Sparse Based Robust Point Set Matching for Partial face Recognition

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ABSTRACT

Numerous methods have been developed for holistic face recognition with impressive performance. However, human faces are easily obstructed by other objects in many real-world scenarios and it is difficult to obtain fully holistic face images for recognition. To address this, we propose a new partial face recognition approach to recognise person of interest from their partial faces. Using a pair of gallery image and probe face patch we first detect keypoints and extract their local textural features. Then, we propose a robust point set matching method to discriminatively match these two extracted local feature sets, where both the textural information and geometrical information of local features are explicitly used for matching simultaneously. Finally, the similarity of two faces is converted as the distance between these two aligned feature sets. Experimental results on four public face data sets show the effectiveness of the proposed approach. Hence the proposed method is superior in recognizing both holistic and partial faces without requiring alignment.

Index Terms **–Face recognition, partial face recognition, feature set matching, feature alignment, image matching, biometrics.**

I.INTRODUCTION

A . Motivation and Purpose

A variety of face recognition approaches have been proposed over the past three decades. While most of them have achieved promising performance, they only work well under well-controlled conditions. Most of them use holistic face images to recognise 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 obstructed 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 obstructions in these applications. Some examples of partial faces are shown in fig. 1.

Fig. 1. Several partial face examples. (a) Three partial face patches (in the red ellipse) are from the LFW dataset which are obstructed by heads. (b) Face obstructed by sunglasses. (c) An arbitrary partial face patch.

To make face recognition applicable in the real-life scenarios, several works have been presented to align probe facial images with training images automatically. Active Appearance Model (AAM) endeavors to localize dozens of landmarks on facial images through an iterative search. Jia et al developed an automatic face alignment method through minimizing a structured sparsity norm. However, all these face alignment methods would fail to work if the probe images is an arbitrary face patch.

To deal with face obstructions, various algorithms based on sparse representation have been proposed recently and was pioneer work in this area, where sparse representation was utilized to reconstruct obstructed or stained facial images as well as to align probe face images to gallery images. While these approaches can achieve encouraging recognition performance in case of obstructions, they would fail if the probe image is an arbitrary face patch. In contrast to these methods, our approach processes partial face directly without manual alignment, which is more close to practical applications.

In this work, we 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, we 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.

B . Significance in contributions

The major contributions in this paper as follows:

- We have developed a new feature set matching approach for partial face matching. In this work, we explicitly constrain the affine matrix to address this limitation. Experimental results show that our new feature set matching method achieves better performance.
- The newly extensions include: 1) more results on additional data sets, 2) more face verification evaluations, and 3) more detail parameter analyse of the proposed approach.

II.RELATED WORK

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

A . Robust Face Recognition

Many sparse representation based face recognition methods have been proposed in recent years to deal with obstructions. While these methods have achieved encouraging recognition performance under obstructions, 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, 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, obstructed facial parts are highly unstructured, so that the obstruction detection results are usually unreliable. Li et al proposed comparing non-corresponding facial patches instead of matching corresponding regions. Patch comparison was conducted by canonical correlation analysis. However, their method also requires building face patches correspondences and a preliminary face alignment.

The objective of partial face recognition is to recognize the person from an obstructed partial face or an arbitrary partial face patch. In Partial face recognition –alignment free approach, 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 image with

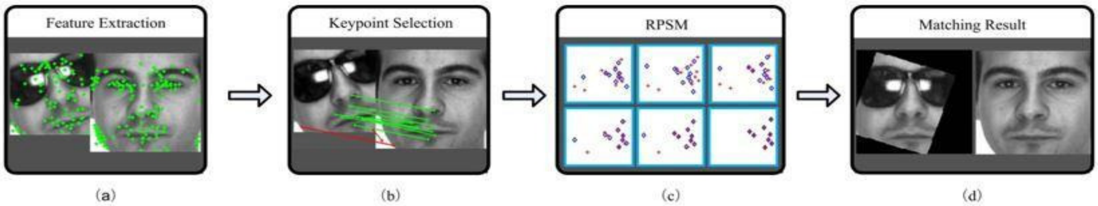

Fig. 2. Our proposed partial face recognition framework. (a) Feature extraction: keypoints detected by SIFT keypoint detector are marked out as green dots on both images. The left image is the probe partial face image, and the right one is the gallery face image. (b) Keypoint selection by Lowe's matching 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.

a gallery image, 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.

B . Feature Set Matching

Feature set matching is a fundamental problem in computer vision and pattern recognition. Feature set matching approach is to align two point sets according to their geometry distribution by learning a non-affine transformation function embedded in a deterministic annealing process. Maier-Hein et al presented a convergent iterative closest point algorithm to accommodate anisotropic and inhomogeneous localization error. The above mentioned feature set matching approaches are not directly applicable for face recognition as most of them utilize only geometric or textural information of local features for matching. The idea of feature set matching has also been exploited in face recognition. They first manually labelled 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 labelling.

III.PROPOSED APPROACH

Since there exist large degree of rotation, translation, scaling and presence of obstructions between the probe and gallery facial images, local features are more competent than holistic features for face representation. In this work, we 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.

A . Feature Extraction and Keypoint Selection

For each face image, we first detect keypoints using Scale-Invariant Feature Transform (SIFT) feature detector. Each keypoint consist of a geometric feature recording its position in the image plane, and textural feature being its feature descriptor. In the existing system the strength of SIFT and SURF (Speeded Up Robust Features) descriptors are combined by a simple concatenation. SURF descriptor was introduced as a compliment to SIFT for its robustness against illumination variations. While this augmented textural feature is robust 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 accommodate the scaling issue, we incorporate the Scale-Invariant LBP (SILBP).

Having detected the keypoints, we select a subset of keypoints to facilitate the matching process. This is because the number of keypoints of facial image could be up to hundreds, matching point sets at this scale is computationally intensive. Moreover, irrelevant keypoints can mislead the matching process to a local minimum, especially when the number of genuine matching pairs is small compared to the imposter pairs. Hence, it's desirable to filter our obvious outliers at the beginning. Here we apply scheme for keypoint selection, i, e., compare

the ratio of distance of the closest neighbour to a predefined threshold. These coarse matched keypoint pairs are then selected for our Robust Point Set Matching for final matching (RPSM) for finer matching.

B. Robust Point Set Matching

To align a probe partial face patch to a gallery image, the corresponding geometrical and textural features are to be matched simultaneously. The matching process has the following three characteristics:

- Subset Matching: since the matching probe image and the gallery image may not be identical, some keypoints in the probe image couldn't find their correspondences in the gallery image.

  Likewise, not all keypoints in gallery image are ensured to be matched. Hence, this point set matching is a subset point matching problem.

- One-to-one Point Correspondence: this trait is obvious since keypoints of different positions in the probe image shouldn't be matched to the same keypoint in the gallery image.

- Non-affine Transformation: the appearance of face changes when the perspective or facial expression changes. Such changes, when projected into the 2D image, are non-affine.

RPSM successfully aligns these partial faces to their corresponding neutral faces. These partial faces are randomly rotated, scaled and cropped. Moreover, some of them are obstructed by sunglasses or scarf, some are with exaggerated expressions.

ALGORITHM USED

Algorithm 1 RPSM

Input: $\mathrm{L}^P, \mathrm{L}^G, \mathrm{C}$

Output: $\mathbf{A}, \boldsymbol{b}, \mathbf{Q}, \mathbf{M}$

Parameters: $\lambda_1, \lambda_2, \lambda_3, \tau, It_{max}, r_1, r_2$

Initialize: $d = d_{init}$, Constraint Set $\Psi = \emptyset$

for

Construct

Add Constraint Set

Clear Constraint Set,

//Trust region shrinkage

for *each* l_i^P **do**

Find outsiders l_j^G, where

Add $\mathbf{M}_{ij} = 0$ to Ψ;

end

//

Outliers detection

Find outliers l_i^P, where $\sum_j \mathbf{M}_{ij}$

Remove l_i^P, $\mathbf{M}_{i\cdot}$ from $\mathbf{L}^P$ and $\mathbf{M}$

Find outliers l_j^G, where $\sum_i \mathbf{M}_{ij} < \tau$;

Remove l_j^G, $\mathbf{M}_{\cdot j}$ from $\mathbf{L}^G$ and $\mathbf{M}$ respectively;

end

Binarize

return $\mathbf{A}, \boldsymbol{b}, \mathbf{Q}, \mathbf{M}$

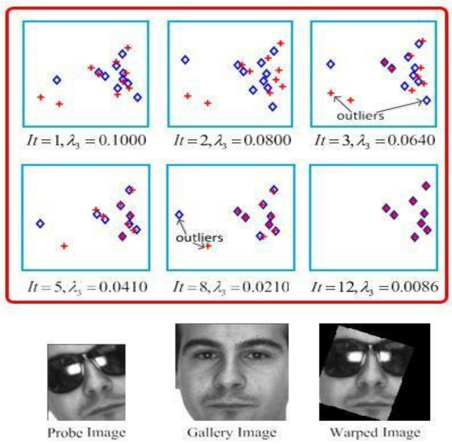

Fig. 3. Illustration of an RPSM matching process. RPSM successfully aligns the input probe image (bottom left) to the gallery image (bottom center), and the result is a warped probe image (bottom right) which fits well with the gallery image. Six iterations of this RPSM matching process are depicted in the upper red rectangle, where each iteration is laid in a light blue square with its corresponding iteration number It and value of λ_3 listed below. Within each iteration, the blue diamonds represent probe keypoints and red crosses represent gallery keypoints. As iteration goes on, probe keypoints are gradually aligned to gallery keypoints, and finally they're perfectly matched in Iteration 12.

C. Point-Set Distance

Having obtained the transformation parameters between probe and gallery feature set, the defined point set distance metric d_R of two facial images as:

$$\bar{d} = \frac{\sum_{i,j} \mathbf{M}_{ij} \left(\lambda_1 \| f(\boldsymbol{l}_i^P) - \boldsymbol{l}_j^G \|_1 + \mathbf{C}_{ij} \right) + \lambda_3 \|\mathbf{Q\Phi}\|_1}{\sum_{i,j} \mathbf{M}_{ij}}$$

$$d_R = \frac{\bar{d}}{\sum_{i,j} \mathbf{M}_{ij}}$$

IV. EXPERIMENTS

To verify the effectiveness of partial face recognition approach, experiments were conducted for arbitrary face patch on the LFW dataset. To comprehensively demonstrate the pros and cons of the approach experiments were conducted on disguised and obstructed partial face recognition on the AR and Extended Yale B, PubFig datasets, respectively.

A. Data Sets

1) LFW: The Labeled Face in the Wild (LFW) dataset contains 13233 labeled faces of 5749 people, in which 1680 people have two or more face images. Images in this dataset exhibit large appearance variations as they were taken from uncontrolled settings, including variations in scale, viewpoint, lighting condition, background, make-up, dress, expression, color saturation, image resolution, focus etc., which pose a great challenge to our recognition task.

2) AR: The AR dataset contains 126 subjects, including 70 males and 56 females, respectively. For each subject, there are 26 face picture taken in two different sessions. In each session, there are 3 images with illumination condition, 4 images with different expressions, and 6 images with different facial disguises (3 images wearing sunglasses and 3 images wearing scarf, respectively).

3) EYB: Extended Yale B dataset has 58,797 images of 200 subjects obtained from totally uncontrolled real-world conditions, wherein images differ with each other in terms of pose, illuminations, facial expressions and scene background etc.. For performance evaluation, photos of 140 people are used as evaluation set and photos of 60 people are taken as the development set. To begin with, there are several issues to be addressed. Firstly, some images are actually duplicates of each other, differing only in image size. These near duplicate images make face verification much easier. Secondly, some URL links are unavailable, and they need be picked out manually. Thirdly, some images are not of the subject as designated. To deal with these problems , for both the development set and evaluation set, manually selected 5 images for each identity, where each of them differ from each other in picture size, pose, illumination, expression, etc..

V.CONCLUSION

In this paper, we have proposed a partial face recognition method by using robust feature set matching. We proposed to use local features instead of holistic features, and these local feature point sets were matched by MLERPM approach, the outcome of which were a point set correspondence matrix indicating keypoint pairs and a non-affine transformation function. This transformation function could align the probe partial face to gallery face automatically. Moreover, a point set distance metric was designed, based on which, a simple nearest neighbor classifier could recognize input probe faces robustly even at presence of obstructions. Experimental results on three widely used face datasets were presented to show the efficacy and limitations of the proposed approach.

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