MAXIMIZING INTRA-INDIVIDUAL CORRELATIONS FOR ILLUMINATION-INSENSITIVE FACE RECOGNITION

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ABSTRACT

Illumination variation has been one of the most intractable problems in face recognition and many approaches have been proposed to handle illumination problem in the last decades of years. The key problem is how to get stable similarity measurements between two face images of the same individual but captured under dramatically different lighting conditions. We propose a framework to optimize the illumination normalization for a pair of gallery and probe face images by maximizing a correlation (MAC) between them. The illumination normalization in the proposed framework tends to maximize the intra-individual correlations instead of both the inter- and intra-individual correlations. Experiments on Extended YaleB and CMU-PIE face databases show the effectiveness of our proposed approach in face recognition across varying lighting conditions.

Index Terms— Illumination-insensitive, illumination normalization, maximizing a correlation, face recognition

1. INTRODUCTION

The challenges that a practical face recognition system has to face include variations in lighting, head pose, facial expression, accessory and so on. Among these variations varying lighting conditions such as shadows, underexposure and overexposure in face imaging are intractable yet crucial problems that a practical face recognition system has to deal with. The intra-individual differences caused by illumination variation may be even larger than the inter-individual ones [1]. Therefore, it is important to get stable similarity measurements for the face images of the same individual but captured under varying lighting conditions. Illumination normalization is one of the common approaches used to eliminate the effects of uneven lighting conditions, which normalizes all face images to the same lighting condition before performing face recognition.

In the last decades, many approaches have been proposed to perform illumination normalization. Histogram equalization (HE) [2] can be considered as one of the simplest illumination normalization approaches, which spreads the pixel intensities of one image over the whole intensity range. HE usually increases the global contrast of one face image, however, it does not particularly considers the details involved in the regions that are of great importance for face recognition. Logarithmic transformation (LT) [1], as a nonlinear transformation, tends to squeeze together the larger intensity values and stretch out the smaller ones in a face image. LT can effectively improve the quality of face images captured under side-lighting, but meanwhile it tends to bring in overexposure for the regions with normal lighting in a face image. The Retinex theory was first proposed by E. H. Land [3] in 1986 to model the lightness and color perception of human vision. Based on reflectance-illumination model, Jobson et al. [4] extended Retinex theory as a single-scale Retinex (SSR) approach to enhance images in improving local contrast and lightness. SSR can improve the quality of regions with underexposure in a face image while preventing overexposure for the regions with normal exposure, however, the overall exposure still tends to be increased too much even when the exposure of the original face image is normal. Local normalization (LN) [5] can effectively eliminate the effect of uneven illumination, and keep the local statistical properties of the processed image the same as in the corresponding image under normal lighting conditions. However, the block size in LN has to be determined empirically for different face databases and LN suffers from heavy computational complexity when it is performed in overlapped pattern. TV-L1 [6] model, which is also based on reflectance-illumination model, was introduced and analyzed in logarithm domain (LTV) by Chen et al. [7] for the purpose of estimating the large-scale illumination component in a face image and then the large-scale component is removed to get the final illumination normalized component corresponding to intrinsic facial features. Again, an appropriate parameter lambda has to be determined for different face databases.

This paper proposes a new a framework to optimize the illumination normalization for a pair of gallery and probe

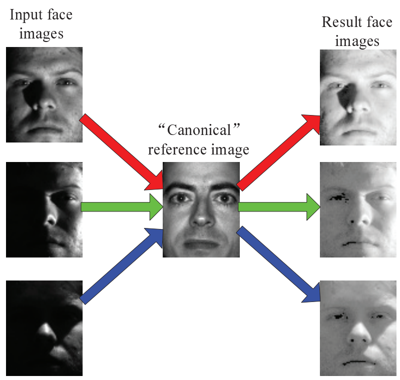


Fig.1 Overview of gamma intensity correction algorithm.

face images by maximizing a correlation (MAC) between them. And then the maximized correlation is used as the similarity score between this pair of gallery and probe face images. The proposed framework tends to maximize the intra-individual correlations instead of both the inter- and intra-individual correlations.

The remainder of this paper is organized as follows: Section 2 gives a brief introduction of the related work. Section 3 details the algorithm of the proposed framework. And then experimental results are shown in Section 4. Finally, we conclude this work in Section 5.

2. RELATED WORK

Different from the above-mentioned illumination normalization approaches, Shan et al. [8] proposed gamma intensity correction (GIC) to correct the overall brightness of a face image in accordance with a pre-defined "canonical" reference face image, which can be seen from Fig. 1. Denote $I(x,y)$ as a face image captured under some unknown lighting condition with M rows and N columns and $x=1,2,\cdots,M$, $y=1,2,\cdots,N$. Then the illumination normalized face image $I'(x,y)$ can be calculated as:

$$I'(x,y)=\Gamma\left(I(x,y),\gamma^*\right) \tag{1}$$

where $\Gamma(\cdot)$ is the gamma transform for image intensities:

$$\Gamma\left(I(x,y),\gamma\right)=c\cdot I^{\frac{1}{\gamma}}(x,y) \tag{2}$$

where c is a constant. γ^* is the parameter for gamma transform, which is estimated by solving the following optimization problem:

$$\gamma^*=\arg\min_{\gamma}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[\Gamma\left(I(x,y),\gamma\right)-I_0(x,y)\right]^2 \tag{3}$$

where $I_0(x,y)$ is the pre-defined "canonical" reference face image.

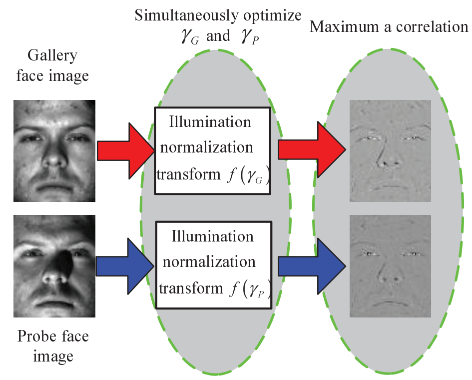


Fig.2 Illustration of optimizing the illumination normalization for a gallery and a probe face images by maximizing a correlation between them.

3. MAXIMIZING INTRA-INDIVIDUAL CORRELATIONS

As described in Section 2, with the constraint of a pre-defined "canonical" face image introduced in GIC, all the illumination normalized face images tend to be in the same scale, and thus the similarities calculated between different pairs of gallery and probe images will be more comparable with each other. However, it is not optimum to constrain all the illumination normalized face images with one uniform pre-defined "canonical" face image, as the inter-individual correlations may also be maximized along with the intra-individual ones. Therefore, from the viewpoint of classification, it is more reasonable to maximize the intra-individual correlation as much as possible instead of both the inter- and intra-individual correlations. For this goal, we propose a new framework to optimize the illumination normalization with the constraint of maximizing a correlation (MAC) between a pair of gallery and probe face images. Different from GIC, in our proposed approach, one face image will serve as the "canonical" reference face image for the other for each pair of gallery and probe face images.

The general formulation and detailed algorithm of our proposed MAC framework are described in this section.

3.1. Problem formulation of MAC

The maximum correlation of two face images from the same individual is supposed to be larger than that of two face image from different individuals after optimizing the illumination normalization of these two face images. Therefore, as illustrated in Fig. 2, we propose a new approach to optimize the illumination normalization for a pair of gallery and probe face images by maximizing a correlation between them. The optimum illumination normalization for a pair of gallery and probe face images can be calculated as:

$$\left\{I_G^{'}, I_P^{'}\right\} = \left\{f\left(I_G, \widehat{\gamma_G}\right), f\left(I_P, \widehat{\gamma_P}\right)\right\} \quad (4)$$

where I_G and I_P are, respectively, a gallery and a probe face image, $f(I,\gamma)$ is a transform for illumination normalization and $\widehat{\gamma_G}$ and $\widehat{\gamma_P}$ are parameters for f, which can be estimated by solving the following optimization problem:

$$\left\{\widehat{\gamma_G}, \widehat{\gamma_P}\right\} = \arg\max_{\gamma_G, \gamma_P} \ corr\left(f\left(I_G, \gamma_G\right), f\left(I_P, \gamma_P\right)\right) \quad (5)$$

where $corr(\cdot)$ computes the correlation between two face images. Once the optimum illumination normalization parameters are estimated, the maximum correlation for this pair of gallery and probe face images can be calculated as:

$$sim(I_G, I_P) = corr\left(f\left(I_G, \widehat{\gamma_G}\right), f\left(I_P, \widehat{\gamma_P}\right)\right) \quad (6)$$

which is also served as the final similarity score for the following face recognition task.

The optimization of illumination normalization for a pair of gallery and probe face images can be directly calculated based on Eq. (5), which optimizes γ_G and γ_P simultaneously. However, the optimization problem in Eq. (5) can also be simplified by optimizing only one of the parameters for illumination normalization transform while fixing the other. The simplified optimization problem can be in one of the following two forms:

$$\left\{\widehat{\gamma_G}\right\} = \arg\max_{\gamma_G} \ corr\left(f\left(I_G, \gamma_G\right), I_P\right) \quad (7)$$

or

$$\left\{\widehat{\gamma_P}\right\} = \arg\max_{\gamma_G} \ corr\left(I_G, f\left(I_P, \gamma_P\right)\right) \quad (8)$$

The former optimization problem defined in Eq. (7) seems more reasonable compared with that defined in Eq. (8), because in Eq. (7) all the gallery images share the same probe image as their "canonical" reference image in performing illumination normalization and then the maximized correlations will be comparable with each other. However, as for the latter simplified optimization problem defined in Eq. (8), the maximized correlations for one probe face image seem not to be comparable with other. Therefore, the simplified MAC optimization problem defined in Eq. (7) is recommended as it simplifies a multivariate optimization problem in to a univariate one and thus largely reduces the computational complexity; meanwhile, it inherits the key idea of the original MAC framework.

3.2 Illumination normalization transforms

Two approaches i.e. GIC and LTV, are utilized as the transform f to perform illumination normalization. In which GIC is defined in Section 2 and LTV performs illumination normalization by calculating the small-scale component v in a face image:

$$I' = v = I - \hat{u} \quad (9)$$

where $\hat{u}$ is the large-scale component corresponding to the illumination variation in a face image I, which is estimated by solving the following variational problem:

$$\hat{u} = \arg\min_u \int\left|\nabla u\right| + \lambda\left\|I - u\right\|_{L^1} \quad (10)$$

where $\int\left|\nabla u\right|$ is the total variation of u and λ is a scalar constant that controls the scale truncation for u and v.

4. EXPERIMENTS

Two representative face databases in this area, Extended YaleB [9] and CMU-PIE [10] face databases, are exploited in our experiments to investigate our proposed approach in face recognition across varying illumination.

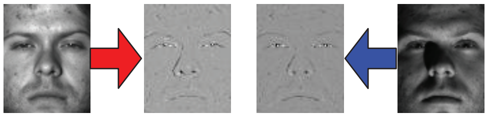
The Extended YaleB face database includes the original YaleB face database with 10 individuals under 64 different illumination conditions and the extended part with 28 individuals that are also captured under 64 different illumination conditions. Totally 2,432 face images of 38 individuals under 64 illumination conditions in frontal view are used for experiments. All the face images are divided into five subsets according to [9], in which subset#1 is used as the gallery set for face recognition algorithm.

For the CMU-PIE face database, totally 1,425 frontal face images of 68 individuals under 21 lighting conditions from *illum* dataset are used in our experiments. Three face images of each individual with most frontal lighting are chosen to form the gallery set.

All the face images are geometrically normalized to the size of 64×80 with the distance between two eyes 30 pixels. For the convenience of our description below, we denote "ORI" as the original face images without any illumination normalization. "MAC-GIC(G,P)", "MAC-GIC(G)" and "MAC-GIC(P)" denote the methods using GIC illumination normalization but based on Eq. (5), Eq. (7) and Eq. (8) respectively; similarly, "MAC-LTV(G,P)", "MAC-LTV(G)" and "MAC-LTV(P)" denote the methods using LTV illumination normalization but based on Eq. (5), Eq. (7) and Eq. (8) respectively. Besides GIC [8] and LTV [7], we also compare our proposed approach with other illumination normalization methods, i.e. HE [2], LT [1], SSR [4] and LN [5].

Illumination normalized face images can be seen from Fig. 3. Face recognition experiments are then performed on the above two face databases following different illumination normalization approaches. For all the approaches we compared, nearest neighbor classifier based on correlation is used as the recognition algorithm. As can be seen from Tab. 1, our proposed approach gets higher face recognition performance on both Extended YaleB and CMU-PIE face databases, i.e. 59.97% on Extended YaleB and 98.61% on CMU-PIE. Compared with GIC and LTV, impressive improvement can be noticed in MAC-GIC and MAC-LTV. MAC-GIC gets 59.97% and 84.13%

(a) MAC-GIC



(a) MAC-LTV

Fig.3 Illumination normalized face image of (a) MAC-GIC and (b) MAC-LTV approaches.

Table 1 Face recognition performance of different illumination normalization approaches on Extended YaleB and CMU-PIE face databases.

Approaches	Recognition Rate (%)	
	Extended YaleB	CMU-PIE
ORI	43.16	50.41
HE	45.15	46.56
LT	49.96	61.87
SSR	52.82	77.00
LN	50.05	84.53
GIC	44.42	49.56
LTV	48.76	84.78
MAC-GIC(G,P)	**59.97**	65.59
MAC-GIC(P)	32.55	50.62
MAC-GIC(G)	55.49	84.13
MAC-LTV(G,P)	53.19	84.94
MAC-LTV(P)	28.58	85.37
MAC-LTV(G)	51.62	**98.61**

recognition rate on Extended YaleB and CMU-PIE face databases compared with 44.41% and 49.56% gotten by GIC. Similarly, MAC-LTV gets as high as 53.19% and 98.61% recognition rate on the two testing databases compared with 48.76% and 84.78% reached by LTV. It is worth to mention that the simplified MAC approaches based on Eq. (7), i.e. MAC-GIC(G) and MAC-LTV(G) result in comparable or even higher recognition performance compared with the original one based on Eq. (5). And as analyzed in Section 3.1, it is not surprising that the simplified MAC methods based on Eq. (8) lead to poor recognition performance.

5. CONCLUSION

In this paper, we present a new framework named MAC that extends the GIC algorithm to optimizing the illumination normalization of a pair of gallery and probe face images by maximizing a correlation between them. The proposed approach tends to maximize the intra-individual correlations instead of both the inter- and intra-individual correlations. Simplified MAC, which inherits the key idea of the original MAC, is analyzed and introduced to reduce the computational complexity. Experimental results show the effectiveness of our proposed approach in face recognition across varying lighting conditions.

6. ACKNOWLEDGEMENT

This paper is partially supported by Natural Science Foundation of China under contracts No.60872124 and No. U0835005, National Basic Research Program of China (973 Program) under contract 2009CB320902, and Grand Program of International S&T Cooperation of Zhejiang Province S&T Department under contract No. 2008C14063, and ISVISION Technology Co. Ltd.

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