Research Journal of Applied Sciences, Engineering and Technology 8(18): 1973-1979, 2014
DOI:10.19026/rjaset.8.1189
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: August 22, 2014 Accepted: October 11, 2014 Published: November 15, 2014

Research Article

Analysis and Reliability Performance Comparison of Different Facial Image Features

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Abstract: This study performs reliability analysis on the different facial features with weighted retrieval accuracy on increasing facial database images. There are many methods analyzed in the existing papers with constant facial databases mentioned in the literature review. There were not much work carried out to study the performance in terms of reliability and also how the method will perform on increasing the size of the database. In this study certain feature extraction methods were analyzed on the regular performance measure and also the performance measures are modified to fit the real time requirements by giving weight ages for the closer matches. In this study four facial feature extraction methods are performed, they are DWT with PCA, LWT with PCA, HMM with SVD and Gabor wavelet with HMM. Reliability of these methods are analyzed and reported. Among all these methods Gabor wavelet with HMM gives more reliability than other three methods performed. Experiments are carried out to evaluate the proposed approach on the Olivetti Research Laboratory (ORL) face database.

Keywords: DWT, gabor filter, HMM, LWT, PCA

INTRODUCTION

The main objective of face image retrieval is to get the ranking result from most to least similar face images in a face image database given a query face image. Face image retrieval has many applications in different areas. For example, when it applies on personal multimedia, it can enable automatic face tagging and face image clustering; while in forensics, it can help with crime investigation.

In Face image retrieval, wavelet approaches mainly include direct wavelet coefficients, DWT with PCA, DWT with LDA, LWT with PCA, Wavelet histogram and wavelet moment of image, etc. However, classical wavelet encounters some inherent limitations in image processing. First, classical construction relying heavily on frequency domain is basically unfit for spatial realization, inevitably losing desirable properties exclusively owned in spatial domain. Second, its floating-point operation makes it not only inefficient but also inaccurate when processing integer image coefficients presented in Calderbank *et al*. (1998). Third, finding an ideal pre-processing method from classical view point is somewhat difficult, e.g., hard to seek a boundary extension method ensuring perfect reconstruction while simultaneously maintaining boundary continuity. Hence, traditional wavelet approaches, though effective in general case, may still result in reduced performance in face image retrieval.

Lifting scheme described from Daubechies and Sweldens (1998) a novel approach for constructing the so-called second-generation wavelet, provides feasible alternative for problems facing the classical first generation wavelet in image applications. Constructed entirely in spatial domain and based on the theory of different wavelet filter banks with perfect reconstruction, lifting scheme can easily build up a gradually improved multi-resolution analysis through iterative primal lifting and dual lifting. It turns out that lifting scheme outperforms the classical especially in effective implementation, such as convenient construction, in-place computation, lower computational complexity and simple inverse transform etc. We can also build wavelets with more vanishing moments and more smoothness, contributing to its flexible adaptivity and non-linearity.

Principal Component Analysis (PCA) method described by Kirby and Sirovich (1990) which is called Eigen faces in Pentland *et al*. (1994) is widely used for dimensionality reduction and recorded a great performance in face image retrieval. PCA based approaches typically include two phases: training and classification. In the training phase, an Eigen space is established from the training samples using PCA method and the training face images mapped it for classification.

In this study, we compared the reliability and retrieval accuracy of four methods in that, first two methods used DWT and lifting schemes to decompose Greyscale images into multilevel scale and wavelet coefficients, then further dimensionality reduction is

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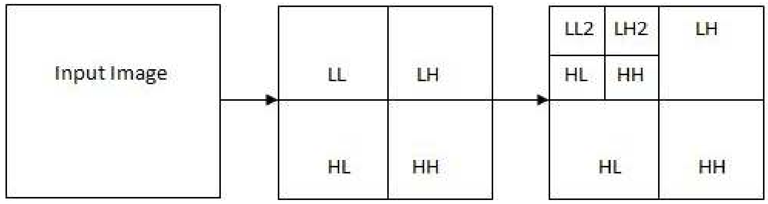

Fig. 1: Flow chart of the DWT sub band coding

done by using PCA with which we perform image feature extraction and similarity match by means of Euclidian distance method. The second two methods uses Hidden morkov model with Gabor wavelets and Singular value decomposition respectively. The retrieval performances are compared with those of its classical counterpart in terms of weighted retrieval accuracy, Precision and Recall rate. The efficiency in terms of retrieval accuracy and reliability by increasing the number of classes in the database is tested with various Face images using ORL database and the results outperform its classical counterpart.

Fundamentals:

Discrete wavelet transform: The speciality of DWT described by Wang *et al*. (2007) comparing to other transforms is time and frequency characteristics which application of it wildly in many different fields.

The flow chart of the Discrete wavelet transform sub band coding on the digital image is shown in Fig. 1, here L refers to low frequency component, H refers to high frequency and the number 1 and 2 refer to the decomposition level of the Discrete Wavelet transform. The result of the 2-D Discrete Wavelet Transform from level one to level three is shown in Fig. 2. The sub image LL is the low frequency component, it is the approximate sub image of the original image; the sub image HL is the component of the low frequency in horizontal direction and the high frequency in vertical direction, it manifests the horizontal edge of the original image; the sub image LH is the component of the high frequency in horizontal direction and the low frequency in vertical direction, it manifests the vertical edge of the original image; the sub image HH is the high frequency component, it manifests the oblique edge of the original image. It is shown that most energy of the original image is contained in the LL2 low frequency region. And the other region in the same size reflect edge feature of the image in different angles. The size of the low frequency sub-image is only-2n power of 2 times of the source image if this transform was done for n times. The algorithm in this study uses the low frequency sub images formed in the 2-D Discrete Wavelet Transform instead of the original face images, so that the dimension of the total population scatter matrix would reduced in the character extraction in the PCA method and consequently lessen the calculation amount.

Fig. 2: The result of the 2-D discrete wavelet transform from level one to level three

Lifting wavelets transform: Any Discrete Wavelets Transform with Finite filters can be decomposed into a finite sequence of simple filtering steps, which are called the lifting steps in Wong *et al*. (2005). Figure 3 shows the forward wavelet transform using lifting scheme.

This decomposition related to a factorization of the polyphase matrix of wavelet or sub band filters into elementary matrices is described as follows. The polyphase representation of a discrete-time filter $h\ (z)$ is defined as:

$$h\ (z) = h_e(z^2) + z^{-1}h_o(z^2)$$

where,

h_e = The even coefficients
h_o = The odd coefficients:

$$h_e\ (z) = \sum_k h_{2k} z^{-k}$$

$$h_o(z) = \sum_k h_{2k+1}\, z^{-k}$$

The low pass filter h (z) and High pass filter $g\ (z)$ can thus be represented by their poly phase matrix P (z) = $\begin{bmatrix} h_e(z) & g_e(z) \\ h_o(z) & g_o(z) \end{bmatrix}$ and $\tilde{P}(z)$can also be defined for the analysis filter analogously. The filters $h_e\ (z)$, $h_o\ (z)$, $g_e\ (z)$ and $g_o\ (z)$, along with their analysis counterparts, are Laurent polynomials. As the set of all Laurent polynomials exhibits a commutative ring structure, within which polynomial division with remainder is possible, long division between Laurent polynomials is not a unique operation. The Euclidean algorithm can be used to decompose $P\ (z)$and $\tilde{P}\ (Z)$) as:

$$P(z) = \prod_{i=1}^{m} \begin{bmatrix} 1 & s_i(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_i(z) & 1 \end{bmatrix} \begin{bmatrix} k & 0 \\ 0 & 1/k \end{bmatrix}$$

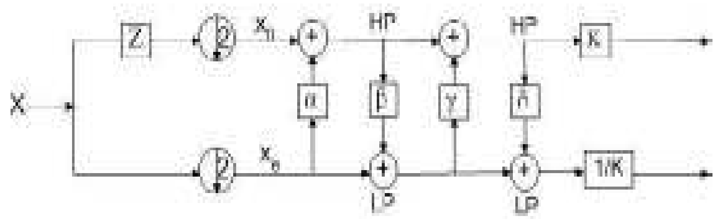

Fig. 3: Block diagram of the forward wavelet transform using lifting scheme

$$\tilde{P}(z) = \prod_{i=1}^{m} \begin{bmatrix} 1 & 0 \\ -s_i(z^{-1} & 1 \end{bmatrix} \begin{bmatrix} 1 & -t_i(z^{-1}) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1/K & 0 \\ 0 & K \end{bmatrix}$$

As this factorization is not unique, several pairs of $\{s_i(z)\}$ and $\{t_i(z)\}$ filters are admissible; however, in case of DWT implementation, all possible choices are equivalent.

Gabor filters: Gabor wavelets were introduced to image analysis because of their similarity to the receptive field profiles in cortical simple cells. They characterize the image as localized orientation selective and frequency selective features. Therefore, low level features, such as peaks, valleys and ridges are enhanced by 2-D Gabor filters. Thus, the eyes, nose and mouth, with other face details like wrinkles, dimples and scars are enhanced as key features to represent the face in higher dimensional space. Also, the Gabor wavelet representation of face image is robust to misalignment to some degree because it captures the local texture characterized by spatial frequency, spatial position and orientation. The commonly used Gabor filter is defined as follows:

$$G(x, y) = \frac{f^2}{\pi\gamma\eta} \exp\left(\frac{-x'^2+\gamma^2 y'^2}{2\sigma^2}\right) \exp(j2\pi f x' + \phi)$$

Here,

$$x' = x\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + y\cos\theta$$

where, f is the frequency of the sinusoidal factor, θ represents the, ϕ is the phase offset and σ is the standard deviation and is the spatial aspect ratio. Gabor wavelet filter employed on whole image to extract the features (Lades *et al*., 2002; Liu, 2004) from the face image. 1D feature vector is obtained from this feature extracted image and used for further processing. The face image is again divided into nine non-overlapping sub-images. The local features extracted are used to overcome the changes in some region of face. Feature vectors are extracted from individual part and these are fused to form a single feature vector. Gabor features demonstrate two desirable characteristic: spatial locality and orientation selectivity as in Fig. 4.

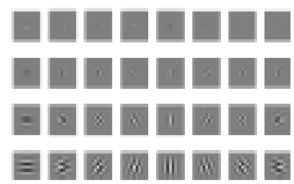

Fig. 4: An example of the real part of gabor wavelets with 4 scales and 8 orientations

The structure and functions of Gabor kernels are similar to the two-dimensional receptive fields of the mammalian cortical simple cells. This representation of face images should be robust to variations due to illumination and facial expression changes. Gabor kernel is used to represent the features from the image. Lower bound and Upper bound frequencies are given by:

$$f_{LB} = \frac{1}{x_1\sqrt{2}} \text{ and } f_{UB} = \frac{1}{x_2\sqrt{2}}$$

The values of x_1 and x_2 are chosen such that $x_1 > x_2$. A set of frequencies to be used at each wavelet point is obtained by starting at f_{LB} and multiplying by 2 until f_{UB} is reached. The number of frequencies is given by P at different wavelet points. The number of orientations is given by Q. The number of wavelet points is given by R and these values are used to calculate the Gabor responses. Gabor improves the performance in the presence of occlusions.

Principle component analysis: Principal component analysis des described in Wang *et al*. (2007) is classical method used in statistical pattern recognition and signal processing for dimensionality reduction and feature extraction.

Every test image can be transformed to low dimensional feature vector to be projected onto the eigenface space which was obtained from the training set. This feature vector can then be compared with the set of feature vectors obtained from the training set. The face classifier can use different distance measures such as Euclidean distance or cosine distance. The PCA algorithm can be detailed as follows.

Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$ then the average of the set is defined:

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n$$

Each face differs from the average by the vector:

$$\Phi_i = \Gamma_i - \Psi$$

This set of very large vectors is then subject to PCA, which seeks a set of M orthonormal matrix C can be defined as:

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T$$

vectors, Um, which best describes the distribution of the data. Then the covariance where the matrix $A = [\Phi_1 \Phi_2 .... \Phi_M]$. The covariance matrix C, however is $N2 \times N2$ real symmetric matrix and determining the $N2$ eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors.

Consider the eigenvectors v_i of A^TA such that $A^TAv_i = \mu_i v_i$. Pre-multiplying both sides by A, we have $AA^TAv_i = \mu_i Av_i$. Where we see that Avi are the eigenvectors and μ_i are the eigenvalues of $C = AA^T$. Following these analysis, we construct the $M \times M$ matrix $L = A^TA$, where $Lmn = \Phi_m^T \Phi_n$ and find the M eigenvectors, v_i, of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces U_I:

$$U_I = \sum_{k=1}^{M} V_{IK} \Phi_k, \ I = 1 \ldots M$$

With this analysis, the calculations are greatly reduced; from the order of the number of pixels in the images ($N2$) to the order of the number of images in the training set (M). The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

A new face image (Γ) is transformed into its eigenface components (projected onto "face space") by a simple operation:

$$w_k = U_k^T(\Gamma - \Psi)$$

for $k = 1,..., M'$. The weights form a projection vector, $\Omega^T = [w_1, w_2, \ldots.. w_T]$ describing the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The projection vector is then used to find which of a number of predefined face classes that best describes the face.

Hidden Markov model: Hidden Markov Models (HMM) are a set of statistical models used to characterize the statistical properties of a signal described in Rabiner (1989) provides an extensive and complete tutorial on HMMs. HMMs are made of two interrelate processes:

- An underlying, unobservable Markov chain with finite number of states, a state transition probability matrix and an initial state probability distribution.
- A set of probability density functions associated to each state. The elements of a HMM are.

N, the number of states in the model. If S is the set of states, then $S = \{S_1, S_2, \ldots.., S_N\}$. The state of the model at time t is given by $q_t \in S$, $1 \le t \le T$, where T is the length of the observation sequence (number of frames):

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- M, the number of different observation symbols. If V is the set of all possible observation symbols (also called the codebook of the model), then $V = \{v_1, v_2, \ldots\ldots. v_m\}$
- A, the state transition probability matrix, i.e., $A\{a_{ij}\}$ where
- $a_{ij} = P\ [q_t = S_j | q_{t-1} = {}_{Si}]$, $1 \le i$, $j \le N$, $0 \le a_{ij} \le 1$, $\sum_{j=1}^{N} aij = 1$, $1 \le i \le N$
- B, the observation symbol probability matrix, i.e., $B = bj\ (k)$, where, $bj\ (k) = P\ [O_t = v_k | q_t = Sj]$, $1 \le j \le N$, $1 \le k \le M$ and O_t is the observation symbol of time t
- Π, the initial state distribution, i.e., $\Pi = \Pi$: where $\Pi i = P\ [q_1 = S_i]$, $1 \le i \le N$
  Using a shorthand notation, a HMM is defined as $\lambda = (A, B, \Pi)$

The above characterization corresponds to a discrete HMM, where the observations are characterized as discrete symbols chosen from a finite alphabet $V = \{v_1, v_2, \ldots, v_m\}$. In a continuous density HMM, the states are characterized by Continuous observation density functions. The most general representation of the model Probability Density Function (PDF) is a finite mixture of the form:

$$bi\ (O) = \sum_{k=1}^{M} C_{ik} N\ (O, \mu_{ik}, U_{ik});\ 1 \le i \le N$$

where, C_{ik} is the mixture coefficient for the k^{th} mixture in the state i. Without loss of generality $N\ (O, \mu_{ik}, U_{ik})$ is assumed to be a Gaussian PDF with mean vector μ_{ik} and covariance matrix U_{ik}.

Singular value decomposition: Singular value Decomposition methods for Face retrieval use the common result stated by the following theorem.

Theorem: Let $I_{p \times q}$ be a real rectangular matrix and Rank (I) = r, then there exist two orthonormal matrices $U_{p \times p}$, $V_{q \times q}$ and a diagonal matrix $\sum_{p \times q}$ and the following formula holds:

$$I = U\sum V^T = \sum_{i=1}^{r} \lambda_i u_i v_i^T$$

where,

$$U = (u_1, u_2 \ldots\ldots u_r, u_{r+1}, \ldots\ldots u_p)$$

$$V = (v_1, v_2 \ldots\ldots v_r, v_{r+1}, \ldots\ldots v_q)$$

$$\sum = \text{diag}(\lambda_1, \lambda_2, \ldots. \lambda_r, 0\ldots., 0)$$

$\lambda_1 > \lambda_2 > \ldots > \lambda_r > 0$, λ_i^2, i = 1, 2,…., r are the eigen values of II^T and I^TI, = λ_I are the singular values of I, u_i, v_j, i = 1, 2,…, p, j = 1, 2,…. q are the eigenvectors corresponding to Eigen values of II^T and I^T I.

PROPOSED METHODOLOGY

DWT with PCA: In this method, all train images are decomposed using Discrete Wavelet Transform. After Level 2 DWT decomposition, we are taking only low frequency components (LL) of the decomposed image for further dimensionality reduction. Then by using Principal Component Analysis (PCA) to every LL components of decomposed train images, we get feature vectors of all train images. Then the feature vectors of all the train images are stored in the face database. Same process is done for query face images. Then query face image vector and Trained face image database vectors are compared using Euclidian distance classifier. Here the shortest distance between query feature vector and trained feature vector is taken as first priority Retrieved image. Then other similar images are displayed by using ascending order of distance between query and trained feature vectors.

LWT with PCA: In this method, all train images are decomposed using Lifting Wavelet Transform. After Level 2 LWT decomposition, we are taking only low frequency components (LL) of the decomposed image for further dimensionality reduction. Then by using Principal Component Analysis (PCA) to every LL components of decomposed train images, we get feature vectors of all train images. Then the feature vectors of all the train images are stored in the face database. Same process is done for query face images. Then query face image vector and Trained face image database vectors are compared using Euclidian distance classifier. Here the shortest distance between query feature vector and trained feature vector is taken as first priority Retrieved image. Then other similar images are displayed by using ascending order of distance between query and trained feature vectors.

Gabor wavelets with HMM: In this dissertation for Face image retrieval we have used two methods:

- Gabor filter
- Hidden Markov Model (HMM)

A Hidden Markov Model (HMM) is a statistical Markov model in which the system being modelled to be Markov process with unobserved (hidden) states. In a hidden Markov model, the states are not directly visible, but output, dependent on the state, is visible. In this dissertation hidden Markov model is used to match a test facial image with an appropriate reference image and Gabor filter is commenced on convolving a face image with a series of Gabor filter to extract the sequence of Gabor features from facial image.

HMM with singular value decomposition: In this method we are taking image as an input if the image is matched with the database image then transaction will proceed. So, by using 7-state HMM and SVD coefficients we are extracting the features of the image i.e., face based on priority i.e., first priority for eyes, mouth and second priority for hair, forehead, eyebrows, nose, chin then based on priority the input image is compared with database image if matched or face is recognized then the transactions are made this is how we are providing the security. Face retrieval using Singular Value Decomposition and HMM consist of steps in which it captures the information content in an image of a face which are further useful for face retrieval efficiently. In processing flow of face retrieval using SVD and HMM approach, it includes extraction of face features by SVD coefficient, Seven state HMM divides face image in seven states then by using classifier, there is comparison of input image with training dataset. If input image matches with training dataset image then face is said to be recognized otherwise face is unrecognized.

Performance measures: The most common evaluation measures used in face Image retrieval in our study are precision, Recall and Weighted Retrieval Accuracy. Here:

$$\text{Precision} = \frac{\textit{Relevant Faces of the Retrieved Faces}}{\textit{Total Retrieved Faces}}$$

$$\text{Recall} = \frac{\textit{Relevant faces of the Retrieved Faces}}{\textit{Total Relevant Faces}}$$

$$\text{WRA} = 35*A + 30*B + 20*C + 10*D + 5*E$$

Here WRA stands for Weighted Retrieval Accuracy. We used the new performance measure called Weighted Retrieval Accuracy for face image retrieval accuracy Calculations. Let us assume that A, B, C, D, E are First five retrieved Face images respectively. Assign weights for each retrieved images. Here we given more weight for first priority retrieved image and least weight for fifth retrieved image. The weighted values 35, 30, 20, 10, 5 are first five retrieved images respectively.

(a)

(b)

Fig. 5: (a) Query image (b) retrieved images

Table 1: Average retrieval accuracy with No. of classes

No. of classes	DWT-PCA	LWT-PCA	Gabor wavelet + HMM	HMM + SVD
	Methods			
10	98.5	97.5	99.8	98.8
15	97.6	95.4	99.5	97.5
20	96.2	94.3	98.4	96.8
25	95.4	93.2	98.1	95.4
30	94.2	92.4	97.6	94.8
35	93.2	91.8	97.1	93.5
40	92.8	91.5	96.4	93.0

Table 2: Weighted retrieval accuracy with No. of classes

No. of classes	DWT-PCA	LWT-PCA	Gabor wavelet + HMM	HMM + SVD
	Methods			
10	96.8	95.5	98.8	97.8
15	95.9	94.4	98.5	96.5
20	94.8	93.3	98.2	95.8
25	93.1	92.2	97.6	95.4
30	92.5	91.4	97.2	94.8
35	91.4	90.8	96.7	93.5
40	90.5	89.8	96.4	93.0

SIMULATION RESULTS AND DISCUSSION

We performed our simulations on the ORL database with the platform of MATLAB 7.8. This database consists of 400 face images attained from 40 people. Each people have 10 images of different expression, poses and different lighting conditions. The resolution rate of each image is 112×92 and the gray scale is 256. Out of the 400 images in the ORL face database, each class 7 images were selected for training and remaining 3 images were used for testing.

Our experiment gives the reliability and performance comparison results of Face image retrieval using DWT (Level2) with PCA, LWT (Level 2) with PCA, HMM with SVD and Gabor Filter with HMM. Here feature extraction is done by using DWT, LWT and Gabor Filters, further dimension reduction is done by using PCA and modeling is done by using HMM.

The Similarity matching is achieved by using Euclidian distance classifier. Figure 5a and b shows the Query face image and the retrieved face images of 5 most similar images illustrated respectively. The Average Precision rate and weighted Average Retrieval accuracy using DWT-PCA (Level 2), LWT-PCA (Level 2), HMM with SVD and Gabor Filter with HMM are shown in Table 1 and 2, respectively.

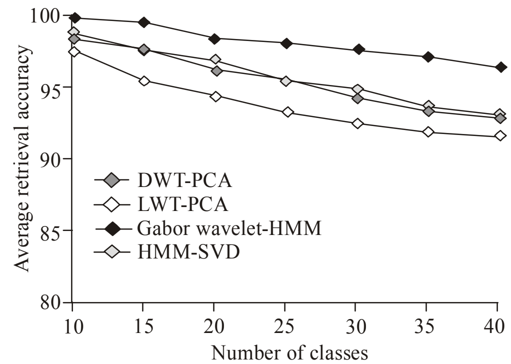

Fig. 6: Plot of average retrieval comparison with No. of classes

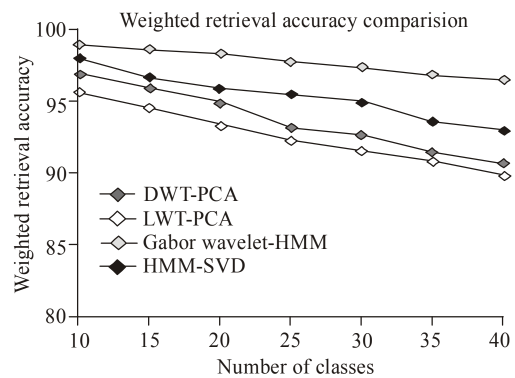

Fig. 7: Plot of average precision rate with No. of classes

The comparison Table 1 and 2 shows the retrieval performance in terms of reliability and also how the method will perform on increasing the size of the database. Figure 6 and 7 shows the performance plots of both Average precision rate and Weighted Retrieval Accuracy for increasing Class of DWT-PCA (Level 2), LWT-PCA (Level 2), HMM with SVD and Gabor Filter with HMM.

CONCLUSION

In this study Reliability and performance comparison of four methods named, Face retrieval using DWT with PCA, Face retrieval using LWT with PCA and HMM with Gabor Wavelet and HMM with SVD are proposed. Comparing to these four methods Gabor wavelet with HMM gives more reliability and Retrieval Accuracy than other methods. LWT with PCA method gives less elapsed time comparing to all other methods. In the future, we will focus on the use of larger and more complicated databases to test the system. For these complicated databases it is simply expected that all the previous methods will not repeat such efficiency reported in the papers. We will try to improve the feature extraction and the modelling of the faces.

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