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Probability Distribution Functions Based Face Recognition System Using Discrete Wavelet Subbands

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1. Introduction

Face recognition has recently been the centre of attention of many researchers (Jain et al. 2004). The earliest work in digital face recognition was reported by Bledsoe in 1964. Statistical face recognition systems such as principal component analysis (PCA) based eigenfaces introduced by Turk and Pentland in 1991, attracted lots of attention. Fisherfaces method based on linear discriminant analysis was introduced later on by Belhumeur et al. (1997).

Many of these methods are based on grey scale images; however colour images are increasingly being used since they add additional biometric information for face recognition (Marcel and Bengio, 381). PDFs obtained from different colour channels of a face image can be considered as the signature of the face, which can be used to represent the face image in a low dimensional space (Demirel and Anbarjafari, VISSAP 2008). Images with small changes in translation, rotation and illumination still possess high correlation in their corresponding PDFs. PDF of an image is a normalized version of an image histogram which have been used in many image processing applications such as object detection (Laptev, 2006) and face recognition (Yoo and Oh, 1999; Rodriguez and Marcel, 2006; Demirel and Anbarjafari, IEEE Signal Processing Letter, 2008).

Nowadays, wavelets have been used quite frequently in image processing. It has been used for feature extraction (Wang and chen, 2006), denoising (Starck et al., 2002), compression (Lamard et al. 2005), and face recognition (Liu et al., 2007; Demirel et al., 2008). The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain subbands (Dai and Yan, 2007). This process results in isolating small changes in an image mainly in high frequency subband images. Hence discrete wavelet transform (DWT) is a suitable tool to be used for designing pose invariant face recognition system.

Another important issue in face recognition system is face localization. There are several methods for this task such as skin tone based face localization for face segmentation. Skin is

a widely used feature in human image processing with a range of applications (Yang et al., 2002; Demirel et al., EECS 2008). Many methods have been proposed to use skin colour pixels for face localization. Chai and Ngan (1999) modelled the skin colour in *YCbCr* colour space. One of the recent methods for face localization is proposed by Nilsson (2007) which is using local Successive Mean Quantization Transform (SMQT) technique. Local SMQT has been claimed to be robust for illumination changes and the Receiver Operation Characteristics of the method is reported to be very successful for the segmentation of faces (Nilsson et al., ICASSP2007). In order to enhance the robustness of the system under changing illumination conditions, a reliable image equalization technique such as dynamic histogram equalization (Abdullah et al., 2007) or singular value decomposition based image equalization (Demirel and Anbarjafari, IEEE Signal Processing Letter, 2008; Sabet et al., ISCIS 2008) can be applied in the pre-processing stage.

In this chapter, after the face localization, 2-norm based image equalization technique has been employed to enhance the robustness of the system under changing illumination. Then the PDFs of the equalized and segmented faces in different subbands obtained from discrete wavelet transform (DWT) are calculated. These PDFs are used as statistical feature vectors for the recognition of faces by minimizing the Kullback-Leibler Divergence (KLD) between the PDF of a given face and the PDFs of faces in the database. The effect of well-known decision fusion techniques such as sum rule, median rule, max rule, product rule, majority voting (MV), and feature vector fusion (FVF), for combining feature vectors in *HSI* and *YCbCr* colour spaces of Low-Low, Low-High, High-Low, and High-High subbands, have been studied in order to achieve higher recognition performance.

The Head Pose (HP) face database (Gourier et al., 2004) and a subset from the FERET (Philips et al., 2000) database with faces containing varying poses changing from -90° to $+90^o$ of rotation around the vertical axis passing through the neck were used to test the proposed system. Both databases include face images with varying poses and face images have little illumination variation. The results are compared with principle component analyses (PCA), and three state-of-art face recognition systems: adaptive local binary pattern [LBP] PDFs based face recognition (Rodriguez and Marcel, 2006), nonnegative matrix factorization (NMF) introduced by Lee et al. (1999, 2001) and supervised incremental NMF (INMF) introduced and described by Wen-Sheng et al. (Wen Sheng et al., 2008).

2. Pre-processing of face images

The proposed face recognition system has been tested on the databases with no significant illumination changes, but singular value decomposition (SVD) based equalization (SVE) (Demirel and Anbarjafari, IEEE Signal Processing Letter, 2008; Sabet et al., ISCIS 2008) have been applied to the input images in both training and recognition stages. In this section SVE technique is explained.

In general, for any intensity image matrix Ξ_A, $A=\{R, G, B\}$, SVD can be written as:

$$\Xi_A = U_A \Sigma_A V_A^T \qquad A = \{R, G, B\} \tag{1}$$

where U_A and V_A are orthogonal square matrices (hanger and aligner matrices) and Σ_A matrix contains the sorted singular values on its main diagonal (stretcher matrix). As reported in (Tian et al., 2003), Σ_A represents the intensity information of a given image. If an image is a low contrast image this problem can be corrected to replace the Σ_A of the image

with another singular matrix obtained from an image with no contrast problem. A normalized intensity image matrix with no illumination problem can be considered to be the one with a PDF having a Gaussian distribution with mean of 0.5 and variance of 1. Such a synthetic intensity matrix with the same size of the original image can easily be obtained by generating random pixel values with Gaussian distribution with mean of 0.5 and variance of 1. Then the ratio of the largest singular value of the generated normalized matrix over a normalized image can be calculated according to equation (2):

$$\xi_A = \frac{\max\left(\Sigma_{g(\mu=0.5,\sigma=1)}\right)}{\max\left(\Sigma_A\right)} \quad , \quad A = \{R, G, B\} \tag{2}$$

where $\Sigma_{g(\mu=0.5,\sigma=1)}$ is the singular value matrix of the synthetic intensity matrix. This coefficient can be used to regenerate a new singular value matrix which is actually an equalized intensity matrix of the image generated by equation (3):

$$\Xi_{equalized_A} = U_A\left(\xi_A\Sigma_A\right)V_A^T \quad , \quad A = \{R, G, B\} \tag{3}$$

where $\Xi_{equalized\,A}$ is representing the equalized image in A-colour channel.

As equation (3) states the equalized image is just a multiplication of ξ_A with the original image. From the computational complexity point of view singular value decomposition of a matrix is an expensive process which takes quite significant amount of time to calculate the orthogonal matrices of U and V while they are not being used in the equalization process. Hence, finding a cheaper method to obtain or estimate ξ_A can be an improvement to the technique. Recall,

$$\|A\| = \sqrt{\lambda_{\max}} \tag{4}$$

where λ_{max} is the maximum eigenvalue of $A^T A$. By using SVD,

$$A = U\Sigma V^T \rightarrow A^T A = V\Sigma^2 V^T \tag{5}$$

This follows that the eigenvalues of $A^T A$ are the square of elements of the main diagonal of Σ, and that the eigenvector of $A^T A$ is V. Because Σ is in the form of:

$$\Sigma = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_k \cdots \end{bmatrix}_{m\times n} \quad \lambda_1 > \lambda_2 > \cdots > \lambda_k \quad k = \min(m,n) \tag{6}$$

Thus,

$$\|A\| = \lambda_1 \tag{7}$$

The 2-norm of a matrix is equal to the largest singular value of the matrix. Therefore ξ_A can be easily obtained from:

$$\xi_A = \frac{\left\| \Xi_{g(\mu=0.5,\sigma=1)} \right\|}{\left\| \Xi_A \right\|} \quad , \quad A = \{R, G, B\} \tag{8}$$

where $\Xi_{g(\mu=0.5,\sigma=1)}$ is a random matrix with mean of *0.5* and variance of *1* and Ξ_A is the intensity image in *R, G,* or *B*. Hence the equalized image can be obtained by:

$$\Xi_{equalized_A} = \xi_A \, \Xi_A = \frac{\left\| \Xi_{g(\mu=0.5,\sigma=1)} \right\|}{\left\| \Xi_A \right\|} \, \Xi_A \quad , \quad A = \{R, G, B\} \tag{9}$$

which shows there is no need to use singular value decomposition of intensity matrices. This procedure reduces the complexity of the equalization procedure. This task, which is actually equalizing the images, will eliminate the illumination problem. The SVE technique has been tested on the Oulu face database (Marszalec et al., 2000) as well as the FERET and HP face databases. Fig. 1 shows the general required steps of the pre-processing phases of the proposed system.

After applying SVE, the equalized images can be used as an input for the face detector prepared by Mike Nilsson (MathWirks, 2008) in order to localize and then crop the face region and eliminate the undesired background. The segmented face images are used as inputs of DWT for the generation of PDFs of different subband images in *H, S, I, Y, Cb,* and *Cr* colour channels. If there is no face in the image, then there will be no output from the face detector software, so it means the probability of having a random noise which has the same colour distribution of a face but with different shape is zero, which makes the proposed method reliable.
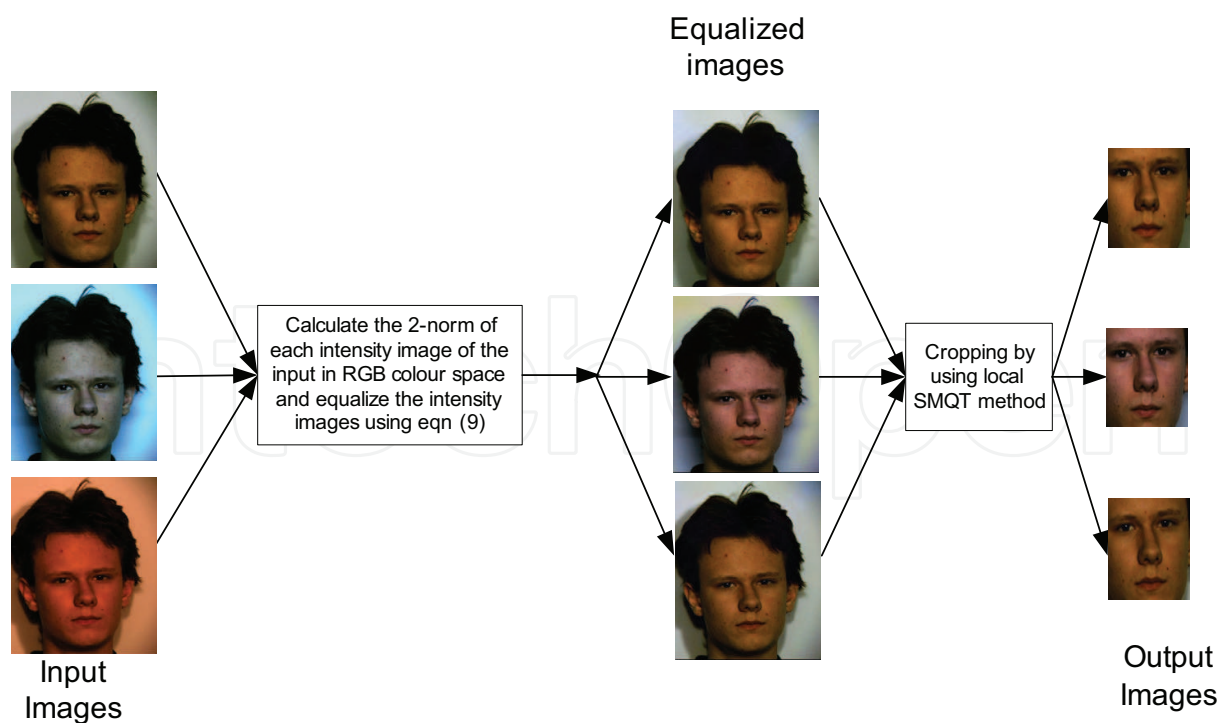

Fig. 1. The algorithm, with a sample image with different illumination from Oulu face database, of pre-processing of the face images to obtain a segmented face from the input face image.

The two-dimensional wavelet decomposition of an image is performed by applying the one-dimensional DWT along the rows of the image first, and then the results are decomposed along the columns (MATLAB 2009). This operation results in four decomposed subband images refer to Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH). The frequency components of those subband images cover the frequency components of the original image.

3. PCA and LBP based face recognition

3.1 PCA based face recognition

Eigenfaces method is based on linear PCA where a face image is encoded to a low dimensional vector. All face images are decomposed into a small set of characteristic feature images called eigenfaces. Each face image is projected on the subspace of meaningful eigenfaces (ones with nonzero eigenvalues). Hence, the collection of weights describes each face. Recognition of a new face is performed by projecting it on the subspace of eigenfaces and then comparing its weights with corresponding weights of each face from a known database.

Assume that all face images in a database are of the same size $w \times h$. Eigenfaces are obtained as the eigenvectors of the covariance matrix of the data points. Let Γ_i be an image from the collection of M images in the database. A face image is a 2-dimensional array of size $w \times h$, where w and h are width and height of the image, respectively. Each image can be represented as a vector of dimension $w \times h$ and the average image, Ψ, is defined as:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i \tag{10}$$

Each image Γ_i differ from the average image Ψ by the vector:

$$\Phi_i = \Gamma_i - \Psi \tag{11}$$

The covariance matrix of the dataset is defined as:

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = \Lambda \Lambda^T \qquad \Lambda = [\Phi_1 \ \Phi_2 \ \dots \ \Phi_M] \tag{12}$$

Since there are M images in the database, the covariance matrix C has only M-1 meaningful eigenvectors. Those eigenvectors u_l, can be obtained by multiplying eigenvectors v_l, of matrix $L = \Lambda^T \Lambda$ (of size $M \times M$) with difference vectors in matrix Λ.

$$u_l = \sum_{k=1}^{M} v_{lk} \Phi_k \tag{13}$$

The eigenvectors, u_l, are called the eigenfaces. Eigenfaces with higher eigenvalues contribute more in representation of a face image. The face subspace projection vector for every image is defined by:

$$\Omega^T = [\omega_1 \ \ \omega_2 \ \dots \ \omega_M]$$

$$\omega_k = u_k^T (\Gamma - \Psi) \quad k = 1, 2, \dots, M \tag{14}$$

The projection vectors are indispensable in face recognition tasks, due to their uniqueness. The projection vector, which represents a given face image in the eigenspace can be used for the recognition of faces. Euclidian distance, ε, between projection vectors of two different images (Ω_1 and Ω_2) is used to determine whether a face is recognized correctly or not.

$$\varepsilon = \left\| \Omega_1 - \Omega_2 \right\|^2 = \sqrt{\sum_{i=1}^{M} \left(\omega_{1i} - \omega_{2i} \right)^2} \tag{15}$$

PCA face recognition system has been applied to the different colour channels (*H, S, I, Y, Cb* and *Cr*) and as it will be shown in section *7*, the recognition rate of PCA based face recognition system is being increased by fusion of the decisions of different colour channels using MV.

3.2 Language, style spelling

The local binary pattern (LBP) is a non-parametric operator which describes the local spatial structure of an image. Ojala et al. introduced this operator and showed its high discriminative power for texture classification (Ojala et al., 1996). At a given pixel position *(x,y)*, LBP is defined as an ordered set of binary comparisons of pixel intensities between the centre pixel and its eight neighbour pixels, as shown in Fig 2.
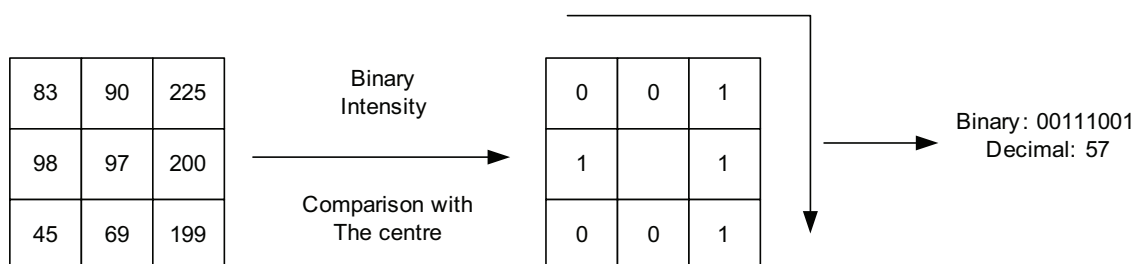

Fig. 2. The local binary pattern (LBP) operator

The decimal form of the resulting 8-bit word of LBP code can be expressed as follows:

$$\text{LBP}(x,y) = \sum_{n=0}^{7} 2^n s\left(i_n - i_{(x,y)} \right) \tag{16}$$

where $i_{(x,y)}$ corresponds to the grey value of the centre pixel *(x,y)*, i_n to the grey values of the 8 neighbour pixels, and function *s(x)* is defined as:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{17}$$

By definition, the LBP operator is unaffected by any monotonic greyscale transformation which preserves the pixel intensity order in a local neighbourhood. Note that each bit of the LBP code has the same significance level and that two successive bit values may have a totally different meaning. Sometimes, the LBP code is referred as a kernel structure index. Ojala et al extended their previous work to a circular neighbourhood of different radius size (Ojala et al., 2002). They used $LBP_{P,R}$ notation which refers to *P* equally spaced pixels on a circle of radius *R*. Two of the main motivations of using LBP are its low computational

complexity and its texture discriminative property. LBP has been used in many image processing applications such as motion detection, visual inspection, image retrieval, face detection, and face recognition.

In most aforementioned applications a face image was usually divided in small regions. For each region, a cumulative histogram of LBP code computed at each pixel location within the region was used as a feature vector.

Ahonen et al. used LBP operator for face recognition (Ahnon et al., 2004). Their face recognition system can be explained as follows: A histogram of the labelled image $f_1(x,y)$ can be defined as:

$$H_i = \sum_{x,y} I\{f_1(x,y) = i\} \qquad i = 0, \cdots, n-1 \tag{18}$$

where n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1 & A \text{ is true} \\ 0 & A \text{ is false} \end{cases} \tag{19}$$

This histogram contains information about the distribution of the local micropatterns, such as edges, spots, and flat areas, over the whole image. For efficient face representation, retaining the spatial information is required; hence the image is divided into regions R_0, R_1, ..., R_{m-1}, as shown in Fig 3.

Fig. 3. An example of a facial image divided into 8x8windows.

As reported in (Ojala et al., 1996), the spatially enhanced histogram is defined as:

$$H_{i,j} = \sum_{x,y} I\{f_1(x,y) = i\} I\{(x,y) \in R_j\} \quad , \quad i = 0, \cdots, n-1 \ , \ j = 0, \cdots, m-1 \tag{20}$$

where m is the number of blocks and n is the LBP bins. In this histogram, a description of the face on three different levels of locality exists: the labels for the histogram contain information about the patterns on a pixel level, the labels are summed over a small region to

produce information on a regional level, and the regional histograms are concatenated to build a global description of the face.

Although Ahonen et al. have mentioned several dissimilarity measures such as histogram intersections and log-likelihood statistics, they used nearest neighbour classifier with Chi square dissimilarity measure in their work (Ahnon et al., 2004).

When the image has been divided into several regions, it can be expected that some of the regions contain more useful information than others in terms of distinguishing between people, such as eyes. In order to contribute such information, a weight can be set for each region based on level of information it contains.

4. PDF based face recognition system

The PDF of an image is a statistical description of the distribution of occurrence probabilities of pixel intensities. In a general mathematical sense, a PDF of an image is simply a mapping to represent the probability of the pixel intensity levels that fall into various disjoint intervals, known as bins. In this work the bin size is set as 256. Given an intensity image, PDF, p, meets the following conditions:

$$p = \left[\tau_0, \tau_1, \cdots, \tau_{255} \right], \tau_i = \frac{\eta_i}{N}, \ i = 0, \cdots, 255 \tag{21}$$

where N is the total number of pixels in an image and η_i is the number of pixels having i intensity.

Given two PDFs the divergence between them can be calculated by using Kullback-Leibler Divergence (KLD). The KLD value, κ, between two given PDFs, p_C and q_C, can be calculated as follows:

$$\kappa(q_C, p_C) = \sum_i q_{i_C} \log\left(\frac{q_{i_C}}{p_{i_C}}\right) \qquad i = 0, 1, 2, \ldots, \beta\text{-}1 \tag{22}$$

where β is the number of bins and C is $(H, S, I, Y, Cb, or Cr)_{LL,LH,HL,HH}$. However, KLD is not a distance measure but it represents the similarity of the two PDFs. In other words, the smaller the KLD value the more similar the PDFs.

$$\chi_{j_C} = \min\left(\kappa\left(q_C, p_{jC}\right)\right), \ C = \begin{cases} (H,S,I,Y,Cb,Cr)_{LL} \\ (H,S,I,Y,Cb,Cr)_{LH} \\ (H,S,I,Y,Cb,Cr)_{HL} \\ (H,S,I,Y,Cb,Cr)_{HH} \end{cases}, \ j = 1, 2, \cdots, M \tag{23}$$

Here, χ_{i_C}, is the minimum KLD reflecting the similarity of the ith image in the training set in C subband colour channel and the query face and M is the number of image samples. The colour PDFs used in the proposed system is generated only from the segmented face, and hence the effect of background regions is eliminated. Fig. 4 shows two subjects with two different poses and their segmented faces from the FERET face database.
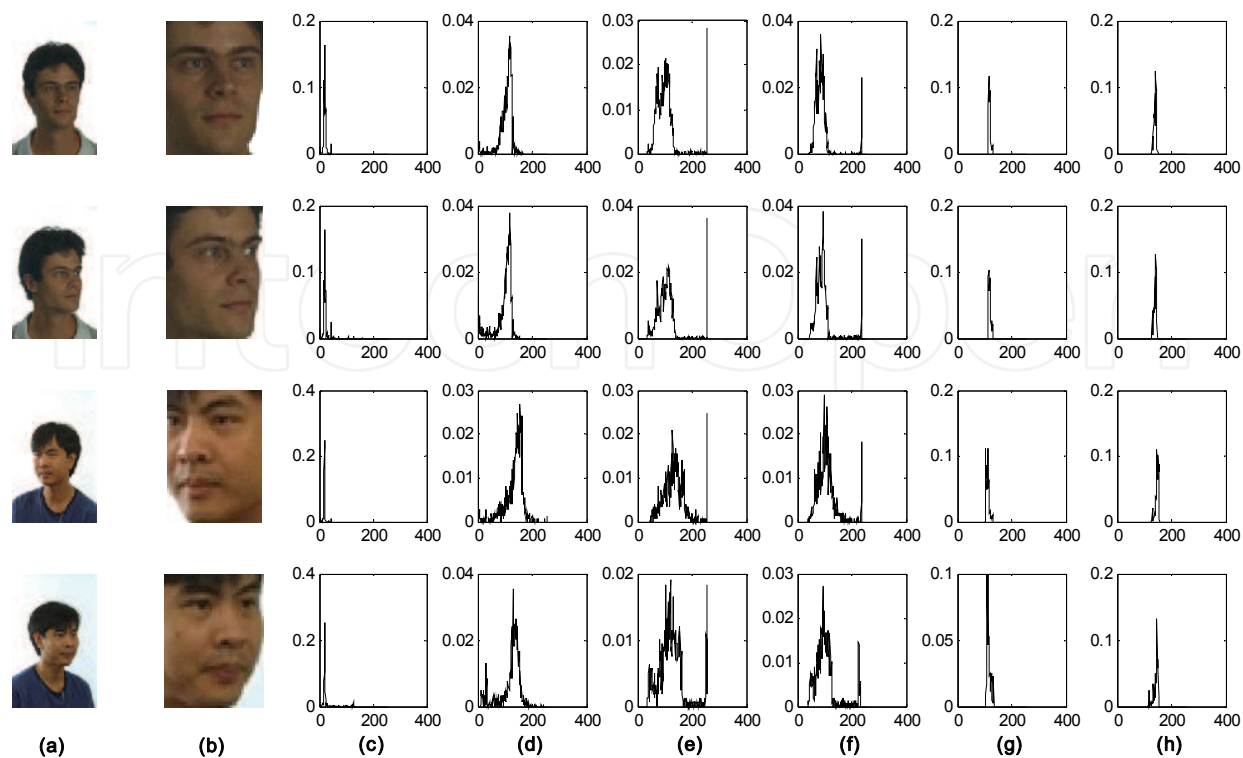
Fig. 4. Two subjects from FERET database with 2 different poses (a), their segmented faces (b) and their PDFs in *H*(c), *S*(d), *I*(e), *Y*(f), *Cb*(g), and *Cr*(h) colour channels in LL subband respectively.

5. Proposed PDF based face recognition using DWT

In this work, the local SMQT algorithm has been adopted for the localization and cropping of faces in the pre-processing stage. Then each face image has been equalized by using the proposed equalization technique in order to reduce the illumination problems. Colour PDFs of the isolated face images in different frequency subbands in *HSI* and *YCbCr* colour spaces are used as the face descriptors. Face recognition is achieved using the KLD between the PDF of the input face and the PDFs of the faces in the training set. In order to increase the recognition performance of the system, several well-known decision fusion techniques which are explained in the proceeding section have been used to improve the recognition performance. Fig. 5 illustrates the building blocks of the proposed face recognition system.

The HP face database and a subset from the FERET database were used to test the proposed system. The HP face database is consisting of 150 face samples of 15 different classes with 10 samples per class and the FERET face database is consisting of 500 face samples of 50 different classes with 10 samples per class. Both databases include face images with varying poses and face images have little illumination variation. The results are compared with conventional techniques such as PCA and LDA, and three state-of-art face recognition systems namely, adaptive LBP PDFs based face recognition, PDF based face recognition system using FVF, NMF, and INMF.
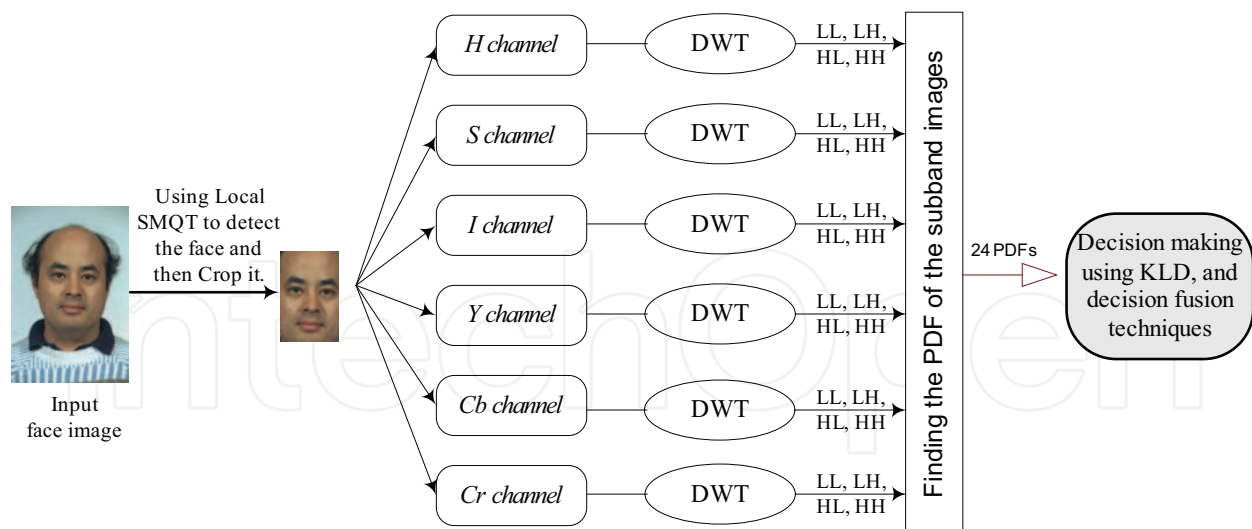
Fig. 5. Building blocks of the proposed system.

6. Decision fusion of different wavelet subbands in different colour channels

The proposed face recognition system as explained in the previous section can be applied to different colour channels (*H, S, I, Y, Cb,* and *Cr*) of different subband images obtained by DWT (*LL, LH, HL,* and *HH*). Hence, given a face image the image can be represented in these 24 channels with dedicated colour PDFs for each channel. Different channels contain different information regarding the image; therefore all of these 24 PDFs can be combined to represent a face image. There are many techniques to combine the resultant decision. In this paper, several well-known techniques such as sum rule, median rule, max rule, product rule, majority voting (MV), and feature vector fusion (FVF) have been used to do this combination. These methods have been described in much detailed in by Polikar (2006). The aim of this work is not to introduce but to implement these fusion techniques on PDF based face recognition system.

These data fusion techniques use probability of the decisions they provide through classifiers. That is why it is necessary to calculate the probability of the decision of each classifier based on the minimum KLD value. This is achieved by calculating the probability of the decision in each colour channel, γ_C, which can be formulated as follows:

$$\varsigma_C = \frac{\left[\chi_1 \quad \chi_2 \quad \cdots \quad \chi_{nM}\right]_C}{\sum\limits_{i=1}^{nM} \chi_i} \qquad C = \begin{cases} (H,S,I,Y,Cb,Cr)_{LL} \\ (H,S,I,Y,Cb,Cr)_{LH} \\ (H,S,I,Y,Cb,Cr)_{HL} \\ (H,S,I,Y,Cb,Cr)_{HH} \end{cases} \qquad (24)$$

$$\gamma_C = \max\left(1-\varsigma_C\right)$$

where ς_C is the normalized KLD value, χ_i is indicating the KLD value of the query image from the ith image in the training set, n shows the number of face samples in each class and M is the number of classes. The highest similarity between two projection vectors is when the minimum KLD value is zero. This represents a perfect match, i.e. the probability of selection is 1. So zero KLD value represents probability of 1 that is why ς_C has been subtracted from 1, the maximum probability corresponds to the probability of the selected class. The sum rule is applied, by adding all the probabilities of a class in different colour

channels of different subbands, followed by declaring the class with the highest accumulated probability to be the selected class. The maximum rule, as its name implies, simply takes the maximum among the probabilities of a class in different colour channels of different subbands, followed by declaring the class with the highest probability to be the selected class. The median rule similarly takes the median among the sorted probabilities of a class in different channels. The product rule is achieved from the product of all probabilities of a class in different colour channels of different subbands. Product rule is very sensitive as a low probability (close to 0) will remove any chance of that class being selected.

MV is one of the most frequently used decision fusion technique. The main idea behind MV is to achieve increased recognition rate by combining decisions of the PDF based face recognition procedures of different colour spaces and subbands. By considering the *H, S, I, Y, Cb* and *Cr* PDFs in different wavelet subbands separately and combining their results by using MV, the performance of the classification process will be increased. The MV procedure can be explained as follows. Consider *{p₁,p₂,....,pₘ}C* to be a set of PDFs of training face images in wavelet subband colour channels (*C=(H, S, I, Y, Cb, or Cr)LL,LH,HL,HH*), then a given a PDF of a query face image, *q*, colour PDFs of the query image *qC* can be used to calculate the KLD between *qC* and PDFs of the images in the training samples by equation (24). The image with the minimum distance in a channel, χ_C, is declared to be the vector representing the recognized subject. Given the decisions of each classifier in each colour space, the voted class *E*, can be chosen as follows.

$$\mathrm{E} = \mathrm{mode}\left(\chi_{H_{LL}}, \cdots, \chi_{H_{HH}}, \cdots, \chi_{Cr_{LL}}, \cdots, \chi_{Cr_{HH}}\right) \tag{25}$$

where *mode* is declaring the most repeated class.

Data fusion is not the only way to improve the recognition performance. PDF vectors can also be concatenated with the FVF process which is a source fusion technique and can be explained as follows. Consider *{p₁,p₂,....,pₘ}C* to be a set of training face images in subband colour channels *C, (H, S, I, Y, Cb, or Cr)LL,LH,HL,HH*, then for a given query face image, the *fvfq* is defined as a vector which is the combination of all PDFs of the query image *q* as follow:

$$fvf_q = \left[\mathrm{q}_{H_{LL}} \cdots \mathrm{q}_{H_{LH}} \cdots \mathrm{q}_{H_{HL}} \cdots \mathrm{q}_{H_{HH}} \cdots\right]_{1 \times 6144} \tag{26}$$

where only the *H* colour channel components are shown in equation (26). This new PDF can be used to calculate the KLD between *fvfq* and *fvfpi* of the images in the training samples. *fvfq* is a vector of 1×6144, where 6144 is multiplication of the bin size (which is 256) by number of colour channels (which is 6) by number of subbands (which is 4).

This new PDF can be used to calculate the KLD between *fvfq* and *fvfpj* of the images in the training samples as follows:

$$\chi_i = \min\left(\kappa\left(fvf_q, fvf_{pj}\right)\right) \quad , \quad j = 1, \cdots, M \tag{27}$$

where *M* is the number of images in the training set and *fvfpj* is the combined PDFs of the *j*th image in the training set. Thus, the similarity of the *i*th image in the training set and the query face can be reflected by χ_i, which is the minimum KLD value. The image with the lowest KLD distance, χ_i , is declared to be the vector representing the recognized subject.

6. Results and discussions

In this paper the PCA, PCA-MV, LDA, LBP, LBP-MV, PDF based face recognition by using FVF, NMF, INMF, and the proposed PDF based face recognition system have been tested on the FERET face database with faces containing varying poses changing from -90° to +90° of rotation of 500 face images of 50 different classes.

6.1 Simulation results

Table 1 shows the performance of PCA based face recognition system of the FERET face database in *HSI* and *YCbCr* colour spaces respectively.

# of face images in the training set	Recognition rates of the proposed PDF based system					
	H	**S**	**I**	**Y**	**Cb**	**Cr**
1	36.89	48.67	49.11	47.33	49.78	49.11
2	41.50	54.75	53.50	52.50	58.25	57.75
3	52.86	62.86	56.29	56.57	67.71	64.00
4	58.00	69.00	64.67	66.00	73.67	70.33
5	62.40	74.80	69.60	72.80	77.60	74.80

Table 1. Performance of the PCA based system in *H, S, I, Y, Cb* and *Cr* colour channels of the FERET face database.

Table 2 shows the performance of LBP based face recognition system of the FERET face databases in *HSI* and *YCbCr* colour spaces.

# of face images in the training set	Recognition rates of the proposed PDF based system					
	H	**S**	**I**	**Y**	**Cb**	**Cr**
1	59.33	50.67	48.22	48.44	61.11	62.67
2	64.50	56.75	54.50	54.75	66.50	66.50
3	74.57	66.00	64.29	64.86	76.86	76.57
4	85.67	79.00	77.00	77.67	87.67	86.67
5	87.60	80.40	78.00	78.40	89.00	89.60

Table 2. Performance of the LBP based system in *H, S, I, Y, Cb* and *Cr* colour channels of the FERET face database.

The correct recognition rates in percent of the PDF based face recognition of LL, LH, HL, and HH subband images in different colour channels of *HSI* and *YCbCr* for the FERET face database are included in Table 3. Each result is an average of 100 runs, where we have randomly shuffled the faces in each class.

Number of training images		Recognition rates of the proposed PDF based system				
		1	2	3	4	5
H	LL	67.16	80.43	86.43	89.83	92.96
	LH	62.89	74.28	76.86	82.43	84.44
	HL	68.84	79.73	84.00	85.13	88.88
	HH	68.40	78.48	83.54	86.07	89.08
S	LL	48.27	60.23	64.20	71.00	74.72
	LH	37.27	48.10	49.14	55.20	57.56
	HL	42.76	51.63	55.46	59.63	64.76
	HH	42.49	52.60	55.83	60.17	65.84
I	LL	44.02	54.93	59.74	66.30	70.16
	LH	37.31	47.88	50.43	55.83	60.44
	HL	41.96	47.90	52.34	57.27	62.36
	HH	40.20	47.78	52.37	57.87	60.68
Y	LL	53.93	64.55	70.14	76.33	81.24
	LH	36.47	48.13	50.54	57.90	60.80
	HL	40.18	47.78	52.31	59.27	63.00
	HH	41.27	49.53	54.34	60.60	63.48
Cb	LL	56.09	67.90	74.43	79.23	83.36
	LH	29.49	33.23	35.89	40.60	42.84
	HL	42.93	50.78	55.37	56.03	58.24
	HH	29.84	33.33	35.14	37.23	38.96
Cr	LL	14.65	15.89	17.31	18.33	20.24
	LH	26.24	32.95	36.94	38.60	40.24
	HL	30.84	39.35	39.94	40.63	43.68
	HH	22.04	37.35	52.60	59.47	62.20

Table 3. Performance of the proposed PDF based face recognition system of the DWT subbands of colour images in *H, S, I, Y, Cb* and *Cr* colour channels separately for the FERET face database.

The performances of the proposed system using data fusion techniques such as sum rule, median rule, max rule, product rule, MV, and FVF, between all 24 decisions (an image with its 4 subband images in 6 colour channels) for the FERET face database are shown in Table 4. The performance of the conventional PCA, PCA-MV, LDA, and the state-of-art face recognition systems: LBP, LBP-MV, PDF based face recognition by using FVF, NMF, and INMF based face recognition systems for the FERET face database are also included in the Table 4.

Number of training images		Recognition rate				
		1	2	3	4	5
MV		82.22	90.45	93.69	95.60	**96.88**
FVF	H (DWT subbands)	80.44	85.50	95.43	96.33	96.40
	S (DWT subbands)	60.89	68.25	81.71	88.00	90.00
	I (DWT subbands)	63.11	68.50	84.57	91.67	93.60
	Y (DWT subbands)	80.67	85.75	95.71	96.67	96.80
	Cb (DWT subbands)	66.89	70.75	84.00	86.33	89.60
	Cr (DWT subbands)	63.33	61.50	74.29	79.67	83.20
	All subbands	82.89	87.00	96.57	98.80	**99.33**
SUM RULE		94.53	97.03	98.08	98.49	98.84
MEDIAN RULE		93.82	96.23	97.80	97.98	98.39
MAX RULE		81.71	87.78	90.37	91.83	92.87
PRODUCT RULE		16.58	0.67	0.67	0.67	0.67
PCA		44.00	52.00	58.29	66.17	68.80
LDA		61.98	70.33	77.78	781.43	85.00
PCA-MV		57.11	62.50	65.71	74.00	77.60
LBP		50.89	56.25	74.57	77.67	79.60
LBP-MV		54.44	58.75	69.14	81.00	83.20
PDF based face recognition by FVF (Demirel and Anbarjafari, IEEE Signal Processing Letter, 2008)		80.44	83.75	94.00	97.67	98.00
NMF		61.33	64.67	69.89	77.35	80.37
INMF		63.65	67.87	75.83	80.07	83.20

Table 4. Performance of the proposed face recognition system using MV, FVF, PCA, LDA, LBP, PDF based face recognition, NMF, and INMF based face recognition system for the FERET database.

The performances of the proposed system using aforementioned data fusion techniques between all decisions for the HP face database are shown in Table 5.

		Recognition Rate				
Number of training images		1	2	3	4	5
MV		77.93	91.00	92.67	95.11	97.53
FVF	H (DWT subbands)	68.89	79.17	85.71	88.89	88.00
	S (DWT subbands)	64.44	77.50	87.62	92.22	93.33
	I (DWT subbands)	54.07	64.17	77.14	87.78	84.00
	Y (DWT subbands)	69.63	80.00	86.67	90.00	89.33
	Cb (DWT subbands)	59.17	60.00	67.62	75.56	77.33
	Cr (DWT subbands)	28.15	34.17	41.90	40.00	48.00
	All subbands	88.15	93.33	97.14	98.67	**98.89**
SUM RULE		83.85	96.42	96.76	96.67	97.33
MEDIAN RULE		84.74	97.00	96.19	97.00	98.53
MAX RULE		74.74	88.17	90.95	91.47	91.67
PRODUCT RULE		84.22	97.33	96.86	97.11	96.27

Table 5. Performance of the proposed face recognition system using MV, and FVF based face recognition system for the HP face databases

6.2 Discussions

The combination of feature vectors, with 5 samples per subject in the training set, achieve 99.33% and 96.88% recognition rates by using FVF and MV methods for the FERET face database respectively. The MV and FVF results are 98.89% and 97.53% for the HP face database, when 5 samples per subject is available in the training set, respectively. The results obtained by the proposed system using FVF for the FERET database shows 30.53%, 21.73%, 14.33%, 19.73%, 16.13%, 1.33%, 18.96%, and 16.13% improvement over PCA, PCA-MV, LDA, LBP, LBP-MV, PDF based face recognition system by using FVF, NMF, and INMF respectively. In all cases both FVF and MV approaches outperform the conventional methods in the literature. As it could be predicted sum rule, median rule, and max rule are improving the recognition rate but as table 4 and 5 are showing, FVF is over performing the other fusion techniques.

7. Conclusion

In this chapter, a new high performance face recognition system using the PDFs obtained from DWT subbands in different colour channels followed by data fusion has been proposed. The PDFs of the equalized and segmented face images in different subbands of different colour channels were used as feature vectors for the recognition of faces by minimizing the KLD between the PDF of a given face and the PDFs of faces in the database. Several fusion techniques including sum rule, median rule, max rule, product rule, MV, and FVF have been employed in order to improve the recognition performance. The system was tested on the FERET and the HP face databases. The results have been compared with the conventional PCA, improved PCA by applying MV, LDA and state-of-art face recognition techniques including LBP, improved LBP by using MV, previously introduced PDF based

face recognition by using FVF, NMF, and INMF. The performance of the proposed face recognition system has clearly shown the superiority of the system over the conventional and state-of-art techniques.

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Edited by Dr. Juuso T. Olkkonen

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