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Face Recognition using 2-DPCA, ICA, 2-DWT, Neural Network and SVM

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Abstract: Face recognition plays a key role in secure authentication of an individual's identity. The features of face can be diverse in nature and cannot be manipulated by single spoofing technique. The benefits of face recognition can thus only be entertained if the algorithms at backend can accurately recognize a face. Till this extent, many of algorithms and combination of algorithms results 90% accuracy in standard conditions. In this research, a comparative study of available algorithms and combination of algorithms is presented to understand the most suitable approach for face recognition. Though face recognition is a supplement study of face detection, the paper only concentrates on later part.

Keywords: Face recognition, face detection.

1. INTRODUCTION

Automatic Face Recognition is a central topic in research on the analysis of faces. The number of possible applications means that it has of importance for several years. Researching in the field of face recognition is probably motivated by the multiplicity of fields of application (high security, remote monitoring and controlaccess. Work in this field, under different lighting conditions, facial expressions and orientations, can be classified into two distinct categories, depending on whether they relate to a geometric approach or a global approach. An automatic face recognition system is divided into three subsystems: face detection, feature extraction and face recognition. The implementation of an automatic and reliable facial recognition system is a technological lock that is still unresolved. Automatic face recognition using 2D images has been carefully studied in recent decades.

A short description of the state of the art for the single samples (only one training specimen per person) is given below, followed by a state of the art of solving the problem of facial recognition from a single image. The advantages of a system able to solve this problem are (1) The ease of collect a training set because a simple picture per person; (2) An economy of memory for storing the database; (3) A saving of learning time can take place since there is only one image per person to consider [1]. Interest and of such a system is therefore quite noticeable whether it is for a system of pursuit of suspect through a network of cameras or for identity verification.

There are various approaches for face recognition, it can classified as [1] three categories Holistic methods [1], local methods [1] and hybrid methods [1].

In holistic Methods input is considered as the complete image in the form of a level vector of grey to decide an identity. It consider the projection methods which take as input a vector constituted by concatenation of the lines of the image. Among these methods, the principal component analysis (PCA) [2-3] and the linear discriminant analysis of Fisher (FLDA) [4-5]. The limitations of these methods come from their sensitivity to the variations of expression and illumination because they consider each face as a combination of basic vectors called "Eigen Face" or "Fisher Face ". Nevertheless, recent developments in the pass over this problem and present correct results. Among these works (PC) 2A [6] followed by its generalization E (PC) 2A [6]; and the 2DPCA [7-8]. Still in the field of holistic methods, strategies consist in widening to overcome its deficiencies.

Local methods divided into two sub-categories based respectively on and local appearances. Here, geometric properties are extracted from the localization of key points on the face. Two weaknesses follow directly: on the one hand the location of such points is not always a thin area when occlusions or variations Position or expression, and all the necessary information? A robust recognition is not necessarily contained in these few key points, and a lot of information passes to the trap when the image is compressed to Information contained in a few places. The DCP method of Gao et. al. [9] which, applied to the problem of facial recognition of persons which shout, presents a fall of performance of nearly 60% [9]. One can note among these methods based on the local characteristics the developments of Gao et. al. [9] mentioned above and EBGM [10, 11]. From the necessary step of the key points, the latter technique fails to be able to request more computing time for its execution than the PCA. Here, there are several vectors corresponding to the characteristics of the face which are used as input. These methods are a priori better pruned for the problem of the unique sample. Firstly, because a set of several small-dimensional vectors instead of one of large size allows the start of tackling the (curse of dimensionality).

Wavelet analysis allows multi-level resolution analysis [12] and transforms local features from time domain to frequency domain. The window size of DWT is generally fixed but it can be updated with requirement. The multi-level resolution allows analysis of low and high frequency components with high resolution in single frame of time. The frequency components are initially referred as mother wavelets and with each iteration, the mother wavelet is bisected into two daughter wavelets [13] [14]. The Euclidian distance is computed for each face image and test images are matched with it.

Hybrid Methods as their name suggests, these approaches combine holistic and Local authorities. The idea is to combine them in a way to use the advantages of one to counterbalance the defects of the other. The effective combination of local characteristics for the time being is a problem and little work on its application to the problem of facial recognition exist [15-19].

The algorithms like PCA, ICA and DWT derives features out of face image and in second stage use a matching formula based on extracted features [20-21]. Generally these formulas are the standard mathematical tools for static comparison of test and dataset image. The advance algorithms like Neural Network (NN) [21-22] generates the output based on training of classification method and serves better in complicated scenarios where large No. of test images are subjected to recognition. Another method Support Vector Machines (SVM) is a binary classification technique [23] to solve K class problems, where K is the count of known individuals. Jonathan Phillips formulated the problem of face recognition in terms of difference space to identify the dissimilarities among two applications. The author modified the decision interpretation of SVM, two classes of face are recognized as same or different peopleand furthermore talk about in recent times created various hybrid algorithmic methodologies for the face recognition schemes taking into account the various arrangements (i.e. combining more than one) of these individual prototypes [23], and this paper inspires with similar multi-algorithmic methodology for the face recognition frameworks in view of the various arrangements yet in group of four of these individual methodologies. The objective is to discover which hybrid method performs better regarding face recognition rate.

This paper is organized as follows. In section 2, we discuss in brief about the pre-processing involves in face recognition systems. In section 3, we discuss in brief about different approaches for features extraction and its impact on training for machine learning. In section 4, we discuss the different classifier for face recognition system. In section 5,combination of different methods for the face recognition has been developed. In section 6, It deals with analyse of the experimental set up and its outcome.

2. PRE-PROCESSING

The initial phase of pre-processing is transform RGB images to grayscale. Also, the facial image is cropped with a specific end goal to eliminate background pixels that simply add noise to the recognition procedure. At last, the image will change over to binary image.

For some utilization of image processing, colour description doesn't help us distinguish imperative edges or different components. In any case, there's a special cases on the off chance that we have to distinguish object of known hue. In the event that we need not bother with colour, then it can considered as noise. The consequence of this stage is no colour in the image yet just degrees of grey [24].

3. FEATURE–EXTRACTION

A. Discreet Wavelet Transform

The wavelet transform is used to decompose low frequency images so as to differentiate high frequency components, in view of its capacity to catch particular transformed information of extracted image.

The arrangement of the data into multi resolution frequency permits to confine the frequency segments acquainted by intrinsic values due with expression or extraneous components (i.e. light) into several sub bands. This techniques cut away these different sub bands, and spotlight on the sub bands which contain the most applicable data [25].

The filtration and recognition using ICA and PCA are required but due to performance drop in case of occlusion, illumination, pose, expression etc. [26] the discreet wavelet transform is used. DWT employees Fourier transform to convert time domain image into frequency domain. The mathematical expression of DWT is given by:

$$\mathrm{DWT}_{x(n)} = \begin{cases} dd_{j,k} = \sum img(n) hh_s^*(n - 2^s r) \\ dp_{j,k} = \sum img(n) ll_s^*(n - 2^s r) \end{cases} \tag{1}$$

where, $dd_{j,k}$ represents detailed coefficients and $ap_{j,k}$ are the approximate coefficients of DWT transform. Functions $hh(n)$ and $ll(n)$ are high and low pass filter respectively. Parameters s and r are wavelet scale and translation factors respectively. Figure 1 is the flow demonstrative representation of 3-Level DWT.

Prior studies reasoned that low frequency data perform a leading part in face recognition. The relationship between varieties in facial appearance and their distortion rangeshas examined by[27]. It is observed that outward obstructions influence the intensity complex in the neighbourhood. Based on frequency representation, just high-frequency range is influenced, is high-frequency occurrence. In addition, changes in stance or size of a face influence the power complex all around, in which just their low-frequency range islow-frequency occurrence. Just an adjustment in face will influence all frequency segments. Along these lines, through observing the Figure 1, a few qualities can be exhibited that:

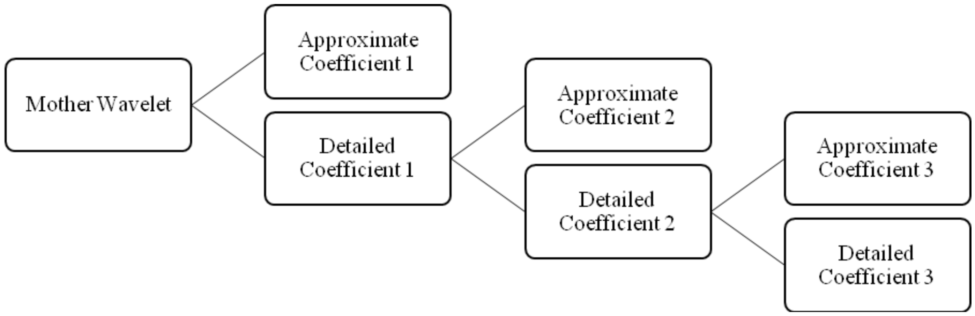


Figure 1: 3-Level DWT to cascade image into various frequencies

1. The impacts of various facial expressions overcome by expelling the high frequency segments.
2. The low-frequency segments are adequate for the face recognition purpose.

Hence in the accompanying, low-frequency sub band coefficients are mostly used for recognition to attenuate common contrast in the pictures of the same individual. In 2D-DWT, processed pictures remains the principle features for the first picture and lessen the measurements of information for feature extraction. In this paper, 112×92 pictures from ORL database are prepared by 1 level 2D-DWT, the determination of low-frequency segment are 63×53.

B. 2D PCA Algorithm

2D-DWT on an image probably give three favourable circumstances; dimensionality reduction, for less computational difficulty; insensitive feature extraction and multi-resolution data approximation. Hence 2D-PCA provides a proper feature extraction with lesser computational difficulty.

Conversion of 2D face matrices to 1D image vectors is necessary in tradition PCA based face recognition. In high-dimensional image vector space covariance matrix can't be precisely Figure out. Dissimilar to traditional PCA, the 2D-PCA depends on 2D matrices. Subsequently, 2D-PCA has two essential points of interest over PCA. To start with, it's less demanding to assess the covariance matrix precisely and faster time approach to decide the relating eigenvectors.

IMG is a arbitrary image with size of $m \times n$ matrix, Let $K \in R^{n \times d}$ be a matrix, where all columns are orthonormal, $n \geq d$. Anticipating IMG onto K yields $m \times d$ matrix.

Z = IMG.K. In 2D-PCA, the total frame of the anticipated elements was utilized to decide a decent estimated matrix K. The accompanying rule is received:

$$G(K) = \text{trace}[E\{Z - EZ\}\{Z - EZ\}^T]$$

$$G(K) = \text{trace}[E\{IMG.K - E(IMG.K)\}\{IMG.K - E(IMG.K)\}^T]$$

$$= \text{trace}[K^T E\{IMG - E.IMG)^T(IMG - E.IMG)\}K] \quad (2)$$

From equation 2 it can be concluded sum of product can be interchanged and it will same for any two matrices. Hence trace (PQ) = trace(QP).

Characterize the image covariance matrix $C = E[(IMG - EIMG)^T(IMG - EIMG)]$, which is square matrix.

Consider L training images, with size of $m \times n$ matrices. $IMG_K(K = 1, 2, ..., L)$. The average image is represented by

$$\overline{IMG} = 1/L \sum_k IMG_k .$$

Then C is:

$$C = 1/L \sum_{K=1}^{L} (IMG_k - \overline{IMG})^T (IMG_k - \overline{IMG}) \tag{3}$$

Extraction of orthonormal eigen vectors $X_1, ..., X_d$ from C, can be written as, $X_{opt} = [X_1, ..., X_d]$. where, d is considered with threshold estimation as,

$$\sum_{i=1}^{d} \lambda_i \Big/ \sum_{i=1}^{n} \lambda_i \geq \theta \tag{4}$$

where, $\lambda_1, \lambda_2, ..., \lambda_d$ is the sorted highest eigenvalues of C. Where threshold θ ranges as $q \geq 0.9$ usually.

For a given image sample IMG, let,

$$Y_k = IMGX_k, k = 1, 2, ..., d \tag{5}$$

$Y_1, Y_2, ..., Y_d$, are the principal component (vectors) of the sample image IMG and considered as projected vectors. Further $m \times d$ sized $B = [Y_1, Y_2, ..., Y_d]$, matrix is created, which is known as feature image of sample IMG, named as Eigen face. Figure 2. Represents Eigen faces of ORL face database.

Figure 2: Sorted Eigen faces with maximum eigenvalues

C. Independent Component Analysis

Principle component analysis is the primary approach for feature extraction. Though it is not wholesome method to obtain adequate results but an efficient initial step that provides a baseline for second and third level extraction. The face images under are first resized to say 256×256 pixels and images are converted to grey image from RGB image. The approach to create Eigen faces is as follows:

(i) Let's say the grey image is $n \times n$ pixels. The two dimensional image Γ_x is transformed to single dimensional vector as

$$\Gamma_x = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \tag{6}$$

(ii) An average is carried out from all the database images

$$\Psi = \frac{\sum_{x=1}^{n} \Gamma_x}{M} \tag{7}$$

where, M is the count of total face images

(iii) The center of mean is than calculated as

$$\phi_x = \Gamma_x - \Psi \tag{8}$$

(iv) Ψ mean centered is represented in a matrix say J. the convergence of J will be

$$C = J^T . J \tag{9}$$

(v) The Eigen vector $V = [v_1, v_2, ..., v_N]$ is a matrix of mean centered images [28] of dimension $n \times n$, then the eigen face space U is given by:

$$U = V . J^T \tag{10}$$

(vi) The row vectors in matrix U are the Eigen face images. In case if the system is designed for low computational cost, the eigen values can be arranged in decreasing order and matrix formed from it is the feature vectors

$$W = w_1, w_2, ..., w_n$$

$$W = U . J \tag{11}$$

Whitening

PCA generated feature vectors are global and non-zeroelements. To convert the vector into a spatially localized feature vector, the commonly used method is ICA. ICA also minimizes the second and higher order dependencies from input. The pre-processing of PCA creates $m \times m$ subspaces [15].

Say R is a matrix of m Eigen vectors m of n face images. If p is number of pixels per image, the ICA will be evaluated on R^T. The m distinguee images of row vector U is:

$$U = W \times R^T \tag{12}$$

$$R^T = W^{-1} \times U \tag{13}$$

Therefore, if L is the matrix of PCA coefficients

$$J = (L \times W^{-1}) \times U = D \times U \tag{14}$$

All rows of D have coefficients that linearly combine basis images to obtain a complete face image according to J.

D. Feature Vector

The feature vector is formed using features of DWT, PCA and ICA from Equation (1), Equation (5) and Equation (14) respectively.

$$FV = \{dd_{j,k}, Y_k \text{ and } J\} \tag{15}$$

This feature vector is further classified using Neural Network and SVM classifiers.

4. CLASSIFICATION

A. Database Training using Neural Network

The recognition of face image involves training of system against the given dataset using a classifier. The Neural network classifier is the mimic of human neural network. The features of training images are given as input with predefined output. The feed forward NN through supervised learning reduces the overhead communication and enhances the accuracy of output. At the output layer computation through a sigmoid transfer function is followed that finally generates the output.

The steps of neural network approach are:

Network Creation → Network Configuration → Training of Network → Simulation of database

Neurons: Neurons are the statistical model that consists adaptive weights tuned by learning algorithm and approximates non-linear functions of inputs.

The N parallel inputs receives sufficient arguments from teaching input to generate required output. The firing rules decides to hold or fire the input in case if input pattern behaves distinct to predefined pattern list.

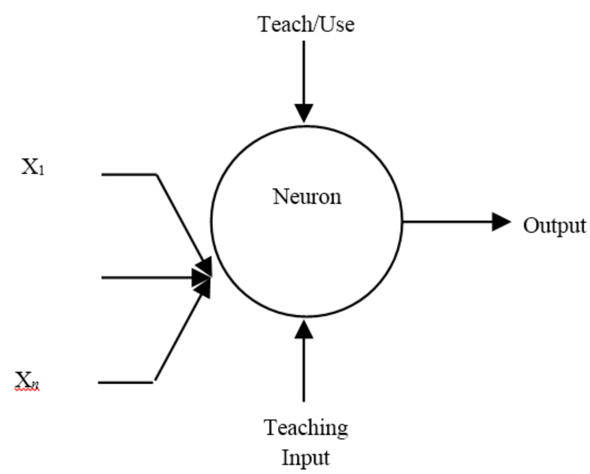


Figure 3: Simple Neuron

Layers: Neural network is a pattern of interconnection nodes with 'activation function'. The pattern is fed at input and communicated to various hidden layers and to output.

Algorithm for Neural Network: The back-propagation algorithm is as follows:

Perform initialization of neural network weights

Do

Let us consider number of images is I in the training from database X.

loop

for

X = neural-network-output (network, i);

Where I is the each images in database.

T = desired output for i

Error=T-X

update the weights till error is minimized in the network; ***until*** *some stopping criterion satisfied*

return *the network*

B. Database Training using SVM

Support Vector Machine is another classifier approach for training and testing. SVM finds the best hyper-plane for separation of both classes. SVM divides whole database in two parts and each part have unlabelled signals as relevant and irrelevant.

Optimal hyper-plane can be precisely calculated using:

$$w = \sum_i a_i x_i \tag{16}$$

Here, the patterns near the line of margin are summed as w. From the feature vectors x_i and class labels y_i an index pair $\{(x_i, y_i)\}$ is generated where $x_i \in$ R and $y_i \in \{+1, -1\}$. Let's say x_i belongs to first class and y_i belongs to second. The hyperplane to separate training data will take the form:

$$f(x) = w_x + b \tag{17}$$

Here, $w_i \in$ R and $b \in$ R are normal vector and scalar basis respectively. For high dimensional realization, kernel functions are used respectively. Among these the RBF Kernel function is widely used:

$$K(x_i, x) = \exp[-\gamma \|x = x_i\|^2] \tag{18}$$

5. EXPERIMENTAL SETUP

In this research work, for a given arrangement of training face images, 2-D wavelet transform gives feature vectors of faces from LL subband. Further this dimensionally reduce image data is processed with 2-D PCA, and extracted feature is stored in database. There are various frame of feature extraction carried out by 2D PCA and ICA. Further it is classified with Neural Network and SVM.

The paper compares two approaches of face recognition. First the image is filtered using PCA, ICA and DWT and then classified with both classifiers separately for comparison.

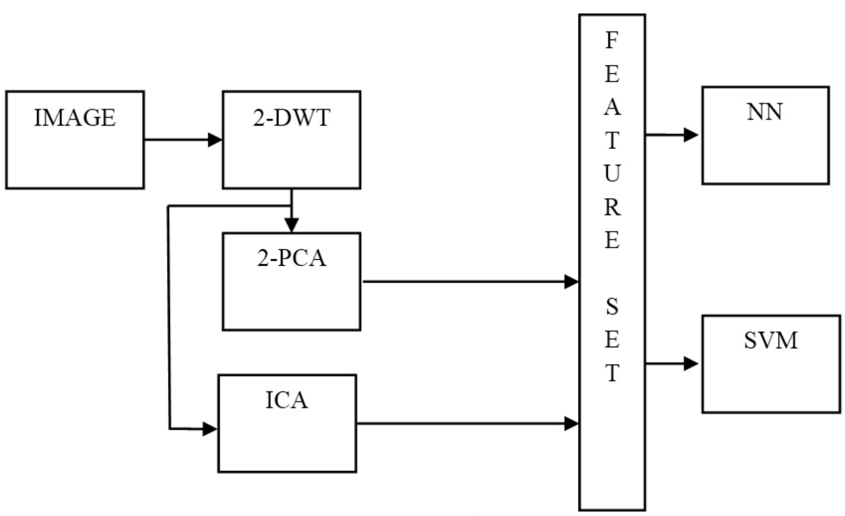


Figure 4: Block Diagram of System Model

The system is simulated on MATLAB 2010(a). The training database is the ORL database of 400 images from 40 persons having 10 sets each. For training, 6 out of 10 sets are chosen randomly. The experiments were done incrementally i.e. with 40, 80, 120 and 160 images. The results are compared with the work of Gumus [15] where, SVM is configured for face recognition in different Kernel Functions.

6. RESULTS AND ANALYSIS

Performance of proposed research work is carried out using:

$$\text{Accuracy} = \frac{\text{TP} +}{\text{P} +} \tag{19}$$

where, TP = True Positives

TN = True Negatives

P + N = Total population.

7. RESULTS

The ORL database is comprised both man and woman. The feature vectors of PCA were extracted and fed to ICA for whitening and transform global features to spatially local features. The images are further processed with 4 level wavelet transform and all these features were trained with neural network. In a parallel test, the features from PCA, ICA and DWT were trained by SVM. The comparative results of both the experiments is summarized in table.

Figure 5: Test images for ORL database [31]

Table 1
Recognition rates according to training set

Technique	*1/160*	*2/160*	*3/160*	*4/160*	*5/160*	*6/160*
DWT-SVM (RBF) [15]	69.4	89	95.3	96.2	96.5	97.5
PCA-SVM (RBF) [15]	55.2	75.3	84.2	86.8	89.5	91.2
DWT-PCA-ICA-SVM	56.3	78.7	85.6	88.7	89.6	89.90
DWT-NN	70.3	81.4	87.4	91.6	92.7	93.3
PCA-NN	68.4	78.8	85.7	90.1	92.5	91.9
DWT-PCA-ICA-NN	85.7	90.1	96.4	97.14	97.17	98.44

The table presents the recognition rates of face images in training set. When only 1 image was selected, the recognition rate was quite low i.e. 69.4%. However, with increase in training sets, the recognition rates of system improved. The proposed one with hybrid of DWT-PCA ICA-NN gives approximately 85.7 % accuracy when single image has been considered.

Table 2
Recognition rate of ORL Database

Eigenface [29]	*SOM + CN [29]*	*WT + SVM [30]*	*WT+SVM [15]*	*This study using NN*	*This study using SVM*
81.8%	88.2%	94.8%	95.3%	96%	90%

Comparing with the previous studies, SVM gives promising output for face recognition. In fact, the wavelet-SVM is providing better results than PCA-ICA-DWT SVM. But the overall performance of SVM when compared with Neural Network, the NN provides much higher recognition rate than SVM. Neural network provides 96% recognition rate (Table 2) as compared to 90% of proposed SVM or previous works of wavelet SVM. Hence the overall performance of proposed system outperforms existing results

Test Case 1: First test case includes 160 images from Indian women dataset with front and tilt faces. Indian dataset comprises11 different images of each of 40 separate subjects. For some subjects, some extra photos are incorporated. The database are in JPEG format and with size of 640×480 pixels per image, with 256 grey levels per pixel.Test images and recognition outputs for some images are given below:

Figure 6: Test images for Testcase-1 [32]

Table 3
Result for Testcase-1

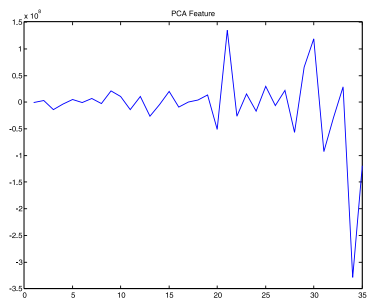
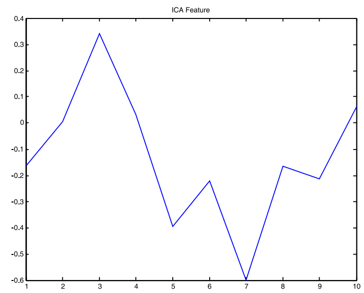
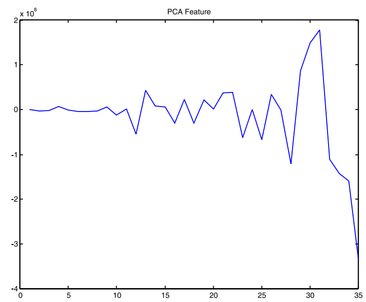
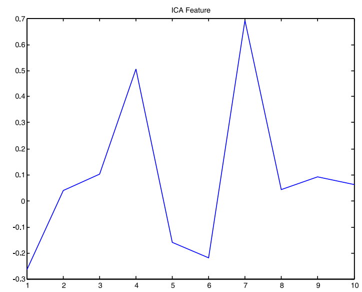
Query Image	*Principle Components*	*Independent Components*	*Recognized Image*
			
			

Table 4
Recognition rates according to training set

Technique	*1/160*	*2/160*	*3/160*	*4/160*	*5/160*	*6/160*
DWT-PCA-ICA-SVM	45.1	71.7	84.3	89.6	90.6	92.12
DWT-NN	56	76.8	89.7	92.6	95.5	96.3
PCA-NN	52.4	72.9	88.3	92.1	93.5	97.9
DWT-PCA-ICA-NN	68.9	79.3	92.3	94.5	96.17	98.78

The table presents the recognition rates of face images in training set. When only 1 image was selected, the recognition rate was quite low i.e. 45.1 %. However, with increase in training sets, the recognition rates of system improved. The proposed one with hybrid of DWT-PCA ICA-NN gives approximately 68.9 % accuracy when single image has been considered.

Table 5
Recognition rate of Indian female Database using 6 images as training

This study using NN	*This study using SVM*
98.78%	92.12%

Comparing with the previous studies, SVM gives promising output for face recognition. In fact, the wavelet-SVM is providing better results than PCA-ICA-DWT SVM. But the overall performance of SVM when compared with Neural Network, the NN provides much higher recognition rate than SVM. Neural network provides 98.78% recognition rate (Table 5) as compared to 92.12% of proposed SVM or previous works of wavelet SVM. Hence the overall performance of proposed system outperforms existing results.

Test Case 2: Second test case includes 40 images from Indian Man dataset with front and tilt faces. Test images and recognition outputs for some images are given below.

Figure 7: Test images for Testcase-2 [32]

Table 6
Result for Testcase-2

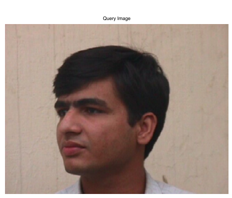
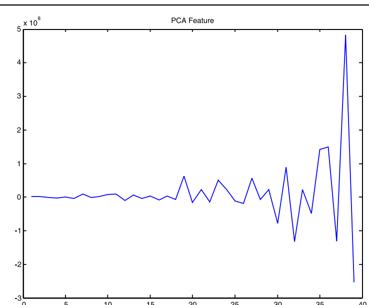
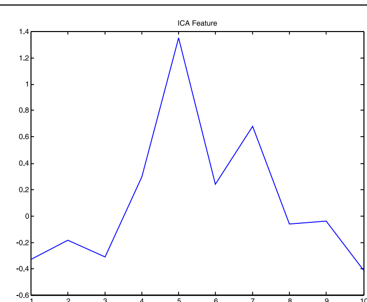
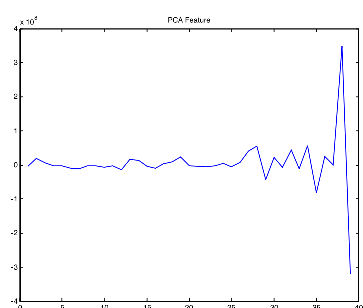
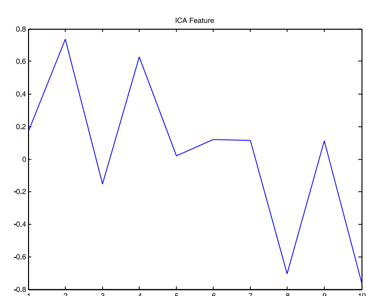
Query Image	*Principle Components*	*Independent Components*	*Recognized Image*
			
			

Table 7
Recognition rates according to training set

Technique	*1/160*	*2/160*	*3/160*	*4/160*	*5/160*	*6/160*
DWT-PCA-ICA-SVM	47.4	67.9	74.3	85.6	90.6	92.6
DWT-NN	62.4	68.9	78.9	89.6	93.5	94.7
PCA-NN	59.4	64.5	77.5	87.1	91.6	93.9
DWT-PCA-ICA-NN	63.4	69.7	79.9	92.5	94.07	95.9

The table presents the recognition rates of face images in training set. When only 1 image was selected, the recognition rate was quite low i.e. 47.4 %. However, with increase in training sets, the recognition rates of system improved. The proposed one with hybrid of DWT-PCA ICA-NN gives approximately 63.4 % accuracy when single image has been considered.

Table 8
Recognition rate of Indian female Database using 6 images as training

This study using NN	*This study using SVM*
95.9%	92.6%

Comparing with the previous studies, SVM gives promising output for face recognition. In fact, the wavelet-SVM is providing better results than PCA-ICA-DWT SVM. But the overall performance of SVM when compared with Neural Network, the NN provides much higher recognition rate than SVM. Neural network provides 95.9% recognition rate (Table 8) as compared to 92.6% of proposed SVM or previous works of wavelet SVM. Hence the overall performance of proposed system outperforms existing results.

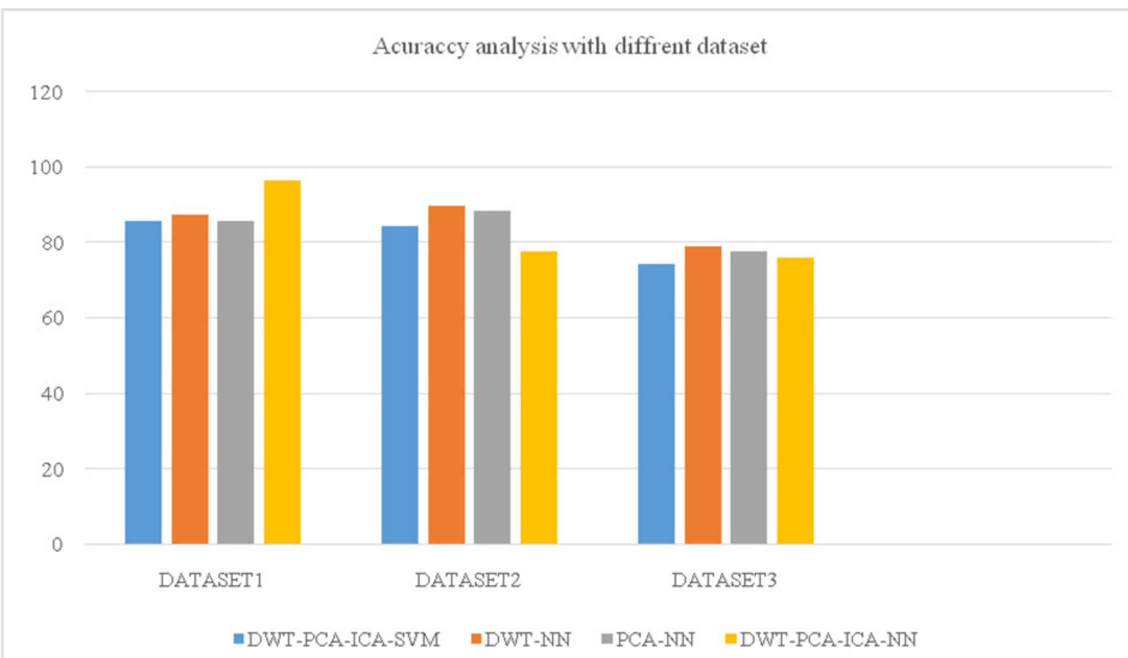


Figure 8: Accuracy estimation with change in datasets

The Figure elaborates the accuracy estimation with change in the dataset. Where 3 images are taken as training data for each class.Dataset 1 represents ORL dataset andDWT_PCA_ICA_NN gives better accuracy then compare to others. Dataset 2 represent the Indian female dataset, where DWT-NN outperforms then other methods. Dataset3 represents the Indian male dataset, where all the hybrid methods yield nearly similar results in terms of accuracy.

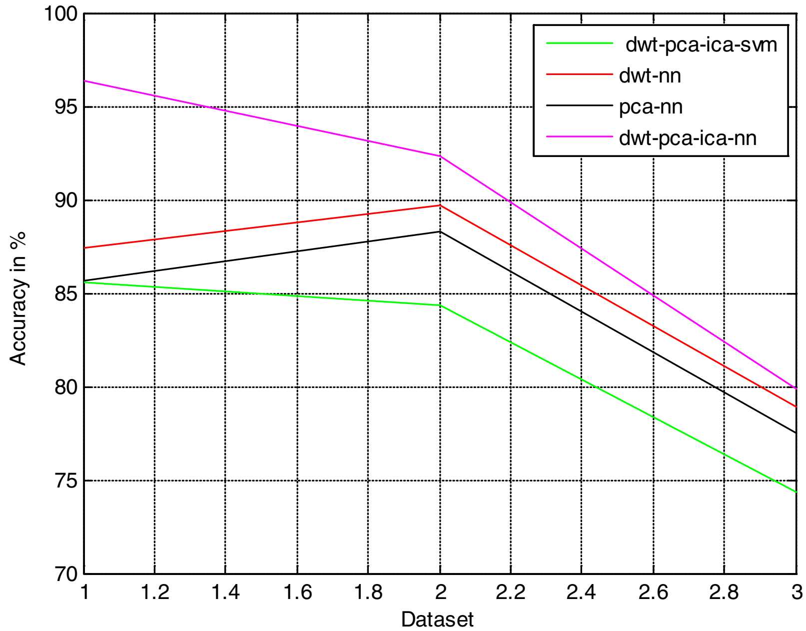


Figure 9: Comparison of accuracy among Hybrid methods

The above Figure shows the dataset vs. accuracy with different dataset (ORL, Indian dataset female and Indian dataset male) [31]. The above comparative graph shows stiff changes in accuracy when dataset has been changed. DWT_PCA_ICA_NN yields better results in all dataset compare to other hybrid method respectively.

8. CONCLUSION

In this paper, two methods of classifiers are compared to face recognition. The feature extraction is processed through 3 stages i.e. of PCA, ICA and DWT. The PCA resulted in second stage global features while ICA modified those features and provided local spatially reduced features. For fine analysis, the DWT was employed further to ICA for feature extraction and the final set of features were classified for face recognition. In recognition, two experiments are parallely conducted; one for SVM and other for Neural Network. The results were compared with the existing works where PCA, SVM-WT and other methods are compared for better analysis of proposed system. The system did not performed optimally with SVM even with higher feature extraction methods were involved. In opposite to it, neural network performed exceptionally well and gave recognition rates up to 96%. In future, the capacity of system to increase recognition rates according to pose can be optimized as in the current system, the optimal performance can only be obtained by using 6 sets of image as training database. In future experiments, fuzzy logic shall be used to overcome this limitation.

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