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Effective Descriptors based Face Recognition Technique for Robotic Surveillance Systems

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Abstract

The aim is to propose SPHORB Face Recognition technique for Robotic Surveillance systems. Surveillance bots with efficient face recognition system becomes even more powerful and adds to the applications of the bots. In this paper we compare the results of face recognition using SPHORB (a new fast and robust binary feature detector and descriptor for spherical panoramic image) [1] algorithm with ORB (Oriented Fast and Rotated Brief) [4] algorithm for classifying 2D and 3D images Database. In the first part 2D face images are randomly selected from LFW [32] with good sample of images across gender and ethnicity. The number of keypoints that were identified and number of matching keypoints between the 2D images using SPHORB and ORB were compared. From the results we determine that the SPHORB algorithm has identified more keypoints for the same 2D image than ORB, it has processed more images but ORB gives better accuracy than SPHORB for 2D images. In the next part we investigated the image matching between a front face 2D image with a 3D image. The front face image and 3D images are randomly selected from the ThatsMyFace.com [2] with good sample of images across genders, ethnicity and age. The front face image is compared with a randomly selected 3D image from the sample class set using SPHORB and ORB algorithms. The number of keypoints that were identified and number of matching keypoints between images using SPHORB and ORB were compared. From the results we determine that the SPHORB algorithm has identified more keypoints for the same image than ORB, it has processed more images and has accuracy comparable to the ORB algorithm.

Keywords: SPHORB; ORB; Keypoints; Front face image

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1. Introduction

The technology of robotics is advancing day by day and is capable of replacing human labor in areas where there are higher chances of errors. One such application is in the field of surveillance. Continuous monitoring of surveillance video is a task that requires very high level of visual attention and is not intellectually engaging, thus making it more prone to errors. In the current scenario, prevention of potentially ruinous incidents is more valued than their investigation. Smart surveillance that employs robots for monitoring activities and providing alerts when necessary, can form an effective security system. Robots equipped with latest technologies of artificial intelligence, facial recognition and machine learning can detect untoward movements and prevent unauthorized access.

Face recognition is a technique to recognize and match a person's face using different face images of the person. Every face has its own distinguishable landmarks, the different peaks and valleys that comprise facial features. Mathematical techniques are employed to recognize these distinct features and identify the points that distinguish faces (keypoints). Once the keypoints are identified the next step is to compare and match the keypoints to match the images with each other.

A typical application of face recognition involves training an algorithm pre-obtained training data containing the known face images. When a test image is given the algorithm matches the test image and identifies based on the knowledge gained in the training phase. Facial recognition proves to be very useful in smart surveillance- robots can identify and recognize individuals and thus allow or prevent their admittance. The face of a person can serve the purpose of an identity card, thus preventing forgery.

The challenge one faces in developing an accurate face recognition algorithm is partially due to the different variables in the image set such as illumination differences, poses of the subjects, facial expression and alignment of faces. Variations in these parameters in images of the same subject make it a very challenging problem to tackle. These problems are crucial to the smart surveillance system as well.

In this direction there has been successful research done by the computer vision community around the world and many methods have been proposed for detecting and matching face key points. The ORB [4] feature descriptor has been proved efficient and faster than the other feature descriptors like SIFT [5] and SURF [6]. ORB is a combination of FAST [15] key point descriptor and the BRIEF [16] key point descriptor. The ORB feature descriptor has been proved to give very accurate results for face recognition of planar images. The SPHORB [1] binary feature is another efficient algorithm that has been developed successfully to match the key points for spherical panoramic images. In the current project we aim to compare the face recognition results of SPHORB and ORB algorithms by applying them to a dataset of 2D images and another dataset of front face images and 3D images.

Nomenclature

SPHORB	Spherical Oriented Fast and Rotated Brief
ORB	Oriented Fast and Rotated Brief

2. Related Work

Scale Invariant Feature Transform (SIFT) [5] was one of the earliest methods developed for face recognition. It extracts features that are invariant to image scale and rotation and partially invariant to change in illumination. It employs fast nearest neighbour matching algorithm followed by Hough transform, verifying it through least squares solution. The major stages of computation include Gaussian function to identify potential interest points. Orientations are assigned to keypoints based on gradients. It then transforms image data into scale invariant coordinates. SIFT has been applied for face recognition and has been proved to be more efficient than Eigen faces and Fisher faces [10] with an accuracy of 96.3% on the ORL database. SIFT features are extracted and is considered to be matched with another feature if the distance between the features is less than a specific fraction so as to reduce the number of false matches.

Speeded Up Robust Features (SURF) [6] has most of its features that are similar to SIFT, however it uses Hessian matrix-based measure for the detector which makes it much faster and accurate. The interest points are selected at corners, blobs of the images and matching is done based on the distance between the feature vectors. SURF features applied to face recognition have been verified to be faster than SIFT. SURF features have only 64 dimensions unlike the 128 dimensional SIFT hence becomes faster during the matching step. Using the Laplacian sign an indexing scheme has been built for the implementation of SURF. The SURF-64 feature gives an accuracy of 95.6%.

Binary Robust Invariant Scalable Keypoints (BRISK) [10] achieves good accuracy with respect to matching keypoints and also has lower computational requirements than SIFT. This algorithm identifies keypoints that are robust to all possible image transformations. The points are identified using a saliency criterion. To achieve better computational cost, keypoints are detected in octave layers of image pyramid as well as in layers in between. Using quadratic function fitting the location and the scale of the keypoints are obtained in a continuous domain. A sampling pattern consisting of points lying on appropriately scaled concentric circles is applied to neighbourhood of the points to retrieve gray values. The oriented BRISK sampling pattern are used to obtain results that are assembled in the descriptor. The BRISK descriptors are binary in nature hence matching is done very efficiently.

Histograms Of Oriented Gradient (HoG) [21] involves the calculation of well-normalized local histograms of image gradient orientations on a dense grid. The distribution of local intensity gradients identifies the shape of object and the meticulous understanding of the corresponding gradient or edge position is not needed. This is performed by splitting the input image into number of small regions referred as cells and local 1-D histogram of gradient directions is collected for each cell. The local histogram energy is collected over larger regions referred as blocks and the cells in these blocks are hence normalized. The obtained normalized descriptors are referred to as Histograms Of Oriented Gradient. HoG based face recognition system for surveillance has been implemented successfully [22, 23, 24]. First face detection is done from the surveillance video and then clustering is applied on the detected face image.

Principal Component Analysis (PCA) [25, 26, 27] is a statistical method used to reduce the dimension of the image vector and hence the number of variables in face recognition. First 1-D vectors are obtained from the 2-D facial image which is transformed into compact principal components using PCA. The basis vectors obtained from PCA will be along the direction of the training vectors. These basis vectors are also referred to as eigen vectors. Each input face image is transformed into its eigen vectors. Hence a large input vector can be replaced by the small eigen vector. The input image can be reconstructed from the eigen vector (acting as key points) with very less error.

Linear Discriminant Analysis (LDA) [28, 29] is a method used to find linear combination of features which separate two classes. The obtained combination can be used as key features for the image. LDA acts as dimensionality reduction technique in which the face images are transformed into fisher faces by projecting the 1-D vector onto the fisher space. The fisher faces obtained has less variables compared to the original image vector. LDA models the difference between the classes which forms the basis for face recognition. Surveillance systems based on LDA have been implemented [30] and proved to be efficient.

Keypoints are the important points of a face image which are used to match images. They can be extracted from a face image using keypoint detectors such as FAST, SIFT, SURF and used for matching. The more the number of matched keypoints between two images, the more is the accuracy of recognizing the face. The FAST keypoint detector[15] does not append the direction of the keypoints unlike the SIFT which uses HoG (Histogram of gradients) where each keypoint is associated with a gradient vector which specifies its direction. But the FAST feature detector has been proved to be faster than the SIFT and SURF due to its less mathematical complexity. Since homography remains the same for corresponding point pairs, at least 4 points are required for homography estimation. More than 4 keypoint matches were considered to identify two images as matching.

3. Proposed Methodology

3.1. ORB and SPHORB

Oriented FAST and Rotated BRIEF (ORB) [4] is a combination of FAST (Features from Accelerated Segment Test) [13, 14] keypoint detector and the BRIEF keypoint descriptor [15]. It has been proved that it is twofold faster than the SIFT and SURF algorithms. It is also computationally efficient and less affected by Gaussian image noise. While the other algorithms pose challenges in real world applications, ORB can work effectively and efficiently even in such systems. Oriented FAST (oFAST) [4] FAST features do not have orientation component. In ORB, orientation component has been added to FAST features using intensity centroid that assumes corner's intensity is offset from its centre. The moments of patch is defined as [33]:

$$mpq = \sum x,y\ x^p y^q\ I(\mathbf{x}, \mathbf{y}) \tag{1}$$

and centroid is given by,

$$C=(m10/m00,m01/m00) \tag{2}$$

A vector is constructed from centre of corner to the centroid. The orientation of the patch is then obtained as

$$\theta = atan2\ (m01,\ m10) \tag{3}$$

The BRIEF descriptor has a large variance and a mean of 0.5. Once BRIEF is oriented along the keypoint, the means are shifted to a disturbed pattern. Hence Rotation Aware Brief (rBRIEF) [4] descriptor was developed which has high variance and is also uncorrelated. ORB is a combination of rBRIEF and oFAST descriptor.

Spherical Oriented Fast and Rotated Brief (SPHORB) [1] is a fast and robust binary feature for front face images. It is based on geodesic grid and works using hexagonal parameterization of the sphere. Robust features are constructed based on the hexagonal grids. It has been proved that SPHORB algorithm outperforms the other existing spherical feature descriptors. SPHORB employs Spherical FAST (SFAST) detector and Spherical rBRIEF descriptor [1] on the geodesic grid. Spherical FAST [1] detector identifies corners based on the brightness of the pixels if there exists nf = 10 to 18 number of neighbouring pixels darker or brighter than that particular pixel i.e.,

$$|I(\mathbf{x}, \mathbf{k}) - I(\mathbf{k})| > t \tag{4}$$

where k is the pixel under consideration, I is the intensity function, t is the threshold. The maximum value of threshold t is calculated based on the point till which it identifies the same pixel as corner. FAST score is then calculated using t. The value of nf decides the different type of detectors. When keypoints are extracted for values of nf from 10 to 18, SFAST-10 is observed to have best detection accuracy. Spherical rBRIEF is a descriptor is built from a keypoint based on the intensity comparisons of the neighboring pixels. The intensity comparison as

$$\tau(\mathbf{k};\mathbf{x},\mathbf{y})= \begin{cases} 1 & \text{if } I(\mathbf{x},\mathbf{k})<I(\mathbf{y},\mathbf{k}) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

x, y are neighbouring pixels of k and I(x, k), I(y, k) are their intensities. Hexagonal Gaussian kernel is used to reduce noise and is given by,

$$g(x)=exp\ (-(\mathbf{Tx})^T\ (\mathbf{Tx})\ /\ 2\delta^2) \tag{6}$$

3.2. Overview of the approach

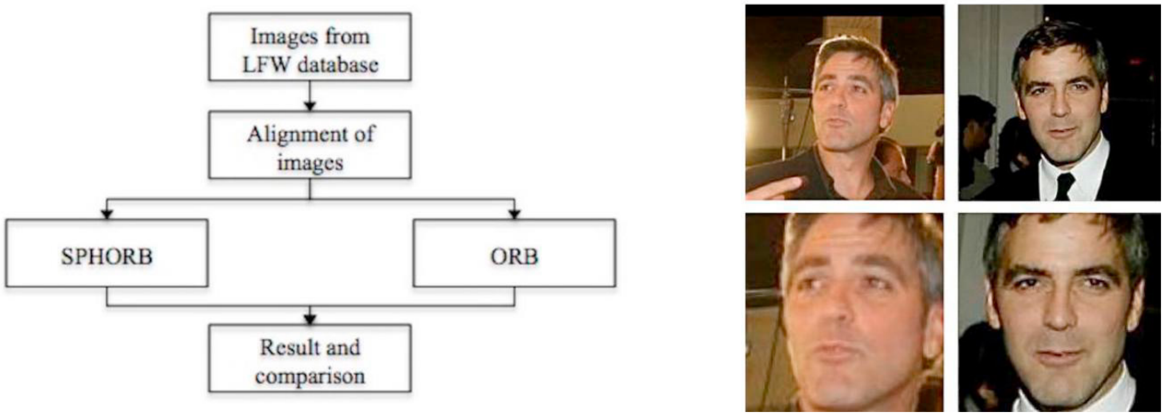
We used the LFW [32] database images first. In order to improve the accuracy of the match process we have done the face-alignment [9] and normalized the images for better comparison and matching. We identified image classes that had more than one image. The image classes with more than one image were 1680 in number. These image classes had 7361 face image files across different classes. Firstly, we aligned the images to center the image, rotate the face and scale the images to identical sizes using a face alignment algorithm [9]. The original images and aligned images of one class are shown in Fig 1b. A randomly selected aligned image was compared to another image classes and matched using SPHORB and ORB and the test results compared.

The algorithm of our approach for matching an image pair using ORB is:

For an image pair
    feature detector and descriptor = ORB
        Matcher = Brute Force descriptor matcher
            For each image
                Detect and Compute keypoints and descriptors
            With kNN Feature Match and k=2
                match descriptors of the images
                match keypoints based on a maximum distance ratio = 0.75 if match keypoints > 4
                    Image pairs match
                else
                    Image pairs do not match

The algorithm of our approach for matching images using SPHORB [1] is:

For an image pair
    feature detector and descriptor = SPHORB
        Matcher = Brute Force descriptor matcher
            For each image
                Detect and Compute keypoints and descriptors
            With basic Feature Match
                match descriptors of the images
                match keypoints based on a maximum distance ration = 0.75 if match keypoints > 4
                    Image pairs match
                else
                    Image pairs do not match

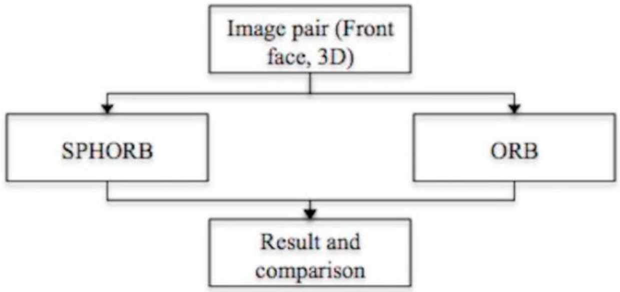


(a) (b)

Fig. 1. (a) Schematic of the system for processing LFW database; (b) Original (top) and aligned faces (bottom) from LFW database

We have next used the ThatsMyFace.com [2] image database for this work as it contains a large dataset of face images with corresponding 3D images of the individuals. We randomly identified image classes that had image samples that represented different gender, ethnicity and age of individuals. For comparison and classification 1000 image pairs of front face image and 3D image were randomly selected across image classes.

A randomly selected front face image was matched with a randomly selected 3D image using the SPHORB algorithm [1]. Using the OpenCV library for ORB matching [4] the same set of image pairs were matched. The number of identified key points and the number of matching key points were tabulated. The matching inlier key points as a percentage of the number of key points of the referring image was calculated. Image pairs with more than 4 matching key points were treated as a match. The test results were then identified for positives and negatives, true or false. Using the positives and negatives the accuracy and sensitivity were calculated.



(a) (b)

Fig. 2. (a) Schematic of the system for processing ThatsMyFace database; (b) Front face image (left) and 3D constructed image (right)

4. Experimental Results

Using the aligned LFW images, an image was randomly selected and matched against the first aligned image of another random selected class as shown in schematic Fig. 1a. For example, the pictures in Fig. 1b show the original images of George Clooney from LFW database and the aligned images of the same pictures. The alignment of the images was performed using the Face Alignment algorithm [9]. In Table 1 the image processing results are tabulated for SPHORB and ORB algorithms. SPHORB algorithm has discovered more key points than the ORB algorithm for the same image. It has also successfully processed many image pairs compared to the ORB algorithm. Table 2 show the image match results of matching a LFW image pair and the accuracy of the processes of SPHORB and ORB respectively.

Table 1. Comparison of LFW image pairs processed SPHORB and ORB

Number of image pairs	Image pairs processed by SPHORB	Image pairs processed by SPHORB (in %)	Image pairs processed by ORB	Image pairs processed by ORB (in %)
9992	9932	99.40%	4688	46.92%

Table 2. Comparison of match results of SPHORB and ORB - matching the LFW images

	SPHORB	ORB
Sensitivity	53.61%	39.53%
Specificity	53.85%	72.53%
Accuracy	53.85%	72.22%

Next, using the ThatsMyFace image database [2], the image pairs selected included a front face image as the first image in the pair and a 3D image as the second image as shown in schematic Fig. 2a. For example, the pictures in Fig. 2b show an image pair for George Clooney. The 3D image is generated by ThatsMyFace.com algorithm from a front face image and an optional side image. In Table 3 the image processing results are tabulated for SPHORB and ORB algorithms. SPHORB algorithm has discovered more key points than the ORB algorithm for the same image. It has also successfully processed many image pairs compared to the ORB algorithm. Table 4 show the image match results of matching the 3D image with a front face image and the accuracy of the processes of SPHORB and ORB respectively.

Table 3. Comparison of ThatsMyFace image pairs processed SPHORB and ORB

Number of image pairs	Image pairs processed by SPHORB	Image pairs processed by SPHORB (in %)	Image pairs processed by ORB	Image pairs processed by ORB (in %)
1000	985	98.50%	228	22.80%

Table 4. Comparison of match results of SPHORB and ORB - matching the 3D image with a front face image

	SPHORB	ORB
Sensitivity	59.89%	82.35%
Specificity	88.13%	85.78%
Accuracy	87.58%	85.53%

5. Conclusion

In this paper we have used the LFW [32] and ThatsMyFace.com [2] image databases. They have images of individuals with different gender, ethnicity and age. With the randomly selected image pairs for LFW, randomly selected front face and 3D image pairs from ThatsMyFace database, SPHORB has successfully processed more image pairs at 99.40% and 98.50% compared to ORB algorithm which processed only 46.92% and 22.80% respectively from LFW and ThatsMyFace database sample image pairs.

The accuracy of SPHORB algorithm is comparable and better at 87.58% compared to ORB algorithm which gave 85.53% accuracy as shown in Table 4 for ThatsMyFace database images while for LFW database ORB gave better accuracy at 72.22% compared to SPHORB which gave 53.85% as shown in Table 2. The Sensitivity and Specificity comparison is shown in Table 2 and 4 for the LFW and ThatsMyFace databases respectively.

From our investigations on the 2D image database of LFW and 3D image database of ThatsMyFace we find that the SPHORB is more accurate for matching with 3D images while ORB is more accurate for matching 2D images.

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