Novel illumination-normalization method based on region information

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ABSTRACT

A region based illumination-normalization method which only uses gray level values in an image as information is proposed in this paper. The general purpose of illumination normalization is to reduce lighting effect when the testing images are captured in different environment and supplies useful and uniform data. We apply the algorithm in our face recognition system. The algorithm first divides the testing face images into two parts using homomorphic filtering method [3]. One is the face feature, F_0, and the other one is the illumination information, I_0. Next, an illumination reference model is constructed from a set of normal face images. The illumination information of the testing face image is then adjusted according to the illumination reference model. The modified illumination information, I_a, and original face feature, F_0, are at last combined to make up the normalized face image. The face recognition result is improved after the algorithm is applied.

Keywords: illumination normalization, homomorphic filtering, illumination reference model, face recognition

1. INTRODUCTION

Illumination normalization is an important preprocessing step for many operations such as face tracking, face detection, and face recognition, etc. All these operations are essential for many applications including video surveillance, object-based video coding and human computer interaction. Therefore, a suitable illumination-normalization is quite useful and plays an important key technology for those applications.

It is well known that the image gray level (or image color) is very sensitive to the lighting variation. The same object with different illumination may produce considerably different images. Some testing images with different illumination variance are show in Fig.1 Psychophysical experiments show that the human visual system is difficult to identify the images of the same face that are captured under considerable changes in illumination [1]. For machine vision system, it is also difficult to produce good classification accuracy if image samples in the training and testing sets are taken under different lighting conditions. Based on the fundamental of image formation theory [2], the testing image is composed by object surface and illumination from the environment. Any one of these two factors will make the testing image significantly different. The proposed method tries to make the testing face image insensitive to the lighting environment or modify the testing image with similar illumination information.

The paper is organized as follows. Section 2 presents the prior art. Section 3 introduces the proposed algorithm. Experiments and comparisons are given in Section 4, and the discussions are in Sections 5.

2. PREVIOUS WORK

Traditional illumination-normalization algorithms usually use global information, like whole image gray levels, to adjust the testing image. Histogram equalization [2] is a classical method in image process used to overcome the lighting effect. The testing images are equalized to make these images having similar histograms which are closed to a uniform

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distribution.

Another approach is trying to separate the image feature F_0, and illumination information I_0 from the testing images. For example, Homomorphic filtering [3] is a traditional method to separate the two components F_0 and I_0. The illumination effect is then removed by adjusting the illumination information I_0, and the combination of F_0 and the adjusted illumination information I_a will be treated as normalized result which is lighting insensitive. For example, [9] proposed by Fang in Siemens is a representation of this kind of approach. Fang models the lighting changes having an additive effect and a multiplicative effect on the input image. The model can be briefly described as the following equation.

$$X(x,y) = \alpha(x,y) \bullet Y(x,y) + \beta(x,y), \qquad \text{(Eq. 1)}$$

where $X(x,y)$ is the input image and $Y(x,y)$ is the output or normalized image,
$\alpha(x,y)$ is the multiplicative effect and $\beta(x,y)$ is the additive effect.

By estimating the multiplicative effect and the additive effect from the input image $X(x,y)$, the normalized image $Y(x,y)$ can be achieved by an inverse function like equation (2).

$$Y(x,y) = \frac{X(x,y) - \beta(x,y)}{\alpha(x,y)}. \qquad \text{(Eq. 2)}$$

The key point of this paper is how to estimate the multiplicative effect and additive effect.

3. ILLUMINATION NORMALIZATION

The proposed illumination-normalization method can be treated as an important preprocessing step in many applications. In this paper we applied it to a simplified face recognition system to show the performance. Fig.2 gives the flow chart of our illumination-normalization algorithm. Fig.3 is the block diagram of a face recognition system. In the follow subsections, we will introduce the detail of the illumination normalization algorithm. The face recognition system will be described briefly. The normalized images and the resulting face recognition performance are used to verify the significance of this new invention.

3.1 Face feature (F_0) and illumination information (I_0)

The main purpose of illumination normalization is to decrease lighting effect. Therefore the illumination information in the face image is what we need to adjust. It is unreasonable to modify the whole face image directly. Based on the past study [3], we can roughly conclude that most of the illumination information concentrates on the low frequencies. We therefore use a Gaussian filter to extract the low-pass component of the face image. The low-pass component can also be extracted by other filter design. This low-pass component then will be treated as illumination information. The spatial size of Gaussian filter is also an important parameter should be careful designed. The Gaussian filter $h(n_1, n_2)$ we used can be described as Eq. 3.

$$h(n_1,n_2) = \frac{h_g(n_1,n_2)}{\sum_{n_1}\sum_{n_2} h_g(n_1,n_2)}, \qquad \text{(Eq. 3)}$$

where

$$h_g(n_1,n_2) = e^{-(n_1^2+n_2^2)/(2\sigma^2)}.$$

In this paper, we use only image gray level for illumination normalization. Therefore, the image data is first transformed from the RGB space to the YC_bC_r space. The Y values are then used as image gray level information, which can be gotten by Eq. 4.

$$Y = 0.299^*\mathrm{R} + 0.587^*\mathrm{G} + 0.114^*\mathrm{B}, \qquad \text{(Eq. 4)}$$

Fig.4 shows four face images and their illumination information extracted by Gaussian filter.

3.2 The illumination reference model

An illumination reference model (IRM) is constructed based on the illumination information of a set of face images in the database. These face images are all captured under the same and normal illumination. The information used to construct the IRM is mainly from the database which is collected off-line. There is no extra effort need to build the IRM. For example, there are 20 persons in the database and each person has a reference face image which is captured under normal illumination. Each person's illumination information corresponding to his reference face image is then extracted using a low-pass filter. The IRM is then constructed from these 20 people's illumination-information. Some strategies can be used to combine the illumination-information and build the IRM. A simple and useful strategy is to average each illumination-information. Fig.5 explains how to generate this illumination reference model using an average strategy. In Fig.5 we can find out that each one's illumination information still includes personal face information which is unsuitable to build the IRM. After averaging all illumination-information, the personal information will be depressed and the true illumination information will be enhanced as we can see in Fig.5.

3.3 Illumination normalization

3.3.1 Region consideration

Traditional illumination-normalization algorithms, like image equalization, usually modify the testing images based on the statistic histogram information. Histogram is a globe statistic. In other word, the whole image is modified based on some linear or nonlinear mapping function without considering the local information. Region information is also an important factor in the illumination normalization. For example, one image has two pixels with the same gray level 'A'. In the ideal case, after normalizing the first pixel may get a new gray level 'B' and the second pixel may get a gray level 'C'. But this is impossible to achieve by using the global histogram-based methods. Because there is no mapping function can map from one gray level to many gray levels by mathematic.

Some other illumination-normalization algorithms use a fixed model to estimate the illumination distribution. The model parameters decide the illumination information. Although the location information is taken into concern in these methods, the model cannot fit every situation.

In this paper we overcome this drawback by importing the localization consideration. The illumination information of the testing image is segmented into several regions. For example, the image is segmented into two regions that one is bright and the other is dark. The segmentation process will merge these pixels that have similar illumination information into the same region. If each region is modified individually, the problem of 'one map to many' we mention above will be resolved and the local information will also be taken into account. There are many famous segmentation algorithms can be used in the segmentation stage, for example, mean-shift segmentation method [4]. Fig.6 shows four observed face images and the corresponding segmentation results.

3.3.2 Nonlinear modification based on histogram information

Once the illumination information of the testing image is segmented into several regions, each region will be adjusted based on the histogram information of the corresponding region of the illumination reference model by its location. For example, if R_a is a region in the testing image and $R_a^{'}$ is the corresponding region in the illumination reference model, the modification strategy [5] we used is to transform the statistic histogram of region R_a to the histogram of region $R_a^{'}$ so that R_a has similar statistic histogram to $R_a^{'}$. The transform between two regions is the one to one function T which can be expressed as follow equation if we treat the intensity histogram of the region as probability density function.

$$T = \widehat{G}^{-1} \circ \widehat{H}\,, \qquad \text{(Eq. 5)}$$

where $\widehat{G}$ is the empirical cdf of region $R_a^{'}$

$\widehat{H}$ is the empirical cdf of region R_a

Each pixel in the region R_a is normalized by using the transfer function T. Let $R_a^{''}$ be the normalized region, then

$$R_a^{''}(x,y) = T(R_a(x,y)) = \widehat{G}^{-1} \circ \widehat{H}(R_a(x,y))\,. \qquad \text{(Eq. 6)}$$

Ideally, $R_a^{''}$ will have similar histogram distribution to the one $R_a^{'}$ has.

3.3.3 Boundary smoothing

The boundary between regions becomes non-continuous after normalizing. This is because each region is normalized individually. Some post-process, like smoothing in the boundary, is needed to make the normalized image more natural. Edge detection process can be used to find out the boundary between regions for example canny edge detection method [6]. The boundary and his neighbors will form a boundary band. All the intensities of the image pixels in this boundary band will be modified using a Gaussian smoothing. The Gaussian smoothing filter we used here is like the one in Eq. 3. The parameter used in filter is decided based on the empirical result. After boundary filtering the whole image become continuous and smooth.

Some results processed by using the proposed method are shown in Fig.8. The first column shows original images of the same person which are taken from different lighting conditions. The second column shows the corresponding face images cropped from the original images, and the third column shows the results after illumination normalization. Apparently, the transformed images are more insensitive to illumination change.

3.4 The face recognition system

The block diagram of a face recognition system can be found in Fig.3. The face images are extracted from the original images manually. In general, an extracted face image is the rectangular portion of image which contains eyebrows, eyes, nose, and mouth of face. Each face image is first normalized to a 61*51 image, which is then applied to the proposed illumination-normalization mechanism and accordingly a compensated image is generated. Some extracted face images and normalized images can be seen in the Fig.8. The principle component analysis (PCA) [8], is then used to analysis these compensated images. An eign-space is constructed. No matter test images or training images will be represented by a feature vector in the space. Euclidean distance between each vector is last measured to determinate the similarity. And, the recognition result is decided based on the similarity measurement.

4 EXPERIMENTS

We apply the proposed illumination normalization mechanism to the MIT face database which is a public database for research on illumination. There are 16 persons in the MIT database. Each person has three images captured under three lighting condition. That is (1) head-on (2) 45 deg (3) 90 deg. We use head-on images as training data and other images as testing data. The recognition result is shown in Table 1. In Table 1, the Error sample means the number of recognition error in 16 samples. The recognition rate is the number of correct recognition divided by 16. Obviously, when lighting angle is large the recognition result is relatively bad. But the proposed mechanism obviously improves the recognition rate especially in large lighting angle.

We also apply the proposed mechanism to our ATC database for more testing. There are 20 persons involved in the face database. Each person has a reference face image as training data. We collect 1500 testing images which are different people captured under different illumination condition. Each testing image is compared with the training data and the recognition result is decided based on the similarity measurement. Some testing images with different illumination variance are show in Fig.1. The recognition rate of the above face classifier with the proposed illumination normalization mechanism is about 82.73% but the one without the any illumination-normalization mechanism is about 44.93%. If the generous histogram equalization is used to modify the 1500 testing images, the recognition rate is about 73.2%. If the lighting normalization method in [9] is used, the recognition rate is about 76.6%. Thus, the recognition rate is improved significantly by the proposed illumination-normalization mechanism. Table 2 is the summary of recognition results using different illumination-normalization mechanism. We use a Matlab® program to simulate the new illumination-normalization process. The average computation time is about 0.619 seconds for normalizing a testing image. If the histogram equalization and the Fang's method [9] are used to normalize a testing image, the average computation time are about 0.128 and 0.423 seconds, respectively. All the simulations are run on a Pentium® 4 1.3GHz PC.

5. CONCLUSION

The proposed algorithm can be used as a preprocessing step in many applications. For instances, face images should be illumination-normalized before any face tracking or face recognition algorithms to ensure the result of them is accurate and useful. As we know, face tracking and face recognition are crucial for many applications including video surveillance, object-based video coding and human computer interaction. Therefore, the proposed algorithm can be used as an important module for those applications. More works are still need to improve the whole algorithm. The IRM can be extracted using more intelligent method. The filtering method used to extract the illumination information can also be modified or replaced using other mechanism.

6. ACKNOWLEDGEMENT

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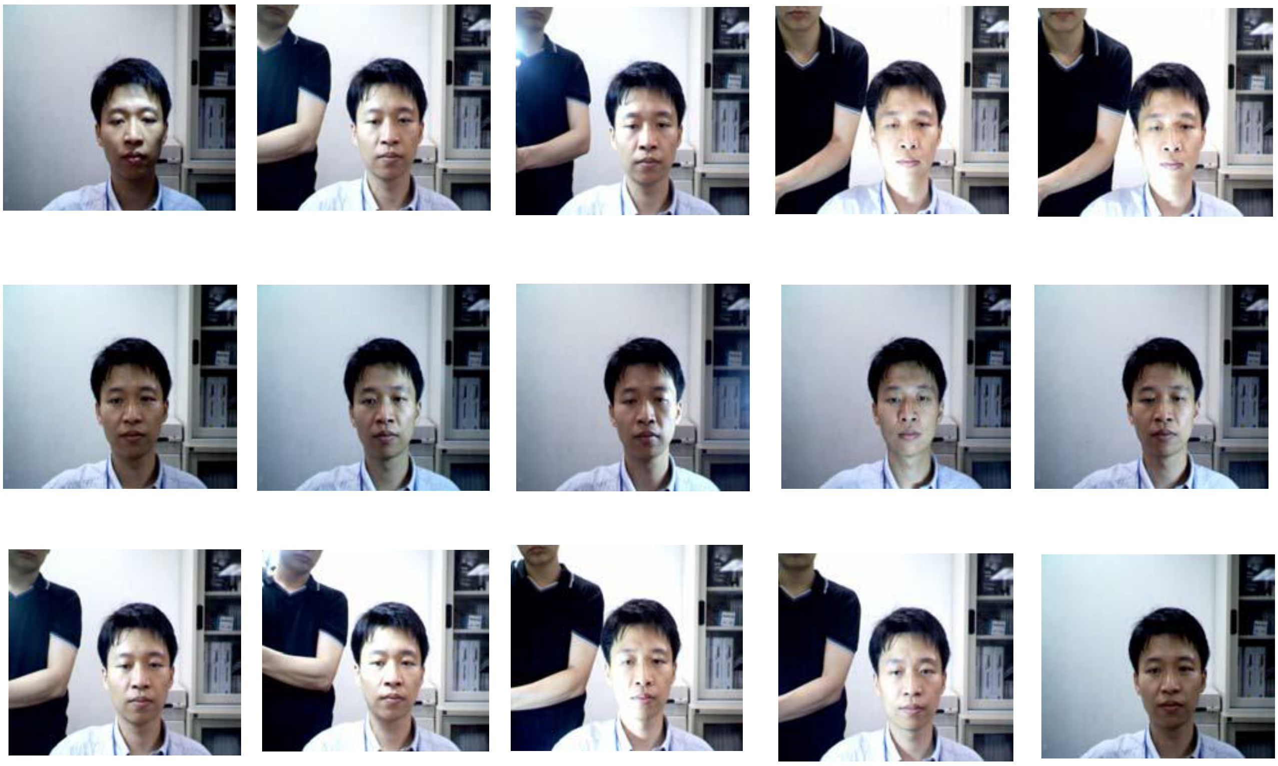


Fig.1: Face images taken from different lighting conditions.

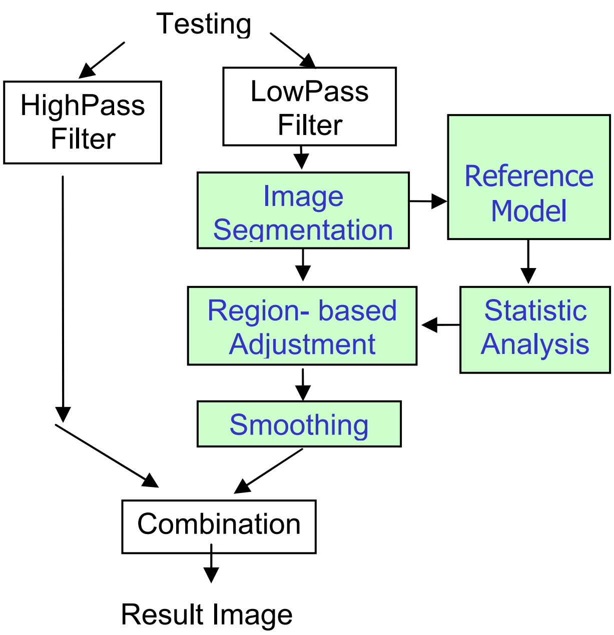


Fig.2: The flow chart of illumination-normalization algorithm

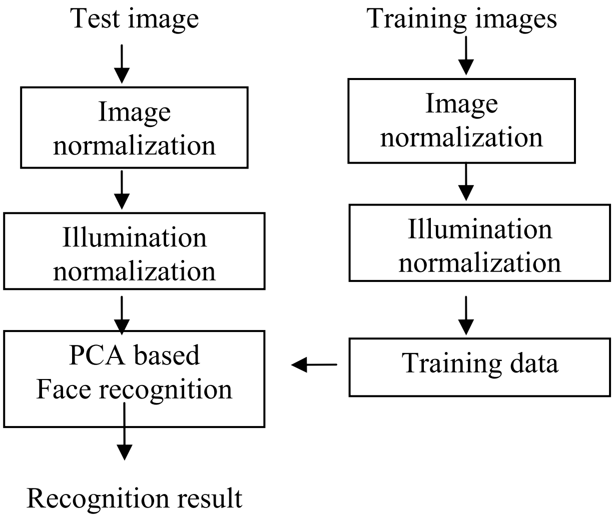
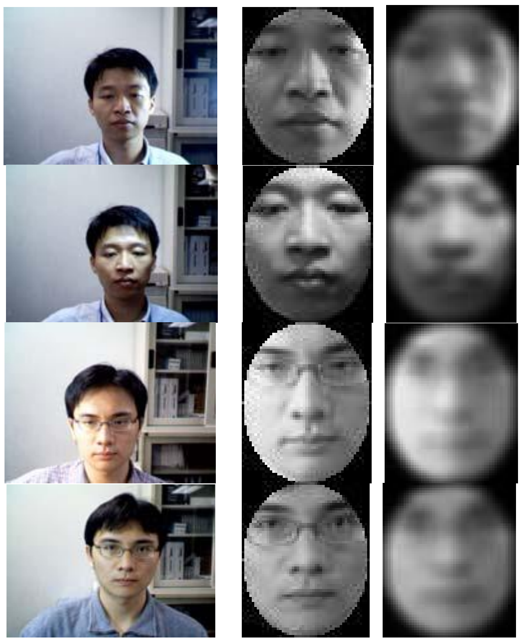


Fig.3: The block diagram of a face recognition system



(a) (b) (c)

Fig.4: Four face images and their illumination information. (a) Four testing images (b) Corresponding face images. (c) Corresponding illumination information.

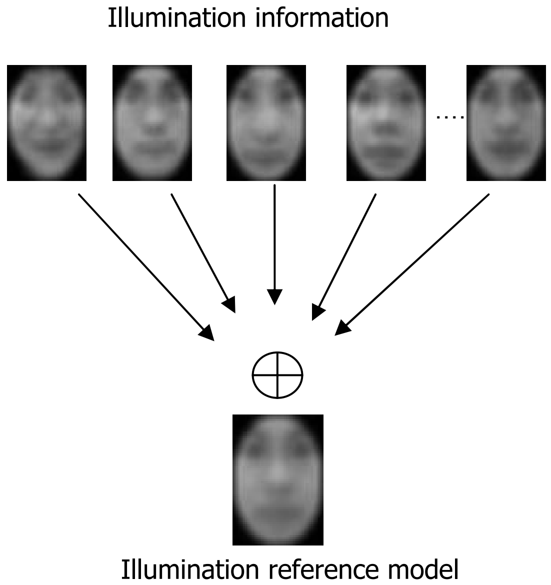


Fig.5: The illumination reference model

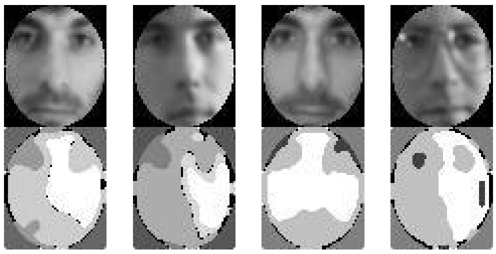


Fig.6: Four face images and the corresponding segmentation results

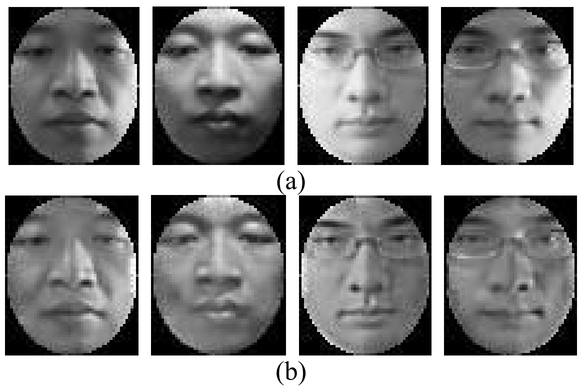
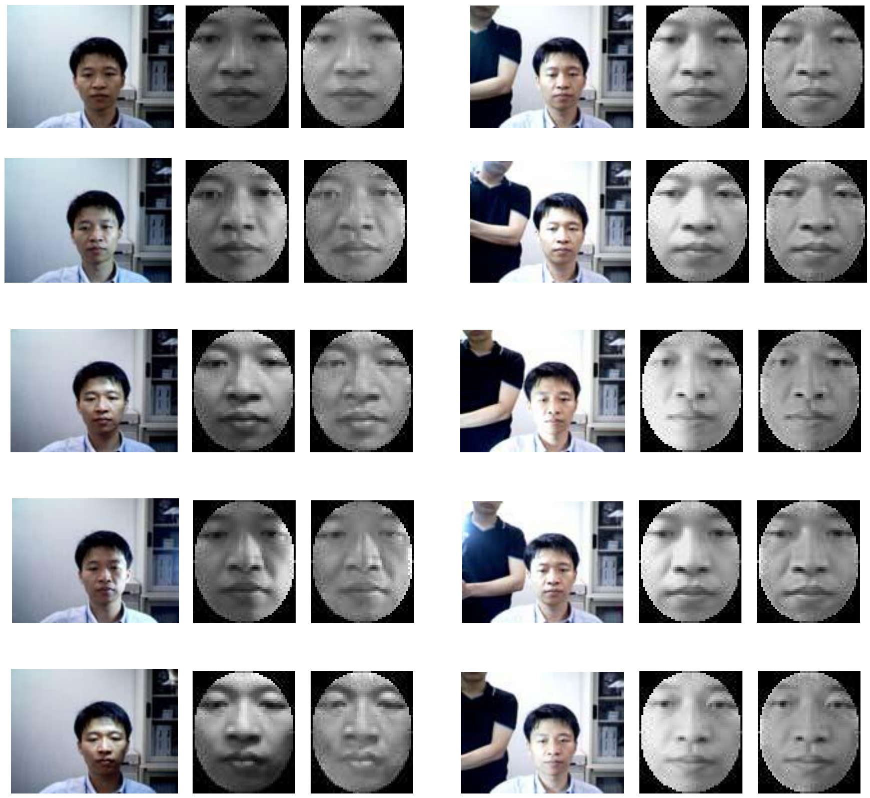


Fig.7: (a) Four face images. (b) The corresponding images after region-based histogram modification and boundary smoothing



(a) (b) (c) (a) (b) (c)

Fig. 8: Some results after the illumination-normalization mechanism. (a) The original images (b) The face images (c) The images after illumination-normalization

45degree (16 samples)	Error samples	Recognition rate
Method A	6	10/16
Method B	2	14/16
Method C	1	15/16
Method D	1	15/16

90 degree (16 samples)	Error samples	Recognition rate
Method A	7	9/16
Method B	6	10/16
Method C	6	10/16
Method D	2	14/16

Table 1: The recognition result using different illumination-normalization mechanism in MIT face database. Method A means no illumination normalization is used. Method B uses histogram equalization as illumination normalization. Method C uses the method proposed in [9]. Method D uses the proposed method.

Total samples (1500)	Error samples	Recognition rate	Comput-ation time
Method A	826	0.4493	0.0 seconds
Method B	402	0.7320	0.128 seconds
Method C	351	0.7660	0.423 seconds
Method D	259	0.8273	0.619 seconds

Table 2 : The recognition result using different illumination-normalization mechanism on ATC database. The computation time means the average time used to normalize a testing image.