A Modern Approach to Partial Face Recognition

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Abstract

Various methods have been proposed and implemented for holistic face recognition with superior performance. But out of them, only a small number of researches and studies manage to recognize an arbitrary patch of a face image in the particular scenario. Subsequently, in unconstrained scenarios, it can be seen that partial faces appear very intermittently, with peculiar images captured by surveillance cameras or handheld digital devices (e.g., smart phones & tablets) and thus we didn’t get the clear and exact image. In this paper, taking consideration into all such things, a general approach for partial face recognition has been proposed, that does not require face alignment by eye coordinates or any other fiducially point as it is the case in earlier methods. But, here we have promoted an alignment-free face representation method based on Multi-Key point Descriptors (MKD), where the descriptor size of a face and its parts are determined by the local content of the image. By this method, any probe face image, holistic or partial image, which cannot be identify easily can be sparsely represented using a huge dictionary of gallery descriptors. This Proposed method is very efficient in recognizing holistic as well as the partial faces without requiring alignment, i.e.: we can say that the proposed method is alignment free.

Key Words: Partial face recognition, alignment free, keypoint descriptor, Multi-Key point Descriptors (MKD), open-set identification.

1. Introduction

All Face recognition (FR) has been a rapidly growing research area due to an increasing demand for biometric-based security applications. Due to varying factors such as cosmetics, illumination, and face disguise the FR performance can be affected up to a large extent. The capability to recognize a person in both day and night time environments, is one of the toughest tasks. In order to mitigate such a challenge, FR operation in the infrared (IR) spectrum (active and passive) has become very significant. Face recognition (FR) is the process of identifying or analyzing a face from its image. Since, last three decades, it has been acclaimed critically, because of its contribution in understanding how FR process works in humans as well as in addressing many challenging real world applications, that may includes the duplication of various identity documents (e.g., driving license, pan card, passport), access control, and video surveillance. Typical applications of face recognition in uncontrolled environments include recognition of individuals in video surveillance frames and images captured by handheld digital devices (e.g., smart phones & tablets), where a face may be captured in an arbitrary pose without knowledge and user co-ordination. In such scenarios, it is the case where it may happen that the captured image may consists of just a partial face.

The paper is organized in such a way that the Section II depicts related works that consists of various techniques used for load balancing in fat tree data centre network. In Section III, we present comparative analysis between various techniques. Section IV contains research design and describes characteristics & impact of the proposed system.

In recent years, the facial expression recognition has been accepted globally in the area of computer vision, facial feature point tracking and pattern recognition. Because of the difficulty to extract features and their motion information and due to complexity and variability characteristics of facial expression, it is somewhat complex to recognize or identify a peculiar image, exactly as compare to the original one. Hence, nowadays the traditional facial expression recognition technology is using facial expression images without occlusion. However, face occlusion is very common in real life, spectacles,
mask, long hairs and face movements will cause different facial occlusions. Therefore, the algorithm of robust facial expression recognition under facial occlusion condition has become an important direction.

Typical applications of face recognition in uncontrolled environments include recognition of individuals in video surveillance frames and images captured by handheld devices (e.g., smart phones), which facilitates that; a face may be captured in an arbitrary pose without user cooperation and knowledge. What is common in such cases is that the captured image contains only a partial face and not the clear image. For this purpose, we organized the categorization of partial face images, some facial parts and some further illustrations we come across. The final emerging problem out of this is called as a Partial Face Recognition [PFR] problem, in order to differentiate it and to avoid confusion 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; it matches the two eyes with to align a given face, while PittPatt [4] requires several predefined landmarks for face alignment to detect. Thus, innovations and research in the field of PFR is very crucial to advance the state of the art in face recognition and enlarge the application domain.

Law enforcement agencies are also in urgent need of a system which is enabling of recognizing partial faces. Accordingly, a PFR system will enable the agencies to identify a suspect in a by matching a partial face captured by, say, a smart phone to a watch list by a wireless link in real time. After that, if in a given scenario, a photo of a certain illegitimate event, a Partial Face Recognition [PFR] is required for identifying and recognizing the identity of a suspect which is based on a partial face or some partial face parts. For an example, if we take the example of London riots [5], we get to see that, while automatic face recognition resulted in many arrests in the 2011 London riots [5], many suspects in partial face images were not recognized by COTS FR systems [6]. As a result, even though, there come across some suspects but some of the partial face images were not recognized by it.

2. Related work

2.1. MWIR based feature segmentation

In the automatic mode, canonical (normalized) faces are used and minutia points are extracted from physiologically based (when using subcutaneous facial characteristics) and geometrically based face features (e.g. nose tip, eye edges, lips and eyelashes), which are extremely unique belonging to a particular person only. In the manual mode, human experts have been used to annotate minutiae points that are visually perceived as important for recognition. During matching step and decision making step, using the application of our feature extraction scheme, an input image (probe) is matched with the stored template (gallery). As a result, a final matching score is obtained from our minutiae-based feature extraction method. In this case, if the score does not match and if it is less than a pre-defined threshold, it is assumed that the input image successfully matched with the template. In addition, the matching algorithm is also optimized for fiducially points instead of minutiae points, and it does not take the orientation into consideration.

Figure 1. Overview of the methodology used to perform fully automated pre-processing, MWIR based feature extraction, fiducially annotation, and matching.

The MWIR-based features extracted include: (a) veins, (b) edges, (c) wrinkles, and (d) face perimeter outlines header.

Figure 2. (i) Geometrically normalized face (before elliptical masking), (ii) Diffused and top hat segmented face (before elliptical masking): (a) veins, (b) edge, (c) wrinkle and (d) part of the face perimeter.

This method achieved the best overall identification performance (in terms of rank-1 rates) for the whole face as well as in the majority of the sub-facial regions, and their combinations. This is considered a very interesting result. However, it need to point out that the identification rates when using manual annotated face
images were achieved on the original MWIR feature extracted image, i.e. before the elliptical masking is applied.

### 2.2 Semi-Coupled Dictionary Learning Technique

This is a new method for computing the similarity of partial 3D data for the purpose of face recognition. This method can result into a more better existing Semi-Coupled Dictionary Learning method by computing a jointly-optimized solution that results into a solution which consolidates the discrimination cost, the matching parameters cost, the reconstruction cost and the semi coupling cost. In this way, this experiments shows that, adopting this method can facilitates, a huge improvement in the recognition performance of existing state-of-the art wavelet signatures used for the purpose of 2D & 3D face recognition. They fit an Annotated Face Model (AFM) for normalizing the effects of expression, pose & lightening.

The Annotated Face Model (AFM) provides a frame of reference and it is annotated with semantic information (for e.g. to identify & recognize which region is mouth and which region is eye) which, in turn, carry extra information (e.g., different weights can be attached to different regions). By applying an AFM for each input mesh, provides the facility such that we can normalize its position and orientation. Then, by using the AFM’s UV mapping, the geometry image representation of these fitted meshes can be generated for further processing while retaining their alignment on the grid.

Here they demonstrated how to use dictionary learning to address the problem of partial face recognition and formulation addressed the previous methods shortcomings by simultaneously optimizing for our semantically clear objective terms (reconstruction, discrimination, and semi coupling). Thus, in this way, we can say that this approach offers an improvement over previous approaches.

### 2.3 Scale-Invariant Feature Transform (SIFT) Technique

Here they proposed a new partial face recognition approach which provides a feature set matching, and which is very useful to align partial face patches to holistic gallery faces automatically and is strong enough to occlusions and illumination changes that may occur during this process. For each gallery image and probe face patch, our first task will be to detect key points and second task will be to extract its features. Here, we introduce a (MLERP) method i.e., Metric Learned Extended Robust Point Matching method to discriminatively match local feature sets of a pair of gallery and probe samples respectively. Finally, the verdict is suppose if it is found that the two faces are similar then they are converted as the distance between two feature sets.

They used local features for matching instead of holistic features that has been used usually for partial face representation. Here, we choose to apply the Scale-Invariant Feature Transform (SIFT) feature detector in order to identify and detect local feature keypoints, which are then concatenated with the Speeded Up Robust Features (SURF). Before matching, keypoints selection is performed to filter out obvious outliers. These selected keypoints of probe and gallery images are then matched by our MLERP based on their geometric distribution and textural information, through which we obtain a one-to-one point set correspondence matrix to indicate the genuine matching pairs, as well as a non-affine transformation function to register geometric distributions of these matched keypoints. With the help of matched keypoint pairs, we select the method to design a point set distance metric to describe the difference between two faces based on MLERP, where the lowest matching distance achieved would be reckoned as positive match.

### 2.4 Bag of words (Bow) model

Here they demonstrated how to use dictionary learning In face recognition, the order less collection of local patches in BoW model cannot provide strong distinctive information since the objects (face images) belong to the same category. The original BoW model was applied to the area of text processing, which can be useful in classifying and identifying the documents. In this model, a text (such as a sentence or a document) is represented as an unformal collection of sentences, phrases, words without taking into consideration the sequence of words and the grammar. Recently, researchers in the field of computer vision have tried to apply the same idea to the image processing and
3. Proposed method

Given a gallery set, that can be used as the dissimilarity score for face identification. The SRC algorithm was originally proposed for face identification, but a very small research and a very few work has been done in the field of SRC-based face verification and due to this many researchers move the face of their studies into this direction. In the given paper, we have provided just a simple extension of the MKD-SRC algorithm for face verification. Briefly, the face verification task is to judge whether a given pair of face images, for e.g. M and N, belong to the same subject or whether it has been related to another subject. For this task, we use a set of background face images together with image M as a virtual gallery set, while for the other input face image N, it is taken as the probe. This should be noted that, among the set of background face images, neither any set having the same subject nor any of the two inputs face images. Finally, now the MKD-SRC algorithm is applied, and we take c is the class for image M. In order to make, the verification score a symmetric function of M & N, we will also put N in the gallery set and use M as the probe, and finally, we computed the average score which is considered as the final score. To handle pose variations and pose discrimination, mirrored facial images have been used to improve FR performance in different views. Inspired by this, firstly, the input face image, M, is horizontally mirrored as M0, then both M and M0 are put in the virtual gallery set. Thus, in this way, we can see that now, chances of matching a left profile face image as compare to the corresponding right image, will be more.

3.1 Partial Face Recognition For Arbitrary Patch

Here synthetically generated a large database of partial faces taken from 16,028 frontal face images of about 466 subjects from the Face Recognition Grand Challenge Ver2.0 (FRGCv2.0) database [66]. Base upon this database, we conducted a large-scale open-set identification experiment. The gallery set G includes 466 full face images of the 466 subjects, in such a way, that exact one image belongs to the corresponding one object. For making the task of identification for complex, we encompassed an additional 10,000 full frontal facial images (one image per subject) from a private database to expand the gallery set to 10,466 subjects. The probe set PG is composed of 15,562 partial facial images of the exact 466 subjects in total, from the FRGC database. For the other probe set which is PN, we encompassed 10,000 partial facial images of total 10,000 subjects which are taken from the private database, where not any of these subjects were included in the given gallery set which are already defined. The extended database which is also encompassed earlier is also denoted as FRGCv2.0p, just for the sake, not to get confused with the FRGCv2.0 databases.

3.2 Holistic Face Recognition With Occlusion

The AR database contains 135 subjects, consisting of some face images wearing sunglasses or a scarf. We selected 135 non-occluded face images (one image/subject) with neutral expression from the AR database as the gallery set G. Again, an additional 10,000 full frontal faces (one image/subject) were also added, which causes, the gallery size to a total 10,135 in number. For the probe set PG, exactly total number of 1,530 images was selected from the Arbitrary Database, which includes images with sunglasses or scarf. On the other hand, each probe image may have left or right side illumination. From the private database, the probe set PN, 10,000 subjects (not present in the gallery set) with full frontal faces (one image/subject) were selected.

The extended database is denoted as AR; on the other hand the original database is denoted as AR in order to avoid confusion with the extended databases. For the proposed alignment-free methods, we choose a method in which we will firstly crop all images to 128*128 pixels, after face detection.

In practice, the size (K) of the dictionary D can be of the order of millions, making it difficult to solve (10). For this reason, we select a rapid approximately solution. In this solution, for every probe descriptor $y_i$ we first compute the following linear correlation coefficients between $y_i$ and all the descriptors in the dictionary D:

$$c_i = \frac{1}{n} D^T y_i; i = 1, 2, \ldots, n$$

Then, for each $y_i$, we keep only L $\delta L K$ descriptors.
MKD-SRC algorithm, along with its complete method is explained in the following Algorithm. We collected and computed all the parameter values which are used in this paper, and are encapsulated in Table 3 shown above. They were fixed for all the experiments reported in the paper.

### 3.3 MKD-SRC Algorithm

**Input:** As gallery images of C classes; probe image I; parameter L.
**Output:** We get Identity C of the probe image I.

1. **Enrollment:** Initially, Extract multi-keypoint descriptors (MKD) from every gallery image, once it has been done, construct the Dictionary
   \[ D = \{ D_1, D_2, \ldots, D_L \} \subseteq \mathbb{R}^{M \times K} \].
2. **Recognition:**
3. Extract MKDs from the probe image:
   \[ Y = \{ y_1, y_2, \ldots, y_N \} \subseteq \mathbb{R}^{M \times n} \].
4. For i = 1 To n do
5. Compute top L descriptors from (12), resulting in a subdictionary \( D_M^{i*} \).
6. Solve (10) with \( D_M^{i*} \).
7. end
8. Solve (11) to determine the identity c;

### 4. Conclusion

Given a gallery set, the residual defined in (11) can be used as the dissimilarity score for face identification. However, the SRC algorithm was originally proposed for face identification purpose, the work which has been done so far for SRC-based face verification, is not sufficient. Here, we propose a simple extension of the MKD-SRC algorithm for face verification. The face verification task is to judge whether a given pair of face images, say M and N, whether belong to the same subject or it has been belongs to another pair. Therefore, here we have used a normal set of background face images along with the image I as a virtual gallery set, and the other input face image J as the probe which gives a brief idea. It should be noted that even though the set of background face images does not contain the same subject as either of the two input face images, we will get the result. Finally, the MKD-SRC algorithm is applied to he set , for which the verification score is defined as \( 1 - r_c \), where \( r_c \) is defined in (11) and c is the class for image I. To make the verification score a symmetric function of I and J, we also put J in the gallery set and use I as the probe, and the average score is computed as the final.

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