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A New Approach to Partial Face Recognition

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Abstract— Face Recognition is the technique to verify whether the entered image or input is exactly similar to the available images present in the databases. The technique comes under the Artificial Intelligence. Updation to the existing technique and also new technique is introduced day by day. Different types of facial recognition techniques are Finding faces in images with controlled background, Finding faces by color, Finding faces by motion, Finding faces in unconstrained scenes etc. Each and every approach has its different techniques. Subsequently various algorithms are also exist which gives us result based as per our expectation.

We are implementing face recognition approach by using MKD-SRC Algorithm. The advantage of this algorithm is that we can apply it on partial or incomplete faces also, even if the given input is partial, then also we can use this method. Also we can compare the left part of the given image with the available right one to determine whether they belongs to same object or not. Compare with the FaceVACS and PittPatt, our algorithm provides the solution on general face recognition problem. Our technique will also do the object categorization, to determine whether the object belongs to the same category or different.

Key Words: MKD-SRC Algorithm, FaceVACS, PittPatt, and object categorization.

I. INTRODUCTION

Over the decades the Face Recognition technology has received a great demand due to which many researchers has focus on this area. Physical Science shows that there are some part of body of human being which has its unique identity like Nose Structure, Eyes, Facial Parts etc. Considering these parameters, we can easily determine whether these objects are the part of given Human Body or not.Thus, Face Recognition approach by using MKD-SRC Algorithm; provide an approach through which we can compare partial face images with the available database images to verify whether the input images are the part of available images. The advantage of this method is that, we can compare partial input with the available ones. Partial Face Recognition, provide a solution to the following questions: (i) Whether is it possible to recognize a person from a partial image of his face? , (ii) Which portion of the face? and What size of the partial face are critical for exact recognition?

Face recognition has its applications in information security and access control, law enforce, surveillance and more generally image understanding. A general approach of partial face recognition method based on Multi-Key point Descriptors (MKD) which is the method that does not require face alignment by eye coordinates or any other fiducial points. The invariant shape adaptation makes image matching more robust to viewpoint changes which are desired in face recognition with pose variations. In Multi-Key Point Descriptor (MKD), the descriptor size of a image is determine based on actual content of the image. The MKD-SRC (Sparse Representation-based Classification) framework that works for both holistic faces and partial faces can be sparsely represented by a large dictionary of gallery descriptors. Multitask sparse representation is learned for an each probe face and the Sparse Representation-based Classification (SRC) approach is applied for face recognition a fast atom filtering strategy for MKD-SRC to address large-scale face recognition (with 10,000 gallery images).

II. PROPOSED WORK

In this paper, we present a general formulation of the partial face recognition problem. It do not require the presence of the eyes, face alignment or any other facial component within the image. In this case, we are not aware of a priori whether the input face is partial or holistic. By using this information, our aim is to give a general matching solution to acclimatize all types of partial faces listed in Table 1. Briefly, this approach is based on a Multi-Keypoint Descriptor (MKD) representation which can be used for the probe image as well as the gallery dictionary. For each probe face, a Multitask sparse representation is to be learned, and thus for face detection, Sparse Representation-based Classification (SRC) approach [7] is implemented. This method, we used to call is MKD-SRC. Fig. 2. shows the flowchart of the proposed method :

The uniqueness of the proposed approach includes:

1. A general partial face recognition approach without requiring face alignment, the MKD-SRC framework that works for both holistic faces as well as partial faces, and surpass SRC[7] for addressing the one-sample-per-class problem.
2. A new keypoint descriptor, called the Gabor Ternary Pattern (GTP), which outperforms the Scale Invariant Feature Transform (SIFT) [8] descriptor,
3. Finally, a fast atom filtering strategy for MKD-SRC to address large-scale face recognition (with 10,000 gallery images).

Scenario	External occlusion	Self occlusion	Facial accessories	Limited field of view (FOV)	Extreme illumination	Sensor saturation
Examples	occlusion by other objects	non-frontal pose	hat, sunglasses, scarf, mask	partially out of camera's FOV	gloomy or highlighted facial area	underexposure or overexposure
Image						

Table 1: A categorization of Partial Face Image

This paper is built upon the preliminary work reported in [9]. The main differences are summarized as follows: 1) While the method in [9] uses the SIFT descriptor, instead of it, a new keypoint descriptor (GTP) which outper-forms SIFT is proposed by us. 2) We address the one-sample-per-class problem in large-scale open-set identification setting for PFR, and it shows that as compare to the FaceVACS and PittPatt, the proposed MKD-SRC method performs better, on the FRGCv2.0, AR, and PubFig databases. 3) Here, for the purpose of partial face verification, we have extended the MKD-SRC method, which gives better results on the LFW database.

III. LITERATURE REVIEW

Some various popular face alignment methods include the Active Shape Model (ASM) [10] and the Active detect the two eyes and Appearance Model (AAM) [11], which depend on localizing a certain fixed number (typically 68) of landmarks on holistic face. In [12], a sparse representation-based alignment method under controlled scenarios, was proposed

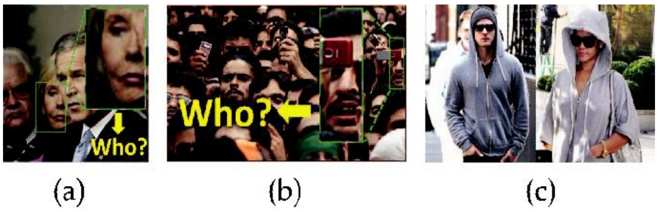

Fig. 1. Partial face examples. (a) Partial faces in the LFW database [2]. (b) Partial faces in a crowd (http://www.textually.org/picturephoning/archives/2008/09/021247.htm). (c) Occluded faces by hooded sweat-shirt and sunglasses (http://www.howtovanish.com/2010/01/avoid-nosy-surveillance-cameras/).

Nonfrontal face recognition has also attracted significant attention by multiview [19], [20] and cross-view [21], [22], [23],[24], [25], [26] face recognition. In case of cross-view FR, most approaches apply 2D or 3D appearance models to synthesize face images in specific views. Multiview face recognition requires that the gallery contain a large number of poses for the corresponding subject, that is not practically possible to satisfy in practice. In these approaches, a critical step is to localize a certain fixed number of representative facial landmarks and establish correspondences between two images in different views accordingly. Due to this, the images are expected to have visible anchor points irrespective of the view.

Yang et al. [27] and Yi et al. [28] proposed an automatic partial face alignment and matching approach, for partial faces resulting from a limited field of view. But, their approach requires high-resolution images (with an interpupil distance of more than 128 pixels) with good skin texture, but it is not applied to pose variations.

Some FR approaches only require face subimages as input, such as eye [29], nose [29], one half (left or right portion) of the face [30], or the periocular region. Again, these methods require the presence of certain facial components and prealignment.

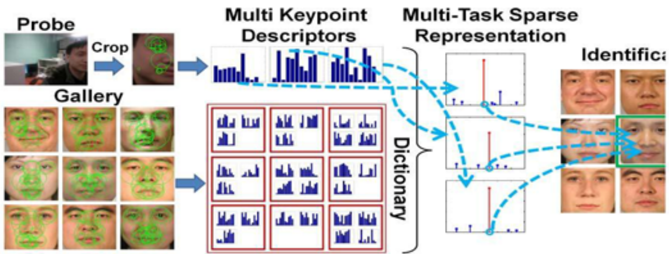

Fig. 2. Proposed partial face recognition approach

In contrast with the above SRC-based approaches, the proposed MKD-SRC approach uses a different feature representation. To represent a face, since both SRC and LBP-SRC require aligned faces and use a single fixed-size feature vector (e.g., concatenated image pixels or LBP histograms), each column of their corresponding dictionary is related to one gallery image. On the other hand, a partial face might be difficult to align and represent due to unknown missing facial regions, in such a scheme. On the contrary, MKD-SRC uses a variable-size description intendly, in ordet to represent each face by a set of descriptors. As a whole, the MKD dictionary is comprised of a large number of gallery descriptors, making it possible, for a probe image to sparsely represent descriptors, irre-spective of whether it represents a holistic or partial face.

Furthermore, SRC requires a sufficient number of training samples covering all possible illumination variations for each subject, which limits its applicability in each area. On the other hand, MKD-SRC performs satisfactorily in scenarios where only one training sample per class is available.

The bag-of-words (BoW) representation in the field of visual object categorization is another representation scheme that has been applied to face recognition. However, in the BoW representation, the underlying assumption is that the object image should not be significantly occluded; if not, the descriptor histogram of a partial view will be quite different from that of the whole view. Because of this reason, the BoW representation is not suitable for PFR.

A number of papers have been published on SIFT-based face recognition[1]. However, all of them were applied on prealigned face images. But the most significant feature of SIFT matching is that, it is fast and it treats each image pair independently and that is the reason, in the gallery set, it does not utilize collaborative representation of different subjects. A many local facial patches may look similar like others, it can be possible that, for an impostor pair, apparently SIFT matching would find more matches than a genuine pair [9]. To palliate this and to get more perfect result, the proposed MKD-SRC approach performs keypoint matching via sparse representation of all gallery images to select the best match automatically.

Characteristics of MKD-SRC in comparison with various existing approaches are encapsulated in Table 2. The rest of this paper of this paper is formulated as follows: If we see closer into the Section 2, it shows a well described and proposed alignment-free partial face representation method. For Section 3, an MKD-SRC algorithm introduced by us is depicted. Extensive experiments are demonstrated in Section 4, shown in the table, and ultimately this work has been concluded by us in Section 5.

IV. MKD-SRC ALGORITHM

Wright et al. [7] showed that a sparse linear combination of gallery images represents a probe image very effectively. Thus the resulting algorithm is been called as SRC. In this paper, by using a large dictionary of keypoint descriptors, we have planned to apply SRC instead of applying it directly to raw face image pixels; this is the key to the proposed alignment-free partial face recognition approach.

4.1 Gallery Dictionary Construction

The gallery dictionary is constructed as follows: First, an MKD representation (as introduced above) is constructed for each image. Suppose k_c keypoints, say, p_{c1} ; p_{c2} ; . . . ; p_{ckc} , are detected for class (subject) c in the gallery. Suppose if we assume that class c has multiple face images in the gallery, now we just incorporate the keypoints which are obtained from all of them. The corresponding k_c GTP descriptors are denoted by d_{c1} ; d_{c2} ; . . . ; d_{ckc} , where each descriptor is an M-dimensional vector (in our case, M ¼ 128). Let

D_c ¼ ðd_{c1} ; d_{c2} ; . . . ; d_{ckc} Þ: ð5Þ

This way the descriptors from the same class form a subdictionary of size M k_c representing class c. A gallery dictionary for all the C classes is built as

D ¼ ðD_1; D_2; . . . ; D_C Þ: ð6Þ

Note that D has a total of K C k descriptors, resulting in an M K dictionary. ¼ P c¼1 c

Typically, K is very large (e.g., over 1 million), which makes D an overcomplete description space of the C classes. Therefore, any descriptor from the C classes can be linearly represented in terms of the dictionary D. According to the theory of compressed sensing (CS), a sparse solution is possible for an overcomplete dictionary; therefore, we can express any descriptor from a probe image by a sparse linear combination of the dictionary D.

4.2 Multitask Sparse Representation

For a probe face image with n descriptors in the given scenario:

Y ¼ ðy_1; y_2; . . . ; y_nÞ; ð7Þ

Subsequently, sparse representation problem is formulated as

n
^
X ¼ arg min X i¼1 xik k 0 ; s:t:Y ¼ DX; ð8Þ
X

where X ¼ ðx_1; x_2; . . . ; x_nÞ 2 $R^{K\ n}$ is the sparse coefficient matrix, and k k_0 is denoted as the ‘$_0$ norm of a vector, which is kxk$_0$ ¼ $_i$ Iðx_i ¼6 0Þ

where IðsÞ ¼ 1 if the statatement s is true; P

NP-hard. Based on the results from compressed sensing [61], sparse signals can be recovered with a high probability via the ‘$_1$-minimization. Therefore, we solve the following ‘$_1$-minimization problem[3] instead of (8):

n
^
X ¼ arg min i¼1 k xik 1 ; s:t: Y ¼ DX; ð9Þ
X

where k k_1 denotes the ‘$_1$ norm defined as kxk$_1$ ¼ P$_i$ jx_ij. Since both X and Y have multiple columns, it can be seen that this is a multitask problem Similarly, the following set of n ‘$_1$-minimization problems can also be solved, one for each probe descriptor y_i:

x
^ arg min x ; s:t: y Dx ; i 1; 2; . . . ; n: 10
i ¼ xi k ik1 i ¼ i ¼ ð Þ

TABLE 3 Parameter Values

Parameter	*t*	*a*	*M*	*L*
Value	**0.03**	**20**	**128**	**100**

A number of efficient fast ‘$_1$ minimization algorithms can be used to solve (10), including the ‘$_1$ Homotopy method. Since the n ‘$_1$-minimization problems in (10) are indepen-dent, it is straightforward to accelerate the algorithm via parallel computation.

Inspired by Wright et al. [7], we adopt the following multitask SRC to determine the identity of the probe image:

min r Y 1 n k y i D c ^ ð i Þ k ; 11
c n i¼1 c x 2 ð Þ
X

where $_c$ð Þ is a function which selects only the coefficients corresponding to class c. Equation (11) applies a sum fusion among reconstruction residuals of the n descriptors with respect to each class efficiently, apparently the identity based on the least residual is also analysed by it. For this reason, an unknown partial face in the probe can be recognized by computing (10) and (11). The resulting algorithm is called as the MKD-SRC, and the most significant feature of it is that , it is independent of the face alignment. Fig. 2 depicts the flowchart of the MKD-SRC algorithm.

4.3 Fast Filtering

In practice, the size (K) of the dictionary D can be of the order of millions, making it difficult to solve (10). Therefore, we adopt a fast approximate solution. For each 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 ¼ D^T y_i; i ¼ 1; 2; . . . ; n: ð12Þ

Then, for each y_i, we keep only L ðL KÞ descriptors according to the top L largest values of c_i, resulting in a small subdictionary $D^{ð}{}_{M}{}^{iÞ}{}_{L}$. Next, D is replaced by $D^{ðiÞ}$ in (10), and (11) is adjusted accordingly.

We set L ¼ 100 in our algorithm. According to our previous finding [9], this approximate sol ution speeds up the computation, due to this, a significant degradation in recognition performance is not observed. According to (12) and the selec-tion of the top L elements (note that this can be done in OðK Þ by the Introselect algorithm), the computation time of the filtering step scales linearly with respect to K. Therefore, the algorithm scales almost linearly with respect to the gallery size for each probe image (considering an average number of keypoints per image). MKD-SRC algorithm, alongwith its complete method is explained in the following Algorithm. Finally, all the parameter values which are used in this paper are encapsulated in Table 3 shown above. They were fixed for all the experiments reported in the paper.

ALGORITHM

Algorithm 1. The 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 then after this, build the Dictionary
D ¼ ðD_1; D_2; ; D_C Þ 2 $R^{M\ K}$.

2: Recognition:

3: Extract MKDs from the probe image:
Y ¼ ðy_1; y_2; . . . ; y_nÞ 2 $R^{M\ n}$;

4: For i ¼ 1 To n do

5: Compute top L descriptors from (12), resulting in a subdictionary $D^{ð}{}_{M}{}^{iÞ}{}_{L}$;

6: Solve (10) with $D^{ð}{}_{M}{}^{iÞ}{}_{L}$;

7: end

8: Solve (11) to determine the identity c;

4.4 MKD-SRC for Partial Face Verification

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 score.

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