Illumination Invariant Face Recognition

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Abstract— **Few of the face recognition methods reported in the literature are capable of recognising faces under varying illumination conditions. This paper discusses a new method which can achieve a higher recognition rate than those obtained for existing methods. The novelty of this new method is the use of an embossing technique to process a face image before presenting it to a standard face recognition system. Using a large database of face images, the performance of the proposed method is evaluated by comparing it against the performances of three existing methods. The experimental results demonstrate the successfulness of the proposed method.**

I. Introduction

Automatic face recognition is a difficult problem in computer vision. Existing automatic face recognition systems have demonstrated good recognition performance with frontal, centred, and expressionless views of faces captured under controlled lighting conditions. [4], [6]. However, variability in appearance due to changes in lighting condition, pose, expression, and age reduces significantly the recognition performance of these systems [1]-[3] and [8]. This paper only deals with the variations that are due to changes in illumination.

A few methods have been proposed for recognising faces under varying lighting conditions. In a recent paper, Adini et al. [1] examine four existing image representations considered to be insensitive to illumination changes when employed for face recognition. The image representations considered in their paper are: the edge map of the image, the image filtered with 2D Gabor-like filters, the first and second derivatives of the gray-level image, and the logarithmic transformation. They constructed each of these image representations with several different parameter settings of the operator concerned. It has been reported that for most image representations considered, the percentage of miss-recognised faces was above 50%. The best performance was obtained with Gabor-like filters for which the number of miss-recognised faces was reduced by 20%. The reported results indicate that these approaches are not suitable for developing an illumination invariant face recognition system.

In addition to the methods stated above, two other approaches are also reviewed here. The first approach has been proposed by Brunelli [3] in which the illumination direction is first estimated in a face image. Then the illumination effects are compensated for and a face image with standard illumination is produced. The drawback of this approach is that the calculation and compensation of the illumination direction are done based on a simple lighting model of the light source that does not represent a variety of complicated lighting conditions which exist in practical situations.

The second approach which was proven to perform better than the others has been proposed first by Swets et al. [8] as Most Discriminating Feature (MDF), and later by Belhumeur et al. [2] as fisherfaces. The idea is to produce classes in a low dimensional face image subspace obtained from linearly projecting a high-dimensional image space to the subspace. Belhumeur et al. have conducted experiments on fisherfaces and three standard face recognition methods including eigenfaces, and have reported lower error rates for the fisherfaces method.

The fisherfaces method is not perfect. A drawback of this approach is that it needs to be trained using a set of known face images classified into different groups. When more known faces are added to the database, the training with and transformation of known face images have to be carry out again. Another shortcoming of this method is that the transformation coefficients of different classes are very close to each other, compared to the other methods. This will cause false recognition of unknown faces as elaborated in Section 3.

In this paper a method is introduced that achieves a better performance than that of the fisherfaces.

Fig. 1. Images of a person's face taken under different illumination conditions (top row), and their corresponding embossed images (bottom row).

The proposed method does not require any retraining and re-transformation when new face images are added to the database. An image is first embossed and then presented to a standard face recognition system such as eigenfaces [9]. Different kernels can be used for embossing an image. The embossing kernel used in this work has been determined through experiments designed to minimise the recognition error.

II. Methods

In this section, the three existing methods mentioned in the previous section, together with the proposed embossing method and an embossing-fisherfaces combination method, are described for solving the illumination invariant face recognition problem.

A. Eigenfaces

The eigenfaces method [9] is the most popular and widely used method for representation and recognition of human faces. The eigenfaces are calculated using Principal Component Analysis (PCA). In PCA, a dimensionality reducing linear projection that maximises the scatter of all projected samples is selected. The optimal basis is given by the eigenvectors of the total scatter matrix. Let the training set of n-dimensional face images be $\{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\}$. The average face of the set is defined by $\boldsymbol{\mu} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{x}_i$. An $n \times m$ $(m < n)$ matrix W with orthonormal columns is sought to best describe the distribution of the data. If the total scatter matrix S_T is defined as

$$S_T = \sum_{i=1}^{N} (\boldsymbol{x}_i - \boldsymbol{\mu})(\boldsymbol{x}_i - \boldsymbol{\mu})^T, \qquad (1)$$

then after applying the transformation W^T, the scatter of the transformed vectors is $W^T S_T W$. W contains m eigenvectors of S_T corresponding to the m largest eigenvalues. These eigenvectors are called eigenfaces.

B. Logarithmic Transformation

Logarithmic transformation is a non-linear transformation which is believed to approximate the responses of cells in the retina of the human eye. When applied to face recognition, the transformation is first performed on images before they are presented to a standard face recognition system.

C. Fisherfaces

The fisherfaces method performs dimensionality reduction using linear projection. Since the training set is labelled, the method produces classes in a low dimensional face image subspace. Assume that each image in the training set belongs to one of c classes $\{X_1, X_2, \ldots, X_c\}$. The between-class scatter matrix is defined as

$$S_B = \sum_{i=1}^{c} N_i(\boldsymbol{\mu}_i - \boldsymbol{\mu})(\boldsymbol{\mu}_i - \boldsymbol{\mu})^T, \qquad (2)$$

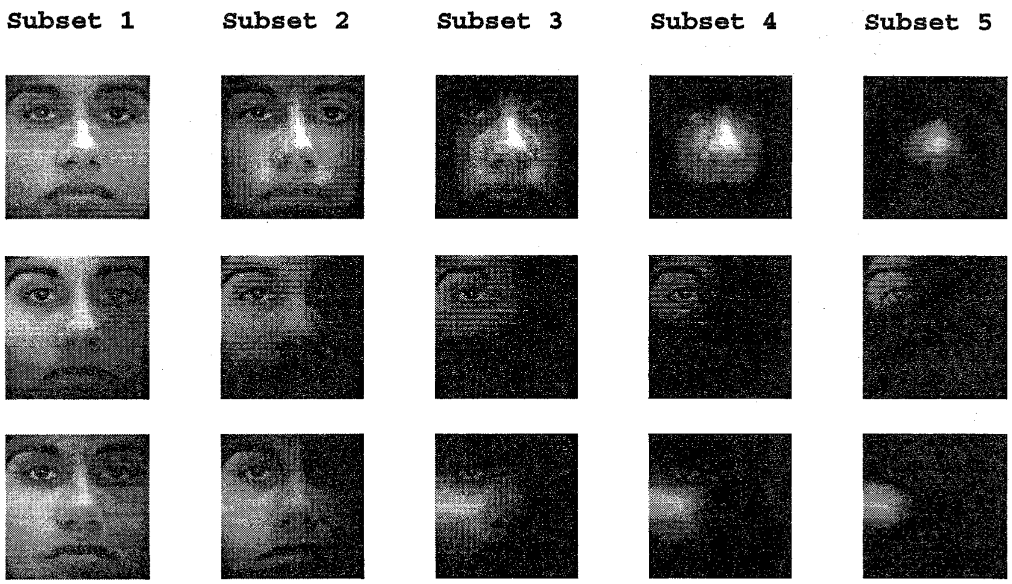

Fig. 2. Sample face images from each subset.

and the within-class scatter matrix is defined as

$$S_W = \sum_{i=1}^{c} \sum_{\boldsymbol{x}_k \in X_i} (\boldsymbol{x}_k - \boldsymbol{\mu}_i)(\boldsymbol{x}_k - \boldsymbol{\mu}_i)^T, \qquad (3)$$

where $\boldsymbol{\mu}_i$ is the mean image of class X_i, and N_i is the number of images in that class. W contains m eigenvectors of $S_W^{-1} S_T$ corresponding to the m largest eigenvalues. However, since S_W is always singular, the matrix W cannot be computed. To overcome this problem, the image set is first projected onto a lower dimensional space using PCA to produce a singular S_W, and then W is calculated using PCA.

D. Embossing

Embossing refers to a filter that causes areas to appear raised in relief. This is achieved by suppressing the colour in the area and outlining it with a selected colour such as gray. Embossing a face image and then using the result for face recognition can significantly reduce the effects of changes in illumination conditions on the image, while maintaining the most important information of the image required for recognition. Different kernels can be used for embossing an image. The 7×7 embossing kernel used in this work has been found through experiments designed to minimise the recognition error. This idea is used to develop a face recognition system. The eigenfaces method is utilised as a standard method for recognition using the embossed images. Figure 1 illustrates three images of a person's face taken under different illumination conditions, and their corresponding embossed images.

E. Embossing-Fisherfaces

In this method, the images are first embossed and then presented to the fisherfaces method.

III. Experimental Results

In this section, the five methods are analysed through a set of extensive experiments, to evaluate their relative performances under varying lighting conditions. The experiments are based on the use of a common database of 2710 face images. The results of the experiments are presented and discussed. In order to speed up the development of the face database containing images taken under varying illumination conditions, the variation in illumination in the images is artificially introduced.

A basic set of face images of 10 people is used to build the database. 271 masks are superimposed on each face image to generate 271 images under different lighting conditions. Each mask models the effect of a single light source projected onto the face from a specific direction and distance. The images in the database are grouped into five subsets. The numbers

TABLE I

ERROR RATES OF FIVE RECOGNITION METHODS TRAINED ON FACE IMAGES FROM SUBSET 1, AND TESTED ON FACE IMAGES FROM SUBSETS 1-5.

Trained From Subset 1							
Method	Reduced Space	Error Rate (%)					
		Subset1	Subset2	Subset3	Subset4	Subset5	Total
Eigenfaces	100	0	8	42	72.9	85.3	68.5
	20	0	13.5	51.9	78.6	87.1	72.4
	9	0	32.5	68	83.5	88.7	77.7
Logarithmic	100	0	22.5	67	82.3	88.1	76.2
	20	0	23.5	71.6	83.4	88.2	77.2
	9	0	33	74.2	84.2	88.3	78.3
Fisherfaces	9	0	0	7.7	54.7	78.8	56.2
Embossing	100	0	0	1.6	17.5	49.3	30.8
	20	0	0	2.2	24.3	53.9	34.9
	9	0	0	3.8	26.6	54.3	35.9
Embossing-Fisherfaces	9	0	0	0.9	12.1	27.3	17.6

TABLE II

ERROR RATES OF FIVE RECOGNITION METHODS TRAINED ON FACE IMAGES FROM SUBSET 1 AND SUBSET 5, AND TESTED ON FACE IMAGES FROM SUBSETS 1-5.

Trained From Subset 1 and Subset 5							
Method	Reduced Space	Error Rate (%)					
		Subset1	Subset2	Subset3	Subset4	Subset5	Total
Eigenfaces	1550	0	5.5	28	26.3	0	9.9
	20	0	30.5	69	67	0	26.2
	9	0	67	91.3	85.8	0	35.9
Logarithmic	1550	0	12	76.1	77.5	0	28.2
	20	0	63	84.8	86.6	0	35.1
	9	0	75	85.1	87.8	0	36.3
Fisherfaces	9	0	0	0.9	8.3	0	2.1
Embossing	1550	0	0	0	0	0	0
	20	0	0	0.3	4.3	0	1
	9	0	0	0.6	7.8	0	1.9
Embossing-Fisherfaces	9	0	0	0	0.06	0	0.03

of images in Subset 1 to Subset 5 are 100, 200, 310, 650, and 1450, respectively. The distances between the light sources and the faces are smallest within Subset 1 and largest within Subset 5. Figure 2 illustrates sample face images from each subset.

Two experiments are carried out on this database. In the first experiment, each recognition method is trained on images from Subset 1 and then tested on images from all subsets. Table I displays the results obtained from this experiment.

In the second experiment, each recognition method is trained on images from Subset 1 and Subset 5, and then tested on images from all subsets. The results obtained from this experiment are given in Table II.

As can be seen in Tables I and II, the embossing-fisherfaces method has lower error rates than the others for both experiments. The error rates given by the embossing method are slightly higher than those of the embossing-fisherfaces method, but still lower than those of the fisherfaces, logarithmic, and eigenfaces methods as indicated by both experiments.

To elaborate more on the relative recognition performances of the proposed method and the fisherfaces method, a third experiment is performed. In this experiment, a second face database containing the face images of 40 people not used in the training phase is employed. This unknown face database is to the fisherfaces and the embossing methods which have been trained on Subset 1. It is discovered that the false recognition rate of unknown faces using the fisherfaces method is much higher than that of the embossing method. To reject an unknown face, it is necessary to set a rejection threshold value in such a way that the calculated error for all unknown faces is located above the threshold, whereas that for known faces lies below the threshold. Figures 3 and 4 illustrate the distributions of recognition errors obtained for presenting both the known face database and the unknown face database to the fisherfaces method (Figure 3) and the embossing method (Figure4).

In the fisherfaces method, if the threshold is set to 2.5% to allow the rejection of all unknown faces (see Figure 3(b)), then the correct recognition of the 2710 known faces drops by 60% from 1187 to 500 (see Figure 3(a)). In the embossing method, however, if the threshold is set to 12.5% to allow the rejection of all unknown faces (see Figure 4(b)), then the correct recognition of the 2710 known faces drops by only 4% from 1743 to 1670 (see Figure 4(a)). This proves the superiority of the embossing method for recognising faces under different illumination conditions.

A fourth experiment is also performed on a database of face images which is particularly constructed for testing the effects of multiple light sources on recognition rates. Three light sources are used in this experiment. It is observed that both the embossing-fisherfaces method and the embossing method can achieve lower error rates than those of the other three methods. This observation is similar to that obtained from the first and second experiments for a single light source. For the sake of brevity, the detailed results for this fourth experiment are not included in this paper.

IV. Conclusions

In this paper, a method for recognising face images under varying lighting conditions has been presented. An embossing kernel has been designed and used to filter images before presenting them to a standard recognition system. A database of 2710 face images under varying illumination conditions has been constructed. The performances of the two systems based on the proposed embossing method have been evaluated and compared with those of three existing face recognition systems. The results obtained from the experiments indicate that the proposed embossing method significantly improves the recognition rate for face images taken under varying lighting conditions.

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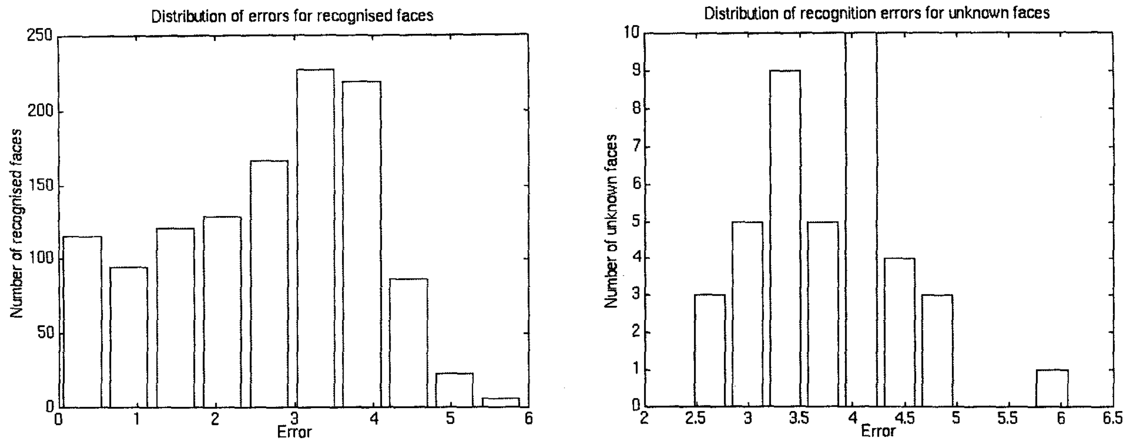
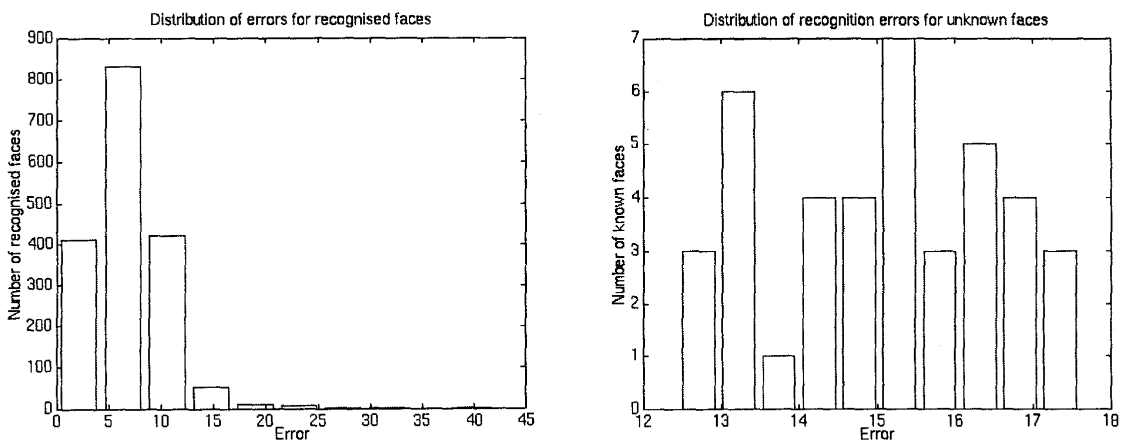


(a) **(b)**

Fig. 3. Distribution of recognition errors for the fisherfaces method when presented with (a) 2710 known face images and (b) 40 unknown face images.



(a) **(b)**

Fig. 4. Distribution of recognition errors for the embossing method when presented with (a) 2710 known face images and (b) 40 unknown face images.