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Integrate the original face image and its mirror image for face recognition

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ABSTRACT

The face almost always has an axis-symmetrical structure. However, as the face usually does not have an absolutely frontal pose when it is imaged, the majority of face images are not symmetrical images. These facts inspire us that the mirror image of the face image might be viewed as a representation of the face with a possible pose opposite to that of the original face image. In this paper we propose a scheme to produce the mirror image of the face and integrate the original face image and its mirror image for representation-based face recognition. This scheme is simple and computationally efficient. Almost all the representation-based classification methods can be improved by this scheme. The underlying rationales of the scheme are as follows: first, the use of the mirror image can somewhat overcome the misalignment problem of the face image in face recognition. Second, it is able to somewhat eliminate the side-effect of the variation of the pose and illumination of the original face image. The experiments show that the proposed scheme can greatly improve the accuracy of the representation-based classification methods. The proposed scheme might be also helpful for improving other face recognition methods.

1. Introduction

As we know, the main challenges of face recognition are that the face image might severely vary with the various poses, facial expression and illumination [1–3]. A face recognition method greatly suffers from these challenges. In order to address these challenges, people have made many efforts. For example, Jian et al. proposed the illumination compensation method for face recognition [4]. Sharma et al. proposed pose invariant virtual classifiers for face recognition [5]. We also note that if the available training samples of a face can sufficiently show possible variations of the pose, facial expression and illumination, it will be possible to obtain a high accuracy. Unfortunately, in real-world applications a face usually has only a very small number of training samples, which cannot convey many variations of the face [6–10]. In order to overcome the problem that the training samples of a face do not convey sufficient variations of the face, previous literatures have proposed some approaches to generate new (i.e. virtual or synthesized) face images and to enlarge the size of the set of the training samples.

It is known that both the facial structure and the facial expression are symmetrical [11]. Previous literatures have successfully exploited the symmetrical structure of the face for face detection [11–14]. However, it should be pointed out that in real-world face recognition applications, a large number of face images are not symmetrical images due to non-frontal and non-neutral pose [15]. Xu et al. proposed an approach to generate “symmetrical” face images and exploited both the original and “symmetrical” face images to recognize the subject [15]. As the “symmetrical” face image is generated with the assumption that the facial structure is symmetrical, it is an axis-symmetrical image. However, as shown later, the “symmetrical” face images obtained in [15] is not a natural face image and even appear to be strange.

A real-world face recognition application also often suffers from the misalignment problem of the face image. This problem certainly makes the face image not symmetrical and is advantageous for correctly recognizing the face. Fig. 3 presented later shows an example of misalignment of the face image.

It should be pointed out that though previous literatures have made many efforts in making virtual or synthesized face images which reflect the variation of the face as much as possible, almost

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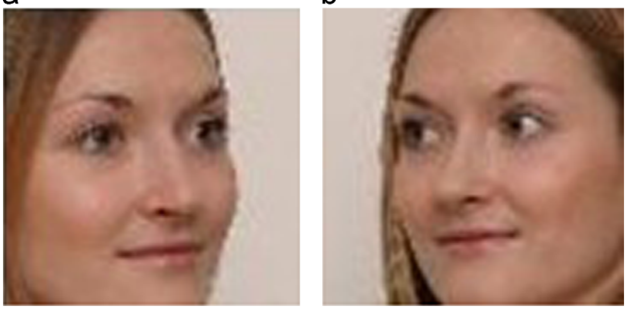

Fig. 1. An original face image with a left tilt pose (a) and another original face image right tilt pose (b) of a same subject. It is clear that these two face images have great difference in terms of the distance metric.

no literature generated virtual or synthesized face images by exploiting the special nature of the face i.e. the symmetry of the structure. This motivates us to exploit the symmetrical structure of the face to improve previous face recognition methods.

In this paper, we propose a novel scheme to improve the face recognition method. The proposed scheme first generates the mirror image of the original face image and then applies a representation-based classification (RBC) method to both the original face image and its mirror image to perform face recognition. We also refer to the mirror image of the original face image as face mirror image. The rationales of the proposed scheme are as follows: first, the face mirror image reflects some possible change in pose and illumination of the original face image. For example, if two original face images of a same subject have a left tilt pose and right tilt pose, then the difference between them will be great in terms of the distance metric. If these two face images from the same face are used as training and test samples, then the test sample will be hard to be correctly classified. The example shown in Fig. 1 clearly illustrates this. As a consequence, the face recognition method using only the original face images will be very hard to obtain satisfactory accuracy. However, the difference between either of the two original face images and the mirror image of the other original face image might be very little in terms of the distance metric. As a result, the use of the face mirror image will be very useful for correctly classifying the test sample. For detailed demonstration, refer to Section 5. Second, the face mirror image is very useful to overcome the possible misalignment problem of the original face image (for detail refer to Section 5). The results of various experiments on face recognition also show that the proposed scheme is quite feasible and can improve the state-of-the-art representation-based classification methods.

This paper has the following main contributions. First, it proposes the scheme to integrate the original face images and their mirror images for representation-based face recognition. It also describes the rationale of the proposed scheme. Second, it shows that a number of representation-based classification methods can be improved by using the proposed scheme.

The remainder of the paper is organized as follows. Section 2 presents related works. Section 3 presents representation based classification methods. Section 4 describes our proposed scheme. Section 5 describes the rationales of the proposed scheme. Section 6 shows the experimental results and Section 7 offers the conclusion.

2. Related works

Because our proposed scheme is based on representation-based classification (RBC) methods and the generated virtual face images, this section mainly reviews the literatures of generating virtual or synthesized face images and those literatures on RBC methods. A number of previous works focus on generating virtual or synthesized face images and on enlarging the size of the set of the training samples. For example, Tang et al. [16] obtained "virtual" facial expression by exploiting the prototype faces and optic flow. Jung et al. [17] obtained new samples of the face by using the noise. Thian et al. [18] used simple geometric transformations to make virtual samples. Ryu et al. [19] exploited the distribution of the training samples to produce virtual training samples of the face. Sharma et al. [5] extended training samples by generating multiple virtual views of a person under different poses and illumination from a single face image. Beymer et al. [6] and Vetter et al. [7] also addressed this issue by generating new samples with virtual views.

Among a variety of face recognition methods, the representation-based classification (RBC) method can achieve a very high accuracy and has received much attention [20–23]. The conventional RBC method is also referred to as sparse representation classification (SRC) method [20–22]. RBC including SRC assumes that the test sample can be well represented by a linear combination of all the training samples. SRC obtains its solution using the constraint of the ℓ_1 norm minimization. In other words, SRC achieves its solution with the sparsity constraint which assumes that a number of the coefficients of the linear combination are equal or close to zeroes. We also say that SRC uses a sparse linear combination of all the training samples to represent the test sample.

Besides SRC, RBC can be also implemented by using the constraint of the ℓ_2 norm minimization [24–26]. The corresponding method can be referred to as RBC with the ℓ_2 norm minimization constraint. It seems that the algorithm of RBC with the ℓ_2 norm minimization constraint is simpler and easier to implement than that of SRC. There are two kinds of RBC with the ℓ_2 norm minimization constraint. The first kind exploits the training samples from all the classes to represent the test sample and uses the representation result to perform classification [24–26]. The sparsity constraint is imposed on only a few methods of this kind. For example, the methods proposed by Shi et al. [23] and by Zhang et al. [25] have no sparsity constraint. In other words, these two methods do not require that the coefficients of the linear combination to represent the test sample are equal or close to zeroes. On the other hand, the sparsity constraint is imposed on the method proposed in [26] in a special way. The second kind exploits the training samples from each class to represent the test sample and the classification is also performed in terms of the representation result [27,28]. The sparsity constraint is also not imposed on this kind of method. Specially, this kind of method usually assumes that the test sample can be respectively approximately represented by a linear combination of the training samples of every class and no any constraint sparsity is imposed on the coefficients of the linear combination. A typical example of this kind of method is linear regression classification (LRC) [27]. The sparse representation has also been used to other problems such as sparse graph based image annotation [29], super-resolution reconstruction [30], image alignment [31] and image de-noising [32]. The sparsity has also been used to modify discriminant analysis [33,34] and locality preserving projection [35,36]. The sparse graph is also used in video semantic annotation [36] and representative image selection [37,38]. For recent advances and more applications of RBC, refer to literatures [39–41].

3. Representation based classification (RBC)

In this section, we introduce representation based classification (RBC) briefly. Because LRC has a distinct characteristic, we describe it in Section 3.1 and present other RBCs in Section 3.2. We assume that there are c classes and each class has n training samples in the form of column vectors. Let $x_1, \ldots, x_N$ be all the N training samples in the form of column vectors ($N = cn$). Column vector $x_{(i-1)n+k}$