2015 Intl. Conference on Computing and Network Communications (CoCoNet'15), Dec. 16-19, 2015, Trivandrum, India

An improved feature extraction method based on DWT and 2DSubXPCA methods

D. V. Rajeshwari Devi*,#
*Research Scholar at Department of ECE
BMS College of Engineering
Bengaluru, India 560019
#Department of ECE, KSIT
Bengaluru, India 560062
Email: rajeshwaridevidv@gmail.com

Dr. K. Narasimha Rao
Professor
Department of EIE
BMS College of Engineering
Bengaluru, India 560019
Email: knr2011@gmail.com

***Abstract*—Face is one of the popular biometric used in human authentication for providing secured access. Feature reduction is a challenging task for fast and efficient recognition. Many techniques like Discrete wavelet transform (DWT), Principal component analysis (PCA) and Linear discriminant analysis (LDA) have been used for feature reduction. Some issues like pose variation, change in facial expression and poor illumination make the recognition process a difficult task. In this paper, we bring in a hybrid approach based on DWT and 2DSubXPCA for feature extraction and use nearest neighbor for classification. A maximum classification accuracy of 97.5% with highest dimensionality reduction is obtained for ORL database.**

Keywords - Face recognition, DWT, PCA, 2DSubXPCA, Partitioning

I. Introduction

Biometric recognition is used to check the authentication for secured access in applications like banking systems, attendance, defence,etc. Face biometric is widely used since it can be captured without human co-operation. Any biometric system has three stages: First stage is feature extraction which reduces redundant data using techniques like DWT, PCA, LDA, etc; Second stage is matching, wherein the reduced image is compared with a database having priori-reduced face images; The last stage is decision making which decides the grant of access to the user, depending on the result of classification [1].

Discrete wavelet transform (DWT) is a multiresolution approach which gives time and frequency resolution by using standard wavelets. DWT finds application in denoising, image compression and feature reduction [2]. PCA is a feature reduction technique which represents image as a vector [3]. Since PCA is tedious and time consuming, a 2DPCA approach was proposed which represents image as a two dimensional matrix and is faster than PCA [4]. 2DPCA is a global approach to feature reduction which does not consider local dependencies. A subimage based PCA was proposed which divides the image into subimages, to exploit local dependencies [5]. Face images are affected by pose variation, different facial expressions and poor illumination. To overcome these issues, a multi-resolution approach like DWT is applied on the face images which divides the image into four different subbands. The subbands which are less sensitive to facial expressions are used for recognition [2]. Many experiments have been conducted on DWT and PCA using various classifiers. In [6], three level DWT decomposition is performed and the approximations are combined to form a new image. The eigenfaces are generated from the new images and radial basis neural network classifier is used. In [7], the performance of PCA and DWT (four level Haar wavelet) are evaluated separately on face images using nearest neighbor and SVM for classification. In [8], DWT and two dimensional PCA is explored with 92% classification accuracy. In [9], the finer detail subband is extracted using DWT and PCA is applied on it. In [10], low frequency subband is extracted using DWT and is divided into subimages. 2DPCA is applied on each subimage to result in sub features. Sub feature distances is calculated using nearest neighbor and combined using adaptive membership grade.

To exploit both local and global information, SubXPCA [11] and FLPCA [12] were proposed; they were proven to be better as compared to PCA, 2DPCA and other methods. In this paper, we exploit the benefits of both DWT and SubXPCA by proposing a hybrid method. In the proposed method, we apply DWT (to extract low frequency features, which are robust against facial expressions) followed by 2D version of SubXPCA to extract global features using local features of subimages.

The paper is organized as follows: Section 2 deals with review of PCA, DWT and 2DSubPCA methods. Section 3 presents the proposed method in detail. Section 4 discusses the experimental results followed by conclusion in section 5.

II. Review of DWT, 2DPCA, 2DSubPCA and 2DSubXPCA methods

In this section, we outline DWT [2], 2DPCA [3], 2D version of original SubPCA [5] and 2D Cross SubPCA [11] methods.

A. Discrete Wavelet Transform (DWT)

Discrete wavelet transform is a multiresolution approach used in the analysis of coarse and detail information in a signal or an image. DWT is realized using decomposition filters, lowpass filter and highpass filter which divide the information into low frequencies and high frequencies respectively. For an image, two dimensional DWT is used which divides the image into 4 subbands - low frequencies (LL) and high frequencies in diagonal (HH), horizontal (LH), and vertical (HL) directions [2]. The coarse information of an image is present in low frequency subband and finer details of the image(horizontal, vertical and diagonal directions) are present in the subbands LH, HL and HH respectively. The size of each subband will be half that of the original image due to downsampling. The original image can be reconstructed by upsampling the four subbands and passing them through reconstruction filters.

B. Two-dimensional PCA (2DPCA)

PCA is a well-known method for extraction of prominent features in a given image [3]. PCA treats image as a single dimensional vector, whereas 2DPCA is a two dimensional approach [4]. Consider N images, $\mathbf{I}_1, \mathbf{I}_2, \ldots \mathbf{I}_N$, each of size $p \times q$. The mean of the images is calculated as

$$\mathbf{m} = \frac{1}{N}\Sigma_{i=1}^{N}\mathbf{I}_i(x,y)\ \forall x,y \tag{1}$$

Mean is subtracted from each face image $\mathbf{I}_i = \mathbf{I}_i - \mathbf{m}$ for $i = 1,2,3,\ldots,N$. Covariance matrix is found using

$$\mathbf{Cov}_{q\times q} = \Sigma_{i=1}^{N}\mathbf{I}_i^T\mathbf{I}_i \tag{2}$$

Using Covariance matrix $\mathbf{Cov}_{q\times q}$ eigen vectors $\mathbf{V}_{q\times q}$ are found and sorted in descending order of eigen values $\mathbf{D}_{q\times q}$. If s eigen vectors are selected ($s < q$), then the reduced image is found as,

$$[\mathbf{J}_i]_{p\times s} = [\mathbf{I}_i]_{p\times q}[\mathbf{V}]_{q\times s} \tag{3}$$

C. Two-dimensional Sub-pattern based PCA (2DSubPCA)

Here, we briefly explain the 2DSubPCA method. In 2DSubPCA, an image is divided into k subimages of equal size [5]. The 2DPCA is applied on each of k subimage groups. The reduced k subimages are concatenated to form the reduced image.

D. Two-dimensional Cross Sub-pattern based PCA (2DSubXPCA)

In 2DSubXPCA, an image is divided into k subimages of equal size [11]. The local redundancies are reduced by applying PCA on each of the k subimage groups. The reduced k subimages are concatenated to form the locally-reduced image. Further, global features are extracted using dependencies across the subimages by applying PCA on the reduced images. The same idea of SubXPCA is extended using 2DPCA instead of PCA in another related work, FLPCA [12].

III. Proposed DWT based 2DSubXPCA method (DWT+2DSubXPCA)

Consider N training images $\mathbf{I} = \mathbf{I}_1, \mathbf{I}_2, \ldots \mathbf{I}_N$ of size $p \times q$. The proposed method is a hybrid version based on DWT and 2DSubXPCA. The algorithm is given in detail as follows:

1. *Extraction of low frequency features.* Apply DWT on every training image, $\mathbf{I}_i; i = 1,2,\ldots,N$, to extract low frequency features, $\mathbf{L}_i$, which are robust against change in facial expressions, as given by

$$[\mathbf{L}_i]_{p_1\times q_1} = DWT(\mathbf{I}_i) \tag{4}$$

where $i = 1,2,\ldots,N$. The DWT can be applied repeatedly many levels as required. The image is reduced by 50% after application of DWT each time.

2. *Partitioning images.* Divide images $[\mathbf{L}_i]_{p_1\times q_1}$ into k subimages, $\mathbf{L}_i^1$, $\mathbf{L}_i^2$, ..., $\mathbf{L}_i^k$, each of size $\frac{p_1}{\sqrt{k}} \times \frac{q_1}{\sqrt{k}}$.

3. *Extraction of local features.* Apply 2DPCA on respective groups of subimages to obtain subimages with local features. The application of 2DPCA on j^{th} subimage group is given by

$$(\mathbf{M}_1^j, \mathbf{M}_2^j, \ldots, \mathbf{M}_N^j) \leftarrow 2DPCA(\mathbf{L}_1^j, \mathbf{L}_2^j, \ldots, \mathbf{L}_N^j) \tag{5}$$

where $[\mathbf{M}_i^j]_{p_2\times q_2}$ is the locally-reduced subimage of $\mathbf{L}_i^j$, $j = 1,2,\ldots,k$.

4. *Combining locally-reduced subimages.* Form locally-reduced image, $[\mathbf{P}_i]_{\sqrt{k}p_2\times\sqrt{k}q_2}$ using k locally-reduced subimages related to the original image $\mathbf{I}_i$, as given by

$$[\mathbf{P}_i]_{(\sqrt{k}p_2\times\sqrt{k}q_2)} \leftarrow Combine(\mathbf{M}_i^1, \mathbf{M}_i^2, \ldots, \mathbf{M}_i^k) \tag{6}$$

where $i = 1,2,\ldots,N$.

5. *Extraction of Global features.* Extract global features by applying 2DPCA on locally-reduced images, $\mathbf{P}_i; i = 1,2,\ldots,N$, as given by

$$(\mathbf{Q}_1, \mathbf{Q}_2, \ldots, \mathbf{Q}_N) \leftarrow 2DPCA(\mathbf{P}_1, \mathbf{P}_2, \ldots, \mathbf{P}_N) \tag{7}$$

where $[\mathbf{Q}_i]_{p_3\times q_3}$ is the globally-reduced image related to original image $\mathbf{I}_i; i = 1,2,\ldots,N$.

The proposed algorithm with classification is represented as shown in the block diagram Fig.1.

IV. Experimental Results and Discussion

A. Datasets used

For experimentation, ORL database is used which has 10 pose images for 40 subjects. Five non-overlapping datasets are generated randomly by selecting five images as testing and five images as training images for each subject. Each dataset has 200 images for training and 200 images for testing. The size of each image is 112×92.

B. Experimental Setup

The existing methods 2DPCA, DWT, 2DSubPCA, DWT+2DPCA and DWT+2DSubPCA are compared with our method DWT+2DSubXPCA. Nearest neighbor classifier is used after feature reduction.

1) Method-1 (2DPCA): By applying 2DPCA on the training set images, the columns of the images are reduced by selecting 1 to 12 principal component vectors in each case. The size of the images after reduction will be 112×1, 112×2, ..., 112×12.

2) Method-2 (DWT): DWT decomposition of the test and training images is performed for level 1 to level 5. Only the approximate coefficients are used for analysis. The size of the image 112×92 gets reduced to 56×46, 28×23, 14×12, 7×6 and 3×3 after applying DWT decomposition from level 1 to level 5.

3) Method-3 (2DSubPCA): 2DSubPCA is applied on training images by dividing each image into four parts, the size of each subimage being 56×46. For feature reduction, 1 to 12 principal component vectors are selected in each case. After reduction, the size of the subimages is 56×1, 56×2, $\ldots$, 56×12. The subimages are recombined to form new reduced images of size 112×2, 112×4, $\ldots$, 112×24.

4) Method-4 (DWT+2DPCA): A three level DWT decomposition is performed on training images which reduces the image size to 14×12. 2DPCA is applied further by selecting 1 to 12 principal component vectors. The size of the images after reduction will be 14×1, 14×2, $\ldots$, 14×12.

5) Method-5 (DWT+2DSubPCA): A three level DWT decomposition is performed on training images, which reduces the image size to 14×12. Each image is divided into four parts of size 7×6. 2DPCA is applied on each subimage by extracting 1 to 6 principal component vectors in each case. After recombination, the image size will be 14×2, 14×4, $\ldots$, 14×12.

6) Proposed Method (DWT+2DSubXPCA): In the proposed method, a three level DWT is applied on the training images using Daubechies1 wavelet. Each image gets divided into four subbands of size 14×12. We use the low frequency subband and divide it into four parts with subimage size as 7×6. Local redundancy is removed by applying 2DPCA on each subimage by selecting 1 to 6 principal component vectors in each case. The subimages are recombined to form reduced images of sizes 14×2, 14×4, $\ldots$, 14×12. To perform global reduction, 2DPCA is applied on the recombined image.

C. Discussion on Recognition rates

The performance of our method is compared with 2DPCA, DWT, 2DSubPCA, DWT+2DPCA and DWT+2DSubPCA methods as shown in Figs.2-5 and Table 1.

For Dataset-1, the proposed method shows improved recognition as compared to DWT, 2DSubPCA and DWT+2DSubPCA with highest dimensionality reduction as shown in Table 1 and Fig.2. In comparison with DWT+2DPCA, the proposed method achieves higher recognition at lesser number of features and gives same recognition with increased number of features. The proposed method gives the same recognition rate as 2DPCA, but at lesser number of features.

For Dataset-2, the proposed method gives the highest recognition rate of 96.5% when compared to all other methods as shown in Table 1 and Fig.3. The dimensionality reduction of the proposed method shows improved recognition rate over DWT and competitive rates over other methods.

For Dataset-3, the proposed method outperforms other methods by giving a highest recognition rate of 94.5% as

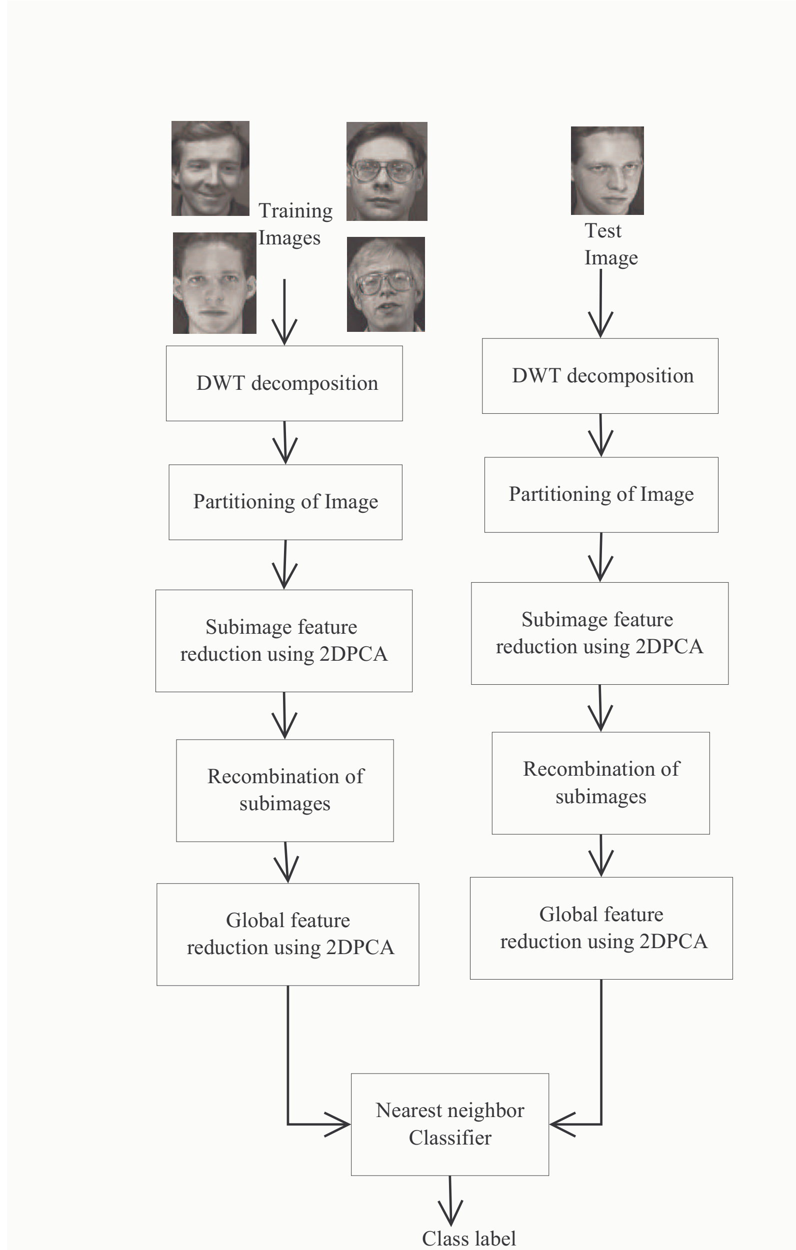

Fig. 1. Proposed method

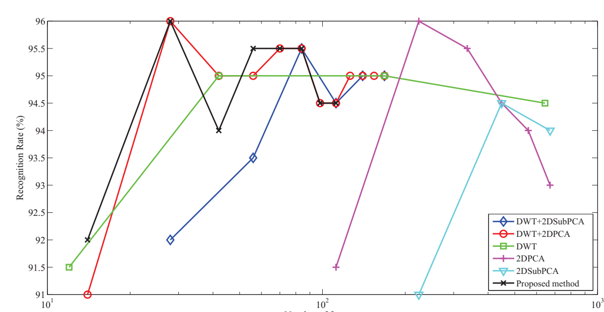

Fig. 2. Recognition rates for Dataset-1

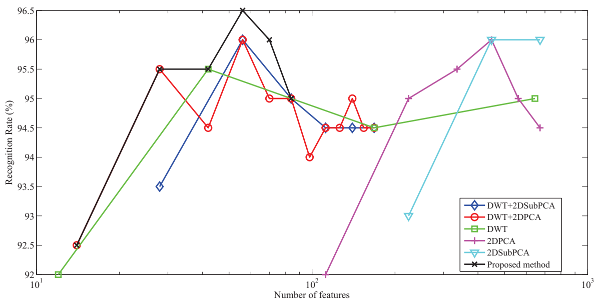

Fig. 3. Recognition rates for Dataset-2

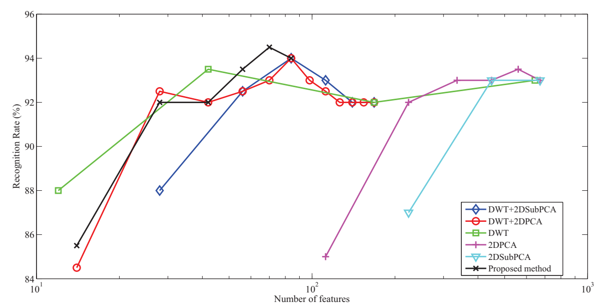

Fig. 4. Recognition rates for Dataset-3

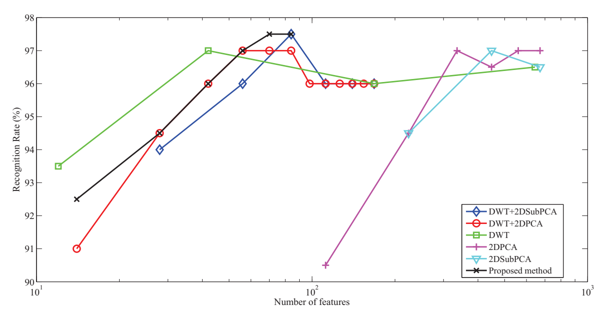

Fig. 5. Recognition rates for Dataset-4

shown in Table 1 and Fig.4. The dimensionality reduction of the proposed method shows improved recognition rate over DWT and competitive rates over other methods.

For Dataset-4, the proposed method gives better recognition rate of 97.5% as compared to 2DPCA, DWT, 2DSubPCA and DWT+2DPCA; it shows same recognition as DWT+2DSubPCA, but with lesser number of features as shown in Table 1 and Fig.5. The proposed method shows highest dimensionality reduction over 2DPCA, 2DSubPCA and DWT+2DSubPCA methods. However it shows lower dimensionality reduction rates as compared to DWT and DWT+2DPCA methods.

In a nutshell, the proposed method gives better performance in terms of recognition and dimensionality reduction over other methods (DWT, 2DPCA, 2DSubPCA, DWT+2DPCA, DWT+2DSubPCA).

TABLE I
COMPARISON OF MAXIMUM RECOGNITION RATE AND CORRESPONDING DIMENSIONALITY OF VARIOUS METHODS

Method	**Recognition rate and Dimensionality**			
	Dataset-1	Dataset-2	Dataset-3	Dataset-4
2DPCA	**96%** (224)*	96% (448)	93.5% (560)	97% (336)
DWT	95% (42)	95.5% (42)	93.5% (42)	97% (42)
2DSubPCA	94.5% (448)	96% (448)	93.5% (1568)	97% (448)
DWT+ 2DPCA	**96% (28)**	96% (56)	94% (84)	97% (56)
DWT+ 2DSubPCA	95.5% (84)	96% (56)	94% (84)	**97.5%** (84)
Proposed method	**96% (28)**	**96.5%** (56)	**94.5%** (70)	**97.5%** (70)

*: Indicates the dimensionality

V. CONCLUSION

An efficient method for face recognition is presented in this paper. The proposed method exploits the advantages of DWT (extraction of low frequency features) and 2D version of SubXPCA (extraction of local and global features). The proposed method was shown to be superior in terms of recognition and dimensionality reduction. Our method can be extensively used in various biometric applications such as palmprint recognition, fingerprint recognition, etc. The proposed method may not perform well when local variations are prominent in the dataset. In future, we would like to extend our investigation on multimodal biometric data.

REFERENCES

[1] M. Faundez-Zanuy, "Data fusion in biometrics," *IEEE A & E Systems Magazine*, vol. 20, NO. 1, pp. 34–38, 2005.
[2] H. K. Ekenel and B. Sankur, "Multiresolution face recognition," *Image and Vision Computing*, vol. 23, pp. 469–477, 2005.
[3] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Science*, pp. 71–86, 1991.
[4] Yang, D. Zhang, A. F. Frangi, and J. Yang, "Two-dimensional PCA: A new approach to appearance-based face representation and recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, NO. 1, pp. 131–137, 2004.
[5] S. Chen and Y. Zhu, "Subpattern-based principle component analysis," *Pattern Recognition*, vol. 37, pp. 1081–1083, 2004.
[6] B. Li and Y. Liu, "When Eigenface are Combined with Wavelets," *Knowledge-Based Systems*, vol. 15(5-6), pp. 343–347, 2002.
[7] E. Gumus, N. Kilic, A. Sertbas, and O. N. Ucan, "Evaluation of face recognition techniques using PCA, wavelets and SVM," *Expert Systems with Applications*, vol. 37, pp. 6404–6408, 2010.
[8] L. Song and L. Min, "Face recognition based on 2DPCA and DWT," in *Cross Strait Quad-Regional Radio Science and Wireless Technology Conference*, 2011, pp. 1459–1462.

[9] M. K. Rao, K. V. Swamy, and K. A. Sheela, "Face recognition using DWT and eigenvectors," in *1st International Conference on Emerging Technology Trends in Electronics, Communication and Networking*, 2012.

[10] Y. T. Chou, S. M. Huang, S. H. Wu, and J. F. Yang, "DWT and Sub-pattern PCA for face recognition based on fuzzy data fusion," in *International Conference on Intelligent Computation and Bio-Medical Instrumentation*, 2011, pp. 296–299.

[11] K. Vijayakumar and A. Negi, "SubXPCA and a generalized feature partitioning approach to principal component analysis," *Pattern Recognition*, vol. 41, No.4, pp. 1398–1409, April 2008.

[12] K. VijayaKumar and A. Negi, "Novel approaches to PCA of image data based on feature partitioning framework," *Pattern Recognition Letters*, vol. 29, Issue 3, pp. 254–264, Feb 2008.