Neurocomputing 214 (2016) 143–154

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Symmetrical singular value decomposition representation for pattern recognition

Yuhui Chen [a], Shuiguang Tong [a], Feiyun Cong [a,*], Jian Xu [b]

[a] State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University, No.38, Zheda Rd, Hangzhou 310027, China
[b] Institute of Thermal Science and Power Engineering, Zhejiang University, No.38, Zheda Rd, Hangzhou 310027, China

ARTICLE INFO

Article history:
Received 16 November 2015
Received in revised form
11 March 2016
Accepted 19 May 2016
Available online 6 June 2016

Keywords:
Pattern recognition
Face recognition
Face representation
Singular value decomposition (SVD)
Symmetry prior

ABSTRACT

This paper proposes a novel and powerful pattern recognition method named symmetrical singular value decomposition representation (SSVDR) and presents its application to face recognition. The SSVDR method is based on singular value decomposition (SVD) and symmetry prior. In this method, the given image is firstly decomposed into a composition of a set of base images by the singular value decomposition technique. Then, the first few base images (which can be proved to be the low-frequency asymmetrical base images) are turned into symmetrical base images according to facial symmetry. Finally, a new representation of the original image is reestablished for the final recognition. For evaluating the performance of the SSVDR method, some experiments are conducted in two famous face databases: extended Yale B and CMU-PIE database. The experiment results show the proposed SSVDR method can reestablish a new homogeneous representation of the original image and has an encouraging performance on face recognition compared with the current state-of-the-art methods.

1. Introduction

Over the past decades, pattern recognition has received significant attention due to its potential values as well as applications in face recognition. As a result, there has been a variety of effective pattern recognition methods for human face images, with innumerable encouraging results, reported in the literature [1,2].

However, in many real-world face recognition circumstances, faces are always suffering from the large facial variations, especially the effect of illumination. Varying illuminations in faces often lead to some undesirable problems, e.g. features under the shadow will be covered due to low illumination conditions, the asymmetrical illumination distribution caused by the shadow [3,4]. Under these circumstances, most existing face recognition methods have defects more or less. Thus, how to deal with the varying illuminations in faces is a fundamental and challenging task in real-world applications of face recognition [5].

Recently, a variety of methods have been proposed to deal with the problem by generating a better face representation of the original image, which can be roughly divided into two categories [4,6–8]:

The first category tries to extract the illumination-invariant features to rebuild an illumination-invariant representation of face images. For example, Wang et al. proposed the self-quotient image (SQI) method, which reduces the effect of illumination by utilizing the weighed Gaussian filter to divide a smoothed face images of the original image itself [9]. Chen et al. assumed that illumination variations mainly lie in the low-frequency band, and employed discrete cosine transform (DCT) to obtain illumination-invariant images by truncating an appropriate number of the DCT coefficients [10]. On the other hand, Chen et al. utilized the total variation model to factorize the face images into small-scale and large-scale facial components, and only selected the small-scale facial components as the illumination-invariant represen`tation [11].

Most of these illumination-invariant methods assume that the face images can be divided into the illumination-invariant facial parts (eyes, nose, etc.) correspond to relatively higher spatial frequencies, and the illumination-variation ones correspond to lower spatial frequencies. However, the illumination-invariant methods only select the illumination-invariant facial parts to rebuild an illumination-invariant representation of face images, thus the information containing in the lower spatial frequencies is missing.

The second category focuses on compensating the illuminated image with traditional image processing methods. For instance, histogram equalization (HE) [12], logarithm transform (LT) [13] and gamma correction (GC) [3] are widely used for illumination normalization. However, in these methods, the illumination normalization is performed directly on the whole face image, some representative algorithms even only work well when the image is

* Corresponding author.
E-mail address: cloudswk@zju.edu.cn (F. Cong).

http://dx.doi.org/10.1016/j.neucom.2016.05.075
0925-2312/

intensified or darkened globally. As a result, it is hard to get good recognition performance and generate normalized face image with good visual results for face images with asymmetrical lighting. Besides, facial symmetry is often identified as an inherent feature of bodily asymmetry. Based on this, Zhang et al. proposed a method utilizes the facial symmetry to generate the illumination normalization image [14]. More recently, Hsieh et al. proposed a shadow compensation method (MR-HEIA) relied on facial symmetry and histogram equalization, and Xu et al. also proposed a method based on facial symmetry to exploit symmetrical face images [15,16]. Nevertheless, these methods have major limitations in real-world applications toward face recognition since the face images are just simply mirrored.

Due to the fact above, we propose a novel and simple method based on singular value decomposition (SVD) and symmetry prior for robust face recognition in this paper. The rationale behind our method is that the first few base images generated by the SVD of the face image capture the great variances of the face image, and they are always symmetrical because of the facial symmetry prior when the face is under uniform lighting conditions. Compared to previous methods which often fail when suffered from varying illumination conditions, the proposed method has the ability to successfully suppress the effect of various illuminations of the face while homogenizing the distribution of the illumination. Moreover, the proposed method can greatly preserve the detail texture information of the original face image since the rest of base images generated by the SVD of the face image are kept unchanged. This is fairly desirable to achieve a robust face recognition in a wide range of scenes. The experimental results demonstrate that our SSVDR method achieves significant performances among the traditional methods for face recognition.

The rest of this paper is organized as follows: Section 2 detailed describes the methodology of the proposed method. Experimental results and discussion are shown in Section 3. Finally, conclusions are presented in Section 4.

2. Methodology with SSVDR

2.1. History of SVD technique for face recognition

The SVD technique for face recognition was first used as algebra feature extraction (e.g. the singular value feature), which is one of the earliest image representations in face recognition field. Hong et al. firstly proposed the concept of the algebra feature and proved that singular value feature could be used as algebra feature with the solid theoretical proof [17]. However, the practical performance of this method is unsatisfactory. Then Tian et al. performed further studies on the SVD technique and pointed out that it is the singular matrix rather than the singular values that contain useful information for face recognition. Based on this, they projected the image on the uniform singular matrix basis of SVD to get a better performance for face recognition [18].

Recently, Liu et al. proposed a fractional order singular value decomposition representation(FSVDR) method for face recognition [19]. Based on the SVD technique, they decomposed the image into a composition of a set of base images, and found that the singular values of the leading base images were sensitive to the illumination and expression variations. Hence, a fractional function with an empirical fractional parameter α was applied to the singular values for alleviating facial variations. More recently, Zhang et al. proposed a nearest orthogonal matrix representation for face recognition. Relied on the specific individual subspace assumption, the method demonstrated good facial representations by simply using the sum of a set of basis matrices generated by the SVD technique on the condition that parameter $\alpha = 0$, which can be seen as a special case of the FSVDR method [20].

However, all those successful application methods mentioned above are experimented in uniform illumination condition. Besides, they are either only based on singular values or kept the base images generated by singular value decomposition unchanged. In fact, they are vulnerable to the non-uniformity generated by the change of illumination conditions.

2.2. Further discussion on the SVD technique for face recognition

2.2.1. Theory of singular value decomposition

In linear algebra, the singular value decomposition (SVD) [21] is one of the most powerful matrix factorization methods to obtain useful information from the matrix, which can be described with the following theorem in real field.

Suppose matrix A is an $m \times n$ matrix whose entries come from the real field, it can be decomposed as follows:

$$A_{m\times n} = U_{m\times m}\Sigma_{m\times n}V^{T}_{n\times n}, \tag{1}$$

where $U_{m\times m} = [u_1, \cdots, u_m]$ is an $m \times m$ real unitary matrix, $V^{T}_{n\times n} = [v_1, \cdots, v_n]^T$ (the transpose of $V_{n\times n}$) is an $n \times n$ real unitary matrix, and $\Sigma_{m\times n}$ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal. Specifically, suppose

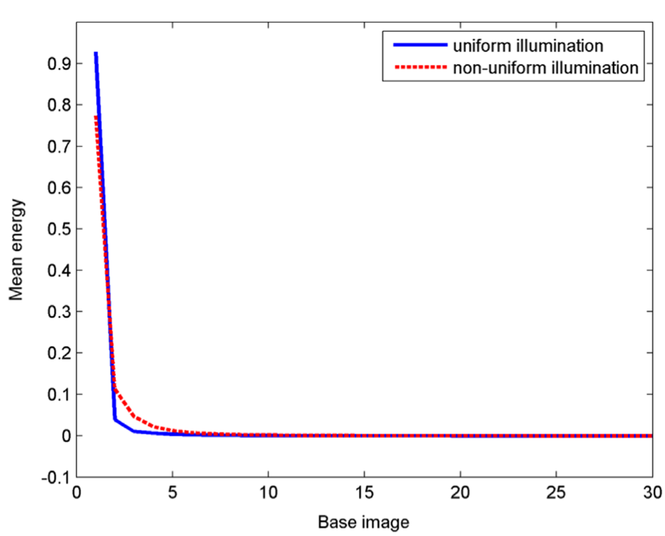

Fig. 1. The mean energy of the subset under different illumination conditions.

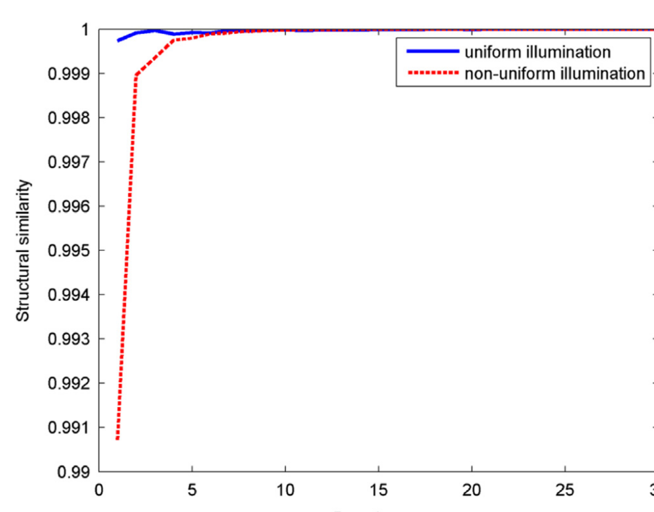

Fig. 2. Each subset's mean SSIM of each base image.