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Recognition of Occluded Facial Images Using Texture Features at SURF Keypoints

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***Abstract*--Partial face recognition is the process of verifying or identifying a face from its partial image. Usually, partial images which are being captured by digital cameras or handheld devices like handy cams and surveillance view cameras are places where we widely use the Face Recognition Technology. In this proposal, we remove the process of identifying the face image by eye position co-ordinates or any other locus points. Instead of old approach in new keypoint detector in surf (speed up robust features) because it find more then blob keypoints. In partial face recognition representation method based on Multi-Keypoint Descriptors (MKD), where the descriptor size of a face is determined by the actual content of the image. In approach, any probe face image, holistic or partial, can be sparsely represented by a large dictionary of gallery descriptors. A new keypoint descriptor called Gabor Ternary Pattern (GTP) is also developed for face recognition. It includes to new features in Grey Level Co-occurrence Matrix (GLCM) it used to increase accuracy in identifying verification score.**

***Index Terms*—Partial face recognition, alignment free, keypoint descriptor, Grey Level Co-occurrence Matrix, sparse representation, open-set identification.**

I. INTRODUCTION

Face recognition (FR) is the process of identifying the face structure from a partial image stored in memory. It has received huge attention over the last three decades due to its value in understanding how Face Recognition process works in humans and well as in addressing many challenging real world applications, including duplication of identity documents (e.g., passport, driver license), access control, and video surveillance. The performance of Face Recognition technology is more powerful than the old existing recognition patterns. At controlled conditions like in galleries, this recognition pattern has produced accurate results with less error margin, there are difficult and uncontrolled conditions where the recognition system needs a push, such as partial occlusions large pose variations, and extreme ambient illumination.

Applications of face recognition in uncontrolled environments include recognition of individuals in video surveillance frames and images captured by handheld devices. In such scenarios, it is quite likely that the captured image contains only a partial face.

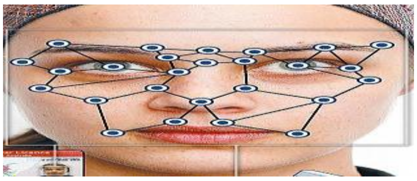

Fig.1.1Face Recognition Image

1.1. Proposed Method

A routine Face recognition pattern requests neither face alignment nor the presence of the eyes or any other facial component in the image. Further, they don't recognise a priority in a image whether it is hostile or not. They provide a general matching solution to accommodate all types of partial faces. Our approach is based on a Multi-Keypoint Descriptor (MKD) representation for both the gallery dictionary and the probe image. Once the input image is obtained from those users, they have to be pre processed for further steps. When considering partial faces, a canonical frame is not always available for feature extraction. Furthermore, most available approaches, either holistic or local use a fixed-length representation for each face. A fixed-length representation assumes that the face image is aligned and cropped to a predefined size. Next, consider a scale invariant canny edge based interest point detector proposed to detect the edges. Once the detected regions are normalized to a fixed size, a local descriptor is constructed within each region as first apply the Gabor filter to each image patch.

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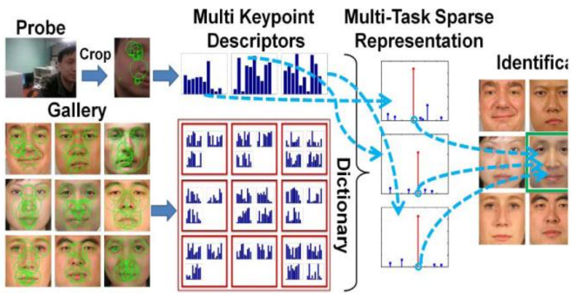

1.1.1proposed system

The GTP region is divided into sub grid cells. A histogram of GTPs is calculated in each grid cell. The gallery dictionary is constructed to the same GTP process. It includes to new features in Grey Level Co-occurrence Matrix (GLCM) it used to increase accuracy in identifying verification score. The SURF, GLCM performs better for face recognition in uncontrolled scenarios, as will be seen in the experiment section.

II. ALIGNMENT FREE PARTIAL FACE REPRESENTATION

The process of Face alignment is based on facial landmarks detection; in this scenario of partial faces there is no guarantee that commonly used landmarks are visible in the image. Therefore, when considering partial faces, a canonical frame is not always available for feature extraction.

2.1 Surf Keypoint Detection

The surf finds many more keypoints than the SIFT detector for face images, since there are more edges than blobs on a face. Speeded Up Robust Features descriptor is a fast multi-scale Hessian keypoint detector that can be used to find the keypoints. SURF is a blob detector; in short, the size of a feature is the size of the blob. It surf makes image matching more robust to viewpoint changes, which is desired in face recognition with pose variations. The size of each feature is the radius of the drawn circle. The lines going out from the center of the features to the circumference the angles or orientations. In this image, the response strength of the blob detection filter is color coded.

2.2 Gabor filter

Commonly used method in **Gabor filter** is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination

2.3 Local ternary pattern

Local ternary patterns (LTP) are an extension of Local binary patterns (LBP).Unlike LBP, it does not threshold the pixels into 0 and 1, and rather it uses a threshold constant to threshold pixels into three values. The local ternary pattern provides a discriminative encoding of the four Gabor filters.

2.4 GLCM

Grey Level Co-occurrence Matrices GLCM) are one of the earliest techniques used for image texture analysis defined a new feature called trace extracted from the GLCM**.** The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image. GLCM texture considers the relation between two pixels at a time, called the reference and the neighbor pixel. In the illustration below, the neighbor pixel is chosen to be the one to the east (right) of each reference pixel. This can also be expressed as a (1, 0) relation: 1 pixel in the x direction, 0 pixels in the y direction. Each pixel within the window becomes the reference pixel in turn, starting in the upper left corner and proceeding to the lower right. Pixels along the right edge have no right hand neighbor, so they are not used for this count.

2.5 Histogram

A **histogram** is a graphical representation of the distribution of data. A histogram is a representation of tabulated frequencies, shown as adjacent rectangles, erected over discrete intervals (bins), with an area equal to the frequency of the observations in the interval. The height of a rectangle is also equal to the frequency density of the interval, i.e., the frequency divided by the width of the interval. The total area of the histogram is equal to the number of data. A histogram of GTPs is calculated in each grid cell.

III. Gallery Dictionary Construction

The gallery dictionary is constructed; an MKD representation is constructed for each image. Sparse solution is possible for an over complete dictionary express any descriptor from a probe image by a sparse linear combination of the dictionary D.

IV. Multitask Sparse Representation

Given a probe face image with n descriptors:

$$Y=(y_1, y_2,...., y_{1n})$$

The sparse representation problem is formulated as

$$\hat{X}=\text{argmin}_X \sum_{i=1}^{n} ||x_i||_0,\text{s.t.}Y=DX$$

Based on the results from compressed sensing sparse signals can be recovered with a high probability via the '1-minimization.

$$\hat{x}=\text{argmin}_X \sum_{i=1}^{n} ||x_i||_1,\text{s.t.}Y=DX$$

A number of efficient fast l_1 minimization algorithms can be used to solve , including the l_1Homotopy method Since the n l_1-minimization problems

$$\min_c rc(Y) = \frac{1}{n}\sum_{i=1}^{n} ||Y_i\text{-}D_c\delta_c(\hat{x_i})||_2^2$$

Where $\delta_c(.)$ is a function which selects only the coefficients corresponding to class c. applies sum fusion among .reconstruction residuals of the n descriptors with respect to each class, and determines the identity based on the least residual.

V. MKD-SRC For Partial Face Verification

Given a gallery set, the residual can be used as the dissimilarity score for partial face identification. SRC algorithm was originally proposed for face identification, little work has been done for SRC-based face verification. Instead of old approach in new key point detector in surf (speed up robust features) because it find more then blob key points. Grey Level Co-occurrence Matrix (GLCM) it used to increase accuracy in identifying verification score. Here 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 I and J, belong to the same subject or not.

For this task, use a set of background face images together with image I as a virtual gallery set, and the other input face image J as the probe. Note that the set of background face images does not contain the same subject as either of the two input face images.

The MKD-SRC algorithm is applied, and the verification score is defined as 1-r_c, where $r_c$is defined 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.

To handle pose variations, mirrored face images have been used to improve FR performance in different views. Motivated by this, the input face image, I, is horizontally mirrored as I', then both I and I' are put inthe virtual gallery set. In this way, there would be more chances for a left profile face image to match with the corresponding right one.It increase the accuracy in verification score in identification of partial face recognition

VI. Result And Discussion

SURF Keypoints

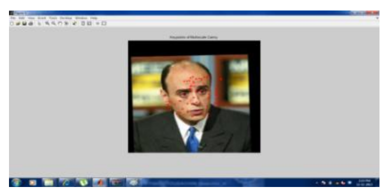

Fig 4.1 SURF Keypoints

The Key points of surf taken from alpaca response. The surf finds many more key points than the SIFT detector for face images, since there are more edges than blobs on a face

Patches

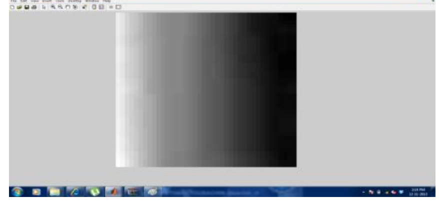

Fig 4.6 Patches

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Any one of patches takes from the surf key point. A local descriptor is constructed within each region.

Once the detected regions are normalized to a fixed size, a local descriptor is constructed within each region.

Gabor kernal

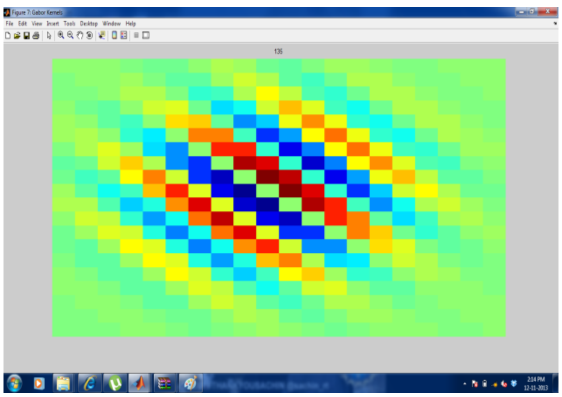

Fig 6.3 gabor kernal

The Gabor kernel is taking from the multi scan canny. It first applies the Gabor filter to each image patch.

Histogram

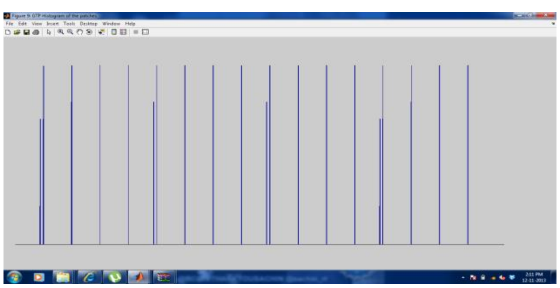

Fig 6.4 histogram

The histogram is taken from the GTP patches. The total area of the histogram is equal to the number of data. A histogram of GTPs is calculated in each grid cell.

Identification

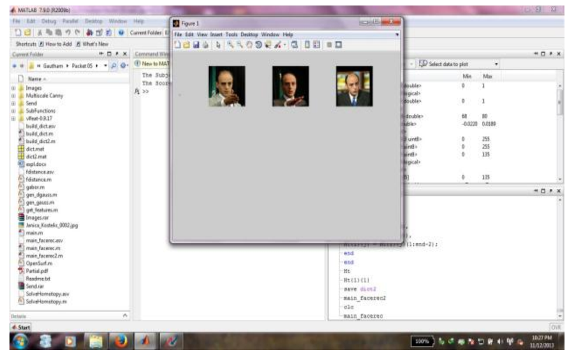

Fig 6.4 identification

Finally identification of given input image from the dictionary face using multi task representation and increase the accuracy in identification score.

As soon as the features are extracted from the user's input, then the generated template can be used to identify the user that whether he/she intended user. The proposed system will provide the user details for the particular if there is any matching.

Performance Analysis

Table 1
Accuracy of Recognition

	Threshold = 0.7	Threshold = 0.8	Threshold = 0.9
SIFT + GTP	81.4 %	89.6 %	84.1 %
SURF + GTP	86.3 %	94.3 %	92.1 %
SURF + LBP	88.3 %	95.7 %	93.4 %

Threshold (t) is the minimum distance below which two feature points are deemed to be similar. The optimal performance is reached for t = 0.8 using LBP features of SURF Keypoints.

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SURF keypoints are more characteristic of facial images and offer better performance than SIFT Keypoints. While GTP captures more information, the dimensions of the features are too large. LBP histograms capture the keypoint features in a more simple and direct way than GTP. The proposed method gives a recognition accuracy of 95.7 %.

Table 2
Computational Efficiency

	Time Taken (seconds)
SIFT + GTP	2.61
SURF + GTP	2.26
SURF + LBP	1.95

The proposed method (SURF+LBP) is computationally more efficient than GTP features. The average time taken is shown in Table 2.

VII. Conclusion And Future Work

This paper presents an approach to solve the problem of recognizing a face from its partial image and increase the accuracy in identification score, and proposed an alignment-free approach called MKD-SRC. It represents each face image with a set of keypoint descriptors (GLCM and SURF), and constructs a large dictionary from all the gallery descriptors. In this way, descriptors of a partial probe image can pesparsely represented by the dictionary, and the identity of the probe can be inferred accordingly. In case a partial face cannot be detected, it can still provide a matching score given a manually cropped face region.

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