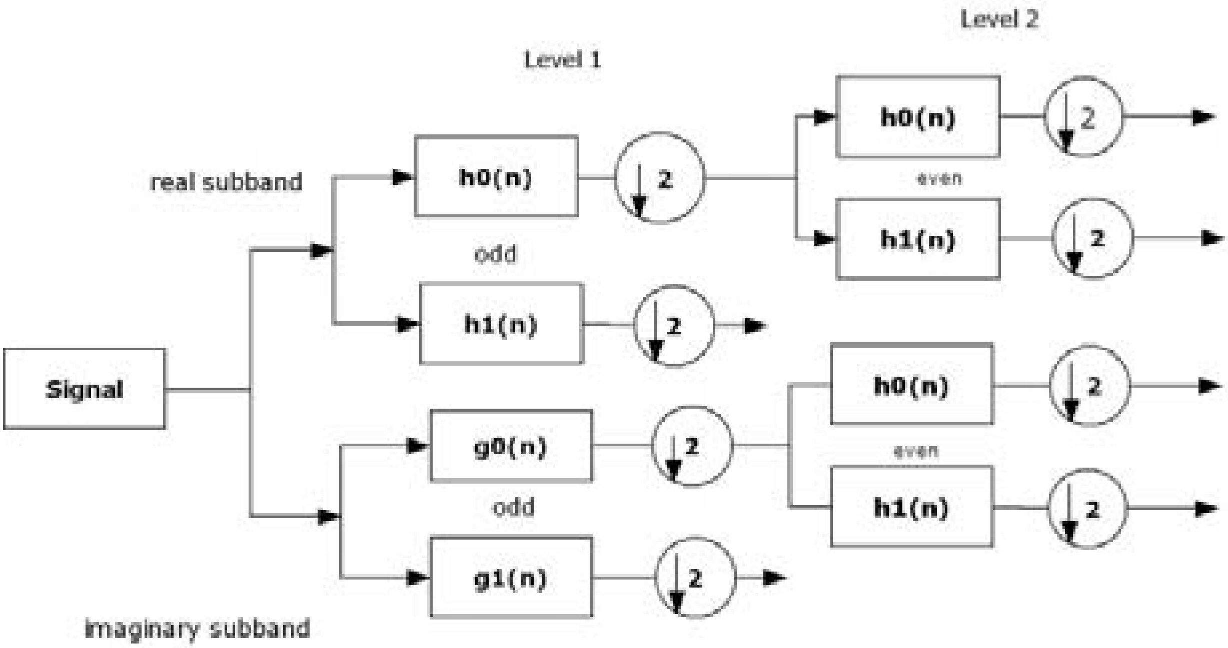
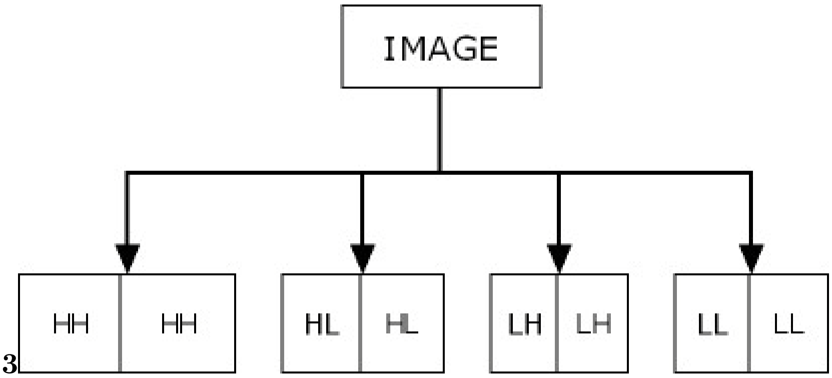


Figure 3:



3

Figure 4: Figure 3 :

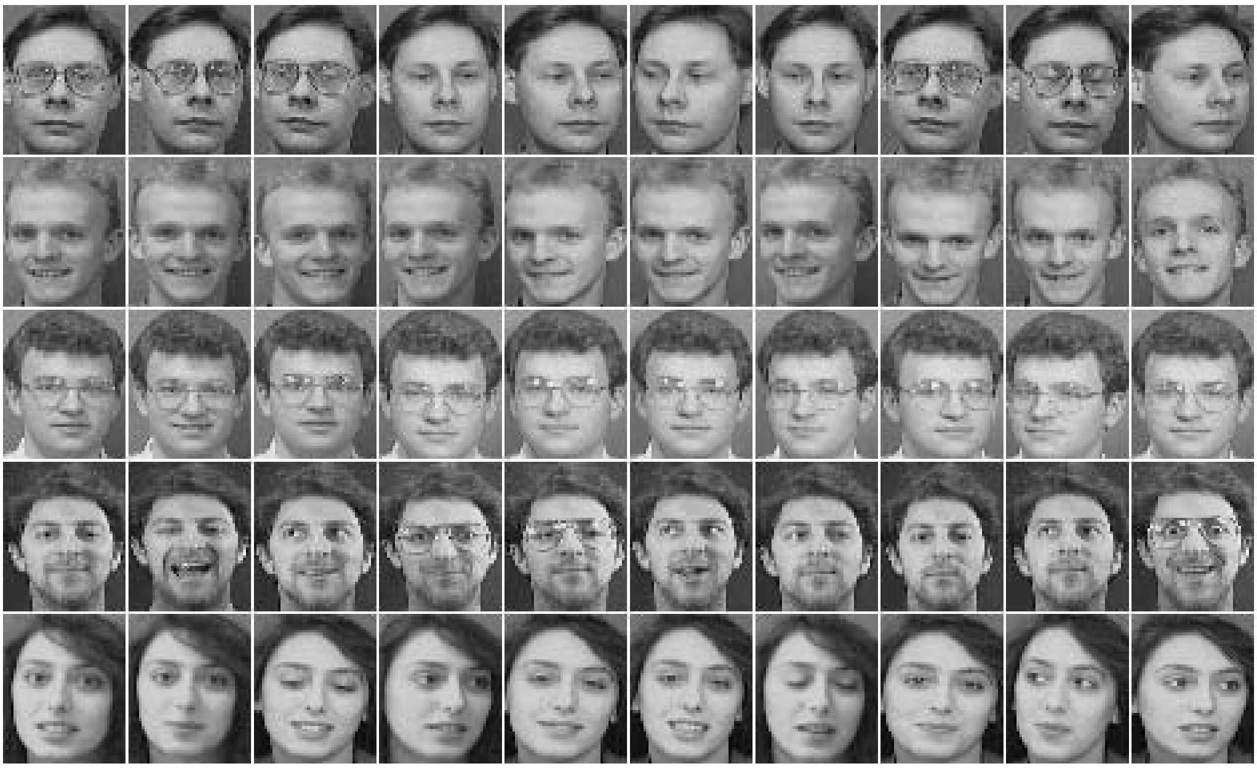


Figure 5: =

4

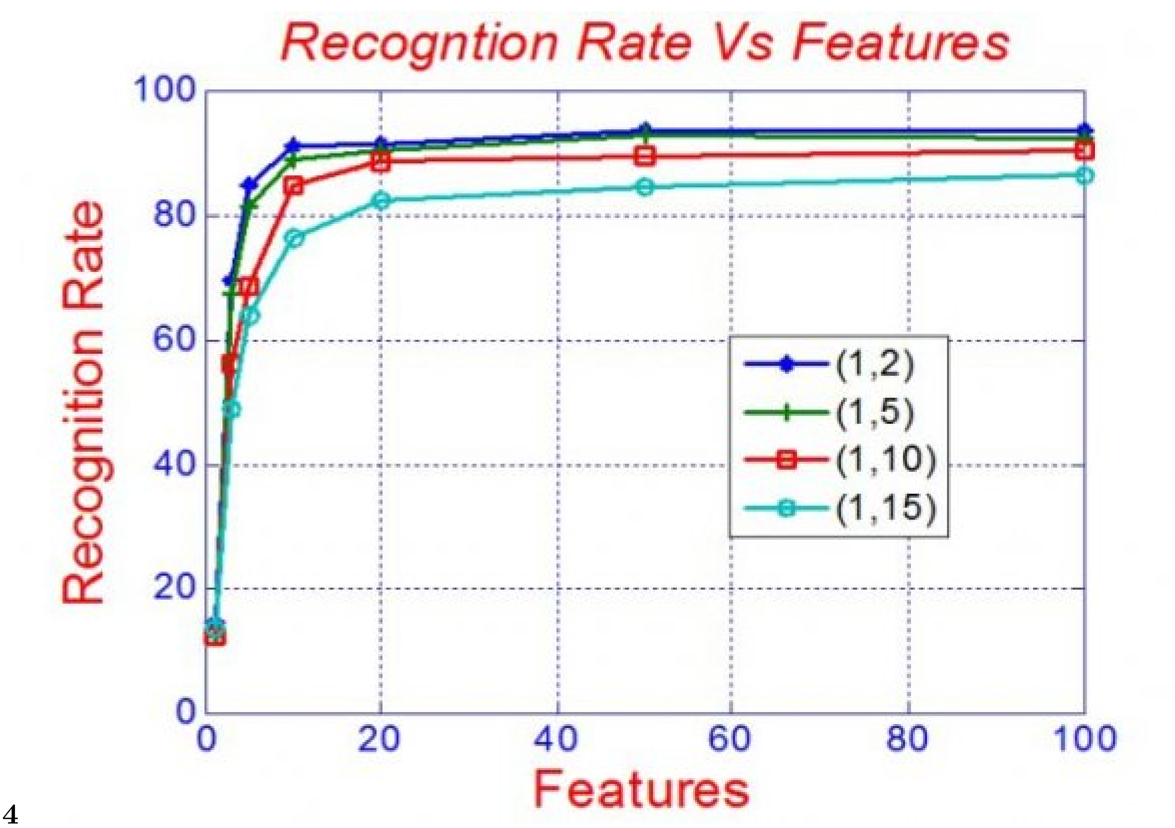


Figure 6: Figure 4 :

1

Recognition Rate Calculation by Using Various

Features	Database	Kernel Parameters (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

Figure 7: Table 1 :

[1]© 2014 Global Journals Inc. (US) representing a set of sampled images. pj's represent the pixel values. xi = [p1 : : : pN]T ; i = 1, ... , M where ( ) x y is complex analytic wavelet, given as Pose Invariant Face Recognition Using DT-CWT Partitioning and KPCA

[2]© 2014 Global Journals Inc. (US)

[3]Pose Invariant Face Recognition Using DT-CWT Partitioning and KPCA

[4]© 2014 Global Journals Inc. (US) Pose Invariant Face Recognition Using DT-CWT Partitioning and KPCA

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