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A comparative study on illumination preprocessing in face recognition

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ABSTRACT

Illumination preprocessing is an effective and efficient approach in handling lighting variations for face recognition. Despite much attention to face illumination preprocessing, there is seldom systemic comparative study on existing approaches that presents fascinating insights and conclusions in how to design better illumination preprocessing methods. To fill this vacancy, we provide a comparative study of 12 representative illumination preprocessing methods (HE, LT, GIC, DGD, LoG, SSR, GHP, SQI, LDCT, LTV, LN and TT) from two novel perspectives: (1) localization for holistic approach and (2) integration of large-scale and small-scale feature bands. Experiments on public face databases (YaleBExt, CMU-PIE, CAS-PEAL and FRGC V2.0) with illumination variations suggest that localization for holistic illumination preprocessing methods (HE, GIC, LTV and TT) further improves the performance. Integration of large-scale and small-scale feature bands for reflectance field estimation based illumination preprocessing approaches (SSR, GHP, SQI, LDCT, LTV and TT) is also found helpful for illumination-insensitive face recognition.

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1. Introduction

Automatic face recognition (AFR) has attracted much attention in the past decades for its wide applications in security, forensic investigation, and law enforcement. The challenges that a practical face recognition system has to face include facial appearance variations due to lighting, pose, expression and so on. Among them, varying lighting conditions such as shadows, underexposure, and overexposure in face images are intractable yet crucial problems that a practical face recognition system has to deal with. In fact, the intra-personal differences due to dramatic changes in face appearance caused by lighting variation can even be much larger than inter-personal differences [1].

As reviewed in [2], various approaches have been proposed to handle lighting variations in face recognition. Among these approaches, illumination preprocessing has drawn much attention in the last decades. The popularity of illumination preprocessing methods roots from its simplicity and feasibility to be applied before traditional face recognition methods. The output of illumination preprocessing is still a face image and thus many feature descriptors, e.g. Gabor [3] and LBP [22], can further be applied after illumination preprocessing. As shown in Fig. 1, illumination preprocessing is one of the preprocessing steps before face matching in AFR systems.

We argue that illumination variations on faces degrade not only the face matching performance but also the face detection accuracy, which is the first step in a face recognition system. Traditional Haar-like feature based face detectors, e.g. Viola–Jones face detector [4], tend to fail under severe illumination variations such as heavy shadows and overexposure. In these circumstances, face detection methods based on skin detection techniques [5–12] might be used to localize the facial skin area, and illumination preprocessing can then be applied to the detected facial skin area. In this paper, instead of investigating the influence of illumination to every stage (e.g. face detection, landmark localization, face normalization and matching) in a face recognition system, we focus on the study of the influence of individual illumination preprocessing methods on various face matching methods.

We do already have had a large number of illumination preprocessing methods in the literature [1,19,20,21,23,24,26,27,28,29,34,35,36,37,38], and many of them have reported promising results on some specific databases [13,14,25,30,31]. There are also several conclusions that can be drawn from existing work: (1) most preprocessing methods perform almost perfectly in handling well-controlled lighting variations [15,16,24] but they are still deficient in handling less-controlled illumination variations [29]; (2) Retinex [32] based approaches is suitable for noise-insensitive feature descriptors, e.g. local ternary patterns (LTP) [29] and Gabor [33] rather than LBP [22]; and (3) for face recognition purpose, better visualization effect after illumination preprocessing does not imply higher recognition accuracy. However, these conclusions have been well-known in face recognition community, and there is seldom novel suggestions on how to improve existing illumination preprocessing methods or design better illumination preprocessing methods.

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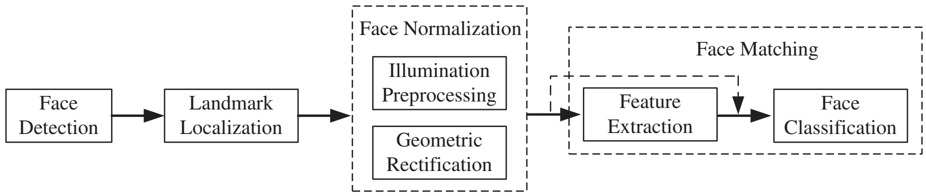

Fig. 1. Typical framework for lighting-insensitive face recognition using illumination preprocessing.

Table 1
Database for testing, recognition methods for evaluation and illumination preprocessing methods for comparison in this paper.

Database for testing	Recognition methods for evaluation	Illumination preprocessing methods for comparison			
		Basic principle	Method	Publication	Year
Extended YaleB [13]	Correlation [17]	Gray-level transformation	HE	[26]	1987
			LT	[1]	1997
			GIC	[34]	2003
CMU-PIE [14]	Eigenfaces [18]	Gradient or edge extraction	DGD	[1]	1997
			LoG	[1]	1997
CAS-PEAL-R1 lighting [30]	Fisherfaces [17]		SSR	[35]	1997
			GHP	[36]	2002
FRGC Ver2.0 Exp.4 [31]	LBP [22]	Reflectance field estimation	SQI	[19]	2004
			LDCT	[37]	2006
	LGBP [39]		LTV	[28]	2006
			LN	[38]	2006
	LEC [40]		TT	[29]	2010

Based on the above analysis, this study focuses on improving existing illumination preprocessing for face recognition by performing a comparative study on 12 different illumination preprocessing methods from two novel perspectives. We also utilize six different face matching algorithms to evaluate the effectiveness of different face illumination preprocessing methods. Both the illumination preprocessing methods we studied and the matching algorithms we utilized are illustrated in Table 1. From Table 1, it can be noticed that the illumination preprocessing methods we studied cover both basic techniques, such as Histogram equalization (HE) [26], logarithmic transform (LT) [1], gamma intensity correction (GIC) [34], directional gray-scale derivative (DGD) [1], Laplacian of Gaussian (LoG) [1], single-scale Retinex (SSR) [35] and Gaussian high-pass (GHP) [36], and several state-of-the-art methods, such as self-quotient image (SQI) [19], logarithmic discrete cosine transform (LDCT) [37], logarithmic total variation (LTV) [28], local normalization (LN) [38] and TT [29]. The selection of face matching algorithms also follows the similar rule. For example, Correlation [17], Eigenfaces [18], Fisherfaces [17] and LBP [22] are all typical face matching algorithms, and local Gabor binary patterns (LGBP) [39] and local ensemble classifier (LEC) [40] are, respectively, one of the state-of-the-art methods without and with supervised learning. Moreover, four public face databases (Extended YaleB [13], CMU-PIE [14], CAS-PEAL lighting [30] and FRGC Ver2.0 Exp. 4 [31]) for studying illumination-insensitive face recognition are employed. We expect the conclusions drawn from such a systemic study can provide an unbiased reference for improving existing illumination preprocessing methods or designing new face illumination preprocessing approaches.

The contributions of the paper are summarized as follows:

1. Illumination preprocessing approaches are analyzed from their principles and grouped into three categories.
2. Performance of 12 illumination preprocessing approaches is fully evaluated with six face matching methods on four public face databases.
3. Existing illumination preprocessing approaches are investigated from two novel perspectives and conclusions in designing better illumination preprocessing methods are drawn.

The remainder of this paper is structured as follows: Section 2 briefly describes different illumination preprocessing approaches for lighting-invariant face recognition. In Section 3, we provide insight into different illumination preprocessing methods from two novel perspectives. Finally, some conclusions regarding this work are given in Section 4.

2. Illumination preprocessing approaches

As shown in Table 1, 12 illumination preprocessing methods are studied in this work. Instead of repeating the descriptions for these methods in the original literature, in this section, we briefly review these approaches by analyzing the principles behind different methods and grouping them into three categories: gray-level transformation, gradient and edge extraction, and face reflection field estimation.

2.1. *Gray-level transformation*

The principle for gray-level transformation in illumination preprocessing is to perform a pixel-wise intensity mapping with one specific transformation function. After gray-level transformation, the intensities in a face image are redistributed and the uneven illumination can also be corrected to some extent. The transformation function can be linear or non-linear but a non-linear transformation is usually more effective compared with a linear one. HE, LT and GIC studied in this work can be regarded as approaches with non-linear gray-level transformation. Cumulative distribution function, logarithmic function and exponential function are, respectively, the non-linear transformations for HE, LT and GIC.

2.2. *Gradient or edge extraction*

The principle of gradient or edge extraction based illumination preprocessing is to extract the gray-level gradients or edges from a face image and use them as a lighting-insensitive representation. The absolute pixel intensities in a face image vary greatly in

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different lighting conditions; however, it is not the same case for gray-level gradient or edges in a face image. DGD and LoG studied in this work are approaches based on gradient and edge features. Specifically, gray-level gradients in horizontal and vertical directions are usually extracted in DGD, while second-order spatial derivatives are employed to highlight the edges in LoG.

2.3. Reflectance field estimation

The principle of reflectance field estimation based illumination preprocessing is to estimate the face reflectance field from a 2D face image. Obviously, face reflectance field is illumination-invariant. This kind of method is usually performed based on some kind of face imaging model, e.g. reflectance-illumination model which represents a face image as the product of face reflectance and illumination component. Specifically, SSR, GHP, SQI, LDCT, LTV and TT studied in this work first estimate the illumination component using Gaussian smoothing filter, discrete cosine transform (DCT) or total variation (TV) model and then calculate the reflectance field based on reflectance-illumination model. In contrast, LN directly calculates the reflectance field based on an observation that illumination component in a small facet is constant.

3. Comparative study

In this section, we present the comparative study for different illumination preprocessing methods. We first briefly describe the face databases and experimental settings utilized in all the experiments. The overall performance of the original illumination preprocessing methods on four databases is shown to give an across category comparison of different illumination preprocessing approaches. Then, we further investigate these illumination preprocessing methods from two novel perspectives.

3.1. Databases and experimental settings

As shown in Table 1, four public face databases, e.g. Extended YaleB (YaleBExt), CMU-PIE, CAS-PEAL lighting and FRGC Ver2.0 Exp. 4, are employed in our study. YaleBExt and CMU-PIE are two widely used benchmark databases for evaluating the effectiveness

Table 2
Evaluation dataset division for the face databases used in our experiments.

Databases Evaluation task		Extended YaleB Close-set identification	CMU-PIE Close-set identification	CAS-PEAL-R1 lighting Close-set identification	FRGC Ver2.0 Exp. 4 Face verification
Training set	#Persons	38	68	300	222
	#Images	266	203	1200	12,776
Target set (gallery)	#Persons	The same as training set	The same as training set	1040	466
	#Images			1040	16,028
Query set (probe)	#Persons	38	68	233	466
	#Images	2166	1222	2243	8014

Note: Since there is not separate training set for Extended YaleB and CMU-PIE, the target sets are the same as training sets for supervised face recognition methods, e.g. Fisherfaces and LEC.

Table 3
Overall comparison of the effectiveness of individual face illumination preprocessing methods.

Databases	Recognition algorithms	Recognition rate (%) with different methods for illumination preprocessing													
		ORI	HE	LT	GIC	DGDx	DGDy	LoG	SSR	GHP	SQI	LDCT	LTV	LN	TT
YaleBExt	Correlation	43.2	45.2↑	50.0↑	44.4↑	37.4↓	42.0↓	44.1↑	52.8↑	53.4↑	86.5↑	73.7↑	48.8↑	50.1↑	**87.4**↑
	Eigenfaces	47.6	31.4↓	58.3↑	**59.3**↑	38.6↓	39.8↓	50.1↑	51.6↑	49.5↑	58.2↑	50.4↑	20.3↓	42.9↓	50.2↑
	LBP	60.7	62.2↑	62.0↑	61.0↑	62.0↑	70.3↑	72.8↑	58.7↓	69.5↑	57.9↓	62.7↑	52.8↓	55.8↓	**90.3**↑
	LGBP	95.4	95.9↑	98.9↑	96.1↑	85.5↓	83.1↓	74.8↓	98.4↑	91.0↓	**99.1**↑	98.3↑	92.1↓	98.2↑	98.9↑
	Fisherfaces	54.2	54.8↑	62.8↑	67.7↑	53.1↓	59.2↑	54.6↑	55.5↑	55.4↑	72.6↑	74.1↑	**78.0**↑	67.4↑	71.6↑
	LEC	57.5	76.0↑	97.3↑	91.3↑	62.9↑	61.6↑	55.2↓	97.1↑	65.0↑	97.6↑	97.3↑	93.5↑	96.5↑	**98.4**↑
CMU-PIE	Correlation	50.4	46.6↓	61.9↑	49.7↓	62.7↑	82.2↑	73.5↑	77.0↑	85.4↑	98.6↑	97.2↑	84.8↑	84.5↑	**99.5**↑
	Eigenfaces	55.5	64.2↑	71.4↑	71.4↑	64.2↑	76.3↑	80.6↑	60.0↑	71.3↑	92.6↑	92.1↑	89.1↑	**97.1**↑	94.4↑
	LBP	84.5	85.5↑	84.8↑	84.6↑	85.9↑	94.9↑	97.5↑	84.0↓	92.2↑	84.9↑	**84.5**=	89.4↑	77.1↓	**99.2**↑
	LGBP	**100**	**100**=	**100**=	99.7↓	99.8↓	99.8↓	99.4↓	**100**=	99.9↓	**100**=	**100**=	**100**=	**100**=	**100**=
	Fisherfaces	77.1	85.2↑	69.8↓	85.3↑	91.7↑	99.7↑	98.5↑	69.0↓	99.4↑	98.6↑	99.7↑	**100**↑	99.8↑	98.1↑
	LEC	79.6	98.7↑	**100**↑	92.8↑	91.7↑	95.4↑	90.8↑	**100**↑	97.1↑	**100**↑	**100**↑	**100**↑	**100**↑	**100**↑
CAS-PEAL lighting	Correlation	4.5	5.3↑	9.6↑	4.6↑	2.1↓	7.2↑	5.5↑	16.5↑	8.4↑	16.9↑	10.6↑	5.1↑	13.8↑	**19.7**↑
	Eigenfaces	8.6	11.5↑	**17.7**↑	11.3↑	4.0↓	7.1↓	6.6↓	17.3↑	9.7↑	13.8↑	11.3↑	3.3↓	12.3↑	12.2↑
	LBP	13.3	14.4↑	13.6↑	13.5↑	11.7↓	15.7↑	28.3↑	14.9↑	14.1↑	14.2↑	17.4↑	9.0↓	13.6↑	**33.5**↑
	LGBP	49.3	40.3↓	67.8↑	50.3↑	36.5↓	40.1↓	31.7↓	63.5↑	43.6↓	**69.9**↑	63.7↑	46.4↓	59.7↑	68.7↑
	Fisherfaces	21.6	29.6↑	27.6↑	24.9↑	17.7↓	19.8↓	16.8↓	28.6↑	21.9↑	27.8↑	21.9↑	14.3↓	**34.4**↑	23.9↑
	LEC	76.0	70.6↓	77.8↑	79.3↑	65.8↓	66.4↓	59.3↓	79.9↑	74.1↓	80.2↑	76.5↑	50.6↓	**82.7**↑	80.7↑
FRGC Ver2.0	Correlation	3.4	2.7↓	4.0↑	1.7↓	4.0↑	6.8↑	3.0↓	4.3↑	9.1↑	**12.6**↑	9.8↑	6.2↑	2.3↓	12.3↑
	Eigenfaces	8.2	8.0↓	11.7↑	9.6↑	12.0↑	12.6↑	8.8↑	10.9↑	9.7↑	**14.7**↑	14.6↑	10.6↑	13.1↑	13.7↑
	LBP	7.80	7.8↓	7.8↓	7.2↓	10.7↑	9.5↑	14.6↑	7.7↓	12.6↑	13.5↑	14.9↑	2.1↓	11.1↑	**21.0**↑
	LGBP	40.3	22.7↓	41.4↑	24.0↓	37.2↓	36.1↓	31.1↓	42.8↑	39.3↓	42.9↑	39.6↓	21.4↓	38.5↓	**44.3**↑
	Fisherfaces	57.1	53.2↓	60.2↑	57.6↑	50.3↓	46.3↓	59.4↑	60.7↑	58.0↑	58.1↑	45.2↓	29.0↓	**62.6**↑	58.6↑
	LEC	84.5	75.6↓	86.6↑	83.7↓	81.4↓	84.0↓	77.0↓	86.9↑	85.3↑	87.5↑	85.1↑	66.7↓	87.0↑	**87.8**↑

Note: For the FRGC Ver2.0 database, face verification is performed following the standard testing protocol of experiment 4, and face verification rate with FAR=0.1% is reported for comparison.

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of illumination preprocessing methods under pure lighting variations. In contrast, CAS-PEAL and FRGC Ver2.0 include variations of pose, expression and blur, besides less-controlled illumination. Therefore, CAS-PEAL and FRGC Ver2.0 are more challenging for face matching. Subset division (training, gallery, and probe sets) of the four databases is illustrated in Table 2. All the face images are normalized to 64×80 pixels with the interpupillary distance (IPD) being 30 pixels. The parameters that lead to best recognition rates are utilized for different illumination preprocessing methods in our experiments.

3.2. Overall performance

We first give an overall performance comparison for all the illumination preprocessing methods in Table 3. For comparison, face recognition rate on original face images without illumination preprocessing is also listed. As there are hundreds of experimental results, for clear comparison, we mark each recognition rate with a sign indicating the negative or positive effect of each illumination preprocessing method. Specifically, a blue upward arrow (↑), a red downward arrow (↓), and a green equal sign (=), respectively, denote that the results are higher than, lower than or equal to the recognition rates without any illumination preprocessing (i.e. the column labeled with ORI). From the table, TT, SQI and LDCT are found to be more effective for illumination-invariant face recognition in both well-controlled and less-controlled lighting conditions. Although the face matching performance on CAS-PEAL and FRGC Ver2.0 after illumination preprocessing is still below 90%, it does not imply that illumination preprocessing approaches cannot handle less-controlled lighting variations. The reason behind is that besides varying illumination, there are also dramatic variations in pose, expression and blur in these two databases. Although these factors are real issues that are worth tackling, they are not the problems that pure illumination preprocessing is likely to resolve.

One characteristic of illumination preprocessing is that the preprocessed result for an input face image is still an image, instead of abstract features. Although all illumination preprocessing methods are proposed to eliminate the lighting variation before face recognition, different principles behind illumination preprocessing approaches may lead to various visual appearances. Therefore, a comparison on the visualization effects of the preprocessed face images is also helpful in better understanding

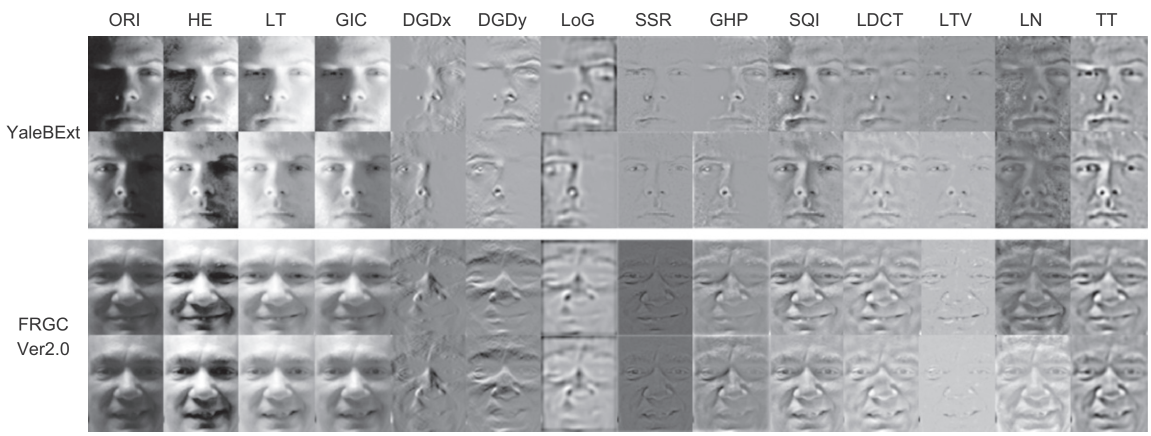

Fig. 2. Visual comparison for face images normalized with different illumination preprocessing methods on databases with controlled and less-controlled lighting.

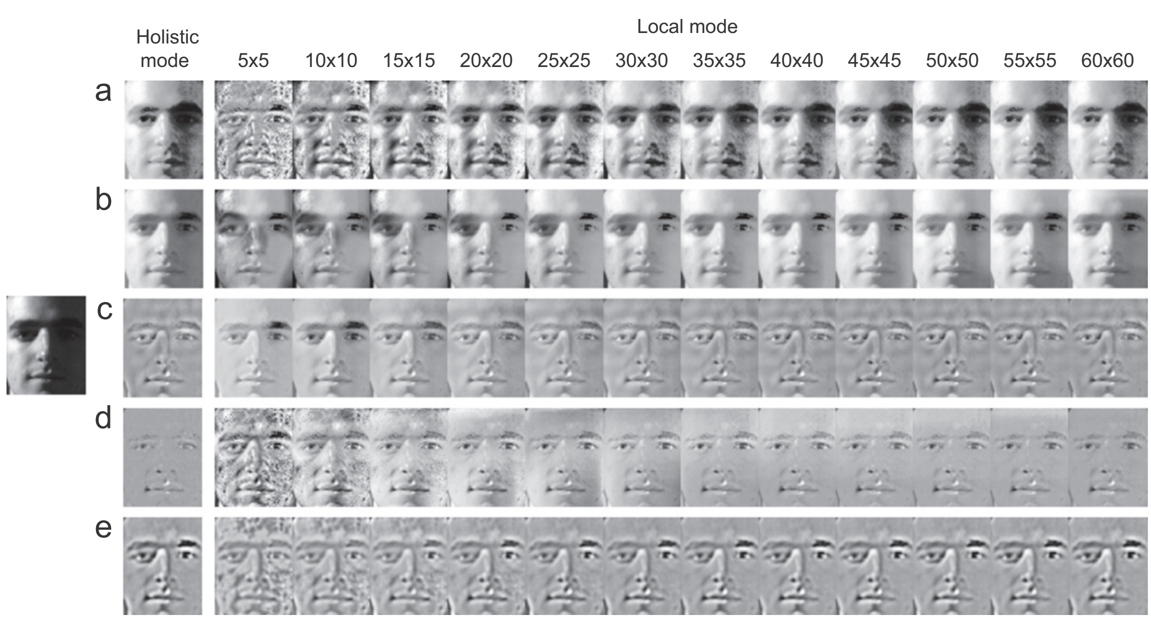

Fig. 3. Illustration of the preprocessed face images using (a) localized HE (LHE), (b) localized GIC (LGIC), (c) localized LDCT (LLDCT), (d) localized LTV (LLTV), and (e) localized TT (LTT) with pixel-wise sampling for each block size.

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the principle behind each illumination preprocessing method. We show some preprocessed face images using different illumination preprocessing methods in Fig. 2. It can be noticed that illumination preprocessing methods of the same category (gray-level transformation, reflectance field estimation or gradient/edge extraction) achieve normalized face images with similar visual appearance. HE, LT and GIC keep more face shading information that corresponds to the 3D shape of faces but do not completely eliminate shadows. DGD and LoG extract the edges or gradients from face images which are robust to absolute intensity variation but are still greatly affected by severe shadows. SSR, GHP, LDCT, LTV, LN and TT enhance facial features for both the regions with ideal lighting and shadows but these methods may also enlarge the photon or sensor noises. By a cross category comparison of three kinds of methods, we can find that approaches based on gray-level transformation (HE, LT and GIC) and reflectance field estimation (SSR, GHP, LDCT, LTV, LN and TT) usually preserve more facial features compared with gradient or edge extraction based methods (DGD and LoG). The visual appearance of normalized face image also explains why gradient or edge extraction based methods are not as effective as the other two categories of approaches (see Table 2). Discriminative facial features are not only contained in the relative changes of pixel intensity [43]. It is insufficient to only use gradient or edge information for illumination-insensitive face recognition.

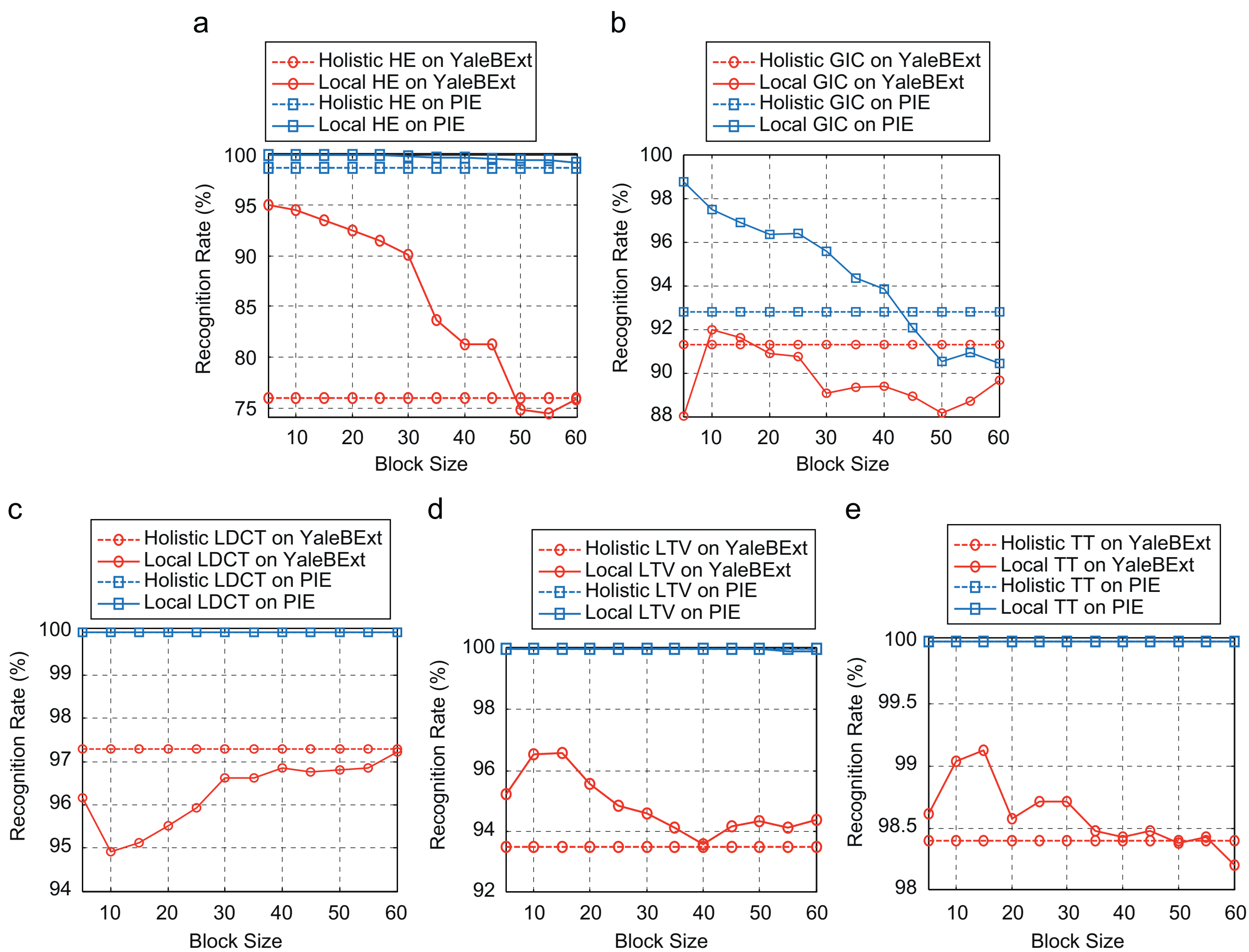

Fig. 4. Performance comparison for (a) HE vs. LHE, (b) GIC vs. LGIC, (c) LDCT vs. LLDCT, (d) LTV vs. LLTV and (e) TT vs. LTT on Extended YaleB and CMU-PIE face databases with LEC as the face matcher.

Table 4
Summary of the performance of holistic and localized illumination preprocessing methods in conjunction with LEC on both controlled and less-controlled databases.

Database	Performance of illumination preprocessing approaches (%) (holistic/localized)				
	HE	GIC	LDCT	LTV	TT
YaleBExt	76.0/95.0↑	91.3/92.0↑	97.3/97.2↓	93.5/96.6↑	98.4/99.1↑
CMU-PIE	98.7/100↑	92.8/98.8↑	100/100 =	100/100 =	100/100 =
CAS-PEAL	70.6/78.3↑	79.3/81.1↑	76.5/76.1↓	50.6/69.6↑	80.7/83.5↑
FRGC Ver2.0	75.6/81.5↑	83.7/85.3↑	85.1/84.7↓	66.7/75.3↑	87.8/88.2↑

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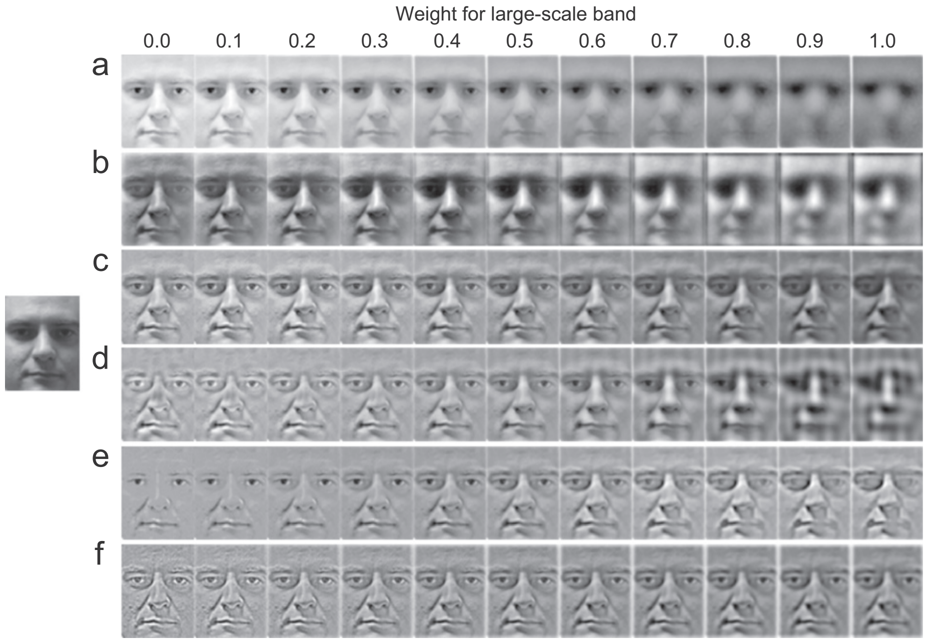

Fig. 5. Illumination preprocessing is performed on a face image by integrating the large-scale and small-scale feature bands in different illumination preprocessing methods (a) SSR, (b) GHP, (c) SQI, (d) LDCT, (e) LTV, and (f) TT.

3.3. *Localization for holistic approaches*

In this section, we provide an insight into illumination preprocessing methods by localizing the holistic approaches. In case of side-lighting, asymmetry in intensity or cast shadow generally appears. However, as shown in Fig. 2, we find that some holistic illumination preprocessing methods, e.g. HE and GIC, cannot handle the side-lighting. Intuitively, if we preprocess the image locally, the side-lighting might be greatly reduced. With this point of view to consider the 12 methods we studied, it is clear that LT, DGD, LoG, SSR, GHP, SQI and LN are already working in a local mode. The remaining methods, i.e. HE, GIC, LDCT, LTV and TT, can also be extended to work on local patches. In fact, HE and GIC have been extended into local mode in [41,42,34]. The localization for LDCT and LTV is evident, which can be directly applied on local image patches. However, the localization for TT is slightly different. In TT, there are three main steps, e.g. gamma correction (GC), difference of Gaussian (DoG) and contrast equalization (CE), and the first two steps are already working in a local mode. Therefore, to localize TT, we only need to perform CE in local blocks.

Experiments are then conducted to verify whether localization can improve the performance of holistic illumination preprocessing methods. The input face image is divided into blocks in an overlapped pattern.[1] For a pixel covered by several blocks, its intensity after preprocessing is computed as the average of the intensities in all overlapped blocks. As shown in Fig. 3, a face image is preprocessed using HE, GIC, LDCT, LTV and TT in both holistic and local modes. In rows (a)–(e) of Fig. 3, the first image is preprocessed with an illumination preprocessing method in holistic mode and the remaining images are preprocessed using the same method in local mode with different block sizes. It can be noticed that small-scale features (both facial details and sensor noises) are greatly enhanced in the preprocessed face images by LHE, LGIC, LLTV and LTT with smaller block sizes. Also, localized illumination preprocessing methods are found to be effective in suppressing side-lighting. With the increase of the block size, the preprocessed face images by LHE, LGIC, LLTV and LTT tend to became more and more smooth. At the same time, some small-scale facial details are lost and side-lighting again appears in the preprocessed face images. However, the behavior of localized LDCT is different. For example, face images preprocessed by localized LDCT with smaller block sizes are heavily smoothed instead of being enhanced (see the first two images in row (c) of Fig. 3). As a result, small-scale facial features, e.g. eyebrow and irregularities, are lost. The reason might be as follows. Different from HE, GIC, LTV and PP, which are performed in spatial domain, LDCT is conducted in frequency domain. The low frequency component in a whole image mainly corresponds to illumination variations; however, the low frequency component in a local block may locate in the high-frequency domain of the whole image. Localized LDCT loses the superiority of global frequency domain analysis.

Face recognition is then performed on the preprocessed face images with both holistic and localized HE, GIC, LDCT, LTV and TT for illumination preprocessing. Since LEC is found to be the most effective face matching method across different face databases in Section 3.2, we utilize LEC as the face matcher to evaluate the effectiveness of localized illumination preprocessing methods. The recognition rates of LEC on databases with controlled lighting (YaleBExt and CMU-PIE) are shown in Fig. 4(a)–(e), respectively. Recognition performance with localized illumination preprocessing methods show that localization does improve the performance of HE, GIC, LTV and TT, especially when appropriate block sizes are used. Face recognition performance with localized LDCT also verifies our above observation. Moreover, we further evaluate the performance of localized HE, GIC, LDCT, LTV and TT on face databases (CAS-PEAL lighting and FRGC Ver2.0 Exp. 4[2]) with less-controlled lighting conditions. The optimal block sizes found on the Extended YaleB database are directly used on CAS-PEAL and FRGC Ver2.0. As shown in Table 4, experiments on databases

[1] In our experiments, we covered the block sizes of $5\times5, 10\times10, \ldots, 60\times60$.

[2] For the FRGC Ver2.0 database, face verification rate with FAR=0.1% is reported for comparison.

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with less-controlled lighting also show that localization of holistic methods, e.g. HE, GIC, LTV and TT, can further improve the performance.

3.4. Integrating features of large-scale band

Another issue in existing illumination preprocessing methods is that reflectance field estimation based approaches usually discard the large-scale band in illumination preprocessing. As a result, face shading information is lost in the preprocessed face images, and the preprocessed images seem to be flattened (e.g. the normalized face images using SSR and LTV shown in Fig. 2). However, the study in [44] reveals that features in large-scale band are also beneficial for lighting-insensitive face recognition. In this section, we provide an insight into facial reflectance field estimation based methods (e.g. SSR, GHP, SQI, LDCT, LTV and TT) by integrating features of both large-scale and small-scale bands.

Specifically, for SSR, GHP, and SQI, the large-scale feature band is calculated with the Gaussian smoothing functions. The large-scale band in LDCT is calculated by performing inverse DCT for the first *d* rows of DCT coefficients in zigzag pattern. In LTV, the large-scale band is calculated by solving a variational optimization problem. In TT, the large-scale band is calculated using the outer Gaussian smoothing function in DoG. Integration of large-scale and small-scale bands in LTV with equal weights is analyzed in [44]; however, it may be not optimal to treat the large-scale and small-scale bands equally. In our experiments, we investigate the importance of these two feature bands by varying their weights in feature band integration. The sum of the weights assigned to individual feature bands equals 1. We first show preprocessed face images by integrating the large-scale and small-scale feature bands in Fig. 5. From Fig. 5, we can observe that the large-scale feature band mainly contains the face shading information. When no large-scale features is included (the weight for large-scale band is zero), the preprocessed face images lack shading information and the faces no longer look like a 3D surface. By contrast, with the increase of large-scale features, more shading information is preserved in the preprocessed face images, and the normalized faces look more like a 3D geometry (see rows (e) and (f) in Fig. 5).

Face recognition is then performed on the preprocessed face image using a state-of-the-art matching algorithm LEC. The performance of integrating large-scale and small-scale feature bands for SSR, GHP, SQI, LDCT, LTV and TT are shown in Fig. 6(a)–(f), respectively. It can be noticed that the performance of individual methods gradually improves with the increase of the large-scale feature band at first, and then degrades rapidly with the further increase of the large-scale feature band. In this section, the

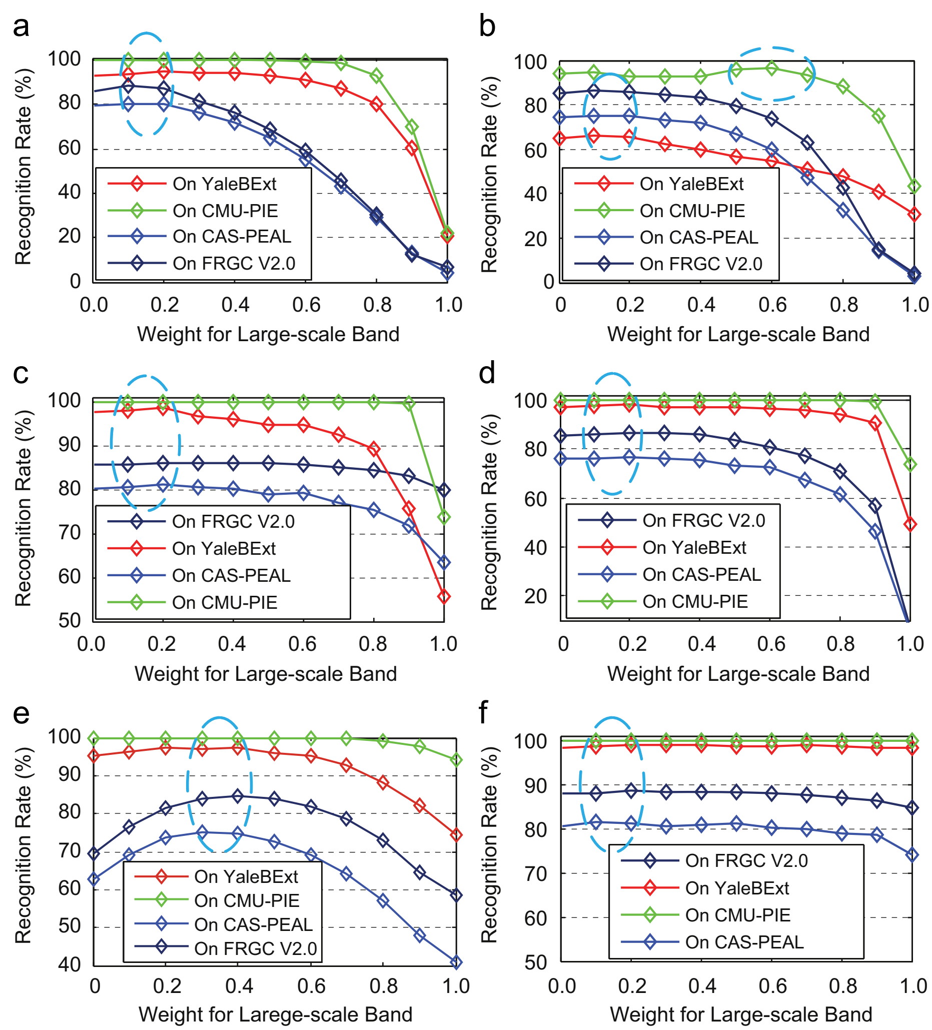

Fig. 6. The effectiveness of integrating large-scale and small-scale feature bands for illumination preprocessing methods (a) SSR, (b) GHP, (c) SQI, (d) LDCT, (e) LTV, and (f) TT, is evaluated using LEC as the face matcher. Following the standard testing protocol, identification task is performed on YaleBExt, CMU-PIE and CAS-PEAL databases, while verification task is performed on FRGC V2.0 database.

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parameters that lead to best performance of SSR, GHP, SQI, LDCT, LTV, and TT in Section 3.2 are used to decompose face images into large-scale and small-scale bands. From the viewpoint of band integration, these parameters might not be optimum; however, even such a simple band integration with these parameters reveals that band integration is beneficial for illumination-invariant face recognition. This conclusion is consistent with that in [44]. However, our experimental results in Fig. 6 also show that different weights should be assigned to large-scale and small-scale feature bands in order to achieve better performance. Our experiments in this section suggest that it would be biased to either abruptly discard the large-scale feature band or treat it equally as the small-scale band in face illumination preprocessing.

From Fig. 6, we have also observed that the integration of large-scale and small-scale bands leads to limited performance improvement. This is due to the inherent limitations of traditional framework in face image decomposition, which decomposes a face image into only two bands (large-scale and small-scale). Signals of individual bands should play different roles for face recognition; however, a rough division of features in a face image into two bands is insufficient for understanding the roles played by individual feature bands. Our recent study in [45] shows that a fine decomposition of facial features in scale-space improves the performance of LTV for illumination preprocessing.

4. Conclusion

Illumination preprocessing is an efficient and effective approach in eliminating lighting variations before face recognition. Representative illumination preprocessing approaches are briefly reviewed by grouping them into three main categories based on different principles, i.e. gray-level transformation, gradient or edge extraction and reflectance field estimation. Besides presenting the overall performance of individual illumination preprocessing methods, this study also provides insight into existing illumination preprocessing methods from two novel perspectives, i.e. localization for holistic approach and integration of large-scale and small-scale feature bands.

Experimental results suggest that localization of some holistic illumination preprocessing approaches, e.g. HE, GIC, LTV and TT, improves the performance. Our study also shows that it is biased to either completely discard the large-scale feature band or treat it equally as the small-scale one for optimum illumination preprocessing.

Currently, most face reflectance field estimation based methods only decompose a face image into two bands. Two-band decomposition is still insufficient for analyzing the importance of individual feature bands in face recognition. In our future work, different methods for multiband decomposition of face images will be studied in designing novel illumination preprocessing approaches. Additionally, face illumination preprocessing cannot be performed when face detection fails to localize the faces due to dramatic lighting variations. Illumination preprocessing on skin areas detected using skein detection techniques can be a complementary approach.

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