LOCAL HISTOGRAM ENHANCEMENT FOR FACE RECOGNITION

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ABSTRACT

Several of the techniques developed for face recognition are susceptible to variations in illumination. The most widely used technique for compensating changes in illumination is global histogram equalization. But face images can exhibit local illumination variations. In this paper we show how a modified version of local histogram enhancement leads to improvement in recognition accuracy. The results are compared with well-known illumination compensation techniques – global histogram equalization and dropping first three principal components. The technique proposed here gives best overall performance. The experiments were performed on the FERET database.

1. INTRODUCTION

Face recognition is currently one of the most sought after applications of computer vision – especially for surveillance. A variety of techniques have been developed for face recognition – from vector space approaches to probabilistic techniques. There are two challenges faced by face recognition research: variations in illumination and variations in pose. The widely used technique for handling illumination changes is *training* on all possible illumination conditions. Since it is impossible to acquire data under many illumination conditions, the emerging approach is to *synthesize* facial images for different illumination conditions [1]. A simpler method is to preprocess the face image and compensate for illumination changes.

A face is a 3-dimensional shape and the effect of illumination can be local. Hence global techniques like histogram equalization [2] are not expected to perform well – though such techniques are widely used. In this paper, we show how *local* histogram enhancement leads to performance improvements.

This paper is organized as follows. Section 2 provides a brief discussion of face recognition techniques. These techniques are used in the simulations reported. Section 3 contains a description of the local histogram modification technique used. Section 4 describes the simulation methodology and results. The paper closes with a discussion.

2. FACE RECOGNITION

Face recognition approaches can be broadly categorized into two classes: template matching based systems and geometrical feature based systems. Template matching systems mostly captures the global features of the images. Support Vector Machines (SVM) [3], Linear Discriminant Analysis (LDA) [4] [5], Principal Component Analysis (PCA) [6], Probabilistic Bayesian Matching [7], etc. are some of the methods in this approach. The geometrical feature based approaches [8], on the other hand, try to find certain attributes in the image like shape, colors or facial features.

In this paper, we use PCA and LDA of Principal Components approach as a common platform to test the performance of the local histogram enhancement.

3. HANDLING ILLUMINATION CHANGES

There are various techniques proposed for handling illumination changes. one of the technique is to discard the three most significant principal components which seems to capture variation due to lighting. Authors in [4], show that the system performance under varying illumination does improve using this approach. However, it assumes that the first three principal components only capture illumination variation. This assumption may not be true. In fact, our experiments shows that though the performance for varying illumination improves, system performance under normally lighted images falls substantially.

Other techniques use 3D information like 3D head models or depth information derived using motion or intensity information [9]. Such techniques are computationally intensive. In this paper, we explore the use of simpler preprocessing techniques like histogram modification.

3.1. Local histogram enhancement

Changes in illumination for facial images are due to variations in factors such as light intensity, direction and number of light sources. This indicates that the effect of illumination is a local phenomenon in the facial images. Because of these reasons the global equalization may not compensate properly for illumination changes. If we apply histogram equalization locally in the image, the contrast improves but this results in creation of spurious objects in the image because of modifications in the level sets. These objects can affect the recognition performance. The basic information of an image is contained in the family of its level-sets and hence should be preserved [10]. Authors in [11] propose a new approach of local histogram equalization which enhances image contrast while preserving the level-sets. The scheme is based on equalizing the histogram in all *connected components* of the image.

We reproduce the algorithm given in [11] for completeness.

Let $u : \Omega \rightarrow [0, L]$ be an image whose pixel values have been normalized in $[0, L]$. Let $\lambda_{k,j} = jL/2^k, k = 0, 1, 2, ..., \log L, j = 0, ..., 2^k$.
Step 1) Construct $w_o = H(u)$ be the histogram equalization of *u*.
Step 2) Construction of w_i, *i* = 1, ..., $\log L$.
Suppose that we already constructed w_o, ..., w_{i-1}. Let us construct w_i. For each *j* = 0, 1, ..., 2^i-1, let

$$O_{i,j} = [\lambda_{i,j} \leq w_{i-1} < \lambda_{i,j+1}] \tag{1}$$

and let $O_{i,j;r}$ be the connected components of $O_{i,j}, r = 1, ..., n_{i,j}$. Let $h_{i,j;r}$ be the distribution function of $w_{i-1}\chi O_{i,j;r}$ with values in the range $[\lambda_{i,j}, \lambda_{i,j+1}]$.
Then define

$$w_i = \sum_{j=1}^{2^i-1} \sum_{r=1}^{n_{i,j}} h_{i,j;r}(w_i - 1)\chi_{O_{i,j;r}} \tag{2}$$

The algorithm equalizes the histogram for all connected components of all "dyadic" sets of the form $[\lambda_1 \leq u < \lambda_2]$ where $\lambda_1, \lambda_2 \in \{\lambda_{i,j} : j = 0, ..., 2^i\}$. There are two shortcomings with this approach.

1. The approach shows an *accumulation* effect at the end points of intensity ranges. For example, if the range set is $[\lambda_1, \lambda_2]$ and we are having two connected components each having highest pixel value of σ_1 and σ_2 such that $\lambda_1 \leq \sigma_1, \sigma_2 \leq \lambda_2$ then histogram equalization on these separate components will push both the pixel values to the maximum in the range, i.e., $h(\sigma_1) = h(\sigma_2) = \lambda_2$.

2. If the pixel counts of connected components is small, then the above accumulation effect is more pronounced.

To avoid this accumulation effect, we modify the above algorithm by *equalizing histogram in the range set instead of equalizing component wise*. So the equation 2 becomes,

$$w_i = \sum_{j=1}^{2^i-1} h_{i,j}(w_{i-1})\chi_{O_{i,j}} \tag{3}$$

Thus we can recursively equalize the histogram up to 8th level ($k = 8$) for 256 gray levels. In our experiments we fixed the value of k to 6 as beyond this point the improvement in performance does not commensurate with the increase in computational complexity.

Evaluation Task	*Probe Name*	*No of images*
Aging of subjects	DUP1 (Duplicate I)	722
Aging of subjects	DUP2 (Duplicate II)	234
Facial expression	FAFB	1195
Illumination	FAFC	194

Table 1. FERET test tasks.

4. SIMULATION RESULTS

We performed a set of experiment to demonstrate the efficacy of the method. The experiments are performed on FERET [12] database. The database contains 3368 images of 1209 subjects. We use CSU Face Identification Evaluation System 5.0 [13] to perform the experiments. PCA and LDA of Principal Components algorithms are used for experiments. The training is performed on regular frontal images of 428 subjects. All the images were preprocessed to normalize geometry and to remove background and hair.

The testing probe sets are divided into four sets according to FERET test protocol 1996. Table 1 gives the division.

We performed three sets of experiments.

Global Histogram Equalization (GHE): This serves as a baseline for comparisons.

Local Histogram Enhancement (LHE): The modified method outlined in the previous section is used.

First Three Principal Components Eliminated (PCA-3): As mentioned in section 3, the first three principal components are thought to capture illumination variations. Hence this serves as another basis for comparison.

We use two classifiers in the experiments.

Principal Components Analysis (PCA): This is the classical eigenfaces approach [6].

Linear Discriminant Analysis of PCA (LDA): Here linear discriminant analysis is performed on a PCA subspace [9]. This is referred to as LDA in the following discussion.

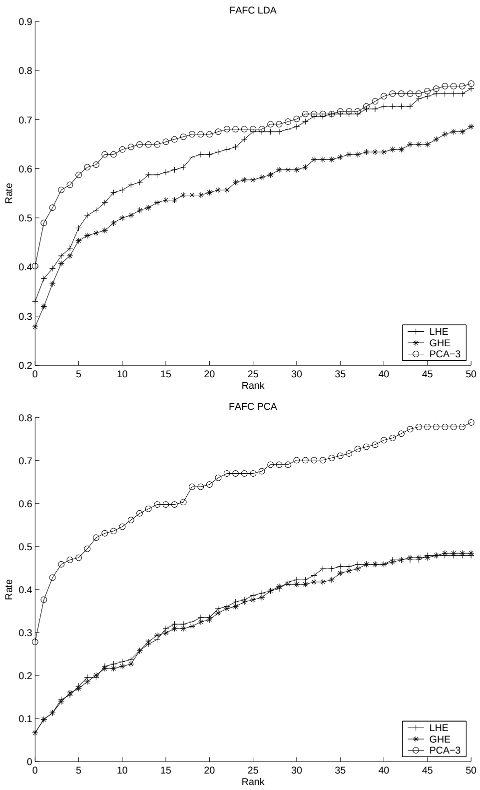

Fig. 1. Performance on illumination test (FAFC).

Figures 1–4 show the results of experiments on different tests. The figures show recognition accuracy as a function of rank. This curves gives the percentage of matches for each rank. The ranks are obtained by sorting the distances of the probes to gallery images. In the following discussion, recognition accuracies corresponding to rank 50 are used.

It can be seen from figure 1 that with LDA, LHE results in an accuracy of 76% – 8% more than GHE. With PCA, both LHE and GHE have comparable performance. With PCA, PCA-3 gives a dramatic increase in performance. With LDA, PCA-3 and LHE have comparable performance after rank 25. The maximum accuracies obtained are: LHE – 76% (with LDA), GHE – 68% (with LDA), and PCA-3 – 78% (with PCA).

Hence it can be concluded that PCA-3 outperforms LHE by 2% while GHE leads to poor results on FAFC test set. It can be seen from figures 2–4 that PCA-3, though performs better for FAFC test set, has the *worst* performance of the three techniques for the remaining test sets. It can also be seen that LHE and GHE have comparable performances except in two cases.

1. GHE outperforms LHE by 1.5% in DUP2 LDA.

2. LHE outperforms GHE by 2.5% in DUP1 LDA.

Probe	Algorithm	LDA	PCA	Best
FAFC	LHE	76.3	47.94	76.3
	GHE	68.56	48.45	68.56
	PCA-3	77.32	78.86	78.86
FAFB	LHE	88.95	97.57	97.57
	GHE	88.87	97.74	97.74
	PCA-3	86.19	92.88	92.88
DUP1	LHE	70.78	69.39	70.78
	GHE	68.28	69.53	69.53
	PCA-3	66.2	66.6	66.6
DUP2	LHE	47.86	59.4	59.4
	GHE	50.0	58.55	58.55
	PCA-3	45.72	57.69	57.69

Table 2. Performance comparison. The table gives recognition rates (in %) for rank=50.

We can conclude from the above observations that LHE gives the best overall performance – across different tasks. See table 2.

5. DISCUSSION

In this paper we have proposed a modified histogram enhancement technique and have demonstrated its effectiveness for face recognition. More specifically we have shown that it improves the performance in the illumination (FAFC) probe set without compromising the performance on other tasks. We have also demonstrated that PCA-3 (with PCA), which performs marginally better than LHE (with LDA) for FAFC, performs consistently worse on all the other tasks. This shows that first three principal components contain non-illumination information.

6. REFERENCES

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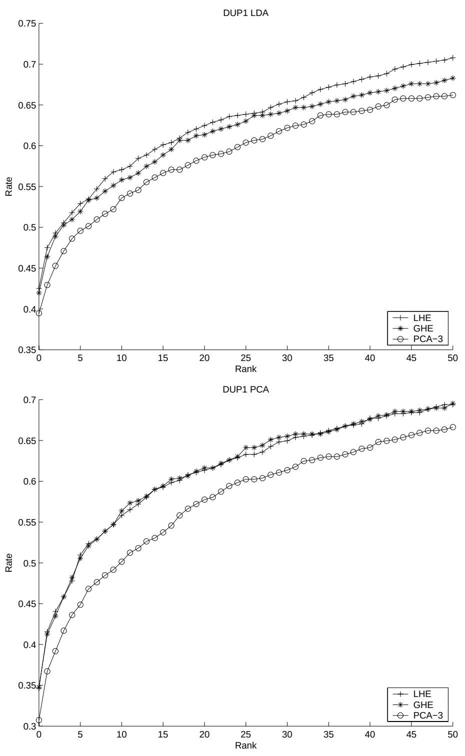

Fig. 2. Performance on duplicates 1 test (DUP1).

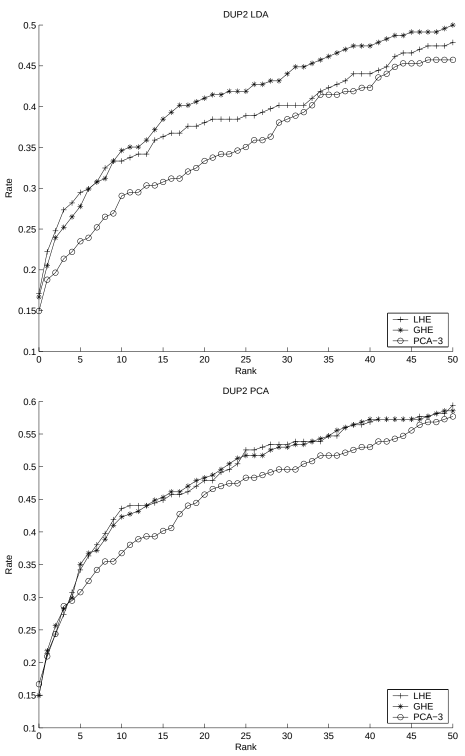

Fig. 3. Performance on duplicates 2 test (DUP2).

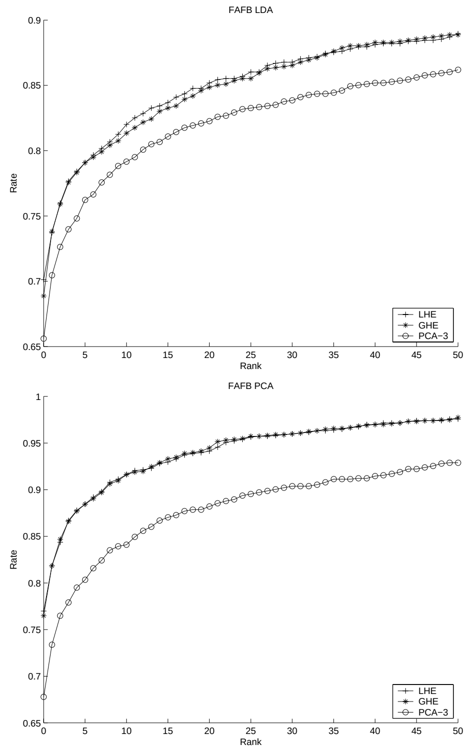

Fig. 4. Performance on facial expression test (FAFB).

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