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Multiresolution and Varying Expressions Analysis of Face Images for Recognition

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Abstract: This study demonstrates a lower dimension multiresolution and facial expression analysis of facial images using wavelet transform and image decimation algorithm. It minimizes heavy computational load, reduce noise, produce a representation in low frequency domain and hence make the facial images less sensitive to facial expressions and small occlusions. An improved recognition rate is achieved through effective image pre processing and novel feature extraction technique. Within class varying facial expressions effects have been minimized by using image decimation. Novel feature extraction methodology has been used to extract the most suitable feature vectors required for recognition. Experiments on ORL, YALE, FERET and EME color datasets have been performed with success rate up to 99.25%. Model has been also tested on CMU AMP face expression and dataset to evaluate the ability of wavelets and decimation algorithm for varying expression compensation. Hundred percent recognition rate on this dataset is achieved.

Key words: Image processing, biometrics, facial expressions face recognition, image decimation, wavelets, morphological operations

INTRODUCTION

Unlike human beings who have the excellent capability to recognize different faces, machines are still lacking this aptitude due to variation in image illuminations, complex backgrounds, visual angles and facial expressions. Therefore face recognition has become a complex and challenging task. A number of automatic and semi automatic strategies and techniques like Hidden Markov Model (Bicego *et al*., 2003), PCA (Turk and Pentland, 1991), LDA (Zhao *et al*., 1998), ICA (Comon, 1994), NMF (Lee and Seung, 1999) and Elastic Bunch (Wiskott *et al*., 1997) have proven difficult and fragile in nature to extend to multiple views, especially varying facial expressions and resolution of images. Face recognition is a high level visual task for which it has been extremely difficult to construct detailed neuropsychological and psychophysical models. This is because faces are complex natural stimuli that differ dramatically from the artificially constructed data often used in both human and computer vision research. The subject has become a major issue, mainly due to the important real-world applications of face recognition like smart surveillance, secure access, telecommunication, digital libraries and medicines. The details of these applications are referred to in the surveys (Chellappa *et al*., 1995; Pentland, 2000; Samal and Iyengar, 1992). Face recognition techniques have been divided into feature-based approach (Hotta *et al*., 2000; Hsu and Jain, 2001; Zhu *et al*., 2003) the appearance-based approach (Belhumeur *et al*., 1997; Chung *et al*., 1999; Moghaddam *et al*., 2000) and the hybrid approach (Edwards *et al*., 1998). In feature-based approach, many methods have been presented for robust feature point extraction from face images. For example, attention points are selected as the feature points through the analysis of output of the Gabor filtered images. Points of maximum curvature or inflection points of the shape of the image function have been used as the face feature points. In the appearance-based face recognition, the eigenface approach has been very popular in the past decade. In hybrid approach, face recognition is achieved using a face model consisting of face shape as well as image intensity information. For example, an Active Appearance Model (AAM), which is a statistical model of shape and grey-level appearance, was proposed to model face images. In (Ginsburg, 1978) it is found that information in lower frequency bands have a dominant role in face recognition as low-frequency components contribute to the global description, while the high-frequency components contribute to the finer details.

Over the last decade wavelets have become powerful and flexible tools for image multi resolution analysis, data redundancy and computation. These properties of

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wavelets along with image decimation have been exploited to obtain the best image resolution for optimum recognition.

RELATED WORK AND MOTIVATION

Some of the previous techniques have achieved successes in constrained scenarios; the general task of face recognition still poses a number of challenges with respect to the changes in resolution, illumination, facial expression and pose. Therefore currently researchers pay more attention to the study of the robustness against the changes in pose, illumination, expression and resolution of face images.

Wavelet transform techniques are not too old and are being used in modern signal and image processing including multiresolution analysis, sound synthesis, computer vision, graphics and image compression (Averbuch *et al*., 1996). Wavelet transform techniques achieve optimal decomposition without affecting much the image quality. At the same time wavelet transform and wavelet packet analysis have provided a new subspace for image recognition. Fotlyniewiez (1996) proposed an automatic face recognition using nonlinear filtering to enhance intrinsic features of face and used a high order neural network classifier for training and recognition of faces. (Lee *et al*., 2000) employed the wavelet-based Fisher Linear Discriminant (FLD) recognition process. Zhu *et al*. (2003) captured local discriminative features in the space frequency domain for face detection using wavelet packet analysis. Ma and Xiaoou (2001) used discrete wavelet face graph matching approach for the purpose. Liu and Wechsler (2001) used Haar wavelet for effective human face detection. Yang *et al*. (2002) is an application of nonlinear wavelet approximation to recognize faces and the advantages of nonlinear wavelet approximation are compared with its linear counterpart. Wiskott *et al*. (1997) used labeled graph based on Gabor wavelet transform for face recognition application.

In this study first inter and within wavelet transform family behavior to face recognition is carried out and latter on image decimation is incorporated to workout the effects of image resolution on recognition.

PREPROCESSING

Gray scale conversion and uniform image background: Color images being in three planes of Hue, Saturation and Value are computationally very extensive. To avoid color images handling they are converted to gray scale images by using expression:-

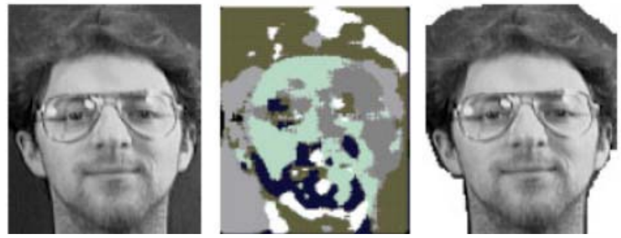

Fig. 1: (From left to right) original, segmentation and final result

$$Y = 0.3R + 0.59G + 0.11B \quad (1)$$

The weights are used to compute gray image because for equal amount of color eye is most sensitive to green, red and then blue (Gonzalez and Woods, 1992; Wyszecki and Stiles, 1982).

Varying background of images contribute in failure rate of pattern recognition techniques. To minimize its influence it is made uniform through image segmentation. Eight bit gray scale images are converted into three bit to reduce the gray scale variation within background regions and later on Median filter of size n = 5 is applied on the image. Median filter forces points with distinct gray levels to be more like their neighbors. Isolated clusters of pixels that are light or dark with respect to their neighbors and whose area is less than $n^2/2$ are also forced to median intensity. Later on image background with low range gray scale values is addressed on region based approach and changed in to single value in corresponding original image to make it uniform through out the dataset (Fig. 1).

Image Scale Normalization Algorithm (ISNA): Scale normalization has been handled through different methods which include stretching algorithm (Beymer, 1994; Reisfeld *et al*., 1994) where locations of several feature points like eyes, nose, or mouth are used. In this paper a new method to extricate the facial part from rest of image is used where first face image is smoothed by Gaussian convolution (Canny, 1986). For smoothing process value of scaling parameter sigma is taken four.

$$X(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}} \quad (2)$$

Then a simple 2-D first derivative operator is applied on smoothed image to highlight regions of the image with high first spatial derivatives. Edges give rise to ridges in the gradient magnitude image. The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top so as to give a thin

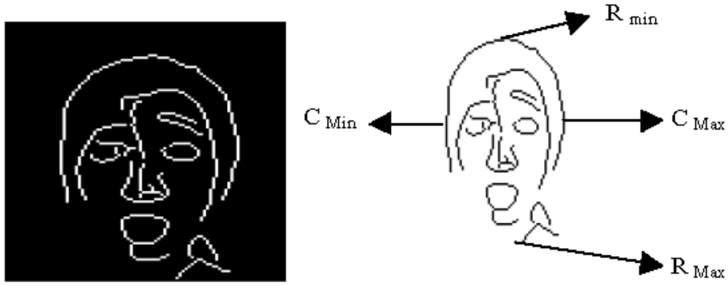

Fig. 2a: Result of Canny Operator (left) Four outer points of face (right)

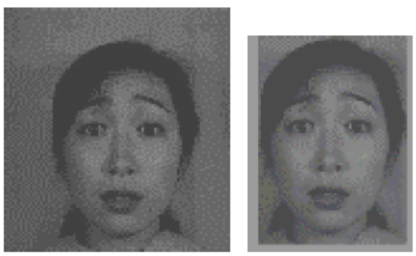

Fig. 2b: Original image and result of ISNA

line in the output, a process known as non-maximal suppression. The tracking process exhibits hysteresis controlled by two thresholds: hysteresis low = 0.2 and high = 0.85. This hysteresis helps in extracting the outer curvature of the face as shown in Fig. 2a.

Binary image obtained in result of this edge detection is scanned from left to right, top to bottom in a classic pattern and four points shown in Fig. 2a are worked out. The image scale normalization (ISN) using the values of Eq. 3 is carried out example is shown in Fig. 2b.

$$\text{ISN} = \text{value}\left(C_{max} - C_{min}\right), \text{value}\left(R_{max} - R_{min}\right) \tag{3}$$

Where C_{Max}, C_{Min}, R_{Max} and R_{min} are maximum and minimum values of column and row, respectively.

Facial tilt removal: Eyes in face image are pivot point in frontal images for tilt compensation, pixel values near eyes change more rapidly as compared to rest of face image. This property of image is used to detect the general eye location in the face image. Iris localization in the rough region of eye is carried out through template matching using normalized cross-correlation. Let g [i,j] is a template and its instances in an image f [i,j] is required to be detected. The match measure M then can be computed using:

$$C_{fg}[i,j] = \sum_{k=1}^{m}\sum_{l=1}^{n} g[k,l]\,f[i+k, j+l] \tag{4}$$

Fig. 3: Image with and without tilt

$$M[i,j] = \frac{C_{fg}[i,j]}{\left\{\sum_{k=1}^{m}\sum_{l=1}^{n} f^2[i+k, j+l]\right\}^{\frac{1}{2}}} \tag{5}$$

The local maxima in the above computation give the position of the iris centers. Let two points (xl,yl) and (xr,yr) be the center of right and the left eye, respectively. These are then used to compute the tilt (slope m and angle θ) in the image using:

$$m = (yr - yl) / (xr - xl) \tag{6}$$

$$\theta = \arctan(m) \tag{7}$$

Finally the tilt compensation is applied using the reverse rotation, i.e., rotating by $-\theta$ as shown Fig. 3.

MULTIRESOLUTION ANALYSIS AND DIMENSION REDUCTION THROUGH WAVELET

The DWT has been used for texture classification (Chang and Kuo, 1993) and image compression (Averbuch *et al.*, 1996) due to its multiresolution decomposition property. The wavelet decomposition technique was also used to extract the intrinsic features for face recognition (Foltyniewicz, 1996). In wavelets packet analysis both the high and low frequency filters are iterated but in wavelet transform, only the low pass filter is iterated where it is assumed that low frequency contents contribute more than the higher frequencies to represent information in face images. This assumption is most valid for face images where the interest lies in the low frequency components which are more suitable for recognition purposes.

Let a discrete signal I(x) be characterized by a trend signal (low frequency signals) and a fluctuating or detailed signal (high frequency signals). In wavelet multiresolution approximation (Mallat, 1989) a unique scaling factor ϕ (x) with compact support exist such that if we denote:

$$\phi_{2^j}(x) = 2^j\phi\left(2^j x\right) \text{for } j \in z \text{ the family of function: } \left(\sqrt{2^j\phi_{2^j}\left(x-2^{-j}n\right)}\right)_{n\in z}$$

is an orthonormal basis in $L^2(R)$. A discrete approximation of signal I(x) at resolution 2^j can be represented by

$$A_{2^j}{}^d I(x) = \left(< I(u), \phi_{2^j}\left(x-2^{-j}n\right) >\right) n \in z \tag{8}$$

which is equivalent to low pass filtering followed by uniform sampling at the rate of 2^j. In this proposed model five DWT of different families (Haar, Daubechies, Symlets, Coiflets and Biorthogonal) are applied on preprocessed face images for face recognition. One of the major advantages of wavelet transform is its lower computational complexity as Fast Fourier Transformation (FFT) has computational complexity of $O(n.\log_2(n))$ whereas in case of wavelet transform it goes down to O(n).

I. Matching algorithm

DWT of different familie decomposes face images into trend and fluctuation coefficients. The trend (low frequency) coefficients of face images reduce the noise and minimize varying facial expressions and provide global description of faces while the high-frequency components contribute to the finer details. In training of the model five images of each subject are used and feature matrix containing feature vectors of trend signals of these images is obtained.

$$X^i = \left[X_1^i \cdots\cdots X_N^i\right]^T \tag{9}$$

i = one to total number of images used for training of model

In matching process a dissimilarity space D (X_i, T) of test image with training images is obtained by using simple Euclidean distance. This dissimilarity space matrix is converted to a vector:

$$E = \left(\sum D\left(\|X_i\|, T\right)\right) \tag{10}$$

$$R = \arg\ \mathrm{Min}\left[E\right] \tag{11}$$

Where T is test image, X is training image and i is 1 to total subjects used in training of model and R is the recognized image.

DATASETS USED FOR EXPERIMENTS

Olivetti research laboratory face dataset: The ORL face dataset consists of 400 images collected from 40 people. Most of the subjects had 20-35 years. The face images were 92×112 pixels with 8-bit gray levels. They included variations in facial expression, luminance, scale and viewing angle and were shot at different time. Limited side movement and tilt of the head were tolerated. Some subjects are captured with and without glasses. These characteristics introduce difficulties to correct recognition and make the dataset particularly interesting. Few training and test images are shown in Fig. 4.

YALE dataset: The YALE database contains 165 gray scale images in GIF format of 15 individuals. There are 11 images per person one per different facial expression or configurations: center-light, with or without glasses, sad, happy, sleepy, surprise and wink. Examples are shown in Fig. 5.

EME color database: EME color dataset consists of 15 sets of color images (NUST, 2004) of different individual with 10 varying poses, sizes and illumination were taken at image processing lab of College of E and ME National University of Sciences and Technology Rawalpindi, Pakistan. These images were obtained with different facial expressions and occlusions (Fig. 6).

Feret database: The FERET database was collected as part of the Face Recognition Technology program to support algorithm development and evaluation. The main advantages of this database are the large number of individuals and rigid testing protocols that allow precise performance comparisons between different algorithms. All images are 256×384 pixels size. We have taken 10 images of 100 persons with total of 1000 images for our experiment. Figure 7 shows few examples.

CMU AMP face expression database: This dataset consists of 13 subjects with 75 images each. All images were collected under same lighting conditions and only facial expressions for each image were allowed to vary. This dataset provides adequate number of images with varying facial expressions for evaluation of affects of expression changes on recognition rate. Few examples of varying expression are shown in Fig. 8.

Fig. 4: Examples of ORL training images (upper row) test images (lower row)

Fig. 5: Examples of YALE training images (upper row) test images (lower row)

Fig. 6: Examples of EME color training images (upper row) test images (lower row)

Fig. 7: Examples of FERET training images (upper row) test images (lower row)

Fig. 8: Examples of CMU AMP face expression database

Table 1: Recognition results of daubechies and biorthogonal, family DWT on ORL and YALE datasets

Wavelet family	Recognition rate (%)		Wavelet family	Recognition rate (%)	
Daubechies	ORL dataset	YALE dataset	Biortho gonal	ORL dataset	YALE dataset
db1	96	93	Bior1.3	96.5	94
db2	96.5	93.5	Bior 2.2	96	93
db3	96	94	Bior 2.6	95	93.5
db4	97	92	Bior 3.9	94	93.5
db5	94	92.5	Bior 4.4	95.5	92
db6	94	94	Bior 5.5	93	93
db7	93	92	Bior 6.8	95	91

Table 2: Recognition results of symlets and coiflets family DWT on ORL and YALE datasets

Wavelet family	Recognition rate (%)		Wavelet family	Recognition rate (%)	
Symlets	ORL dataset	YALE dataset	Coiflets	ORL dataset	YALE dataset
sym1	96	94	Coif1	97	94
sym2	96.5	94	Coif 2	97	92
sym3	95	93	Coif 3	96	91
sym4	97.5	94.5	Coif 4	96	92
sym5	95	94	Coif 5	96	92
sym6	94	93			
sym7	94	93			

EXPERIMENT SET NUMBER 1

In first set of experiments DWT of different wavelet families have been applied on preprocessed images of ORL and YALE dataset, low frequency coefficients of five images of each class are retained as feature vector for classification. Rests of images of dataset are randomly used as test images. The results for different subfamilies of DWT obtained on ORL and YALE datasets are shown in Table1 and 2.

CHOICE OF WAVELET AND CO-EFFICIENTS

Results shown in Table 1 and 2 revealed that DWT symlets4 with decomposition level one provides best recognition results on preprocessed images. Symlets wavelet was proposed by Daubechies as modifications to

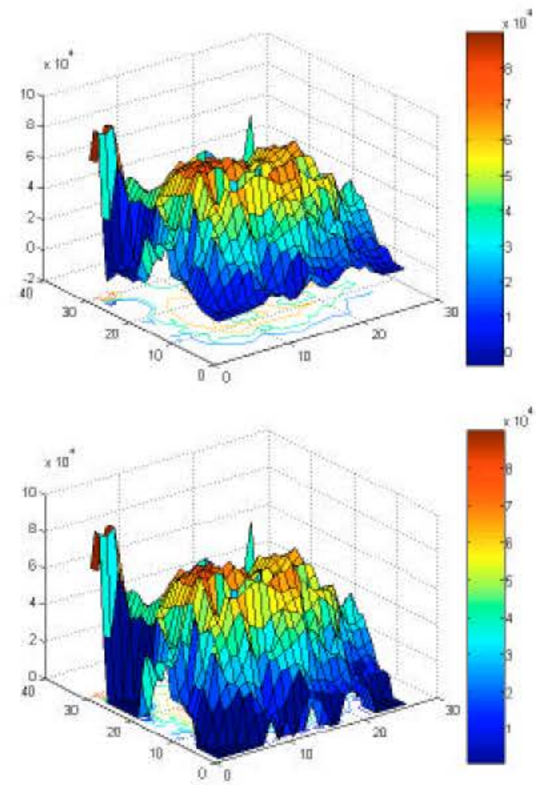

Fig. 9: Wavelet coefficients before applying threshold (left); after applying threshold (right)

the db family. The properties of the two wavelet families are mostly similar. Here the symmetrical, orthogonal and biorthogonal properties of symlets wavelet are exploited to obtain the low frequency image components which provide best image recognition. As not all the coefficients of a wavelet transform have the information needed for classification, the specific dataset threshold value was used to eliminate the less contributing low frequency co efficient. All such coefficients are made zero which helps in reducing overall computational burden plots in Fig. 9 reflects the effect of threshold on wavelet coefficients.

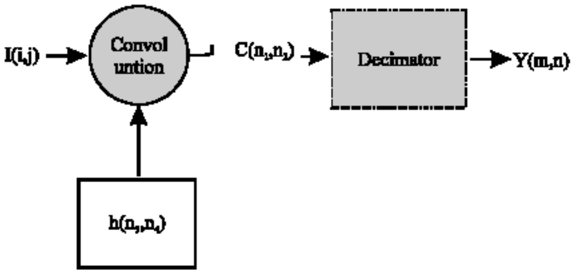

Fig. 10: Image decimation process

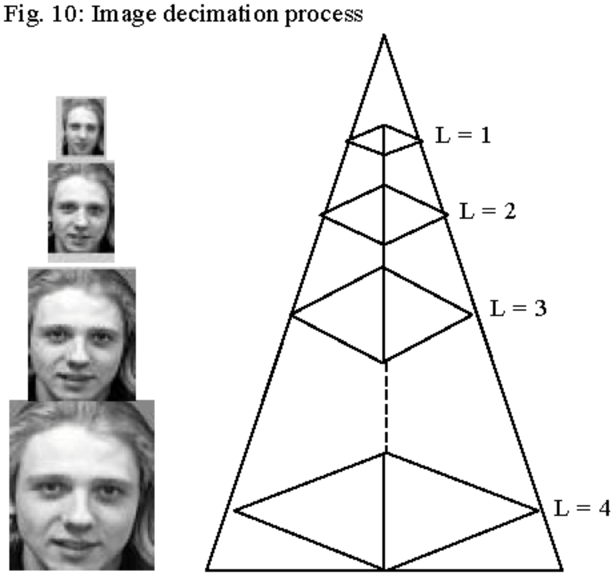

Fig. 11: Image gaussian pyramid

IMAGE DECIMATION

Decimation algorithm (Almas *et al.*, 2005) scans through lines of pixels or group of pixels according to decimation down scale factor (M). As a result Gaussian Pyramid of varying image resolution is obtained. Decimation process is shown in Fig. 10.

Here I(i,j) is input image, $h(n_3,n_4)$ is convolution averaging mask and $C(n_1,n_2)$ is convolved image without zero padding. Y(m,n) is the out put decimated image.

$$Y\ (m, n) = C\ [\ n_1M, n_2M] \tag{13}$$

where M is decimation down scale factor and

$$0 \le m \le (n_1/M),\ 0 \le n \le (n_2/M)$$

The resulting image is a reduced size mirror of the original image faithful in tonality to the original but smaller in size. By varying the values of decimation factor a Gaussian pyramid as shown in Fig. 11 is achieved.

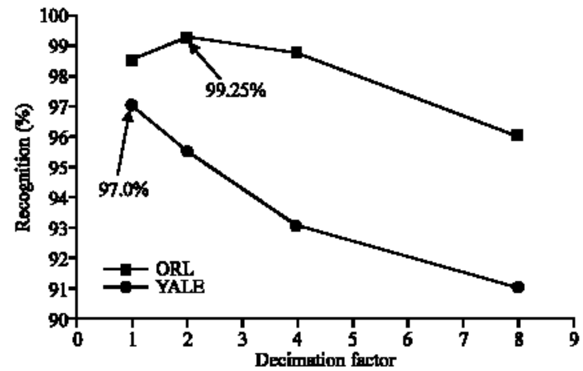

Fig. 12: Results of ORL and YALE database with varying resolution level

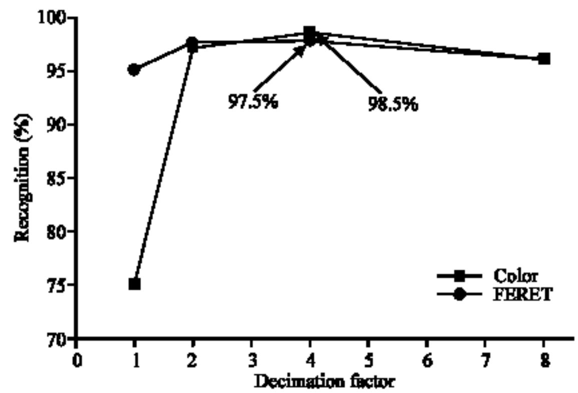

Fig. 13: Results of FERET and color database with varying decimation factor

EXPERIMENT SET NUMBER 2

In second set of experiment Symlet4 (level one) was applied on preprocessed decimated images, experiments on ORL, EME color, YALE and FERET datasets were carried out and it was established that each dataset at a specific resolution provides best recognition results. In all the tests five images of each individual were used for training purpose and rest of the images of complete database were used randomly for recognition. Results are shown in Fig. 12 and 13.

EXPERIMENT SET NUMBER 3

In experiment set number three CMUAMP Face expression dataset was used which has thirteen classes with 75 images in each class. The images were collected under same lighting conditions but with varying facial expressions. Results with varying image resolution and

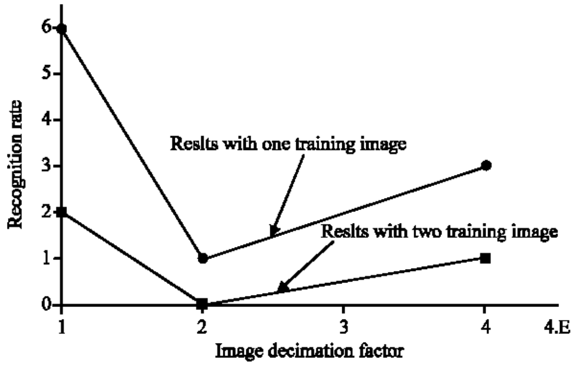

Fig. 14: Results of CMU AMP face expression dataset with varying decimation factor

number of training images shown in Fig. 14 reselects that low frequency components of facial images overcome the facial expression changes and improve the recognition rate.

DATASET SIZE AND RESOLUTION EFFECTS

The performance of face recognition algorithms usually degrades as more subjects are added to the database, due to the increasing probability of the presence of subjects with similar attributes. Image resolution also contributes towards recognition results because as image resolution is varied up to a certain level it compensates the changing facial expressions of same person in different scenarios which improve the success rate.

DISCUSSION AND CONCLUSION

In preprocessing phase, color images are converted to gray scale images and automatic scale normalization is carried out to enhance the computational speed of the system. Through image segmentation varying background is made uniform. Facial tilt is removed through reverse rotation. Inter and within family DWT response to image recognition was evaluated and Symlet4 DWT (level one) was applied on decimated images to obtain recognition results with varying resolution level. Results reflect that images with more high frequency components are more sensitive to resolution variation as compared to face images with lesser high frequency components. Moreover image decimation and DWT decomposition have minimized the facial expression variations and facial changes with in class. Wavelet based recognition technique is computationally less extensive as Discrete Fourier transformation (DFT) has computational complexity of $O(n.\log_2(n))$ and in case of wavelet transform it goes down to $O(n)$. This face recognition model provides recognition results up to 99.25% on images with various constraints like with or without glasses, sad, happy, sleepy, surprise, wink, open/closed eyes, smiling and non smiling faces on front page.

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