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Ecludian Distance based Partial Face Recognition

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***Abstract*— Various approaches have been proposed to recognize complete faces. However, few have dealt with the problem of recognizing an arbitrary partial face. In real-world scenarios, human faces might easily be occluded by other objects. This made traditional face recognition algorithms, which heavily rely on face alignment and face normalization, infeasible. In this paper, we propose an approach for partial face recognition which will be based on matching feature set, and this approach will be able to match partial face patches to gallery data set faces automatically and is robust to occlusions as well as illumination changes.Then, we propose arobust point set matching method to discriminatively match thesetwo extracted local feature sets, where both the textural informationand geometrical information of local features are explicitlyused for matching simultaneously. Finally, the similarity of two faces is been extracted and distance is been calculated based on Euclidian distance formula.**

Keywords*— Face recognition, partial face recognition,feature set matching, feature alignment, image matching,biometrics.

I. INTRODUCTION

Face recognition is a technique of identifying an individual by comparing live image or digital image data with the stored record for that person. A face recognition system is a computer application capable of identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a face database. It is typically used in security systems and is similar to other techniques such as fingerprint or eye iris recognition systems. Recently, it has also become popular as a commercial identification and marketing tool.

FACE recognition (FR) is the problem of verifying or identifying a face from its image. It has received substantial attention over the last three decades due to its value both in understanding how FR process works in humans as well as in addressing many challenging real-world applications, including reduplication of identity documents (e.g. passport, driver license), access control and video surveillance. The performance of automatic FR systems has advanced significantly. While face recognition in controlled conditions (frontal face of cooperative users and controlled indoor illumination) has already achieved impressive performance over large-scale galleries, as indicated in a recent IEEE T-PAMI special issue on real-word face recognition [1], there still exist many challenges for face recognition in uncontrolled environments, such as partial occlusions, large pose variations, and extreme ambient illumination.

Typical applications of face recognition in uncontrolled environments include recognition of individuals in video surveillance frames and images captured by handheld devices (e.g. mobile phones), where a face may be captured in arbitrary pose without user cooperation and knowledge. In such scenarios, it is quite likely that the captured image contains only a partial face. Table 1 lists a categorization of partial face images and some further illustrations are given in We call the resulting problem a Partial Face Recognition (PFR) problem, so as to differentiate it from the holistic face recognition problem. Commercial off-the-shelf (COTS) face recognition systems are not able to handle the general PFR problem since they need to align faces by facial landmarks that may be occluded. For example, Face VACS [3] requires localization of the two eyes, and PittPatt [4] detects several predefined landmarks for facealignment. Therefore, research in PFR is important to advance the state of the art in face recognition and enlarge the application domain.

This paper is an extended version of our previous workpresented at IEEE ICCV 2013 [15]. There are several newcontributions in this work compared to its conference version:

• We have developed a new feature set matching approachfor partial face matching. In our previous conferenceversion [15], the matching algorithm was built based onChui's work [16], where no constraint was enforced onthe affine transformation matrix, so that unrealistic imagewarping can be generated if the difference between theprobe patch and gallery image is large. In this work,we explicitly constrain the affine matrix to address thislimitation. Experimental results show that our new featureset matching method achieves better performance.

• We have conducted more partial face recognition experimentsto further evaluate the performance of ourapproach. The newly extensions include:

1) More resultson additional datasets,
2) More face verification evaluations,and
3) More detailed parameter analysis of theproposed approach.

Feature set matching [7] has been a hot topic in pattern recognition. [24] was the first work that used graph matching for face recognition. However, their work relies heavily on manual landmarks labeling. Chui and Rangarajan [6] presented Robust Point set Matching (RPM) to align two feature sets according to their geometry distribution by learning a non-affine transformation function through iterative updates. However, it neglects textural information offeature points. Liao et al. [15] utilized SRC to reconstruct probe local feature set with gallery feature sets, and they used the reconstruction error as distance metric. The main

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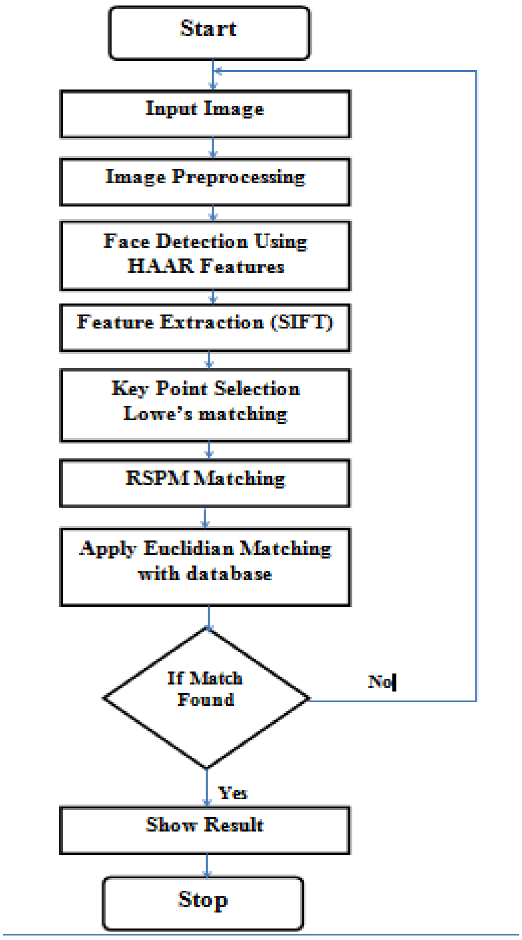
drawback of their method is that they neglected the geometry information of feature sets and their approach is computationally intensive. To address the partial face recognition problem, we propose a new partial face recognition approach by using feature set matching, and devise a Metric Learned Extended Robust Point set Matching (MLERPM) approach to register the extracted local features according to their geometric distribution and textural information. Based on the matching result, a point set distance metric is proposed to describe the similarity of two faces.

II. PROBLEM DEFINITION

Most existing approaches exploit handcrafted blur features that are optimized for a certain uniform blur across the image, which is unrealistic in a real blind de-convolution setting, where the blur type is often unknown. To deal with this issue, we aim at identifying the blur type for each input image patch, and then estimating the kernel parameter in this paper. A learning-based method using a pre-trained deep neural network (DNN) and a general regression neural network (GRNN) is proposed to first classify the blur type and then estimate its parameters, taking advantages of both the classification ability of DNN and the regression ability of GRNN.

III. PROPOSED APPROACH

We propose to use local features instead of holistic featuresfor partial face representation. Specifically, we applythe Scale-Invariant Feature Transform (SIFT) [17] featuredetector to detect local feature keypoints, which are then concatenated with the Speeded Up Robust Features (SURF)[2]. Before matching, keypoints selection is performed to filter out obvious outliers. These selected keypoints of probe and gallery images are then matched by our MLERPMbased on their geometric distribution and textural information, through which we obtain a one-to-one point set correspondencematrix to indicate the genuine matching pairs, as well as a non-affine transformation function to registergeometric distributions of these matched keypoints. With matched keypoint pairs at hand, we design a point set distancemetric to describe the difference between two facesbased on MLERPM, where the lowest matching distanceachieved would be reckoned as positive match. The facematching process is illustrated in Figure1. Throughout therest of the paper, matrix transposition is denoted by.



Gig .3.1 Flow Chart of proposed system

Following is the process flow for designing the proposed approach**:**

3.1 Input Image:

System can give input image by selecting from system/dataset or system can also take image input from real time camera. Any real time partial image can be taken as input from camera or from dataset.

3.2 Image Preprocessing:

In image preprocessing system will preprocess the input image, extract features of image and convert the image in grayscale image using grayscale algorithm.

All grayscale algorithms utilize the same basic three-step process:

a) Get the red, green, and blue values of a pixel
b) Use fancy math to turn those numbers into a single gray value.
c) Replace the original red, green, and blue values with the new gray value.

When describing grayscale algorithms, I'm going to focus on step 2 – using math to turn color values into a grayscale value. So, when you see a formula like this:

Gray = (Red + Green + Blue) / 3

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3.3 HAAR Features Detection:

HAAR-like features are digital image features used in object recognition. They owe their name to their intuitive similarity with HAAR wavelets and were used in the first real-time face detector. Historically, working with only image intensities (i.e., the RGB pixel values at each and every pixel of image) made the task of feature calculation computationally expensive. A publication by Papageorgiou et al.[2] discussed working with an alternate feature set based on HAAR wavelets instead of the usual image intensities. Viola and Jones[1] adapted the idea of using HAAR wavelets and developed the so-called HAAR -like features. A HAAR -like feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums. This difference is then used to categorize subsections of an image. For example, let us say we have an image database with human faces. It is a common observation that among all faces the region of the eyes is darker than the region of the cheeks. Therefore a common HAAR feature for face detection is a set of two adjacent rectangles that lie above the eye and the cheek region. The position of these rectangles is defined relative to a detection window that acts like a bounding box to the target object (the face in this case).

3.4 Feature Extraction

Since there exist rotation, translation, scaling and evenocclusions between probe image and gallery images ofsame identity, it is very difficult to normalize them to eyepositions. Without proper face alignment, holistic featureswould fail to work. Hence, we proposed to use local features. Firstly, we detect keypoints with SIFT feature detector.Normally for a typical 128 × 128 face image, SIFT featuredetector could output hundreds of feature points. Thegeometric feature of each keypoint, denoted as g, recordsits relative position in the image frame.To describe the texture features of these detected keypoints, we combined the strength of SIFT and SURF keypoint descriptor by simple concatenation. SURF keypoint
descriptor was introduced as a complement to SIFT forits greater robustness against illumination variations [14].Hence, this augmented texture feature, denoted as t, is robustagainst in-plane rotation, scale as well as illumination change.

3.5 Keypoint Selection

As we have indicated previously, the number of keypoints of facial image could be up to hundreds. Matchingpoint sets at this scale is computationally intensive. Moreover, irrelevant keypoints might hamper point set matchingprocess, such as misleading the matching process to a localminimum, especially when genuine matching pairs are fewamong all matching features. Hence, it's beneficial to filterout obvious outliers before point matching.We applied the idea of Lowe's matching scheme [17] for keypoint selection, which is to compare the ratio of distance of the closest neighbor to the one of the second-closest neighbor to a predefined threshold. The threshold was setas 0.5 in our experiments. These coarsely matched keypoint. Pairs are then selected for our MLERPM for finer matching. 2.3. Metric Learned Robust Point Matching After feature extraction and keypoints selection, for the probe partial face image, its geometry feature set is $\{g^P_1 , g^P_2 , ...g^P_{NP}\}$, with its correspondent texture feature set as $\{t^P_1, t^P_2 , ...t^P_{NP}\}$, where NP is the number of keypoints in probe feature set. Similarly, for the gallery image, we have $\{g^G_1 , g^G_2 , ...g^G_{NG}\}$ and $\{t^G_1 , t^G_2 , ...t^G_{NG}\}$ correspondingly. To align a probe partial face image to a gallery image automatically, we need match their correspondent geometric features and textural features respectively, which should have three characteristics:

• Subset matching: since the probe image and gallery images are not identical, some keypoints in the probe image couldn't find their correspondences in the gallery image. Likewise, not all keypoints in gallery images 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 as keypoints of different positions in the probe image shouldn't be matched to a single 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.

3.6 Euclidian Distance:

In mathematics, the Euclidean distance or Euclidean metric is the "ordinary" straight-line distance between two points in Euclidean space. With this distance, Euclidean space becomes a metric space. The associated norm is called the Euclidean norm. Older literature refers to the metric as Pythagorean metric. A generalized term for the Euclidean norm is the L^2 norm or L^2 distance.In the context of Euclidean geometry, a metric is established in one dimension by fixing two points on a line, and choosing one to be the origin. The length of the line segment between these points defines the unit of distance and the direction from the origin to the second point is defined as the positive direction. This line segment may be translated along the line to build longer segments whose lengths correspond to multiples of the unit distance. In this manner real numbers can be associated to points on the line (as the distance from the origin to the point) and these are the Cartesian coordinates of the points on what may now be called the real line. As an alternate way to establish the metric, instead of choosing two points on the line, choose one point to be the origin, a unit of length and a direction along the line to call positive. The second point is then uniquely determined as the point on the line that is at a distance of one positive unit from the origin.

$$\begin{aligned} d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) &= \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \cdots + (q_n-p_n)^2} \\ &= \sqrt{\sum_{i=1}^{n}(q_i-p_i)^2}. \end{aligned}$$

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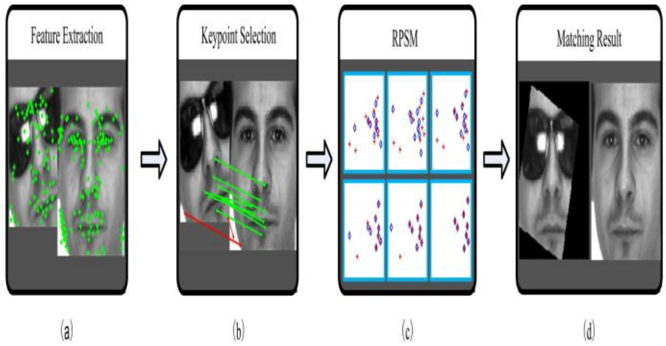

Fig: 1 Our proposed partial face recognition framework. (a) Feature extraction: keypoints detected by SIFT keypoint detector are marked out as greendots on both images. The left image is the probe partial face image, and the right one is the gallery face image. (b) Keypoint selection by Lowe's matching 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) RPSMprocedure: point set of probe image marked out as blue diamonds are iteratively aligned to the red-marked point set of gallery image.

During the trust region shrinkage process, there might occur a scenario where all elements in a row (column) of **M** are close to 0, this happens when an outlier has been detected. Note that the keypoint selection part doesn't guarantee the selected keypoint pairs are genuine matching pairs, some of which are imposter pairs. The geometric distribution of these imposter pairs lies "inharmoniously" against the rest. Detecting and removing them from the matching process not only accelerates the matching process, but also improve matching accuracy.

The Scale-invariant Feature Transform This section reviews the basics of the SIFT algorithm, which according to [4] consists of four computational stages: (i) scale-space extrema detection, (ii) removal of unreliable keypoints, (iii) orientation assignment, and (iv)keypoint descriptor calculation. 2.1 Scale-space extrema detection. In the first stage, interest points called keypoints, are identified in the scale space by looking for image locations that represent maxima or minima of the difference-of-Gaussian function.

Algorithm 1 RPSM

Input: $\mathbf{L}^P, \mathbf{L}^G, \mathbf{C}$
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 $\boldsymbol{\Psi} = \emptyset$
for $It = 1 : It_{max}$ **do**
  Construct $\boldsymbol{\Phi}$;
  Add Constraint Set $\boldsymbol{\Psi}$ to (11) and update $\mathbf{A}, \boldsymbol{b}, \mathbf{M}$;
  Clear Constraint Set, $\boldsymbol{\Psi} = \emptyset$;
  //Trust region shrinkage
  for *each* $\boldsymbol{l}_i^P$ **do**
    Find outsiders $\boldsymbol{l}_j^G$, where $E_d(\boldsymbol{l}_i^P, \boldsymbol{l}_j^G) > 0.5d$;
    Add $\mathbf{M}_{ij} = 0$ to $\boldsymbol{\Psi}$;
  end
  $d = r_1 d, \lambda_3 = r_2 \lambda_3$;
  //Outliers detection
  Find outliers $\boldsymbol{l}_i^P$, where $\sum_j \mathbf{M}_{ij} < \tau$;
  Remove $\boldsymbol{l}_i^P$, $\mathbf{M}_{i\cdot}$ from $\mathbf{L}^P$ and $\mathbf{M}$ respectively;
  Find outliers $\boldsymbol{l}_j^G$, where $\sum_i \mathbf{M}_{ij} < \tau$;
  Remove $\boldsymbol{l}_j^G$, $\mathbf{M}_{\cdot j}$ from $\mathbf{L}^G$ and $\mathbf{M}$ respectively;
end
Binarize $\mathbf{M}$;
return $\mathbf{A}, \boldsymbol{b}, \mathbf{Q}, \mathbf{M}$

IV. CONCLUSION

We have proposed a partial face recognition method by using robust feature set matching and Euclidian distance method. 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.

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