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Fixed Key point Preserving for Face Recognition under Non-Uniform Illumination Conditions

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Abstract: Scale Invariant Feature Transform (SIFT) has shown to be very powerful for general object detection/recognition. And recently, it has been applied in face recognition. However, the original SIFT algorithm may not be optimal for analyzing face images. In this paper, we analyze the performance of SIFT and study its deficiencies when applied to face recognition under different illumination conditions. The proposed method will eliminate undesirable keypoints in different stage. The original face is applied to get the original key point for SIFT and threshold is applied to eliminate low contrast and also noised features. Thus Fixed Keypoints-Preserving-SIFT (FKPSIFT) is introduced to keeps all the initial keypoints as features which are reliable and robust. Experimental results are shown with different illumination condition. The proposed method is significantly improved in face recognition compared with SIFT and other key point detectors.
Keywords: SIFT, Feature extraction, Feature matching.

I. INTRODUCTION

FACE recognition is an important capability of human beings in their social life. We can remember hundreds or even thousands of faces in our whole life and identify a face in different perspective variations, illuminations, ages, etc. Under very poor illumination conditions, a face can still be recognized, as the position of the different facial features and the face contours are usually sufficient for recognition[1]. This suggests an approach to face recognition, where by the geometrical positions of the different facial features are measured first, and then the details of each feature are used for further matching. This is also a common where-to-what approach for object recognition. The problem of human face recognition has been studied for more than 20 years. The existing approaches for face recognition may be classified into two categories, holistic and analytic. The holistic approaches consider the global properties of the pattern. Which projects face images onto a feature space that spans the significant variations among known face images Isodensity lines, which are the boundaries of constant gray level areas after quantizing an image, were also investigated for face recognition Dynamic Link Architecture is an object-recognition system in which learned objects are represented by sparse graphs. Object recognition can be formulated as elastic graph matching. Another method for human face recognition is by means of a similarity discriminant function (SDF) of images. For each class of training image samples, an optimal projection axis maximizing the similarity among these training image samples is calculated. The singular values (SV) feature vector is also used; it has some important properties of algebraic and geometric invariance, as well as insensitivity to noise[2]. All these methods require a long computing time since a face image is considered as a vector in a multidimensional space.

In our approach, we first use a new analytic method to select similar faces from a database. The positions of the different facial features and their outlines are located. A total of 15 feature points are chosen according to their significance, and the reliability of the detection. A head model is built in such a way that the rotation of the face can be estimated by geometrical measurements [3]. The feature points are adjusted to compensate for the effect of perspective variations. Only the similar faces in the database will be considered in the next step of face recognition.

II. FEATURES BASED FACE RECOGNITION

Over the past few years there have been some studies (from the early studies, to more recent ones, such as assessing the feasibility of the SIFT approach for face recognition. Lowe proposed a local feature description approach known as Scale-invariance Feature Transformation (SIFT)[4]. However, the SIFT approach performs the best under scale and rotation changes, but not illumination change since normalizing the vector is caused by the illumination changes. Hence, these problems are investigated in this paper. The

SIFT is based on a local feature description approach that is known for its invariance under rotation, translation, scale changes, blur changes, affine transformation, illumination changes, and other transformations. The procedure of SIFT consists mainly of four steps

A. Scale-space extrema detection,
B. Keypoint localization
C. Orientation assignment, and
D. Keypoint descriptor.

Firstly, the SIFT uses a Difference of Gaussian (DoG) function, Eq. (1), to do convolution on the image. We obtain different scale images by changing. To find interest points that are extremals (maximum or minimum) with regard to both scale and space, various versions of the original image that have greater and greater Gaussian blurring applied to them are created

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

Then, the images which are close in the similar resolution are subtracted to get a DoG pyramid[5]. In other words, subtracting an image from its more-blurred neighbor image gives the DoG. Finally, points that are maximum or minimum in their 3x3x3=27 neighborhood–9 pixels in the less-blurred image, 9 pixels in its own image and 9 pixels in the more-blurred image are marked. The DoG function is a kind of an improvement of a Gaus-Laplace algorithm (see Eq. (2))

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

$$= L(x,y,k\sigma) - L(x,y,\sigma) \qquad (2)$$

Where, $I(x,y)$ denotes an input image, and k denotes a scale coefficient of an adjacent scale-space factor. Secondly, points that have poorly localized along an edge are rejected. The interpolation to locate the keypoint accurately in scale and space is then deployed. Thirdly, $m(x,y)$ assigns a direction to each keypoint based on local image gradients and $\theta(x,y)$ creates a 36-bin orientation histogram and looks for peaks in the histogram (Eq. (3)). It is possible for a keypoint to be assigned multiple orientations.

$$m(x,y)=\sqrt{\big(L(x+1,y) - L(x-1,y)\big)^2 + \big(L(x,y+1) - L(x,y-1)\big)^2} \qquad (3)$$

$$\theta(x,y) = \tan^{-1}\left(\frac{(L(x,y+1) - L(x,y-1))}{L(x+1,y) - L(x-1,y)}\right) \qquad (4)$$

Finally, each keypoint is summarized in a way which allows it to be compared with other keypoints, while retaining its various robustness properties. Then we calculate 16 separate orientation histograms in a 4x4 neighborhood around each keypoint. The histograms are calculated with respect to the keypoint scale and orientation which have been distinct in previous steps[6]. Each histogram has 8 orientation bins. The contents of all of the histograms are concatenated to form a 128-element (16x8) vector. This vector is called the keypoint descriptor. Normalizing the vector makes it more robust to illumination changes.

One of the first attempts to use the SIFT algorithm for face recognition was presented. The algorithm used here, differs from original SIFT algorithm in the implementation of the matching stage. Each SIFT descriptor in the test image is matched with every descriptor in each training image. Matching is done using a distance based criterion[7]. A descriptor from the test image is said to match a descriptor from the training image, if the distance between the 2 descriptors is less than a specific fraction of the distance to the next nearest descriptor. The problem with this method is that it is very time consuming. Matching between two images has a computational complexity of O(n^2), where *n* is the average number of SIFT descriptors in each image.

In the original SIFT algorithm is rendered more robust by following one of two strategies that aim at imposing local constraints on the matching procedure: the first matches only SIFT descriptors extracted from image-windows corresponding to the mouth and the two eyes, while the second relies on grid based matching, Local matching, i.e. within a grid or a cluster, constrains the SIFT features to match features from nearby areas only. Local matching also reduces the computational complexity linearly. The computational complexity required for matching a pair of images by a local method is $O(n^2/s)$, where *s*is the number of grids or clusters. As seen from Fig. 1, where the basic SIFT algorithm from was used to match the SIFT descriptors, there are some keypoints matched, that do not represent the same characteristic of the face. Although we would expect the distance between such keypoints to be high, since they correspond to different regions of the faces, this is clearly not the case. Therefore better results are achieved, if certain subsets of SIFT keypoints are used for matching and only (spatially) corresponding subsets of SIFT descriptors are matched[8].

Only the SIFT descriptors between two corresponding clusters are matched. This ensures that matching is done locally. As a global matching criterion, the total number of descriptor matches is used. In SIFT features are extracted from the frontal and half left and right profiles. An augmented set of SIFT features is then formed from the fusion of features from the frontal and side profiles of an individual, after removing featureredundancy. SIFT feature sets from the database and query images are matched using the Euclidean distance and Point pattern matching techniques.

III. PROPOSED METHOD

A. Adaptive feature extraction

In the first stage of SIFT algorithm, scale-space extrema detection is performed by convolution an input image with scale-normalized Laplacian of Gaussian operators. Laplacian, being a second-order derivative operator, is very sensitive to noise. And it will detect a lot of keypoints along edges. However, keypoints along edges are very unstable, because their locations are very sensitive to small changes of neighboring texture[6]. To remove those unstable keypoints, Lowe proposed stage 2: unreliable keypoints removal. In this stage, keypoints with low contrast and high edge responses are removed. However, it is known that SIFT was designed for general object detection/recognition. General objects are rigid, and there are sharp transitions between different sides of an object. In other words, there are distinct structures with high contrast in general objects. Moreover, corners or straight lines are normal structures in general objects, which have high edge responses. Based on these characteristics of general objects, keypoints with low contrast (sensitive to noise) or along edges (unstable) should be removed. However, different from general objects, faces are non-rigid and smooth. There are no strict corners or lines in face images. And there are fewer structures with high contrast, because changes of pixel values in face images are gradual and slow. To show the deficiencies of unreliable keypoints removal algorithm in the SIFT approach. The initial keypoints detected in face image is shown in the figure 1.

(a) (b)

Figure 1**:** Keypoints detected in a face image: (a) original face (b) The initial keypoints using SIFT.

Hence, the original keypoints removal approaches of SIFT algorithm will eliminate some useful features when applied to face images. As the removal approaches are not reliable, we propose to keep all the initial keypoints as the input features[9]. And this is the rationale behind Fixed Keypoints Preserving-SIFT (FKPSIFT) for face images.

B. Fixed Keypoint Preserving SIFT Algorithm (FKPSIFT):

The Fixed Keypoint SIFT Algorithm is based on the supposition that each face was preliminary localized. Thus, each image consists only of a properly registered face region of a certain person. We assume that for the training procedure only “good” quality images area valuable. This assumption is reasonable, since in most operating face recognition systems the enrollment stage and with it the acquisition of training images is supervised. During training we apply the original SIFT technique and its accompanying keypoint detector to our training images and obtain a number of candidate keypoints for each image in the set of training images. Next, we apply a clustering procedure to the set of candidate keypoints to obtain k=100 centroids, which serve as the fixed keypoints for the computation of the SIFT descriptors

Here, in this proposed method the face image identifies the keypoints locations found by original keypoint detector. In this process unwanted keypoints are also detected which may be eliminated by cropping the face image from the original image[8]. The detected image will be having only face information which is useful for face recognition and to identify the important keypoint on the face. Keypoints remain after applying a threshold on the minimum contrast. This method of thresholding will eliminate keypoint which are necessary for face recognition which may lead to poor results. From this analysis, we concluded that the algorithm to remove unreliable keypoints in SIFT using thresholding approach is not reliable.

The descriptor for each keypoint, a support of 16×16 pixel neighborhoods around each keypoint in the Gaussian blurred image at the Keypoints scale is needed. Obviously, in this case, the keypoint is not describable due to the limitation of image size (the size of the support to generate such a descriptor is larger than the size of the input image)[9]. Hence, this fixed point preserving method will enable the Keypoints detected at large scales or near face boundaries as shown in Fig 2.

(a) (b) (c)

Figure 2**:** Training procedure for learning the keypoint locations (a) sample images processed (b) Original keypoint detect(c) Proposed keypoint locations.

IV. FEATURE MATCHING

Matching: As the number of descriptors for each image is the same (it equals the number of centroids k), the sum of the Euclidean distances between equally located de scriptors of the two images to be compared is used as the matching criterion. By doing so, computational complexity for matching between two images is also reduced to *O*(2k). Let us denote the sets of SIFT descriptors from the training images as $S_j = \{S_{i,j}\ (x_i,y_i);\ i = 1,2, \cdots, k\}$, where j =1,2,····, n denotes the training image index, n stands for the total number of training images, i represents the descriptor index, k denotes the number of fixed keypoint locations (i.e., centroids), and (x_i,y_i) denote the image location for the i-th SIFT descriptor[10]. Let us further assume that the n training images correspond to N different classes (i.e., subjects) with corresponding class labels $\omega_1,\omega_2,\cdots\ \omega_N$.Then, the matching procedure can formally be written as follows:

$$\longrightarrow \delta_{SL_2}(S_g, S_t) = \min_j \delta_{SL_2}(S_j, S_t) \qquad S_t \in \omega_g, \qquad (5)$$

Where S_t stands for the set of SIFT descriptor extracted from the test image at the k predefined image locations, and the matching function is defined as

$$\delta_{SL_2}(S_p, S_r) = \sum_i \delta_{L_2}(S_{i,p}, S_{i,r}) \qquad (6)$$

The above expression postulates that a given test image is assigned to the class ω_g, if the sum of the Euclidian distances between spatially corresponding descriptors of the test image and one of the training images of the g-th class is the smallest among the computed distances to all n SIFT descriptor sets of the training images.

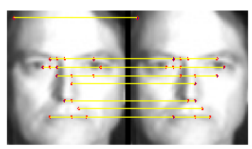
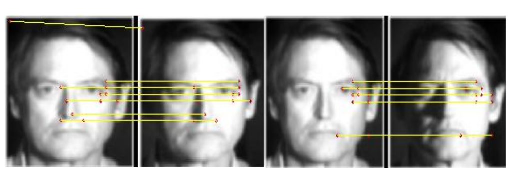


Figure 3: Proposed method keypoint matching.

V. RESULTS

The light is focused on the face from different directon which may cause non uniforn imllumniation on the face. This non uniform illumination may cause poor key point detection which results in poor face recognition. To imporve the face recognition the proposed methos is implemented over a set of images collect from face database with different illumination condition.Two sets of illumination condition are taken with light focusing on the face from left side and another set is from light focus from front down. SIFT Keypoints detected on the differently illuminated images of the same person: by the original keypoint detector. The feature matching with the proposed key points are shown with the original image as shown below in figure 4(a). In this matching all the keypoint are matched. In figure 4(b),4(c),4(d) the original image is matched with 80%,70%,60% and 50% of light focused from the left side of the face. The result shows that the feature key points are reduced gradually.



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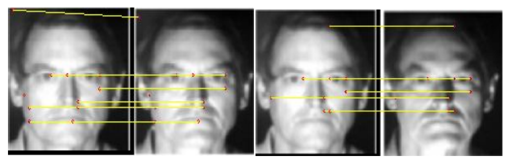
(a) (b)

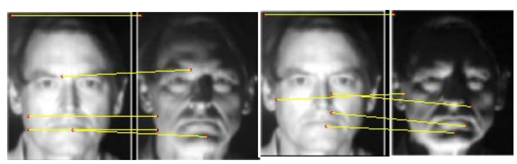
(c) (d)

Figure 4: Keypoint matching with illumination condition with light focused on left of the face

this matching all the keypoint are matched. In figure 5(a),5(b),5(c) and 5(d) shown below the original image is matched with 80%,70%,60% and 50% light focused from the front bottom side of the face.. The result shows that the feature key points are reduced gradually.



(a) (b)



(c) (d)

Figure 5: Keypoint matching with illumination condition with light focused on front bottom side of the face

But in both case of non-uniform illumination the minimum number of key point will help to identify the face. This identification can be done by storing the keypoint of original face and matching the key points of the non-uniform which is under the recognition. The matching can be implemented by and distance measures.

VI. CONCULSION

Thus Fixed Keypoints Preserving SIFT (FKPSIFT) is introduced to keeps all the initial keypoints as features which are reliable and robust. Experimental results are shown with different illumination condition. The proposed method is significantly improved in face recognition compared with SIFT and other keypoint detectors.

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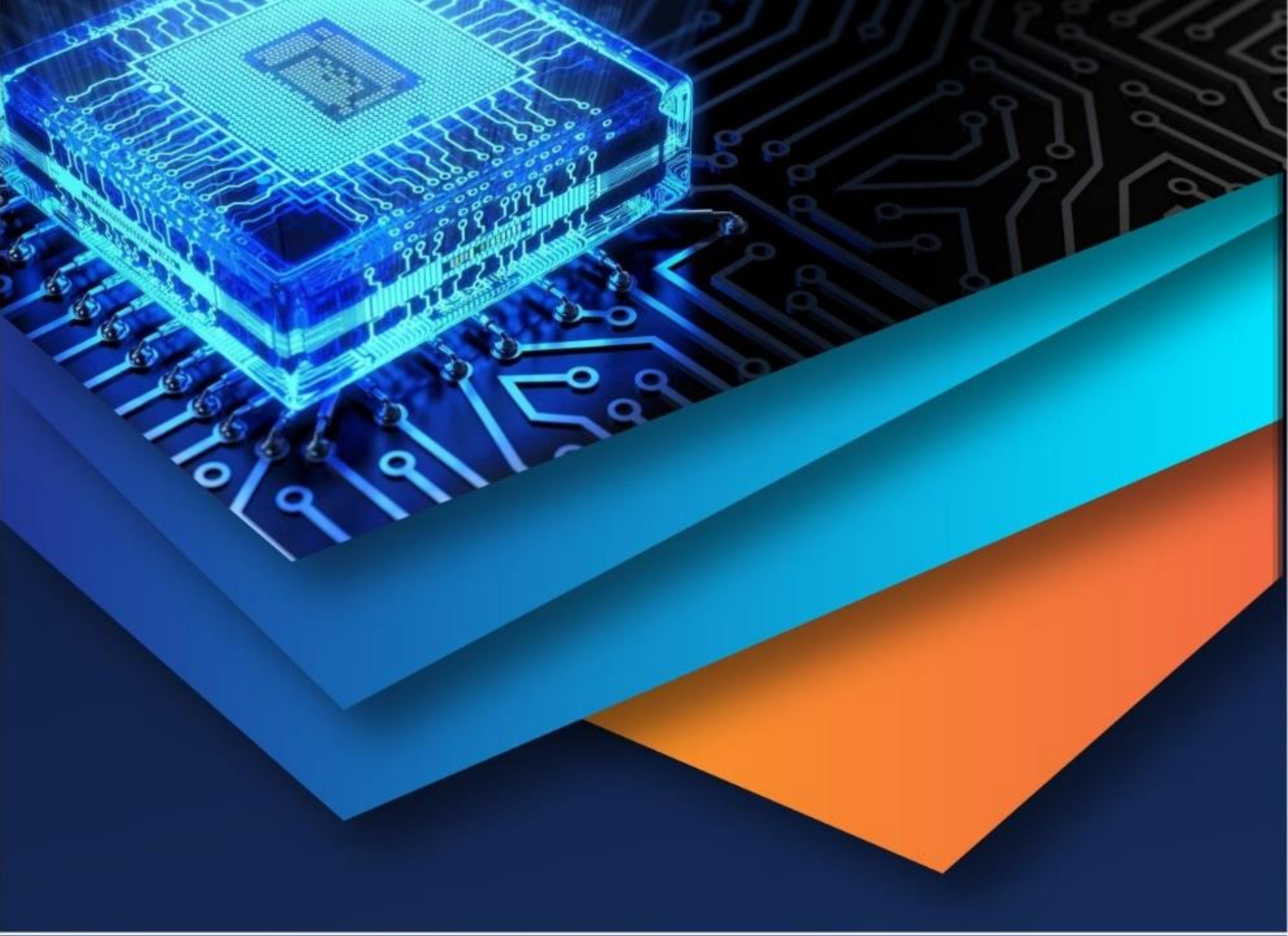

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