International Journal of Emerging Trend in Engineering and Basic Sciences (IJEEBS)
ISSN (Online) 2349-6967
Volume 2 , Issue 1(Jan-Feb 2015), PP329-334

PARTIAL FACE RECOGNITION

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Abstract— There are many more methods for face recognition. Face recognition can be of two types as holistic face recognition and partial face recognition. Most of the methods are useful for holistic face recognition but only few methods can handle partial face recognition. Partial face recognition consists of face captured in an uncontrolled scenario without user's knowledge or co-operation or by using some handheld devices (such as mobile phone) where some of the component of face can be missing. In this paper we are going through various descriptors which can handle the arbitrary patch of an image. The SIFT and CanAff are the key point descriptors which locates key points on an face image. And the new key point is also developed called GTP for robust and discriminative face recognition which will show more promising result than SIFT and Caniff for partial faces without requiring face alignment.

Keywords— Partial face recognition, Alignment free, key point descriptor

I. INTRODUCTION

Face represents physiological biometric identifier. Face Recognition is major component of the body by which person can be identified. Face recognition (FR) is the problem of verifying or identifying a face from its image. Face recognition is the problem of identifying a specific individual, rather than merely detecting the presence of a human face, which is often called face detection. Face recognition accuracy is usually limited by large interclass variations caused by factors such as pose, lighting, expression, and age [1]. Face recognition in controlled conditions (frontal face and uniform illumination) has already achieved satisfactory performance; there still exist many challenges in uncontrolled scenarios, such as no frontal pose, facial occlusion, and illumination variations. 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 an arbitrary pose without user cooperation and knowledge. In such scenarios, it is quite likely that the captured image contains only a partial face 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, FaceVACS [4] requires localization of the two eyes, and PittPatt [5] detects several predefined landmarks for face alignment. Therefore, research in PFR is important to advance the state of the art in face recognition and enlarge the application domain.

Face Recognition process works in humans as well as in addressing many challenging real world applications, including DE duplication of identity documents (e.g., passport, driver license), access control, and video surveillance. The losses of all misclassifications are same is far from a reasonable setting because in almost all application scenarios of face recognition different kinds of mistakes will lead to different losses. Considering an example it would be troublesome if a door locker based on face recognition system misclassified a family member as a stranger such that she/he was not allowed to enter the house but it would be much more serious disaster if the stranger was misclassified as a family member and allowed to enter house.

II. LITERATURE REVIEW

The most popular approach for face alignment is to first detect the two eyes and then normalize the face geometrically. Other popular face alignment methods include the Active Shape Model (ASM) [2] and the Active Appearance Model (AAM) [3], which depends on localizing a certain fixed number (typically 68) of landmarks on holistic face. In a sparse representation-based alignment method was proposed in controlled scenarios. However, all these alignment methods would fail for face images with unknown missing portions of the face. Instead of holistic representation, some face recognition approaches have adopted parts-based representations to deal with occlusion and pose variations. A simple way is to divide the aligned face image into several sub regions match each sub region, and then fuse the matching results. Alternatively, one could detect several predefined components (such as eye, nose, and mouth), and then recognize the face by fusing the matching results for the components.

III. PROPOSED METHOD

In this paper, we present a general formulation of the partial face recognition problem. We require neither face alignment nor the presence of the eyes or any other facial component in the image. Specifically, we apply the Scale-Invariant Feature Transform (SIFT) feature detector to detect local feature key points, we are also applying CanAff detector which is a scale invariant Canny edge [6] based interest point detector proposed in [11], and an affine invariant shape adaptation technique[12].

Fig 1: Original image of partial face

IV. ALIGNMENT FREE PARTIAL FACE REPRESENTATION

A. Affine Invariant Key point Detection

The SIFT detector proposed by Lowe [8] is one of the most popular key point detectors. The SIFT key points have a robust repeatability property against

The SIFT detector proposed by Lowe [8] is one of the most popular key point detectors. The SIFT key points have a robust repeatability property against image translation, rotation, and scaling. This property is important for PFR because the faces we are matching are not aligned. However, SIFT key point regions are not invariant under affine transformation. The Canny's operator is one of the most widely used edge finding algorithms. Canny proposed a method that was widely considered to be the standard edge detection algorithm in the industry. In regard to regularization Canny saw the edge detection as an optimization problem.

B. SIFT

Large numbers of features can be extracted from typical images with efficient algorithms. In addition, the features are highly distinctive, which allows a single feature to be correctly matched with high probability against a large database of features, providing a basis for object and scene recognition. This approach has been named the Scale Invariant Feature Transform (SIFT). Following are the major stages of computation used to generate the set of image features:

1. Scale-space extrema detection:
   The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.
2. Key point localization:
   At each candidate location, a detailed model is fit to determine location and scale. Key points are selected based on measures of their stability.
3. Orientation assignment:
   One or more orientations are assigned to each key point location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.
4. Key point descriptor:
   The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

This is the initial preparation. The first stage of key point detection is to identify locations and scales that can be reputably assigned under differing views of the same object. Detecting locations that are invariant to scale change of the image can be accomplished by searching for stable features across all possible scales, using a continuous function of scale known as scale space. The scale space of an image is defined as a function, $L(x, y, \sigma)$, that is produced from the convolution of a variable-scale Gaussian, $G(x, y, \sigma)$, with an input image, $I(x, y)$:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y),$$

Where $*$ is the convolution operation in x and y, and

$$G(x, y, \sigma) = 1/2\pi\sigma^2 (e^{-(x2+y2)/2\sigma2})$$

To efficiently detect stable key point locations in scale space, we have proposed using scale space extrema in the difference-of-Gaussian function convolved with the image, $D(x, y, \sigma)$, which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k:

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y)$$

$$= L(x, y, k\sigma) - L(x, y, \sigma).$$

Laplacian of Gaussian, $\sigma^2\nabla^2 G$, an efficient approach to construction of $D(x, y, \sigma)$ is shown in Fig. 1.The initial image is incrementally convolved with Gaussians to produce images separated by a constant factor k in scale space, shown stacked in the left column. We choose to divide each octave of scale space (i.e., doubling of σ) into an integer number, s, of intervals, so $k = 2^{1/s.}$. We must produce s +3 images in the stack of blurred images for each octave, so that final extrema detection covers a complete octave. Adjacent image scales are subtracted to produce the difference-of-Gaussian images shown on the right. Once a complete octave has been processed, we resample the Gaussian image that has twice the initial value of σ (it will be 2 images from the top of the stack) by taking every second pixel in each row and column. The accuracy of sampling relative to σ is no different than for the start of the previous octave, while computation is greatly reduced. Please refer figure 2 for the Key points detected by SIFT detector.

C. CanAff

The drawback of SIFT for face image is that it provides a limited number of key point s because SIFT only seeks blob-like structures. Since most faces look generally similar to each other, a limited number of key point s may not be sufficient to discriminate between them. This limits its applicability to face recognition. So consideration of a scale invariant Canny edge [6] based interest point detector proposed in [11], and an affine invariant shape adaptation technique proposed in [12]. We denote the resulting detector as CanAff. The edge based detector finds many more key point s than the SIFT detector for face images, since there are more edges than blobs on a face. The affine invariant shape adaptation makes image matching more robust to viewpoint changes, which is desired in face recognition with pose variations. The CanAff detector first extracts edges with a multistate Canny edge detector [6], followed by a scale invariant local neighborhood for each edge point. The characteristic size of the local neighborhood is detected by seeking extrema in the local responses to the scale normalized LoG operator [10].

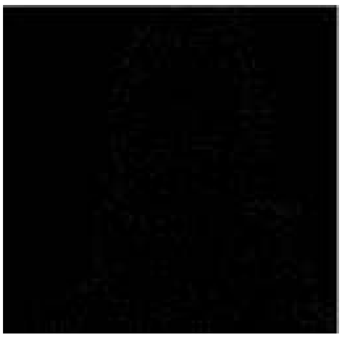

Fig 2: Key points detected by SIFT detector.

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. Canny's aim was to discover the optimal edge detection algorithm. In this situation, an "optimal" edge detector means:

- Good detection – the algorithm should mark as many real edges in the image as possible.
- *Good localization* – edges marked should be as close as possible to the edge in the real image.
- *Minimal response* – a given edge in the image should only be marked once, and where possible, image noise should not create false edges.

To satisfy these requirements Canny used the

Calculus of variations – a technique which finds the function which optimizes a given functional. The optimal function in Canny's detector is described by the sum of four exponential terms, but can be approximated by the first derivative of a Gaussian. Scale invariant Canny edge [6] based interest point detector [11]and an affine invariant shape adaptation technique proposed in [12]. We denote the resulting detector as CanAff.1 The edge based detector finds many more key point s than the SIFT detector for face images, since there are more edges than

Blobs on a face. The CanAff detector first extracts edges with a multistate Canny edge detector [6], followed by a scale invariant local neighborhood for each edge point. Please refer figure 3 for the Key point s detected by Caniff detector.

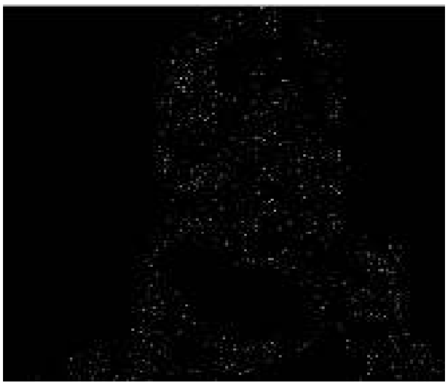

Fig 3: Key points detected by CanAff detector

V. CONCLUSION

The proposed approach shows promising results on synthesized partial faces. It is proved that SIFT(Scale Invariant Feature Transform) helps to locate the key point on face and finds the key point s of the components of the face. It helps to locate the key point s. Another method i.e. CanAff which is Canny Edge based on Interest point is also used to locate the key point s on the partial face. And the result shows that CanAff is better than Scale Invariant Feature Transform and locates many more key point s on the patial face. So we get more appropriate approach for locating face components. Hence it is proved that CanAff is better than SIFT..

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Volume 2 , Issue 1(Jan-Feb 2015), PP329-334

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