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IMPROVED PDF BASED FACE RECOGNITION USING DATA FUSION

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Abstract: *In this paper a high performance face recognition system, based on different data fusion techniques combining the decisions obtained from the probability distribution functions (PDF) based face recognition system in different colour channels, is introduced. The PDFs of the equalized and segmented face images are used as statistical feature vectors for the recognition of faces by minimizing the Kullback- Leibler Distance (KLD) between the PDF of a given face and the PDFs of faces in the database. Well known data fusion techniques such as Median Rule, Sum Rule, Max Rule, Product Rule, Majority Voting (MV) and feature vector fusion (FVF) have been employed to increase the recognition performance. The proposed system has been tested on the FERET, Head Pose, Essex University, and Georgia Tech University face databases. The overall results indicate that the median rule over-performs the other fusion techniques.*

Key Words:

1. INTRODUCTION

Colour images are increasingly used in face recognition systems since they introduce additional biometric information [1]. 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 [2]. 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. There is some published work on application of histograms for the detection of objects [3]. However, there are few publications on application of histogram or PDF based methods in face recognition [4, 5, 6]. In our earlier work introducing PDF based face recognition [6] singular value decomposition was used to deal with the illumination problem. As stated in [6], 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 eq. (1).

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

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 an equalized image using eq. (2).

$$\Xi_{equalized_A} = U_A\left(\xi\Sigma_A\right)V_A^T \quad , \quad A=\{R,G,B\} \qquad (2)$$

Where $\Xi_{equalized_A}$ is representing the equalized image in A-colour channel. This task which is actually equalizing the images of a face subject will eliminate the illumination problem. Then, the local SMQT algorithm [7] has been adopted for face detection and cropping in the pre-processing stage. Usually many face recognition systems use grayscale face images. From the information point of view a colour image has more information than a grayscale image. So we propose not to lose the available amount of information by converting a color image into a grayscale image. Colour PDFs in *HSI* and *YCbCr* colour spaces of the isolated face images are used as the face descriptors. In a general mathematical sense, an image PDF is simply a mapping η_i representing the probability of the pixel intensity levels that fall into various disjoint intervals, known as bins. The bin size determines the size of the PDF vector. In this paper the bin size is assumed to be 256. Given a monochrome image, PDF feature vector, *H*, is defined by:

$$H=\left[p_0,p_1,\cdots,p_{255}\right] \quad , \quad p_i=\frac{\eta_i}{N} \quad , \quad i=0,\cdots,255 \qquad (3)$$

where η_i is the intensity value of a pixel in a colour channel and *N* is total number of pixels in an intensity image. The distance between the PDF of two images can be measured by using the KLD between the PDFs of the respective images. Given two PDF vectors *p* and *q* the KLD, κ, is defined as:

$$\kappa(q,p)=\sum_i q_i \log\left(\frac{q_i}{p_i}\right) \qquad i=0,1,2,\ldots,\beta-1 \qquad (4)$$

where β is the number of bins. Then, a given query face image, the PDF of the query image *q* can be used to calculate the KLD between *q* and PDFs of the images in the training samples, p_i, as follows:

$$\chi_i = \min\left(\kappa(q,p_i)\right), \; i=1,\cdots,M \qquad (5)$$

Here, χ_i, is the minimum KLD reflecting the similarity of the i^{th} image in the training set and the query face and *M* is the number of image samples. Fig. 1 shows two subjects with two different poses and their segmented faces from the FERET face database [8]. The color PDFs used in the proposed system is generated only from the segmented face, and hence the effect of background regions is eliminated.

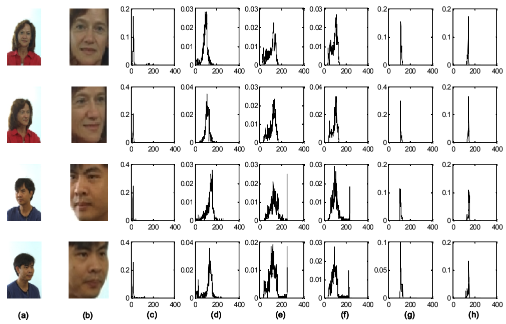

Figure 1 Two subjects from FERET database with 2 different poses (a), their segmented faces (b) and their PDFs in H (c), S (d), I (e), r (f), g (g), and b (h) color channels respectively. [6]

In this paper, several data fusion systems are used to improve the recognition performance of the face recognition system introduced in [6]. Fig. 2 illustrates the building blocks of the face recognition system which combines the decisions of the classifiers in different colour channels, using sum, product, max, and median rules as well as the majority voting (MV) and feature vector fusion (FVF), for improved recognition performance. In this paper, the Head Pose (HP) [9], a subset from the FERET as used in [6], the Essex University [10], and the Georgia Tech University [11] face databases were used to test the performance of the proposed data fusion based face recognition system. In order to have a conclusive decision as to which of the data fusion techniques is performing better in all the available faces, all of the aforementioned four databases are combined to form a mixed face database which contains 265 classes with 10 different poses. The results indicate that the median rule overperforms the two methods reported in [6] by 1.05% and 6.52% for MV and FVF methods respectively.

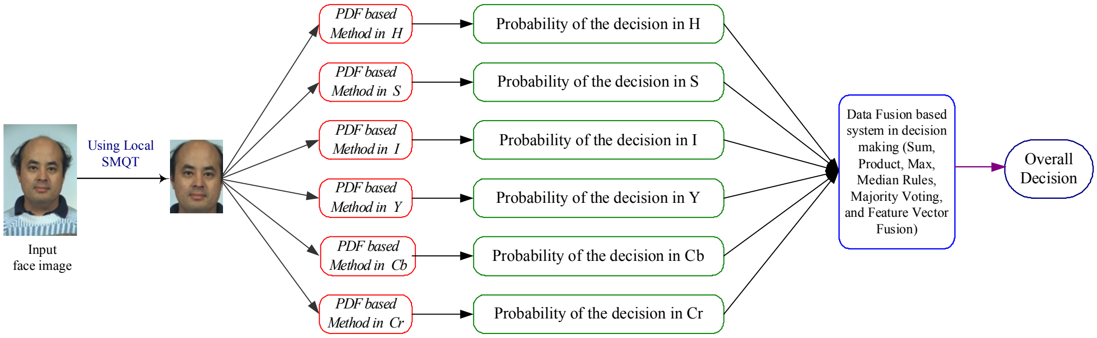

Figure 2 Different building blocks of the proposed system.

2. DECISION FUSION IN DIFFERENT COLOUR CHANNELS

The face recognition procedure explained in the previous section can be applied to different colour channels such as *H*, *S*, *I*, *Y*, *Cb* and *Cr*. Hence, given a face image the image can be represented in these colour spaces with dedicated colour PDFs for each channel. Different colour channels contain different information regarding the image; therefore all of these six PDFs can be combined to represent a face image. There are many techniques to combine the resultant decision. In this paper, sum rule, median rule, max rule, product rule, majority voting, and feature vector fusion methods have been used to do this combination [12].

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 the minimum KLD value. This is achieved by calculating the probability of the decision in each colour channel, κ_C, which can be formulated as follows:

$$\varsigma_C = \frac{\begin{bmatrix}\varepsilon_1 & \varepsilon_2 & \cdots & \varepsilon_{nM}\end{bmatrix}_C}{\sum_{i=1}^{nM} \varepsilon_i} \qquad C = \{H, S, I, Y, Cb, Cr\}$$

$$\kappa_C = \max(1 - \varsigma_C) \tag{6}$$

where ς_C is the normalized KLD value, ε_i is indicating the KLD value of the query image from the i^{th} 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 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 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. It is very sensitive as a low probability (close to 0) will remove any chance of that class being selected [12] (note low recognition rates of the FERET, Essex and Georgia Tech University face databases shown in table 1 and the mixed database in table 2). Majority voting (MV) is another data fusion technique. The main idea behind MV is to achieve increased recognition rate by combining decisions of different colour channels. The MV procedure can be explained as follows. Given, the probability of the decisions, κ_C, in all colour channels, *(C: H, S, I, Y, Cb, Cr)*, the highest repeated decision among all channels is declared to be the overall decision. Data fusion is not the only way to improve the recognition performance. PDF vectors can also be concatenated with the feature vector fusion (FVF) process which is a source fusion technique and can be explained as follows. The fvf_q is defined as a vector which is the combination of all PDFs of the query image q in different colour channels as follow:

$$fvf_q = \begin{bmatrix} q_H & q_S & q_I & q_Y & q_{Cb} & q_{Cr} \end{bmatrix}_{1\times 1536} \quad (7)$$

where each PDF has size of *1x256*, hence six concatenated PDF results in a vector with size of *1x1536*. This new PDF can be used to calculate the KLD between fvf_q and fvf_{pj} of the images in the training samples as follows:

$$\Xi_i = \min\left(\kappa\left(fvf_q, fvf_{pj}\right)\right) \quad , \quad j = 1, \cdots, M \quad (8)$$

where M is the number of images in the training set and fvf_{pj} 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 Ξ_i, which is the minimum KLD value. The image with the lowest KLD distance, Ξ_i , is declared to be the vector representing the recognized subject.

3. RESULTS AND DISCUSSIONS

The proposed system using PDFs in different colour channels as the face feature vector, discussed ensemble based systems as decision making techniques have been tested on the FERET, Essex University, Georgia Tech University, and the HP face databases. The correct recognition rates in percent are included in Table 1. Each result is an average of 100 runs, where we have randomly shuffled the faces in each class. Table 1 also includes the correct recognition of the PCA for the mentioned face databases. The results show that the performance of the product rule dramatically drops when the number of images per subject in the training set is increasing. This is due to the fact that, as the number of training images per subject is increased, the possibility of having a low probability is increased. The multiplication with a low probability is enough to cancel the effect of several high probabilities. The median rule is marginally better than sum rule in some cases, where the marginal improvement of the median rule is due to this fact that having an outlier probability will not affect the median, though it will affect the sum rule.

Table 1 Performance of different decision making techniques for the proposed face recognition system compared with the performance of PCA based face recognition (in percentage)

	# of training image per subject	PCA	SUM RULE	MEDIAN RULE	MAX RULE	PRODUCT RULE	MAJORITY VOTING	FEATURE VECTOR FUSION
HEADPOSE	1	20.74	83.85	84.74	74.74	84.22	74.52	81.48
	2	41.67	96.42	97.00	88.17	97.33	88.92	87.50
	3	56.19	96.76	96.19	90.95	96.86	91.90	96.19
	4	58.89	96.67	97.00	91.67	97.11	94.89	97.33
	5	66.67	97.33	98.53	91.47	96.27	97.33	97.78
FERET	1	44.00	76.89	76.80	66.87	75.60	75.22	80.44
	2	52.00	87.63	88.10	79.98	48.95	86.03	83.75
	3	58.29	89.97	90.26	82.6	14.83	88.54	94.00
	4	66.17	93.80	93.50	87.07	4.83	92.20	97.67
	5	68.80	95.16	95.44	89.84	4.00	94.20	98.00
ESSEX	1	93.16	94.53	93.82	81.71	16.58	92.45	95.33
	2	94.20	97.03	96.23	87.78	0.67	95.51	97.58
	3	94.06	98.08	97.80	90.37	0.67	96.55	97.81
	4	93.87	98.49	97.98	91.83	0.67	96.88	97.33
	5	94.88	98.84	98.39	92.87	0.67	97.41	97.73
GEORGIA	1	52.89	69.24	69.24	68.51	68.98	69.04	73. 20
	2	59.00	86.35	86.45	85.05	64.25	85.65	78.67
	3	58.86	90.71	90.83	89.91	23.97	91.46	74.78
	4	58.67	95.33	95.20	93.17	6.80	94.63	72.54
	5	60.80	95.96	96.04	95.48	3.20	95.84	75.29

In order to achieve an overall conclusion about fusion based decision making techniques and also to demonstrate the efficiency of the proposed face recognition system all faces in the HP (15 subjects), FERET (50 subjects), Georgia Tech University (50 subjects) and Essex University face databases (150 subjects) have been randomly mixed. Total of 2650 faces, 265 subjects with 10 samples for each subject, have been used to test the proposed system. Table 2 lists the correct recognition rates of the mixed face database. The results are average of 100 times iteration.

Table 2 Performance of different decision making techniques for the proposed face recognition system (in percentage)

# of training image per subject	H	S	I	Y	Cb	Cr	SUM RULE	MEDIAN RULE	MAX RULE	PRODUCT RULE	MAJORITY VOTING	FEATURE VECTOR FUSION
1	77.08	68.34	75.82	79.21	70.14	73.84	86.37	85.80	73.80	0.75	84.25	86.08
2	85.99	78.21	83.93	86.42	79.40	82.69	92.50	92.23	83.34	0.38	90.67	90.19
3	90.34	83.18	88.54	90.65	84.99	86.73	95.12	94.93	88.30	0.38	94.01	92.40
4	92.84	86.11	90.57	92.38	87.79	89.41	96.75	96.76	90.64	0.38	95.64	92.77
5	93.80	87.55	91.92	93.90	89.41	90.88	97.38	**97.40**	92.18	0.38	96.35	90.88

The recognition rates stated in Table 2 show that the median and sum rules are performing better than other fusion based decision making techniques. Median rule based face recognition system using PDF performs slightly better than the system based on sum rule. Based on the results obtained in this paper, Median and Sum rules are the recommended data fusion methods for the proposed face recognition system to improve the recognition performance. Almost all the face recognition systems use grey level information (*I* channel only) for recognition. The recognition performance in *I* channel for the mixed database is 91.92% where, the median rule based proposed face recognition system (using six different colour channels) achieves 97.40%, corresponding 5.48% improvement in the recognition performance.

4. CONCLUSION

In this paper, we introduced a high performance face recognition system based on combining the decision obtained from PDFs in different colour channels. Several decision making techniques such as sum, maximum, median and product rules, as well as majority voting and feature vector fusion have been employed to improve the performance of the proposed PDF based face recognition system. The increased recognition performance clearly indicates the superiority of the median rule based face recognition system over the system used in [6], which only uses MV and FVF.

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