Partial Face Recognition Using RPSM Algorithm

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Abstract

Over the past three decades, a number of face recognition methods have been proposed in computer vision, and most of them use holistic face images for person identification. In many real-world scenarios especially some unconstrained environments, human faces might be occluded by other objects and it is difficult to obtain fully holistic face images for recognition. To address this, system propose a new partial face recognition approach to recognize persons of interest from their partial faces. Given a pair of gallery image and probe face patch, system first detect key points and extract their local textural features. Then, system propose a robust point set matching (RPSM) method to discriminatively match these two extracted local feature sets, where both the textural and geometrical information of local features are explicitly used for matching simultaneously. Lastly, the similarity of two faces is converted as the distance between these two aligned feature sets. Experimental results on four public face datasets show the effectiveness of the proposed approach.

Keyword:-*Face recognition, partial face recognition, feature set matching, feature alignment, image matching, biometrics*

1. INTRODUCTION

A variety of face recognition approaches have been pro-posed over the past three decades [1, 2, 3, 4]. While most of them have achieved promising performance, they only work well under well-controlled conditions. More-over, most of them use holistic face images to recognize people, where face images in both the gallery and probe sets have to be pre-aligned and normalized to the same size before recognition. In many real-world applications such as smart surveillance systems in crowded scenes, human faces are easily occluded by other objects in such scenarios and it is difficult to obtain fully holistic face images for recognition. Therefore, it is desirable to develop a face recognition system which is able to recognize partial faces directly without manual alignment and also robust to occlusions in these applications. Some examples of partial faces are shown in Fig. 1.

Fig1: Partial Face

Fig. 1: Several partial face examples. (a) Three partial face patches (in the red ellipse) are from the LFW dataset which are occluded by heads. (b) Face occluded by sunglasses. (c) An arbitrary partial face patch. Similarity. For instance, the occluded facial region should be excluded to compute face similarity. To achieve this, an intuitive idea is to first detect facial landmarks in both the gallery and probe images, and then align them with the detected landmarks and remove the occluded face parts. However, it remains an open problem for facial landmark detection from arbitrary facial patch. In this work, system propose a new partial face recognition approach by aligning the probe partial face to gallery faces using the geometrical and textural information of the extracted local features. Our basic intuition is that if the probe partial face patch and the gallery face image are from the same person, the cost function of our alignment procedure should be minimized. Furthermore, system present a point-set distance metric to compute the similarity of the partial probe patch and the gallery images over the detected face feature points. Experimental results on four widely used face datasets show the effectiveness of the proposed approach.

This system is an extended version of our previous work presented at IEEE ICCV 2013 [5]. There are several new contributions in this work compared to its conference version: This system developed a new feature set matching approach for partial face matching. In our previous conference version [5], the matching algorithm was built based on Chui's work [6], where no constraint was enforced on the affine transformation matrix, so that unrealistic image warping can be generated if the difference between the probe patch and gallery image is large. In this work, system explicitly constrain the affine matrix to address this limitation. Experimental results show that our new feature set matching method achieves better performance. This system conducted more partial face recognition experiments to further evaluate the performance of our approach. The newly extensions include: 1) more results on additional datasets, 2) more face verification evaluations, and 3) more detailed parameter analysis of the proposed approach.

2. RELATED WORK

In this section, this system briefly review two related topics: 1) robust face recognition, and 2) feature set matching.

2.1. Robust Face Recognition

Many sparse representation based face recognition methods have been proposed in recent years to deal with occlusion-s. While these methods have achieved encouraging recognition performance under occlusions, they fail to work well if the probe image is an arbitrary face patch. This is because these approaches usually require the size of each probe image be the same as that of the gallery images. Recently, part-based representation methods have been proposed for robust face recognition [7], where each face image was divided into many blocks and the similarity of small blocks was computed and integrated for face matching. However, in real-world scenarios, occluded facial parts are highly unstructured, so that the occlusion detection results are usually unreliable. Li et al. [7] proposed comparing non-corresponding facial patches instead of matching corresponding regions. Patch comparison was conducted by canonical correlation analysis. However, their method also requires require building face patches correspondences and a preliminary face alignment. To our knowledge, only a few seminal works on partial face recognition have been presented [5]. The objective of partial face recognition is to recognize the person from an occluded partial face or an arbitrary partial face patch. Was the first attempt on partial face recognition, where each partial face image was represented by local MKD-GTP features which were then sparsely reconstructed by gallery feature set. However, the geometrical information of local features was ignored in their method. To robustly match the probe partial face image with a gallery image, our previous work [5] considered partial face recognition as a feature set matching problem, where geometric features and textural features were matched simultaneously. However, no constraint was enforced on the affine transformation matrix, which may generate unrealistic warping.

2.2. Feature Set Matching

Feature set matching is a fundamental problem in computer vision and pattern recognition. State-of-the-art feature set matching techniques include [8, 9]. Chui and Rangarajan [6] presented a feature set matching approach to align two point sets according to their geometry distribution by learning a non-affine transformation function embedded in a deterministic annealing process. Jian and Vemuri [8] deployed Gaussian mixture models to represent the input point sets, and reformulated the problem of point set registration as the problem of aligning two Gaussian mixtures. Maier-Hein et al. presented a convergent iterative closest point algorithm to accomodate anisotropic and in homogenous localization error. The above mentioned feature set matching approaches are not directly applicable for face recognition as most of them utilized only geometric or textural information of local features for matching. Differently, Li et al. [10] proposed a linear programming framework for feature matching, where both the geometric and textural features are employed. Their method is designed to match objects which are locally rigid and globally non-rigid, whereas human faces are globally rigid and locally non-rigid. The idea of feature set matching has also been exploited in face recognition. Wiskott et al. used graph matching for face recognition. They first manually labeled face landmarks and then computed the face similarity based on local features around landmarks. In contrast, our approach is a fully automatic approach, without need of manual labeling.

3. PROPOSED APPROACH

Since there exist large degree of rotation, translation, scaling and presence of occlusions between the probe and gallery facial images, local features are more competent than holistic features for face representation. In this work, system adopt SIFT, SURF and LBP features for partial face representation and matching. The framework of our proposed partial face recognition approach is illustrated in Fig. 2.

3.1. Feature Extraction and Key point Selection

For each face image, this system first detect key points using SIFT feature detector. Each key point consists of a geometric feature recording its position in the image plane, and a textural feature being its feature descriptor. In our previous work [5] system combined the strength of SIFT and SURF descriptors by a simple concatenation. SURF descriptor was introduced as a complement to SIFT for its robustness against illumination variations [11]. While this augmented textural feature is ro-bust against in-plane rotation, scale and illumination, they were originally designed for generic object recognition. To capture more details of facial textures as well as accomodate the scaling issue, system incorporate the Scale Invariant LBP (SILBP). Specifically, uniform rotation invariant version of LBP operator $LBP^{riu}_{P;R}{}^{2}$ is used. In terms of the values of P, R, system deploy 4 different sets of values, namely fP = 8; R = 1g, fP = 8; R = 2g, fP = 16; R = 2g, and fP = 16; R = 3g. These LBP operators are applied on Gaussian blurred image patch with a specified scale to achieve scale invariant. The features generated by each $LBP^{riu}_{P;R}{}^{2}$ are then sampled into a corresponding LBP histogram. Hence, for each key point, system obtain four scale-invariant LBP (SILBP) histograms, one SIFT histogram, and one SURF histogram. These various histograms are concatenated into a single descriptor which is simply coined as “SiftSurfSILBP”. Having detected the key points, this system select a subset of key-points to facilitate the matching process. This is because the number of key points of facial image could be up to hundreds, matching point sets at this scale is computationally intensive. Moreover, irrelevant key points (outliers) can mislead the matching process to a local minimum, especially when the number of genuine matching pairs is small compared to the number of imposter pairs. Hence, it’s desirable to filter out obvious outliers at the beginning. Here system apply Lowe’s matching scheme for key point selection, i. e., compare

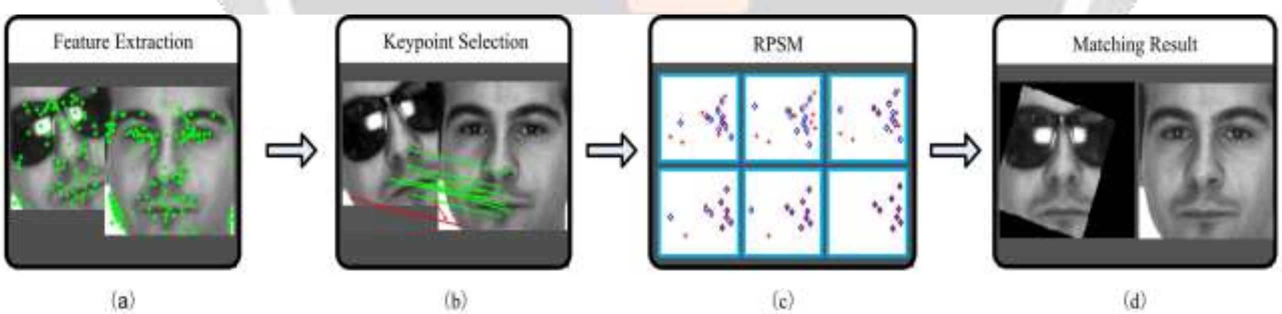

Fig2: System Architecture

Fig. 2: Our proposed partial face recognition framework. (a) Feature extraction: keypoints detected by SIFT keypoint detector are marked out as green dots on both images. The left image is the probe partial face image, and the right one is the gallery face image. (b) Keypoint selection by Lowe’s matching scheme: roughly matched keypoints of these two images are connected by green lines, while two pairs of imposter matches are linked by red lines. (c) RPSM procedure: point set of probe image marked out as blue diamonds are iteratively aligned to the red-marked point set of gallery image. The details of the RPSM process are shown in Fig. 3. (d) Matching result: the left one is the warped image using the transformation parameters derived from the matching process, and the right one is the gallery image. Through RPSM, the probe image is successfully aligned to the gallery image.

4. CONCLUSION

In this system, system have proposed a partial face recognition method by using robust feature set matching. The proposed RPSM method is able to align the probe partial face to gallery facial images robustly even with the presence of occlusion, random partial crop, and exaggerated facial expressions. After face alignment, partial face recognition is achieved by measuring face similarity based on the proposed point set distance, which can be readily acquired with the face alignment result. The hallmark of the RPSM is its robust matching scheme, which considers both the geometric distribution consistency and the textural similarity. Moreover, constraint on the affine transformation is applied to prevent from unrealistic face warping. Experimental results on four widely used face datasets were presented to show the efficacy and limitations of our proposed method, the latter of which pointed out the direction for our future work

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