

# Empirical Comparisons of Several Preprocessing Methods for Illumination Insensitive Face Recognition

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## ABSTRACT

Illumination variation is one of the bottlenecks of face recognition systems. In the past few years, many approaches to coping with illumination variations have been proposed which can be categorized into model-based and preprocessing-based. Although the model-based approaches seem more perfect in theory, they commonly introduce more constraints, which make them not practical enough for the real applications. On the other hand, the preprocessing approaches commonly exploit simple and efficient image processing techniques. The typical approaches based on image processing include histogram equalization (HE), histogram specification (HS), logarithm transform (Log), Gamma intensity correction (GIC), and self-quotient image (SQI). In this paper, we perform extensive experiments to analyze and compare these methods empirically by evaluating them on three large-scale face databases: CMU-PIE database, FERET database and CAS-PEAL database. Our experimental results show that HE, HS and GIC can improve recognition performance for both images with and without illumination variations, while Log and SQI may decrease the recognition rate for face images without much illumination variations though they may facilitate the recognition of face images with illumination variations.

## 1. INTRODUCTION

Face recognition has attracted much attention in the past decades for its wide potential applications in commerce and law enforcement. Much progress has been made in the past few years [1]. However, face recognition remains an unsolved problem in general. The FERET test [2] and the FRVT test [3] revealed that illumination variation is one of the bottlenecks of practical face recognition systems.

There has been much work dealing with illumination variations in face recognition. Generally, these approaches can be classified into two categories: the model-based approaches [10, 11, 12] and the image processing based approaches. Though the model-based approaches are perfect in theory, they always require some additional constraints or assumptions when applying them to real applications. And their computational cost is usually too high. So these methods are not practical enough for recognition systems in most cases. On the other hand, the

approaches based on image processing techniques transform images directly without any assumptions or prior knowledge. Therefore, they are more commonly used in practical systems for their simplicity and efficiency. Except the traditional method such as histogram equalization (HE), histogram specification (HS), logarithm transformation (Log), new methods belonging to this category such as Gamma intensity correction (GIC) [5] and self-quotient image (SQI) [4] have been proposed recently with impressive performance improvement for illumination problem.

However, we found that these preprocessing approaches do not always work well on different datasets. Furthermore, some approaches may bring negative effects for images with normal lighting, though they do facilitate the recognition of face images with illumination variations. These observations have motivated us to investigate and evaluate them systematically in order to guide their application to practical systems. In this paper, we have compared these typical preprocessing approaches systematically on three large-scale face databases: CMU-PIE database [6], FERET database [7] and CAS-PEAL database [8]. We have shown that HE, HS and GIC can improve recognition performance for both images with and without illumination variations, while Log and SQI may hurt the recognition of face images with normal lighting, though they may facilitate the recognition of face images with illumination variations.

The rest of this paper is organized as follows. Section 2 introduces the methods compared in this paper. In Section 3, the experimental design is described and the experimental results are reported. Discussions and conclusions are given in the last section.

## 2. TYPICAL PREPROCESSING METHODS

The methods based on image processing techniques for illumination problem commonly attempt to normalize all the face images to a canonical illumination in order to compare them under the “identical” lighting conditions. These methods can be formulated as a uniform form [5]:

$$I' = T(I), \quad (1)$$

where  $I$  is the original image,  $T$  is the transform formula and  $I'$  is the image after the transform. The transform  $T$  is expected to weaken the negative effect of the varying illumination and the image  $I'$  can be used as a canonical form for a face recognition system. Therefore, the recognition system is expected to be insensitive to the varying lighting.

Histogram equalization (HE), Histogram specification (HS) and logarithm transform (Log) are the most commonly used methods for gray-scale transform. In face recognition systems, they are often used as the illumination preprocessing. Recently, Gamma intensity correction (GIC) [5] and self-quotient image (SQI) [4] were proposed to weaken the effect of illumination variations in face recognition. All these methods are briefly introduced in the following.

**HE and HS:** They are most commonly used techniques of histogram adjustment. HE is to create an image with uniform distribution over the whole brightness scale and HS is to make the histogram of the input image have a predefined shape.

**Log:** Log is another frequently used technique of gray-scale transform. It simulates the logarithmic sensitivity of the human eye to the light intensity.

**GIC:** GIC [5] is coming from the idea of Gamma correction. It corrects the overall brightness of a face image to a pre-defined “canonical” face image  $I_0$ . Thus the effect of varying lighting is weakened.

**SQI:** SQI [4] is based on the reflectance-illumination model:  $I = RL$ , where  $I$  is the image,  $R$  is the reflectance of the scene and  $L$  is the lighting. The lighting  $L$  can be considered as the low frequency component of the image  $I$  and can be estimated by a low-pass filter  $F$ , i.e.,  $L \approx F * I$ . Thus we can get the self-quotient image as  $R = \frac{I}{F * I}$ . For more information,

please refer to [4]. Figure 1 gives some examples of the images after these transforms.

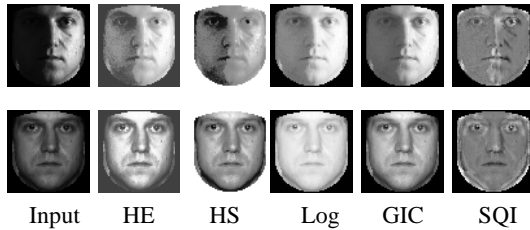


Figure 1. Example effects of the typical preprocessing

However, we found that these preprocessing approaches do not always work well on different datasets. Furthermore, some approaches may hurt the recognition of face images with normal lighting, though they do facilitate the recognition of face images with illumination variations. These observations have motivated us to investigate and evaluate them systematically in order to guide their application to practical systems.

### 3. EMPIRICAL EVALUATION OF TYPICAL PREPROCESSING METHODS

One purpose of this paper is to compare each method’s performance on coping with illumination variation. The other is to investigate their influence on the variations other than illumination, such as accessory and expression.

#### 3.1 The framework of the evaluation system

Linear discriminant analysis (LDA) [9] is one of the best recognition approaches. LDA finds the subspace best discriminating different face classes. It is carried out by

maximizing the ratio of between-class scatter matrix  $S_b$  to the within-class scatter matrix  $S_w$  in the projective subspace. To avoid  $S_w$  being singular, PCA is commonly conducted to reduce the data dimensionality, and then apply discriminant analysis in the reduced PCA space. Therefore the two important parameters of LDA are the dimensionality of the PCA subspace and the dimensionality of the LDA subspace. In our experiment, the dimension of PCA subspace ( $dp$ ) and the dimension of LDA subspace ( $dl$ ) are shown in Table 1. The experimental results given in this paper is the highest rate among all the possible LDA subspaces corresponding to a given PCA subspace.

Table 1. The dimensions of PCA and LDA

$Dp$	$Dl$	
	Range	Step
100	10~90	3
200	10~180	4
300	10~260	4
400	10~260	4

There are some other parameters to be decided for the above-mentioned preprocessing methods. In our experiments, the parameters of the methods are selected as follows, respectively.

- HS and GIC: These methods need to predefine a canonical image  $I_0$ . On CMU-PIE database, FERET database and CAS-PEAL database, we select  $I_0$  from the three galleries respectively as shown in Figure 2.
- SQI: In the experiments, we select five Gaussian kernels whose sigma parameters are 1, 1.25, 1.5, 1.75 and 2 and use  $arctan$  function as the nonlinear transform.



Figure 2. The canonical images for GIC and HS

#### 3.2 Experiments on the CMU-PIE database

The illumination conditions of the CMU-PIE database [6] are well controlled and it includes images of 68 subjects varying in pose, illumination, and expression. In order to compare the performances of each method under different ranges of variation in lighting, We select the frontal images from the “illum” subset which includes the images under 21 different directional flashes, and divided the images into four subsets according to the angle that the light source direction makes with the camera axis—Subset 1 (f06~f09, f11, f12, f20), Subset 2 (f05, f10, f13, f14, f19, f21), Subset 3 (f04, f15, f18, f22) and Subset 4 (f02, f03, f16, f17).

In our experiment, We use the training set provided by the FERET database to produce LDA subspace. And the probes are the above four subsets of the “illum” subset. Table 2 shows the experimental results when the dimension of the PCA subspace is 400 where the recognition rate of no preprocessing method is the highest. We can see that all the methods can work well on the “illum” subset of the CMU-PIE database. Furthermore, the

performances of HE and HS are better than the others when the lighting conditions are worse such as subset 3 and subset 4.

Table 2. The recognition rates of different preprocessing method on the CMU-PIE database

Preprocessing method	Subset1	Subset2	Subset3	Subset4	Mean
No	0.769	0.750	0.666	0.474	0.687
GIC	0.830	<b>0.831</b>	<b>0.816</b>	0.697	<b>0.802</b>
Log	<b>0.853</b>	0.811	0.757	0.651	0.784
HE	0.718	0.752	0.801	0.823	0.763
HS	0.777	0.787	0.802	<b>0.834</b>	0.795
SQI	0.811	0.801	0.735	0.688	0.770

### 3.3 Experiment results on the FERET database and the CAS-PEAL database

The FERET database [7] is one of the most famous databases including images varying in pose, lighting, expression and aging. There are 1196 people in the gallery set, one image per person. We select duplicate I, duplicate II, fafb and fafc as the probe

sets. The CAS-PEAL face database [9] contains 30,900 images of 1040 individuals with varying Pose, Expression, Accessory, and Lighting (PEAL). In our experiment we select the frontal images from the subsets of accessory, distance, background, expression, lighting and aging as probe sets. The experiments on the two datasets are to investigate each method's influence on the variations in both illumination and the others.

Figure 3 gives the results of each method on the lighting subsets of FERET database and CAS-PEAL database. The results show that HS, Log and GIC increase the recognition rate in different PCA subspaces stably.

Figure 4 gives the results on the other subsets of the two databases. The dimension of PCA subspace is 400 and 300 on the two databases respectively, where the recognition rates with no preprocessing method on the lighting subsets of the two databases are the highest. We can see Log decreases the recognition rate of the other subsets though it increases the rate of lighting subset on the CAS-PEAL database. SQI cannot cope with the illumination variations well on the two databases and influences other subsets greatly, especially on the CAS-PEAL database.

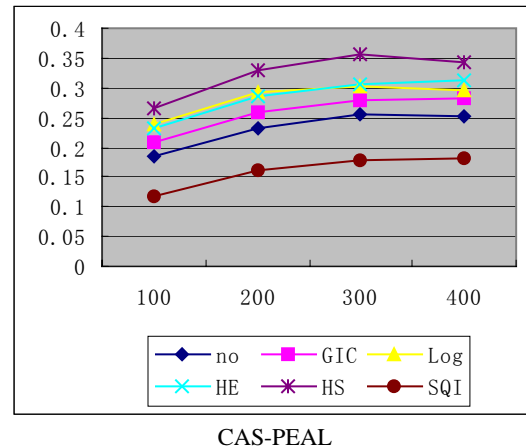
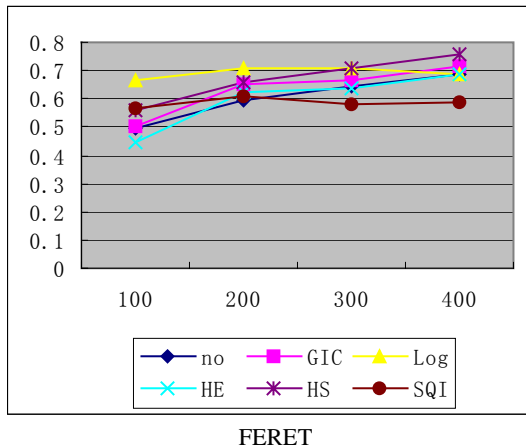
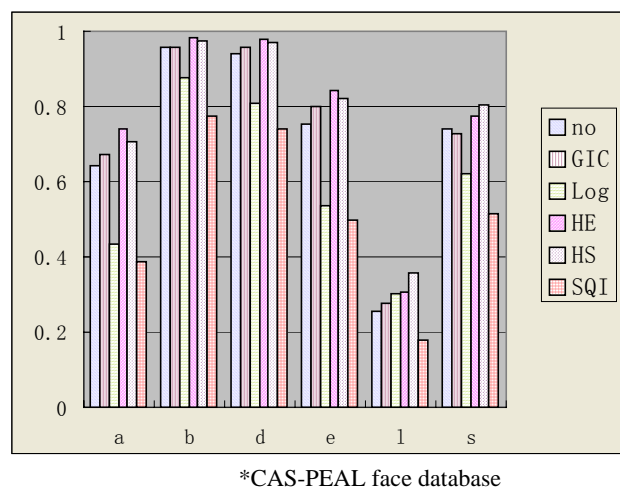
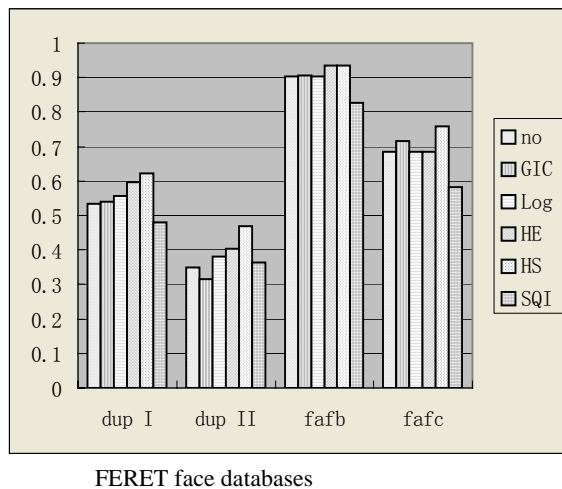


Figure 3. The recognition rates on fafc of the FERET database and the lighting subset of the CAS-PEAL database



\* CAS-PEAL: a (accessory), b (background), d (distance), e (expression), l (lighting), s (aging)

Figure 4. The recognition rates on the other sets of the FERET database and CAS-PEAL database.

### 3.4 Summary and discussion

Table 3 is the summary of the results, which gives the average increased recognition rates of each method on the lighting subsets and the other subsets in the three face databases.

Table 3. The increased recognition rates of each method on the lighting subsets and the other subsets.

Preprocessing method	FERET		CAS-PEAL		CMU-PIE
	Lighting	Others	Lighting	Others	Lighting
GIC	0.03	-0.001	0.023	0.030	0.115
Log	0	0.011	0.049	-0.193	0.097
HE	0	0.044	0.051	0.081	0.076
HS	0.072	0.061	0.102	0.056	0.108
SQI	-0.104	-0.059	-0.077	-0.244	0.083

**HE, HS and GIC:** The experimental results show they are better than the other two methods. (Some images in the FERET database had been processed with HE. Therefore HE has little improvement on it.) Furthermore, they need no complex operations and the complexity of time and space is not high.

**Log:** Although Log is one of the best methods in dealing with the variations in lighting on the three databases; it decreases the recognition rates on the other subsets of the CAS-PEAL database greatly. One possible reason is that the difference between the mean brightness values of the transformed images belonging to the same person is too large.

**SQI:** It uses a weighted Gaussian filter that convolutes with only the large part in edge regions [4]. Thus the halo effects can be reduced. When the lighting variations are large (such as the "illum" subset of the CMU-PIE database), the edges induced by lighting are prominent and this method can work well. However, when lighting variations are not so obvious, the main edges are induced by the facial features. If this kind of filter is still used, the useful information for recognition will be weakened. This is a possible reason that it decreases the recognition rates on the FERET and CAS-PEAL datasets while increasing the recognition rates on the CMU-PIE database.

### 4. CONCLUSION

This paper empirically compares several preprocessing methods for illumination insensitive face recognition including HE, HS, Log, GIC and SQI on the CMU-PIE database, the FERET database and the CAS-PEAL database. From the experimental results, several conclusions can be drawn:

- (1) HE, HS, and GIC can weaken the effect of the lighting variations and do not bring any negative influence on the other variations.
- (2) Log brings much negative influence on the other variation although it can deal with illumination variation well.
- (3) The performance of SQI depends on the datasets. When the lighting variations are obvious its performance is better. Otherwise it cannot work well enough.

These conclusions suggest that for a practical face recognition system where the constraints needed by those model-based

methods are unavailable, HE, HS or GIC should be adopted, while for Log and SQI methods, further researches should be conducted to investigate their ability in case of normal illumination conditions.

### ACKNOWLEDGEMENTS

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