Performance Evaluation for Face Recognition Using Wavelet-based Image De-noising

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Abstract— **In this research we scrutinize the face recognition system performance when the test images are imposed to different levels of noise. We tried to imitate the real world scenarios when the face images are captured from video cameras or scanners and suffer some noise. To investigate the performance of proposed system, we simulate this scenario by adding AWGN (additive white Gaussian noise) to the test images in the face database. For image de-noising, we used two different algorithms namely; Discrete Wavelets Transform (DWT) and Dual-Tree Complex Wavelets Transform (DTCWT). The de-noised images are then fed to a PCA-based face recognition system for better recognition performance.**

Keywords— image de-noising; wavelet transform; face recognition; principal component analysis.

I. INTRODUCTION

One of the most common used biometric techniques is face recognition. Face recognition has been playing a huge role in scientific researches for human recognition, even though the other techniques such as fingerprints [1] and iris [2] are more accurate way of recognition because of its acceptability, universality and collectability without the cooperation of the subject. In a literature researchers investigated different algorithms for face recognition problem.

Principal Component Analysis [3][4] is one of the most popular feature extraction techniques used among various approaches. PCA, popularly called "eigenfaces" [5][6], have played a vast role in dimensionality reduction and demonstrated excellent performance. Principal Component Analysis based approaches typically cover two basic steps: training and classification of the system. In training step of PCA, eigenvalues and eigenvectors of images are computed from training row dataset by using principal component analysis method. And in second step of PCA, input dataset is transformed linearly to the same eigenspace projection and classification is performed by proposed method. In Contrast to the PCA which transforms the image-based data in a linear combination of features to explain the data in clear manner, the linear discriminant analysis (LDA) method [7][8] which is also known as fisherfaces method, is another example for image-based techniques that tries to transform discriminatory information between classes and within classes in a linear combination of separable feature space, where the base features are not necessarily orthogonal. There is also other recognition algorithms such as Gabor wavelet, discrete wavelets and dual-tree complex wavelet transform. In [9] authors explained how 2D wavelet transform is applied using 1D wavelet transform algorithm to the both rows and columns of 2D dimensional data in a very clear manner.

Gabor wavelets are the most widely used algorithms in face recognition, because it offers good spatial locality characteristics and feature selectivity in different directions [10]. Dual-tree Complex Wavelet Transform also provides good directional selectivity in six different fixed orientations at different scales [11].

In real life, images obtained from video cameras or scanners might be exposed to different levels of noise. In this work we tried to imitate this situation by adding AWGN to the test images in the database. For image de-noising, we will use Discrete Wavelet transform DWT and Dual-Tree Complex Wavelet Transform DTCWT before feeding the data to PCA-based face recognition system to improve recognition performance.

In this paper, section 2 explains the DWT and DTCWT algorithms. In section 3, Feature extraction and dimensionality reduction methods are described. In section 4, proposed approach is explained. Experimental results with simulations and discussions are given in section 5 followed by the conclusions section.

II. DUAL-TREE COMPLEX WAVELET AND DISCRETE WAVELET TRANSFORM

A. Discrete Wavelet Transform.

Discrete wavelet transform (DWT) is application of wavelet transform to the given signal in discretely sampled order. The Computation of DWT is done by decomposing the signal by passing it through low-pass filter followed by high-pass filter in discrete time-domain. This signal decomposition is called the Mallat algorithm [12].

The 2D wavelet transformation is computed by performing 1D wavelet transformation to both rows and columns of a given 2D data, consecutively. In figure 1, you can see the decomposition of one level 2D wavelet to the R×C sized image called $\mathbf{A}_j$. In this figure, capital H denotes high-pass filtering and capital L denotes low-pass filtering, while "↓2" indicate sub-sampling process of rows and columns of image by 2. In the final stage of the decomposition process we got four R/2×C/2 resolution sub-band decompositions of $\mathbf{A}_j$. First $\mathbf{A}_{j+1}$ sub-band wavelet includes approximation details. The other three $\mathbf{H}_{j+1}$, $\mathbf{V}_{j+1}$, $\mathbf{D}_{j+1}$ wavelet sub-bands, corresponding to horizontal, vertical and diagonal components, respectively, include the details coefficients.

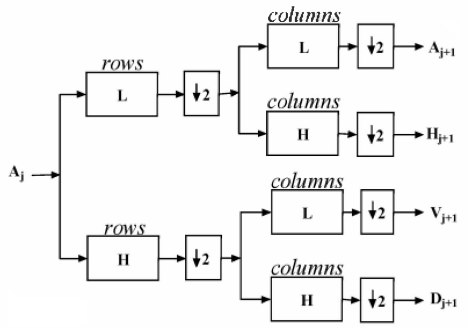
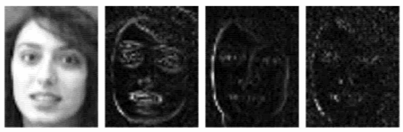


Figure 1: 2-Dimensional wavelet decomposition.



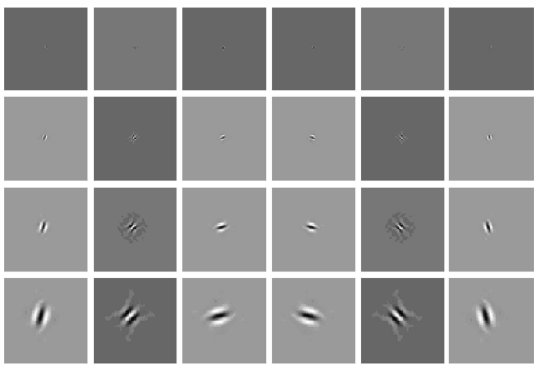
(a) (b) (c) (d)

Figure 2: Discrete Wavelet Transform decomposition: (a) $\mathbf{A}_{j+1}$ (b) $\mathbf{H}_{j+1}$, (c) $\mathbf{V}_{j+1}$, (d) $\mathbf{D}_{j+1}$

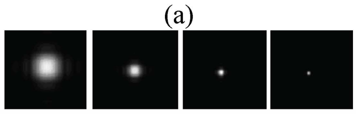
B. Dual Tree Complex Wavelet Transform.

In [13][14] Kingsbury, introduced the dual tree complex wavelets transform. Some of DT-CWT properties are: approximate shift invariance in high degree, offers good directional selectivity in 2D data, limited redundancy and efficient computation.

Standard DWT can extract the features of image only in 3 directions, whereas DT-CWT has 6 fixed directions at angles of ±15°, ±45°, ±75° in 2-D as shown in figure 3. A better directionality with more orientations suggests the advantage of DT-CWT in a wide range of directional selectivity image processing applications, e.g. texture analysis [15], and face recognition [16].



(a)



(b)

Figure 3: DT-CWT wavelets. (a) The real part of the DT-CWT kernels at four scales and six directions. (b) The magnitude of the DT-CWT kernels at four different scales.

III. Feature Extraction & Dimensionality Reduction: PCA

Principal Component Analysis is a standard known data reduction algorithm. Basic task of it is to calculate the eigenvectors of the given data, and approximate the original data by a linear combination of the leading eigenvectors. The feature vectors here are PCA projection coefficients.

Let $\mathbf{X}=(x_1, x_2, \ldots, x_k, \ldots x_N)$ represent the data matrix with dimension of $d \times N$, where each x_k is 1D-vectorized form of 2D face image with size d. Capital N represents the number of training face images taken from the related database. PCA is briefly transforming vectorized original face images linearly to projection feature vectors such that,

$$\mathbf{Z} = \mathbf{W}^{\mathrm{T}}\mathbf{X} \tag{1}$$

Where $\mathbf{Z}$ is the feature vectors matrix with size $m \times N$, m is the dimension of the feature vector, and $\mathbf{W}$ is $d \times m$ eigenvectors transformation matrix whose columns corresponding to the m largest eigenvalues obtained by:

$$\lambda e_i = \mathbf{S} e_i \tag{2}$$

Where $\mathbf{S}$ is the total scatter matrix, which uses the mean image of all training samples and defined as;

$$\mathbf{S} = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T \tag{3}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4}$$

After performing linear transformation $\mathbf{W}^{\mathbf{T}}$, the scatter of the transformed feature vectors $\mathbf{Z}=(z_1, z_2 \ldots z_N)$ is $\mathbf{W}^{\mathbf{T}}\mathbf{S}\mathbf{W}$. $\mathbf{W}_{opt}=[w_1\, w_2, \ldots, w_m]$ is spanning PCA subspace set, which is a set of eigenvectors of $\mathbf{S}$ corresponding to the largest m eigenvalues. The projection $\mathbf{W}_{opt}$ satisfying;

$$\mathbf{W}_{opt} = \max_{\mathbf{W}} |\mathbf{W}^{\mathrm{T}}\mathbf{S}\mathbf{W}| \tag{5}$$

Each of the eigenfaces are contributing to the representation of input face image, the eigenfaces are treated as a basis set for faces. The feature vector is then used in a standard pattern recognition task to classify which of a number of predefined face classes, if any, best match the face. Classification is performed by comparing the feature vectors of the training images with the feature vector of the input image. This comparison is based on the Sum Square Error (SSE) between the face classes and the input image, equation of SSE is below, where x and y are representing the training and testing vectors, respectively;

$$SSE = \sum (x - y)^2 \tag{6}$$

Figure 4 shows sample images from ORL Database, and Figure 5 shows first 20 eiganfaces from ORL database.

Figure 4: Sample images from ORL Database

Figure 5: first 20 eigenfaces obtained using ORL database.

IV. PROPOSED APPROACH

In this paper, we proposed both DWT and DT-CWT as de-noising algorithms. To imitate the real world scenarios, test images from database were exposed to additive white Gaussian noise AWGN with zero mean and different variance values.

Figure 6 shows examples from ORL database for face images with different AWGN levels. ORL Image Database includes 40 people each having 10 different face images. We used 5 images for training and 5 images for testing for each person in the database making totally 200 training and 200 testing images.

Block diagram of proposed approach is shown in figure 7.

(a) (b) (c)

Figure 6: Example of face images with different AWGN levels. (a) Original face, (b) face with μ=0, σ^2 = 0.01 AWGN (b) face with μ=0, σ^2 = 0.1 AWGN.

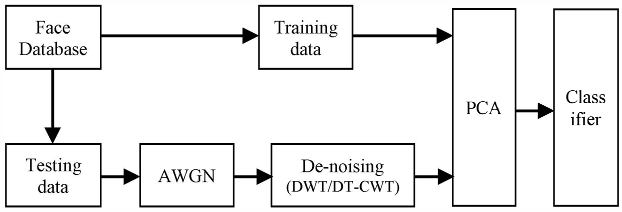


Figure 7: Block Diagram of the proposed approach

V. SIMULATION RESULTS & DISCUSSIONS.

Experiments for evaluating the proposed approach were conducted on ORL database. Results in Table 1 were obtained by averaging 10 runs of the system. For each run, the training and testing images for each person were chosen randomly. Test images were exposed to AWGN with zero mean and different variance values. For de-noising images we applied two different algorithms, namely DWT and DTCWT. For feature extraction stage we used PCA algorithm with SSE distance as a classifier.

TABLE I. Performance using ORL with DWT and DTCWT de-noising algorithms applied on AWGN noisy images.

AWGN(μ=0) σ^2	De-noising Algorithm	PCA (de-noised images)
	Noiseless	95, 25%
0.01	DWT	95, 10%
	DTCWT	94, 90%
0.03	DWT	94, 70%
	DTCWT	94, 60%
0.05	DWT	94, 20%
	DTCWT	94, 05%
0.07	DWT	93, 85%
	DTCWT	93, 65%
0.1	DWT	93, 10%
	DTCWT	92, 90%
0.2	DWT	88, 55%
	DTCWT	87, 65%
0.3	DWT	78, 40%
	DTCWT	77, 75%
0.4	DWT	62, 90%
	DTCWT	62, 60%
0.5	DWT	50, 85%
	DTCWT	49, 50%

It is clear from results in table 1 that, in general, the performance of the system is degraded when the AWGN variance increased. With low variance values between 0.01 and 0.1, both DWT and DT-CWT managed to de-noise the noisy face images and keep the performance above 92%. With noise having higher variance values the performance starts to drop. Considering the obtained recognition rates, both DWT and DT-CWT had comparable performances.

VI. CONCLUSION

The performance of a face recognition system when the test images are imposed to different level of noise was investigated. By adding AWGN (additive white Gaussian noise) to the test images in the face database, we tried to imitate the real world scenario when face images obtained from scanners or cameras might be exposed to noise. Before feeding the test image a PCA-based face recognition system we used DWT and DTCWT algorithms to de-noise these images. The performance of the proposed approach shows very good performance with the presence of AWGN with low variance values up to 0.1 variance.

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