# Illumination Normalization for Robust Face Recognition Against Varying Lighting Conditions

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## Abstract

*Evaluations of the state-of-the-art of both academic face recognition algorithms and commercial systems have shown that recognition performance of most current technologies degrades due to the variations of illumination. This paper investigates several illumination normalization methods and proposes some novel solutions. The main contribution of this paper includes: (1) A Gamma Intensity Correction (GIC) method is proposed to normalize the overall image intensity at the given illumination level; (2) A Region-based strategy combining GIC and the Histogram Equalization (HE) is proposed to further eliminate the side-lighting effect; (3) A Quotient Illumination Relighting (QIR) method is presented to synthesize images under a pre-defined normal lighting condition from the provided face images captured under non-normal lighting condition. These methods are evaluated and compared on the Yale illumination face database B and Harvard illumination face database. Considerable improvements are observed. Some conclusions are given at last.*

## 1. Introduction

Face recognition technologies have a variety of ongoing and potential applications in public security, law enforcement and commerce, such as mug-shot database matching, identity authentication for credit card or driver license, access control, information security, and intelligent surveillance. In addition, there are many emerging fields that can benefit from face recognition technology, such as the new generation intelligent human-computer interfaces and e-services, including e-home, tele-shopping and tele-banking. Related research activities have significantly increased over the past few years [1,2, 3].

As for the early researches, both geometric feature based methods and template-matching methods were regarded as typical technologies, which were compared by Brunelli and Poggio in 1992. And the result of the comparison revealed that template matching outperforms the geometric feature based ones [2]. Therefore, since the 1990s, appearance based methods have been playing a dominant role in the area, from which a number of technologies were derived: holistic appearance feature based, and analytic local feature based. Popular methods belonging to the former paradigm include Eigenface [4, 5], Fisherface [6], Probabilistic and Bayesian matching [7, 8, 9], subspace LDA [10], and Active Shape/Appearance Models (ASMs/AAMs)[11,12,13] based methods. Local Feature Analysis (LFA)[14] and Elastic Bunch Graph Matching (EBGM)[5, 15] are typical instances of the latter category, among which LFA has been developed to the most successful commercial face recognition system, named FaceIt®, by Identix Corp. FERET evaluation has provided extensive comparisons of these algorithms [16, 17] as well as a kind of evaluation protocol for face recognition systems. More recently, Support Vector Machine (SVM) has also been applied to face recognition successfully [18].

However, face recognition remains a difficult, unsolved problem in general. The performance of almost all current face recognition systems, both the best academic results and the most successful commercial systems, is heavily subject to the variations in the imaging conditions. It has been discovered by the FERET and FRVT2000 test that pose and illumination variations are among the several bottlenecks for a practical face recognition system [16]. So far, no revolutionary and practical solutions are available for these problems. However, some solutions to pose and illumination problems do have emerged including invariant feature based methods [19], 3D linear illumination subspace [6], linear object class [20], illumination and pose manifold [21], Symmetric Shape-From-Shading [10], photometric alignment [22], Quotient Image [23], illumination cones [24], Lambertian Reflectance and Linear Subspace [25], light-fields [26] and parametric linear subspace [27] and individual PCA combining the synthesized images [28, 29].

Generally, the approaches for coping with variation in appearance due to illumination fall into three categories: invariant features, variation modeling, and canonical form [28].

The first approach seeks to utilize features that are invariant to the changes in appearance. Examples of such

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representation considered by early researchers are edge maps, image intensity derivatives, and images convolved with 2D Gabor-like filers. However, Adini's empirical study shows that "None of the representations considered is sufficient by itself to overcome image variations because of a change in the direction of illumination"[19]. Most recently, the Quotient image [23] is reported to be invariant to illumination and may be used to recognize faces when lighting conditions change.

The idea of variation modeling is to learn the extent of the variation in some suitable subspace or manifold. Recognition is then conducted by choosing the subspace or manifold closest to the novel image. Currently, this paradigm has been recognized as the dominant [20, 21, 22, 24, 25, 26, 27]. In addition, since subspaces/manifolds must be learnt by sufficient examples, some work has been done to enlarge a small learn set by virtually re-imaging the input face image [28, 29, 31].

The canonical form approaches attempt to "normalize" the variation in appearance, either by image transformations or by synthesizing a new image from the given image in some normalized form. Recognition is then performed using this canonical form. Examples of this approach include [10, 30]. The most commonly used Histogram Equalization (HE) belongs to this category too.

This paper investigates several illumination normalization methods belonging to the "canonical form" framework. The main contribution of this paper includes: (1) We present a Gamma Intensity Correction (CIC) method to normalize the overall image intensity to a given intensity level; (2) Region-based strategy is proposed to further eliminate the side-lighting effect by combining GIC and Histogram Equalization (HE); (3) A Quotient Illumination Relighting (QIR) method is investigated to synthesize an image under normal lighting condition from the provided face images captured under known non-normal lighting condition. These methods are then compared on the Yale face database B and Harvard face database, in which faces are captured under well-controlled illumination conditions. The experiments show that QIR can significantly improve the performance of the face recognition systems as long as the lighting modes of the images are known. However, generally, the region-based method combining HE with GIC is practically effective when it is hard to estimate the lighting modes of the input images.

This paper is organized as follows: In Section 2, the general computational framework for illumination normalization is discussed followed by one instance, GIC, as well as its combination with the region-based strategy. Section 3 mainly describes the proposed QIR methods. Experiments and conclusions are given in the following two sections.

## **2.**General Computational Framework For Illumination Normalization

Firstly, we formulate the general computational framework for illumination normalization method. Let $I_{fk}$ be any given face image of the face *f*, captured under some unknown lighting condition *k*. Illumination normalization method attempts to obtain a face image $I_{fo}$ which is the image of the same face $f$ "captured" under the pre-defined known lighting condition, *0*, by finding a transform, *T*, satisfying:

$$I_{fo} = T(I_{fk}) . \tag{1}$$

After this transform, all the face images to be processed are virtually "captured" under the same lighting condition. Therefore, the recognition system is expected to be insensitive to the varying lighting. In fact, the commonly used Histogram Equalization (HE) can be categorized into this framework. In the following, we propose Gamma Intensity Correction (GIC) method.

### 2.1 Gamma Intensity Correction (GIC)

Gamma correction is a technique commonly used in the field of Computer Graphics. It concerns how to display an image accurately on a computer screen. Images that are not properly corrected can look either bleached out, or too dark. Gamma correction can control the overall brightness of an image by changing the Gamma parameter. Unlike the traditional Gamma correction technique in Computer Graphics, but motivated by its idea, we propose the Gamma Intensity Correction (GIC) method to correct the overall brightness of the face images to a pre-defined "canonical" face images. It is formulated as following:

Predefine a canonical face image, $I_0$, which should be lighted under some normal lighting condition. Then, given any face image, *I*, captured under some unknown lighting condition. Its canonical image is computed by a Gamma transform pixel by pixel over the image position *x, y*:

$$I'_{xy} = G(I_{xy}; \gamma^*) , \tag{2}$$

where the Gamma coefficient $\gamma^*$ is computed by the following optimization process, which aims at minimizing the difference between the transformed image and the pre-defined normal face image $I_0$:

$$\gamma^* = \arg\min_{\gamma} \sum_{x,y} [G(I_{xy}; \gamma) - I_0(x, y)]^2 , \tag{3}$$

where $I_{xy}$ is the gray-level of the image position *x,y*; and

$$G(I_{xy}; \gamma) = c \cdot I_{xy}^{\frac{1}{\gamma}} ,$$

is the Gamma transform; $c$ is a gray stretch parameter, and $\gamma$ is the Gamma coefficient.

From equation 2 and 3, intuitively, the GIC is expected to make the overall brightness of the input images best fit that of the pre-defined normal face images. Thus, its intuitive effect is that the overall brightness of all the processed face images is adjusted to the same level as that of the common normal face $I_0$. See the experiments part for its intuitive effect.

### 2.2 Region-based Strategy for HE and GIC

It is obvious that both HE and GIC are global transforms over the whole image area. Therefore, they are doomed to fail when side lighting exists. To partly solve this problem, we propose to process the face images based on different local regions, that is, performing HE or GIC in some pre-defined face regions in order to better alleviate the highlight, shading and shadow effect caused by the unequal illumination. Ideally, it is expected to strictly partition the face according to the structure of the facial organs, for instance, as illustrated in Figure 1.

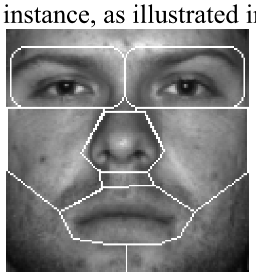

**Figure 1. An example of ideal region partition**

However, complex region partition needs complicated region segmentation approach, which is often impractical. And, since the possible side lighting mainly cause the non-symmetry between the left and right part of the face, as well as the intensity variance between the top region and the bottom region. In our strategy, we simply partition the face into four regions according to the given eye centers as shown in Figure 2.

**Figure 2. The four regions for illumination normalization**

After the coarse partition of the face regions, HE or GIC can be conducted in the four regions separately. Hereafter, we abbreviate the region-based HE to RHE, and the region-based GIC to RGIC. The effects of the RHE and RGIC can be seen from Figure 4 and Figure 7 in the experimental part.

## 3. Quotient Illumination Relighting (QIR)

Both HE and GIC are gray-level transform approaches without considering the imaging model. Therefore, as we can see from Figure 4 and Figure 7, they cannot essentially remove the side lighting effect. In this section, we present a Quotient Illumination Relighting (QIR) method based on some of the concepts in the well-known Quotient image method proposed by Shashua etc [23] most recently.

### 3.1 Background and Definitions

As a class of object, faces can be regarded as Lambertian surface, i.e., the face image can be described by the product of the albedo and the cosine angle between a point light source and the surface normal:

$$I(x,y) = \rho(x,y)n(x,y)^T s \qquad (4)$$

where $0 \le \rho(x,y) \le 1$ is the surface reflectance associated with point *x,y* in the image, *n(x,y)* is the surface normal direction associated with point *x, y* in the image, and *s* is the light source direction (point light source) and whose magnitude is the light source intensity [23].

Based on this Lambertian model, Shashua further defines the "Ideal class of Objects" [23] as a collection of 3D objects that have the same shape but differ in the surface albedo function. Though faces do have different 3D shapes, however Shashua et al show that one can tolerate significant shape changes without noticeable degradation in performance even there is no need to establish any dense alignment among the images beyond the alignment of the center of mass and scale. Based on these assumptions, recognition problem and re-rendering problem is further defined by introducing a bootstrap set in [23]. In this paper, we propose the Quotient illumination relighting method based on the ideal class of objects.

### 3.2 Quotient illumination

***Definition 1. Ideal class of Objects [23]****. An ideal class is a collection of 3D objects that have the same shape but differ in the surface albedo function. The image space of such a class is represented by:*

$$\rho_i(x,y)n(x,y)^T s_j \qquad (5)$$

*where $\rho_i(x,y)$ is the albedo of object i of the class, n(x,y) is the surface normal of the object (the same for all objects of the class), and $s_j$ is the light source direction, which can vary arbitrarily.*

***Definition 2. Quotient illumination.*** *Let $S_0$ (point light source) be the pre-defined canonical lighting condition. The quotient illumination for the lighting condition $S_j$ of an ideal class of objects (whose shape is n) is:*

$$R_j(x,y) = \frac{n(x,y)^T \cdot s_j}{n(x,y)^T \cdot s_0} \qquad (6)$$

*where x, y range over the whole image.*

Obviously, the Quotient illumination is completely independent of the surface reflectance (albedo), and depends only on the variance of the lighting condition from the pre-defined canonical lighting one (considering all the shapes is assumed to be the same). Thus, quotient illumination can be computed easily by calculating the quotient between the images of the object *i* of the ideal class of objects as explained by Equ.7:

$$R_j(x,y) = \frac{\rho_i(x,y)n(x,y)^T \cdot s_j}{\rho_i(x,y)n(x,y)^T \cdot s_0} = \frac{I_{ij}(x,y)}{I_{i0}(x,y)}, (7)$$

where *x, y* range over the whole image, $I_{ij}$ is the image of object *i* captured under the *j*-th lighting condition, and $I_{i0}$ is the image of the same object *i* captured under the canonical lighting condition.

Equation 7 provides a practical way to compute the Quotient illumination directly from face images without needing to separate the reflectance from the lighting. However, as is well known, faces are not strictly ideal class of objects since the 3D shapes of faces are different despite their approximate similarity. Therefore, a learn set to cover all kinds of 3D face shapes is expected.

***Definition 3. Quotient Illumination Bootstrap Set.*** *Quotient illumination bootstrap set is a set of pairs of face images captured under some non-canonical lighting condition and under the pre-defined canonical lighting condition, i.e.,*

$$\{(I_{ij}, I_{i0}) \mid i = 1,2,...,N; j = 1,2,...,L\}.$$

Given such a bootstrap set, Quotient illumination can be statistically modeled, or computed simply as the mean over all the faces in the set, for instance:

$$R_j(x,y) = \frac{1}{N}\sum_{i=1}^{N}\frac{I_{ij}(x,y)}{I_{i0}(x,y)}, \text{ j=1,…, L}$$

where *x, y* range over the whole image.

### 3.3 Quotient Illumination Relighting (QIR)

After defining the ideal class of objects and Quotient illumination, for face object case, illumination normalization is formulated as following. Given an input face image $I_{ij}$ we assume that it is the image of the *i*-th face taken under *j*-th lighting condition. Our goal is to relight the face to obtain $I_{i0}$, i.e., the image of the face taken under the canonical lighting condition. This can be done by the following Proposition.

***Proposition 1.*** *Given an image of arbitrary face, $I_{ij}$. Assume that it is lighted by the j-th known lighting condition, and the j-th quotient illumination $R_j$ has been computed too. Then, its canonical image captured under the pre-defined 0-th lighting condition can be derived by:*

$$I_{i0}(x,y) = \frac{I_{ij}(x,y)}{R_j(x,y)}, \qquad (8)$$

*where x, y range over the whole image.*

**Proof.** According to Equation 5, 6 and 7, we have:

$$R_j(x,y) = \frac{n(x,y)^T \cdot s_j}{n(x,y)^T \cdot s_0} = \frac{\rho_i(x,y)n(x,y)^T \cdot s_j}{\rho_i(x,y)n(x,y)^T \cdot s_0} = \frac{I_{ij}(x,y)}{I_{i0}(x,y)}.$$

So:

$$I_{i0}(x,y) = \frac{I_{ij}(x,y)}{R_j(x,y)},$$

where *x, y* range over the whole image.

Proposition 1 provides a direct and simple way for illumination normalization provided that the direction of the lighting source of the image can be known. See Figure 4 and 7 for its intuitive effect, obviously, QIR has significantly eliminate the unequal brightness effect caused by the strong side lighting.

## 4. Experiments

In this section, we present the experiments to evaluate the above-mentioned illumination normalization methods using two public face database specialized on illumination variation, i.e., the Yale face database B and the Harvard face database. Lighting conditions in both of the database have been systematically controlled.

### 4.1 Classification method

Since our goal is to compare the performances of different illumination normalization methods, the distance measurement and classification method are not important for us. Therefore, the simplest normalized correlation, i.e., cosine of the angle between two image vectors, is exploited as the distance measurement, i.e., the similarity between two images $I_j$ and $I_k$ is defined as:

$$\Phi(I_j, I_k) = \cos(\angle < I_j, I_k >) = \frac{I_j \cdot I_k}{\|I_j\| \cdot \|I_k\|}$$

And for all experiments, classification is performed using the nearest neighbor classifier. In addition, as we can see from the example images in the following sections, all the faces are cropped to remove the background and the hair.

### 4.2 Results on Yale face database B

Yale face database B is publicly available for studying pose and illumination problem in face recognition. Since this paper mainly deals with the illumination problem, we only choose the 64 frontal images captured under 64 different lighting conditions for each of the ten persons. Example images of one person in frontal pose are shown in figure 3. The images are divided into five subsets according to the angle that the light source direction makes with the camera axis—Subset 1(up to 12$^o$), Subset 2(up to 25$^o$), Subset 3(up to 50$^o$), Subset 4(up to 77$^o$), and Subset 5(up to 90$^o$). See [24] for details.

Experiments are then conducted on the database with the above-mentioned illumination normalization methods including:

- HE: Histogram equalization globally over the images;
- RHE: Region-based Histogram equalization;
- GIC: Gamma Intensity Correction globally. The mean face of all the images from the subset 1 of the ten persons (70 images totally) is used as the pre-defined canonical image.
- RGIC: Region-based GIC. Its canonical image is the same as for GIC;
- GIC+RHE: perform RHE after GIC;
- RGIC+RHE: perform RHE after RGIC;
- RHE+RGIC: perform RGIC after RHE;
- HE+RGIC: perform RGIC after HE;
- QIR: Quotient Illumination Relighting. For each person, the image captured under the frontal light source (A+000E+00) is chosen as the *normal* light mode. The Quotient illuminations for the remaining 63 non-frontal lighting modes against the normal one for each person are computed according to the "Leave-one-out" strategy, i.e., when computing the 63 quotient illuminations for one person, only the remaining nine persons' images are used as the Quotient Image Bootstrap Set.

The effect of these processing methods is illustrated in Figure 4 (and Figure 7), from which intuitive effect can be observed for their performance against extreme lighting conditions.

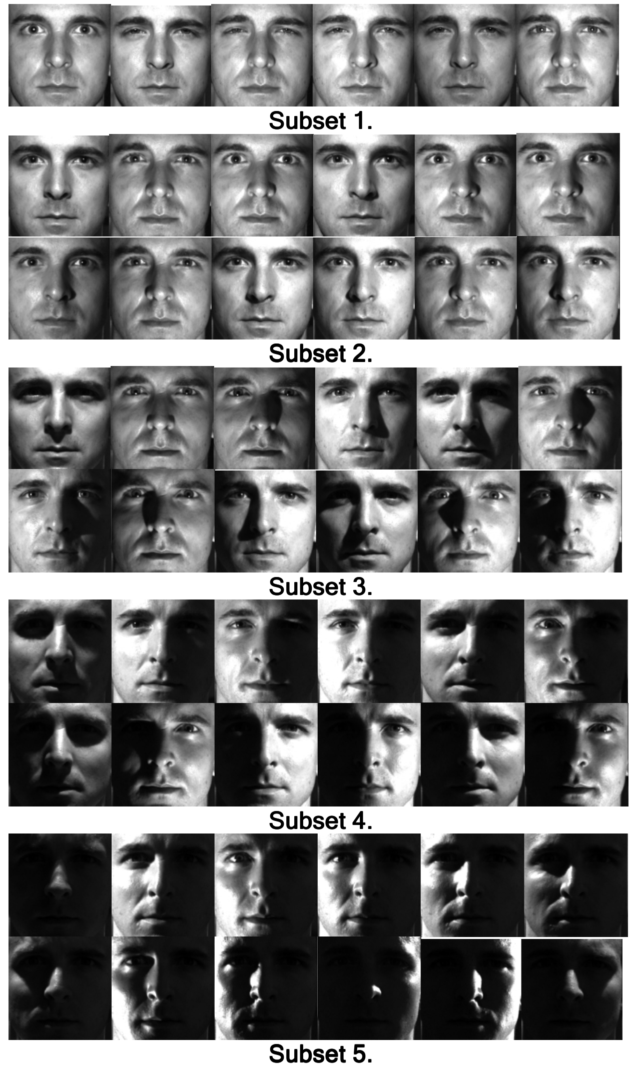


Figure 3. Example images of an individual in frontal pose from the Yale face database B with the variability due to illumination.

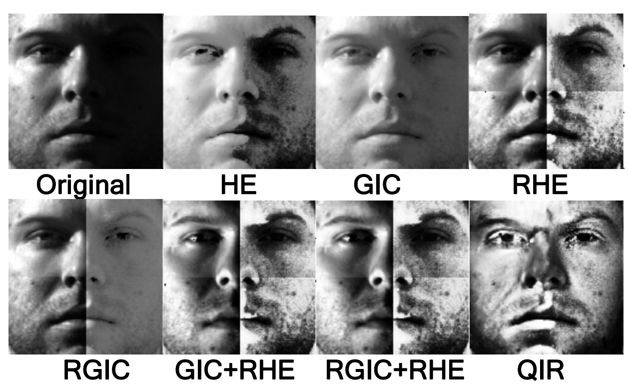


Figure 4. The processed images after different illumination normalization methods for one image in the Yale face database B. The acronym label below each image shows the processing method.

All these methods are then compared by recognition experiments. In all the experiments, the Subset 1 (7 images for each person) is chosen as the gallery and each of the images in the remaining 4 subsets are matched in the gallery to find a nearest neighbor based on cosine similarity. The experimental results are illustrated in Table 1 and Figure 5.

**Table 1. Recognition rate comparisons of different illumination normalization methods on Yale Face Database B (Subset 1 containing 7 images is used as the gallery for each person)**

| Methods | Subset No. (Total Number of probes*) | | | | |
|---|---|---|---|---|---|
| | 2 (118) | 3 (118) | 4 (138) | 5 (189) | Mean (563) |
| Non | 100 | 88.1 | 49.3 | 20.1 | 58.3 |
| GIC | 100 | 88.1 | 39.9 | 27.5 | 58.4 |
| RGIC | 100 | 97.5 | 57.2 | 35.4 | 67.3 |
| HE | 100 | 89.0 | 55.1 | 44.4 | 68.0 |
| RHE | 100 | 100 | 59.4 | 32.8 | 67.5 |
| RHE+RGIC | 100 | 100 | 68.1 | 36.0 | 70.7 |
| HE+RGIC | 100 | 99.2 | 63.8 | 43.4 | 72.0 |
| GIC+RHE | 100 | 100 | 60.1 | 33.3 | 67.8 |
| RGIC+RHE | 100 | 99.2 | 59.4 | 33.3 | 67.5 |
| QIR | 100 | 100 | 90.6 | 82.5 | 91.8 |

*Note: Totally 7 images in our version of the face database are absent.

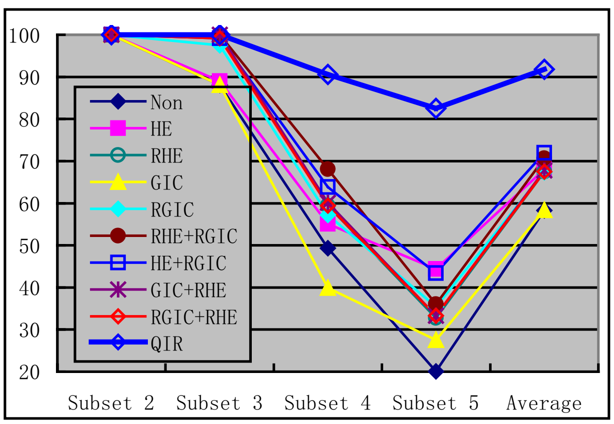


**Figure 5 Recognition rate comparisons of different illumination normalization methods on Yale Face Database B**

Note that these experiments are all the interpolation of the varying illumination since subset 1 contains faces lighted under light sources with smaller angles, while those of the images in the other subsets are much greater.

### 4.3 Results on Harvard face database

To further verify the experimental results on the Yale face database B, similar experiments are organized on the Harvard face database, which is also specialized on illumination. In each image in the database, one subject held his/her head steady while being illuminated by a dominant light source. The space of light source directions, which can be parameterized by spherical angles, was then sampled in 15° increments. In the database, there are totally 660 images of totally 10 subjects, and they are divided into 5 subsets according to the greater of the longitudinal and latitudinal angles of the light source direction from the camera axis—Subset 1(15°), Subset 2(30 °), Subset 3(45 °), Subset 4(60 °), and Subset 5(75 °). See [6] for details.


**Figure 6. Example images of an individual in frontal pose from the Harvard face database with the variability due to illumination.**

Similar experiments as in section 4.2 are then conducted. The tested illumination normalization methods are all the same as in section 4.2. The effect of these processing methods is illustrated in Figure 7. All these methods are then compared by recognition experiments. In all the experiments, the Subset 1 (6 images for each person) is chosen as the gallery, and each of the images in the remaining 4 subsets are matched in the gallery to find a nearest neighbor based on cosine similarity. The experimental results are illustrated in Table 2 and Figure 8.


**Figure 7. The processed images after different illumination normalization methods for one image in the Harvard face database. The acronym label below each image shows the processing method.**

**Table 2. Recognition rate comparisons of different illumination normalization methods on Harvard Face Database. For each methods, subset 1 containing 6 images is used as the gallery for each person.**

| | Subset No. (Total Number of Probes*) | | | | |
|---|---|---|---|---|---|
| | 2 (90) | 3 (130) | 4 (170) | 5 (201) | Mean (591) |
| Non | 94.4 | 45.4 | 22.9 | 15.4 | 36.2 |
| GIC | 94.4 | 51.5 | 25.3 | 16.4 | 38.6 |
| HE | 98.9 | 53.1 | 30.0 | 12.4 | 39.6 |
| RGIC | 98.9 | 68.5 | 37.6 | 19.4 | 47.5 |
| RHE | 100 | 73.8 | 41.8 | 17.4 | 49.4 |
| RHE+RGIC | 100 | 73.1 | 42.9 | 14.9 | 48.7 |
| HE+RGIC | 100 | 64.6 | 36.5 | 14.4 | 44.8 |
| GIC+RHE | 100 | 72.3 | 38.2 | 16.9 | 47.9 |
| RGIC+RHE | 100 | 75.4 | 44.7 | 18.9 | 51.1 |
| QIR | 100 | 83.8 | 57.1 | 29.4 | 60.1 |

*Note: Totally 9 images in our version of the face database are absent.

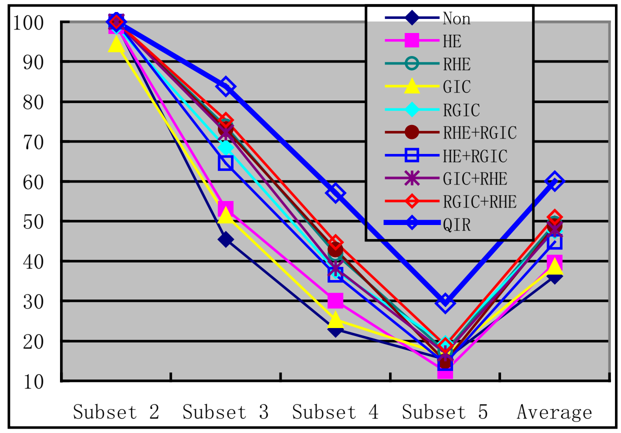


**Figure 8 Recognition rate comparisons of different illumination normalization methods on Harvard Face Database.**

## 5. Conclusions and Future Work

The experimental results both on Yale and Harvard face database in Section 4 reveal a number of interesting points:

(1) Simple illumination normalization method, e.g. the HE or the proposed GIC can generally improve the recognition performance compared with the non-preprocessing case;

(2) Region-based HE and/or GIC can significantly improve the recognition rate compared with the non-preprocessing case since it can eliminate the heavy side lighting effects.

(3) If the light mode of the input image is known or can be estimated, the proposed QIR methods can further considerably improve the performance of the recognition system even compared with the Region-based HE combining GIC.

Note that the terrific performance of QIR is based on the assumption that the lighting modes of the images are known or can be estimated. This is a strong constraint in a practical application system. Therefore, one of our future works will be the clustering and classification (estimation) of the lighting conditions for a practical QIR method.

In contrast, the RHE combed with RGIC methods are more general and practical to be exploited in a recognition system efficiently, since they need not the illumination estimation procedure.

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