

Restoration of a Frontal Illuminated Face Image Based on KPCA

Xiaohua Xie

School of Mathematics &
Computational Science,
Sun Yat-sen University,
Guangzhou, China
sysuxieh@gmail.com

Wei-Shi Zheng

Department of Computer
Science, Queen Mary,
University of London,
London, UK
wszheng@ieee.org

Jianhuang Lai*

Department of Automation,
Sun Yat-sen University,
Guangzhou, China
stsljh@mail.sysu.edu.cn

Ching Y. Suen

CENPARMI,
Concordia University,
Montreal, Canada
suen@cenparmi.concordia.ca

Abstract—In this paper, we propose a novel illumination-normalization method. By using the combination of the Kernel Principal Component Analysis (KPCA) and Pre-image technology, this method can restore the frontal-illuminated face image from a single non-frontal-illuminated face image. In this method, a frontal-illumination subspace is first learned by KPCA. For each input face image, we project its large-scale features, which are affected by illumination variations, onto this subspace to normalize the illumination. Then the frontal-illuminated face image is reconstructed by combining the small- and the normalized large- scale features. Unlike most existing techniques, the proposed method does not require any shape modeling or lighting estimation. As a holistic reconstruction, KPCA+Pre-image technology incurs less local distortion. Compared to directly applying KPCA+Pre-image technology on the original image, our proposed method can be better at processing an image of a face that is outside the training set. Experiments on CMU-PIE and Extended Yale B face databases show that the proposed method outperforms state-of-the-art algorithms.

Keywords—illumination normalization; face restoration; KPCA

I. INTRODUCTION

Restoring a frontal-illuminated face image has been widely applied in face recognition and digital art. However, such a restoration from a single face image is still a very challenging problem. In order to solve the problem, many algorithms have been proposed, such as Quotient Image (QI) relighting [9], [11], Spherical Harmonic Basic Morphable Model (SHBMM) [12], and Pixel-Dependent Subspace-based face relighting (PDS) [10].

Some algorithms, such as SHBMM, require a strict face alignment. QI-based algorithms are under the assumption that all objects of the same class have the same surface normal. This assumption makes the algorithms inaccurate and may cause local distortion. The PDS is a novel method without any shape modeling and deals with the non-Lambertian reflectance. However, the pixel-dependent model ignores the spatial relationship between pixels and may bring some undesirable results, such as the distortion of facial features. In addition, most of the existing methods,

including the three above-mentioned ones, have to perform lighting estimation, which is also a challenging problem.

In summary, the existing methods have always been developed based on an explicit shape model, lighting estimation, or some other assumptions. In this paper, in order to overcome these limitations, we introduce the Kernel Principal Component Analysis (KPCA) [2] in conjunction with Pre-image technology [5], [8] to restore the frontal-illuminated face image. The KPCA+Pre-image technology can reconstruct a normal face image from the frontal-illumination subspace, based on the input face image. As a holistic reconstruction, KPCA+Pre-image technology can avoid local distortion. Unfortunately, the direct KPCA+Pre-image technology cannot accurately reconstruct an image of a face that is outside the training set. To address this problem, we propose to incorporate the KPCA+Pre-image technology into our recently proposed illumination-normalization framework [7]. Under this framework, an input face image is first decomposed into large- and small-scale features. Then, the KPCA+Pre-image technology is performed on the large-scale features to normalize the illumination, while the small-scale features are simply smoothed. Finally, the processed large- and small- scale features are combined to reconstruct the frontal-illuminated face image. The proposed method does not rely on any shape modeling or lighting estimation. It can successfully reconstruct the frontal-illuminated face image from a single input image of a face, even when no image of that face is in the training set.

II. PROPOSED METHOD

A. Background

1) KPCA+Pre-image

The KPCA [2] is a popular technique which has been widely used in face image analysis, such as image denoising [2][8] and disocclusion [5]. In brief, KPCA performs the linear PCA in a kernel space, so as to accurately handle the nonlinear structure data. However, for the reconstruction of an image, a pre-image algorithm is required to learn the pre-image in the image space, from the projection in the kernel space. Zheng et al. [4][14] tried to apply the KPCA+Pre-image technology in illumination normalization of face images. For an input image of a face to be normalized, their

*Corresponding author.

method requires the training set to contain several frontal as well as non-frontal illuminated images of the same subject. This requirement may not always be satisfied in real-life applications. However, this limitation may be overcome, under the framework introduced in the following subsection.

2) Illumination normalization framework

Based on the Lambertian reflectance model, Chen et al. [1] proposed the Logarithmic Total Variation (LTV) model to decompose a face image as follows:

$$I(x, y) = \rho(x, y)S(x, y) \quad (1)$$

where I is the intensity, ρ contains the small intrinsic structures of a face, S contains the extrinsic illumination, shadows cast by bigger objects, and the large intrinsic facial structures. Generally, ρ is illumination invariant and S is affected by illumination changes. In our prior work [7], we identified ρ as small-scale features and S as large-scale features. We proposed an illumination-normalization framework and suggested that, in order to avoid distorting the invariant facial features, the illumination normalization should be performed mainly on the large-scale features rather than on the original image. Furthermore, as shown in the next section, a low-dimensional kernel subspace is capable of modeling the large-scale features of human faces. These have motivated us to use the KPCA+Pre-image technology to normalize the large-scale features, for the restoration of a frontal-illuminated face image.

B. Motivations & Algorithm

Based on the multi-linear representation [13], the set of face images from all objects, under the same illumination condition, can be approximated by a linear subspace. This property can be used to reconstruct a frontal-illuminated face image from the frontal-illumination subspace. However, due to the differences of individual characteristics, it needs enormous dimensions to reconstruct an image of the object that is outside the training set. This is the main reason why Zheng’s method [4] requires the training set to contain the images of the processed object.

According to the characteristics of S and ρ , individual discriminant features are mainly contained in ρ . So, the distribution of samples in the large-scale-feature space is more cohesive than that in the original-image space. To verify this assumption, we conducted an experiment on a total of 640 face images of 10 subjects. Each image was decomposed to get the large-scale features. Then, we respectively learned the KPCA subspaces of the original images and their large-scale features. Fig. 1 shows the cumulative eigen ratios of KPCA. As shown, to capture the same energy (cumulative eigen ratio), fewer dimensions on the large-scale-feature subspace are needed than that on the original-image subspace. Therefore, a low dimensional subspace is capable of modeling the large-scale features of human faces. This result supports us to perform KPCA+Pre-image technology on the large-scale features for the reconstruction of the frontal-illuminated image.

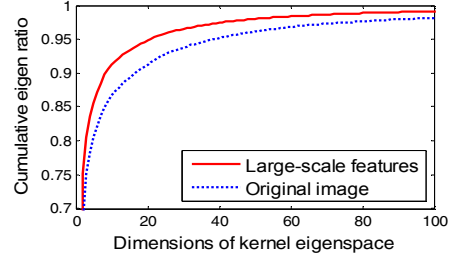


Figure 1. Cumulative eigen ratios of KPCA.

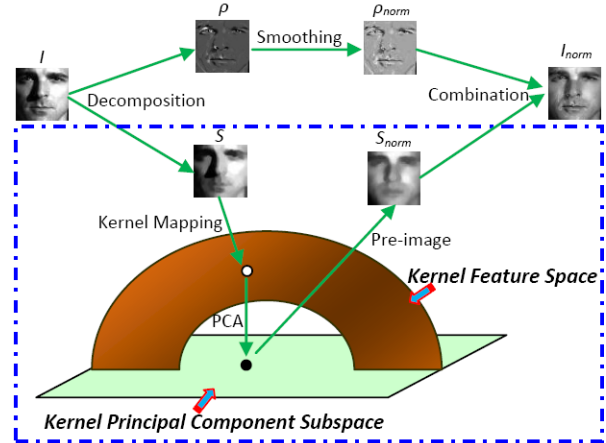


Figure 2. Diagram of the proposed method. The process of KPCA+Pre-image is contained inside the blue (dotted) box.

Accordingly, this paper proposes a novel method for restoring the frontal-illuminated face image. It consists of four steps:

a. Image decomposition. The input image I is first decomposed into ρ and L based on (1) by using the LTV model [1].

b. Smoothing on the small-scale features. In cast shadows, the small-scale features ρ may not be correctly recovered and some “light spots” may appear in the estimated result. For obtaining a better visual result, a threshold-average filtering is performed on ρ . Suppose (x_0, y_0) is the centre of the convolution region, then the average filter kernel will convolute if only if $\rho(x_0, y_0) \geq \theta$, where θ is the threshold. In our experiment, a 10×10 filtering mask was used, and the θ was chosen individually for each ρ , such that the values of 99% pixels were smaller than θ , and the values of the remaining 1% pixels were larger than θ . In other words, this threshold-average filtering replaces the largest 1% value of ρ by the local average value. This threshold smoothing almost does not change the facial structures.

c. Normalizing the large-scale features by KPCA+Pre-image technology. First, the large-scale features, which are decomposed from the frontal and nearly-frontal illuminated face images, are used to learn a kernel space and the KPCA subspace, where 95% of the energy is maintained. Then, for an input image I , its large-scale

features S are projected onto that KPCA subspace to eliminate the illumination variation. Finally, a normalized large-scale features S_{norm} are attained by learning the pre-image of that projection. In our experiment, the Regularized Locality Preserving Learning (R-LPL) [5] was applied to learn the pre-image, since R-LPL requires no iteration and avoids numerical instability with a unique solution.

d. Reconstruction of normalized images. Similar to (1), the frontal-illuminated face image, I_{norm} , is finally generated by a combination of the normalized large-scale features S_{norm} and the smoothed small-scale features ρ_{norm} :

$$I_{norm}(x, y) = \rho_{norm}(x, y)S_{norm}(x, y) \quad (2)$$

A block diagram of the proposed method and the result of each step are displayed in Fig. 2, where the procedure of the KPCA+Pre-image technology is shown inside the blue (dotted) box. In our method, the large-scale features can be normalized by KPCA, while the facial details (small-scale features) can be well preserved during the reconstruction process, making KPCA a feasible approach to restoring the frontal-illuminated face image from a single input image.

III. EXPERIMENTAL RESULTS

The performance of the proposed method was evaluated by the visual quality of the reconstructed images from the original images of Extended Yale B [3] and CMU-PIE [6]

face databases. Images in the Extended Yale B database were obtained from 38 individuals, under 64 different lighting conditions on 9 poses. In the experiment, only the frontal face images with various illuminations were selected. The CMU-PIE database consists of the images obtained from 68 individuals. The frontal face images under 21 different illumination conditions, with background lighting off, were selected in our experiments. All images were simply aligned and each image was resized to 100×100 pixels.

The following algorithms were involved in our comparative study: direct KPCA+Pre-image, Non-Point Light Quotient Image relighting (NPL-QI) [9], PDS [10], and our proposed method. The direct KPCA+Pre-image projects an original input face image onto the frontal-illumination subspace, and then reconstructs the normal image. For both the direct KPCA+Pre-image algorithm and our proposed method, the frontal and nearly-frontal illuminated images and their large-scale features were respectively used for learning the kernel matrix and the KPCA subspace. For the Extended Yale B database, 5 images per subject with lighting angles of less than 12° were selected as the training samples. For the CMU-PIE database, the images under the 8-th, 9-th, 11-th, 12-th and 20-th lighting conditions were selected to form the training set.

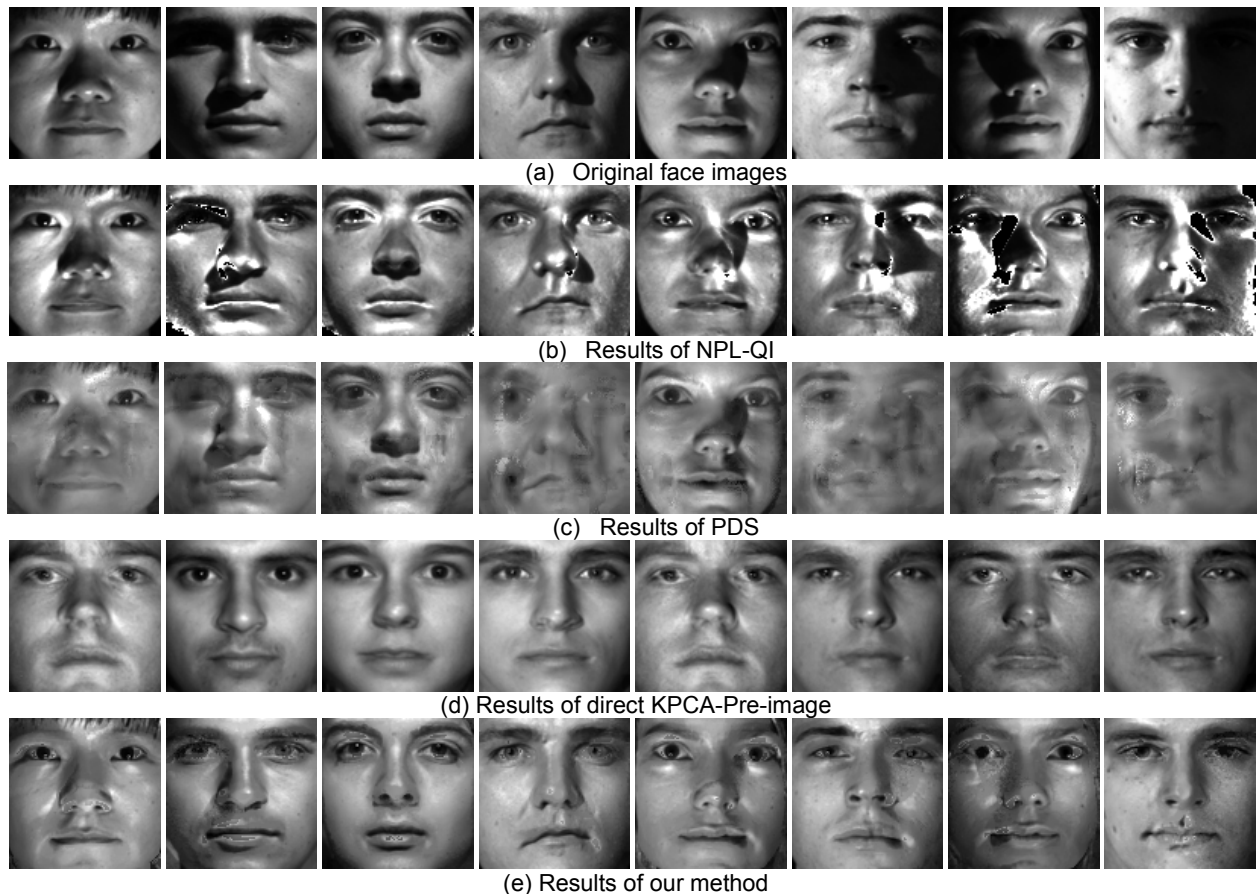


Figure 3. Reconstruction of frontal-illuminated face images by different methods.

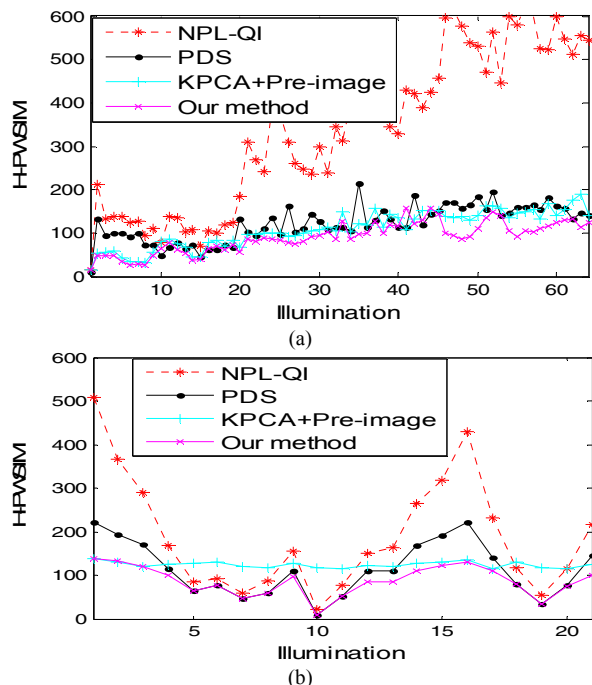


Figure 4. Quality assessment of the reconstructed images from (a) Extended Yale B, and (b) CMU.

The leave-one-out manner was used, so that all the images of the processed object were excluded from the training set.

Fig. 3 illustrates the reconstruction results of different methods. It shows that our method preserves the intrinsic facial features well. In contrast, by using the direct KPCA+Pre-image technology, the identities of the processed faces are always changed. NPL-QI and PDS both achieve good results for the images with small variations in illumination. However, for the images with a harsh illumination, NPL-QI may incur local artifacts. PDS also yielded some undesirable results, such as the reversal of facial features, since the pixel-dependent subspace method ignores the spatial relationship between pixels.

It is a well-known fact that human visual perception is highly adaptive for extracting the high-frequency structural information from a scene. Correspondingly, the wavelet-based assessment was used to quantify the visual quality of a reconstructed image. For each reconstructed image of an individual, the true frontal-illuminated image from the same individual was treated as the reference image. Both the reconstructed image and the reference image were decomposed by Daubechies-3 wavelet to extract the high-pass features. Then, the square error of their high-pass features was used as the quality measure. We identified this assessment as High-Pass Wavelet Subband Image Measure (H-PWSIM). A smaller H-PWSIM means a better visual quality of the reconstructed image. The average results with respect to different illumination conditions are shown in Fig. 4. As shown, our algorithm achieved lower H-PWSIM values than other methods. Due to the local distortion, NPL-QI got very high H-PWSIM values.

IV. CONCLUSIONS

A novel technique for restoring the frontal-illuminated face image from a single face image has been presented. For an input face image with uneven illumination, we used KPCA+Pre-image technology to normalize its large-scale features and then synthesized the normalized image. By retaining the small-scale features, the facial details and the identity of a face can be preserved. Experimental results on CMU PIE and Extended Yale B databases have shown that, the proposed method outperforms the related state-of-the-art methods and the direct KPCA+Pre-image technology, with regards to the visual quality of the reconstructed images.

ACKNOWLEDGMENTS

The authors would like to thank the authors of [1] for supplying the code of LTV, and to especially thank Ms. Shira Katz for her editorial assistance. This project was supported by the NSFC (U0835005, 60633030), the 973 Program (2006CB303104), and the GuangDong Program (2008A090400013).

REFERENCES

- [1] T. Chen et al., "Total Variation Models for Variable Lighting Face Recognition," *IEEE TPAMI*, vol. 28, pp.1519-1524, 2006.
- [2] B. Schölkopf, A. Smola, and K. R. Müller, "Nonlinear Component Analysis as a kernel eigenvalue problem," *Neural Comp.*, vol. 10, pp.1299-1319, 1998.
- [3] A. Georghiades, P. Belhumeur, D. Kriegman, "From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose," *IEEE TPAMI*, vol. 23, pp.643-660, 2001.
- [4] W.-S. Zheng, J. Lai, and P.C. Yuen, "Weakly Supervised Learning on Pre-image Problem in Kernel Methods," *Proc. ICPR*, Hong Kong, 2006.
- [5] W.-S. Zheng and J. H. Lai, "Regularized Locality Preserving Learning of Pre-Image Problem in Kernel Principal Component Analysis," *Proc. ICPR*, Hong Kong, 2006.
- [6] T. Sim, S. Baker and M. Bsat, "The CMU Pose, Illumination, and Expression (PIE) Database," *Proc. FGR*, Washington, D.C., 2002.
- [7] X. Xie, W.-S. Zheng, J. Lai, and, P.C. Yuen, "Face Illumination Normalization on Large and Small Scale Features," *Proc. CVPR*, Alaska, 2008.
- [8] S. Mika et al., "Kernel PCA and De-noising in Feature Spaces," *Proc. NIPS*, Denver, 1998.
- [9] H. Wang, S. Z. Li, and Y. Wang, "Generalized Quotient Image," *Proc. CVPR*, Washington, D.C., 2004.
- [10] H. Shim, J. Luo, and T. Chen, "A Subspace Model-Based Approach to Face Relighting under Unknown Lighting and Poses," *IEEE Trans. IP*, vol. 17, pp. 1331-1341, 2008.
- [11] A. Shashua and T. Riklin-Raviv, "The Quotient Image: Class-Based Re-rendering and Recognition with Varying Illuminations," *IEEE Trans. PAMI*, vol. 23, pp. 129-139, 2001.
- [12] L. Zhang, S. Wang, and D. Samaras, "Face Synthesis and Recognition from a Single Image under Arbitrary Unknown Lighting Using a Spherical Harmonic Basis Morphable Model," *Proc. CVPR*, San Diego, 2005.
- [13] M. A. O. Vasilescu and D. Terzopoulos, "Multilinear Analysis of Image Ensembles: TensorFaces," *Proc. ECCV*, Copenhagen, 2002.
- [14] W.-S. Zheng, J. Lai, and P. C. Yuen, "Penalized Pre-image Learning in Kernel Principal Component Analysis," *IEEE Trans. Neural Networks*, vol. 21, pp. 551-570, 2010.