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Propose retina identification system based on the combination of SURF detector and BRISK descriptor

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Abstract

In this paper the design of hybrid retina matching algorithm that is used in identification systems is considered. Retina based recognition is apparent as the most secure method for identification of an identity utilized to differentiate persons.

The characteristics of Speeded up Robust Feature (SURF) and Binary Robust Invariant Scalable Key-Points (BRISK) algorithm have been used in order to produce a fast matching algorithm than the classical ones, those characteristics are important for real-time applications which usually need quick processing of a growing quantity of data. The algorithm is divided into three stages: retinal image processing and segmentation, extracting the local features from the retinal images using SURF and BRISK descriptors and finally matching those features using KNN matcher. The algorithm was trained with structured analysis of retina (STARE) database giving accuracy that reach 100%.

Keyword: Retina, Speeded Up Robust Feature, Binary Robust Invariant Scalable Key-Points.

اقتراح نظام لتحديد شبكيه العين بالاعتماد على دمج SURF detector و descriptor BRISK

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الخلاصه

في هذا البحث تم وصف التصميم الخاص بخوارزميه التطابق الهجينه المستحدمه في نظم التعرف على الاشخاص باستخدام شبكيه العين. تمييز الاشخاص بواسطه شبكيه العين يعتبر واحد من اكثر الانظمه الامنه المستخدمه للتعرف على هويه الاشخاص.

الخصائص الخاصه بخوارزميه Speeded Up Robust Feature وخوارزميه Binary Robust Invariant Scalable Key-Points تم أستخدامها من اجل انتاج خوارزميه تطابق اسرع من الخوارزميات الكلاسيكيه، وهذه الخصائص تعتبر مهمه لتطبيقات ال real-time والتي تتطلب عادةً معالجه سريعه لكميه كبيره من البيانات. الخوارزميه تقسم الى ثلاثه مراحل: معالجه وتقسيم صور شبكيه العين، استخراج الخصائص المحليه من صور شبكيه العين باستخدام واصف ال SURF و ال BRISK واخيراً مطابقه هذه الخصائص باستخدام KNN. هذه الخوارزميه تم تدريبها باستخدام قاعده البيانات STARE حيث وصلت نسبه دقتها 100%.

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1. Introduction

In the recent years retinal identification systems has gain an increasing attention because of its ability to solve security problems as a result of its comprehensiveness, distinction, time-invariance and that it cannot be faked. Also retinal patterns have very particular features, these features that taken from retina can recognize persons efficiently, even between genetically identical twins. The pattern will remain invariant during the person's life, except when a dangerous disease occurs within the eye [1].

Geethu Sasidharan (2014) [2] proposed Retina based Personal Identification System but instead of using SURF descriptor they utilize skeletonization process to detect the keypoints, and they use similarity transformation in order to check similarity with keypoints of reference images in database. This system gives an accurate results and also very low error rate.

Many systems have been developed for reaching these characteristics. Takwa Chihaoui, Hejer Jlassi, Rostom Kachouri, Kamel Hamrouni, and Mohamed Akil (2016) [3] proposed a new recognition framework based on retina and SURF. This method is very fast and robust against affine transformations such as rotation, scale changes and translation. They use of Optical Disc interest Ring (ODR) technique as a preprocessing step in order to further speed up the system and improve the performance. The system evaluated with VARIA database. It reaches a high quality with 100% of verification accuracy range.

Zhitao Xiao, Wan Zhu, Fang Zhang, Jun Wu, Lei Geng and Wen Wang (2016) [4] proposed a registration method based on speed-up robust feature, which is based on the original retinal image instead of vessels. They test the system on 120 retinal images of 20 person, the outcomes viewed that for various resolutions, angles, and translations, this method can be achieved automatic registration, average matching range can reach 93.3%, and precision can reach sub pixel level.

Fahreddin Sadikoglu, Selin Uzelaltinbulat (2016) [5] proposed a retina identification system based on neural network. First they extract the features of retinal image and then classify the features using neural network. For training the neural network they used back propagation algorithm. The accuracy of recognition the image patterns was achieved as 97.50 %.

The retinal identification systems can suffer from some problems such as imperfections in background intensity variation and affine transformations variations from pattern to other. These problems can effect on the extraction of retinal image features.

2. SURF (Speeded up Robust Feature)

SURF is an approach to detect and describe native features in image and finding the interest points in particular images that have totally different size of images and different viewpoints, completely different depths, scale changes and invariability during rotation, and strong to alternative typical geometric and mensuration transformation. It primarily uses for scale and rotation invariant feature transformation. It is inspired from Scale Invariant Feature Transform (SIFT) descriptor [6].

The detection of key-points with SURF is done in robust way more than SIFT because SURF use Hessian based detectors which are more stable than Harris based detectors that used by SIFT. In addition, SURF uses Laplacian of Gaussian to make distinction between background and foreground features, for this it uses only 64 dimensional vector while SIFT uses 128 dimensional vector [7] .The core concept of SURF is that the interest points are detected by the utmost determinant of the Hessian matrix. The Hessian matrix H(X, σ) in X for a point X=(x,y) of an image I [8], at particular scale can be seen as follows:

$$H(X, \sigma) = \begin{bmatrix} Lxx(X, \sigma) & Lxy(X, \sigma) \\ Lxy(X, \sigma) & Lyy(X, \sigma) \end{bmatrix} \quad (1)$$

Where Lxx (X, σ) is the convolution of the Gaussian second order derivative with the image I in point X. The SURF approximates the Hessian matrix determinant $HL(x, \sigma)$ by utilizing box filters, the 9 x 9 box filters, are approximations of a Gaussian with $\sigma = 1.2$ and represent the lowest scale. They will indicated by Dxx, Dyy and Dxy where w is the weight = 0.9 [8].

$$\mathrm{Det(Happrox)} = \mathrm{Dxx\ Dyy} - (\mathrm{wDxy})^2 \quad (2)$$

Also, SURF utilizes the integral image to approximate the various levels of scale space by adapting the box filters magnitude instead of the main image. This makes SURF faster in feature computation and quickly in matching capability.

The description of key-points with SURF is considered more appropriate than Histogram of Oriented Gradients (HOG), where the image is defined by the distribution of intensity gradients or edge directions that may be not very clear in poor illumination. The SURF descriptor depends on Haar wavelet responses and it is computed expeditiously by using the integral images.
As a way for being constant to the rotation of images, the Haar wavelet responses can be calculated in both directions horizontal and vertical in a circular neighborhood [7].

SURF approach consists of two major phases, first is the detection of interest point, and the second is the description in which the feature vector extraction that related to every interest points.
In spite of the fast of SURF computation, SIFT and SURF depend on gradients histogram. In which, the gradients of all pixels in the area need to be calculated. All these calculations cost time. Despite the speed provided by SURF through the use of integral images, it still not fast enough for some type of applications.

3. BRISK (Binary Robust Invariant Scalable Key-Points)

BRISK is new local features extraction technique and like other local technique such as SIFT and SURF, consist of detection phase (which detect the key-points) and description phase (which characterize its neighborhood).BRISK is considered as binary descriptor in which one can convert most of the information of an area as a binary string using only comparison of intensity images. This can be done very fast, as only intensity comparisons need to be made.

In general, binary descriptors are composed of three parts: A sampling pattern, orientation compensation and sampling pairs. BRISK features are invariant to scale and rotation operations due to the additional step of local maxima search that is not only in image space, but also in the scale space [9].

BRISK technique can achieve similar robustness of SIFT but with far less processing time due to the use of faster corner detector technique. This technique is Adaptive and Generic corner detection based on Accelerated Segment Test (AGAST) which is an improvement of Features from Accelerated Segment Test (FAST) detector that increases the speed of detecting key-points while maintaining the same detection performance.

BRISK descriptor uses a point-pair sampling pattern. This sampling pattern is symmetric and circular patch. This pattern composed of 60 total points arranged in four concentric rings. The point-pairs are classified into two subsets: the long-distance subset (which is used with the region gradients to obtain direction and angle of the descriptor) and the short-distance subset (which provide a binary descriptor vector of 64 bytes based on comparing pairs of points to form the descriptor. BRISK procedure is consisting of two phases, key-points detection phase and key-points description phase [10].

4. Proposed Methodology

In this paper, a new retinal identification system based on SURF detector and BRISK descriptor has been proposed in order to extract the local features of the retinal image. In the proposed system, an automated blood vessel segmentation algorithm that based on histogram equalization technique has been used as shown in section (4.1), Next, the fast detection of SURF key-points is explained in order to detect the key-points. Then, instead of using SURF descriptor a binary descriptor (BRISK) has been utilized in order to extract the local features of retina because binary descriptors depend on making a comparison between pixels that result in binary strings of short length (usually 256 bits). These comparisons are greatly faster than gradients operations, so binary descriptors can be extracted in a portion of the time required to calculate the common gradient based descriptors as shown in section (4.2).

All These characteristics are important for real-time applications which usually need greatly fast processing of a growing quantity of data. The final step is implementation of k-Nearest Neighbor (KNN) search as a matcher as shown in section (4.3). A 200 images from STARE database has been used to train the system and 50 images to test it the proposed system is shown in Figure-1.

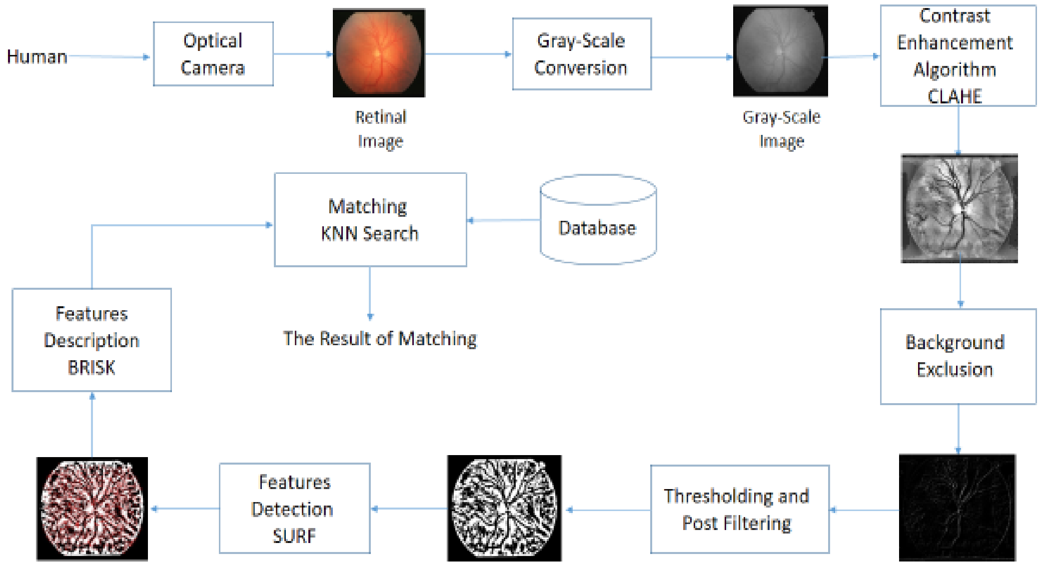

Figure 1-The proposed system.

4.1 Retinal Image Processing and Segmentation

The blood vessels of retinal image have a special pattern, this pattern is different from eye to eye and individual to individual. This characteristic has been utilized for designing a new person identification system. This technique extract the blood vessels of retinal image by taking the advantages of robust processing and segmentation techniques. This algorithm consist of four phases:

1. Convert image to gray-scale.
2. Enhancement of image contrast.
3. Background exclusion.
4. Image thresholding.

4.1.1 Convert Image to Gray-Scale

First the color retinal image is converted to gray-scale image in order to simplify the blood vessel segmentation and reduce the processing time as shown in Figure-2.

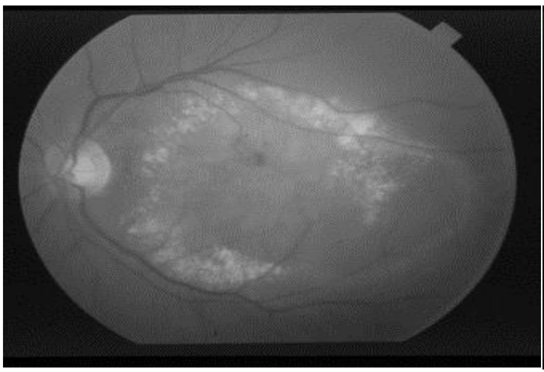

Figure 2-(a) RGB image.

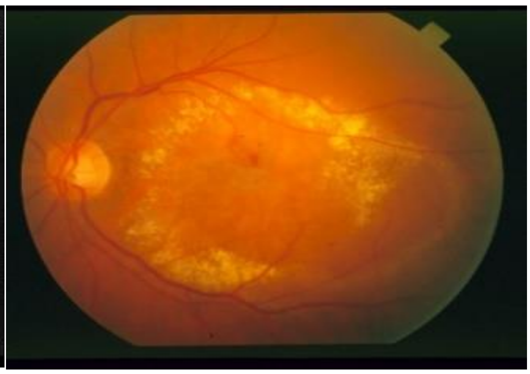

Figure 2-(b) Gray-scale image.

4.1.2 Enhancement of Image Contrast

There are many techniques are employed to enhance the contrast by stretching the domain of the intensity values of the image in order to convert the whole domain of the image, but Contrast Limited

Adaptive Histogram Equalization (CLAHE) algorithm [11] is considered as one of the most widely used in medical images. CLAHE has been performed on the retina gray-scale image as shown in Figure-3.

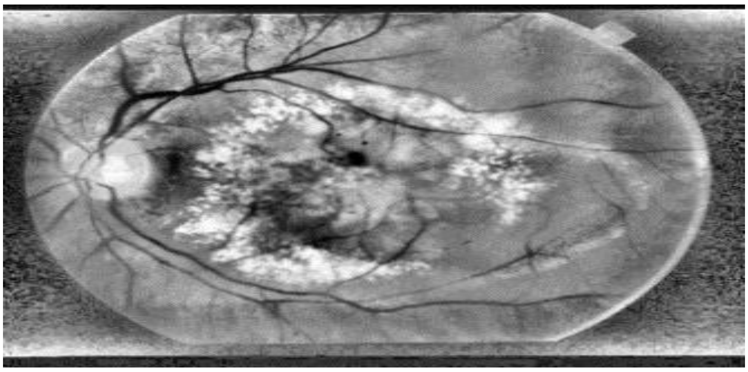

Figure 3-retinal image after performing CLAHE.

4.1.3 Background Exclusion

The major aim of this step is to remove the background variations in illumination from the retinal image, by subtracting the CLAHE image (in Figure- 3) from the average filtered image (in Figure-4). For implementing the average filter a window of size 9x9 pixel has been used on the CLAHE image as shown in Figure-4, and then subtract it from the average filter image, the final result is shown in Figure- 5.

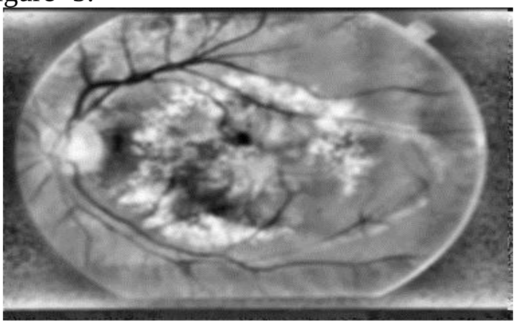

Figure 4-Average Filter image.

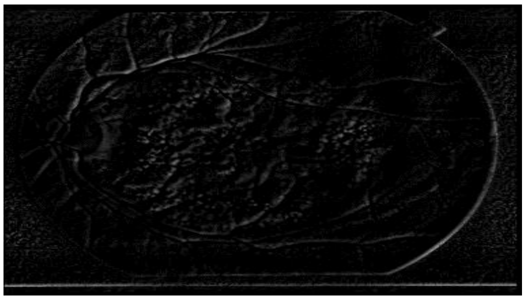

Figure 5- Subtracted image.

4.1.4 Image Thresholding

In order to produce a binary image that has two values 0 and 1 (1 the background and 0 the blood vessels) the adaptive thresholding has been applied (adaptive thresholding changes the threshold dynamically over the image) so that the retinal image can be invariant to different lighting condition. The algorithm compute the threshold for a small areas of the image an NxN region around the pixel location is selected, the image resulted from the thresholding is shown in Figure- 6. As a result we get different thresholds for different areas of the same image because for each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value. Then in order to remove the noise a mask image has been created and subtract it from the binary image and apply the median filter on it as shown in Figure- 7.

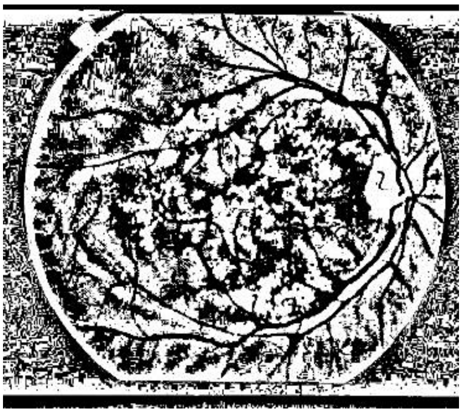

Figure 6-Image result after thresholding.

Figure 7-Binary blood vessels image.

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4.2 The Proposed Hybrid Detection and Description Algorithm

The classical detection and description algorithms have the problems of large computation and slow speed [12]. Because of the problems existing in the classical algorithm, a fast matching algorithm based on the combination of SURF key-points detector and BRISK descriptor has been proposed as shown in algorithm 1.

First, the binary blood vessel image (shown in Figure-7) will be considered as input image for the proposed algorithm, then the combination of SURF key-point detector and BRISK descriptor has been used in order to present local feature description algorithm that is faster and more accurate than if they have been used separately.

The SURF detector extract the key-points from the image based on the approximation of the Hessian matrix determinant as shown in equation 2. Also in order to make the system work faster and to reduce the very large number of key-points that SURF detect in retinal image, the number of octaves and layers of the SURF scale space has been reduced from 4 octaves and 2 layers to only one octave and one layer.

For BRISK descriptor it compute the orientation of the key-points that is been localized as shown in Figure- 8 by the SURF detector by utilizing local gradients [13] as shown in as follows:

$$g(pi,pj) = (pj - pi).\frac{I(pj,\sigma j) - I(pi,\sigma i)}{||pj - pi||^2} \quad (3)$$

Where g(pi,pj) is the local gradient between the sampling pair (pi,pj), I is the smoothed intensity value, $I(pj,\sigma j)$ is the intensity values of these points and σ Gaussian smoothing with standard deviation. As all binary descriptor BRISK make comparison between intensity values [13] as follows:

$$b = \begin{cases} 1, & I(pj^{\propto},\sigma j) > I(pi^{\propto},\sigma i) \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

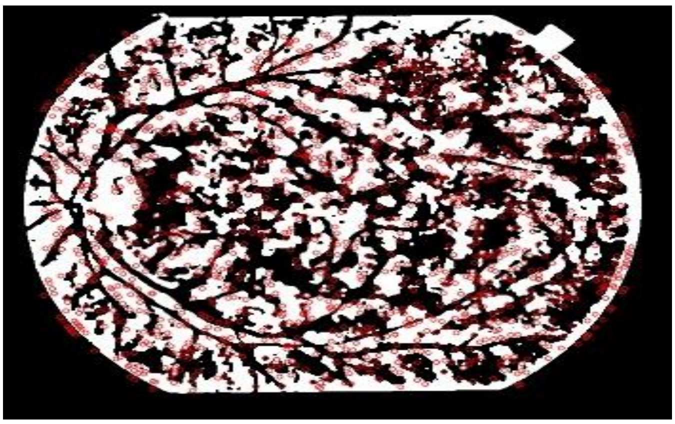

Figure 8-key-points on the binary retinal image.

Algorithm 1: The Proposed Hybrid Algorithm.
Input: Binary retinal image of blood vessels Rbinary, number of SURF Octaves =1, number of SURF layers =1. **Output:** Feature vector from Rbinary.
Begin **Step1:** For each Rbinary in the data base compute SURF detector. **1.1:** For each pixel in Rbinary compute the integral image Rintegral. **1.2:** Constrict the scale space by applying 9x9 box filters Dxx, Dyy, Dxy which are approximations of Gaussian for Computing the key-points. **1.3:** Compute the approximated determinant of the Hessian matrix for each patch in Rintegral the resulting image is RHessian as defined in equation (2). **1.4:** Setup the minimum Hessian threshold to 300. **1.5:** If the detected key-point < minimum Hessian threshold then The key-point is rejected. **Step2:** For each image key-points compute BRISK descriptor. **2.1:** Calculate the key-point orientation by using local gradients between the sampling pairs. **2.2:** For each key-point compute its angle by summing every local gradients among each long pairs and divide the arctangent of the y gradient component by the x gradient component. **2.3:** For each key-point check the intensity value. **2.4:** If the value of the first point intensity in the short pair is larger than the intensity value of the second point the corresponding bit of the descriptor is set to 1 otherwise set to 0 as defined in equation (4),The result is binary feature vector for each image. **End**

4.3 Matching using KNN Search

K Nearest Neighbor (KNN) algorithm is one of machine learning algorithm that is considered as non-parametric lazy learning algorithm. Effective implementations can store the data using complex data structures like k-d trees to make search and matching of new patterns during prediction efficient [14].

In the proposed system the KNN search will calculate the distance between the query image descriptor and all the image descriptors in the database to find the best match by return K number of pairs with the lowest distance. The bad matches are thrown keeping only the good one.

There are many SURF features detected in the query image have no matching feature in the database. In order to avoid wrong matches, it would be essential to eradicate those matches that are far from their query feature. The features that are poorly matched can be spotted by comparing the distances of the first and second nearest neighbor. If the distances are similar, as calculated by their ratio, the match is disallowed. Furthermore, disregard matches that are far apart.

5. Results

The results were obtained from testing 50 images taken from the structured analysis of retina (STARE) database after training it with 200 images in order to evaluate the system. The system has been evaluated with precision metric according to the following equation:

$$P = TP / TP + FP \tag{5}$$

Where TP is the number of true positive and FP is the number of false positive.

The images were captured using a TopCon TRV-50 fundus camera with FOV equal to thirty-five degree [15].

Table-1 shows examples of retinal images from STARE database that have been used in this system. First the results of SURF and BRISK implementation on this retinal images have been shown and then compare it with the proposed hybrid algorithm in the term of number of key-points, matching time and matching correctness as shown in Table-(2, 3).

Table 1-Subset of retinal images From STARE.

No.	Retinal Image	No.	Retinal Image
Image1		Image5	
Image2		Image6	
Image3		Image7	
Image4		Image8	

Table 2-Comparison between original SURF and the proposed algorithm in the term of number of key-points, time efficiency and the detection precision

	The Original SURF			The Proposed Algorithm		
NO.	Number of Key-points	Matching Time	Matching Correctness	Number of Key-points	Matching Time	Matching Correctness
Image1	3668	16.8 sec.	True	1349	3.8 sec.	True
Image2	3528	15.5 sec.	True	1406	3.2 sec.	True
Image3	3882	16.4 sec	True	1511	4.2 sec.	True
Image4	4100	16.1 sec.	True	1676	3.0 sec.	True
Image5	3604	16.4 sec.	True	1402	3.6 sec.	True
Image6	3485	15.4 sec.	False	1359	2.3 sec.	True
Image7	3872	17.6 sec.	True	1529	5.1 sec.	True
Image8	3572	15.3 sec.	False	1356	2.9 sec.	True
Total	29711	129.6 sec.		11588	28.1 sec.	100%

Table 3-Comparison between original BRISK and the proposed algorithm in the term of number of key-points, time efficiency and the detection precision

The Original BRISK				The Proposed Algorithm		
NO.	Number of Key-points	Matching Time	Matching Correctness	Number of Key-points	Matching Time	Matching Correctness
Image1	4917	17.5 sec.	True	1349	3.8 sec.	True
Image2	4696	12.2 sec.	True	1406	3.2 sec.	True
Image3	5013	15.1 sec.	False	1511	4.2 sec.	True
Image4	4959	9.3 sec.	False	1676	3.0 sec.	True
Image5	4373	12.2 sec.	True	1402	3.6 sec.	True
Image6	3511	7.4 sec.	True	1359	2.3 sec.	True
Image7	4988	17.5 sec.	True	1529	5.1 sec.	True
Image8	4714	9.2 sec.	True	1356	2.9 sec.	True
Total	37171	100.4 sec.		11588	28.1 sec.	100%

The experimental results in Table2 and table3 show that the SURF algorithm gives a false result in detecting rotated images (image 6 and image 8), but gives us a good result when it detects blurred or contrast images also the time of SURF matching is considered to be very long as compared with BRISK.

While the BRISK algorithm gives us superior results as compared with SURF in the term of time and matching accuracy because the BRISK descriptor is robust against transformations.
Thus, BRISK descriptor has been used in order to make the algorithm resulting from the integration of this descriptor with the SURF detector gives excellent results that reaches 100% with all images (rotated, blurred and contrast) and the time is reduced by 78.3% as compared with SURF and 72.01 % as compared with BRISK.

Table 4-Comparison between the proposed system and previous retina identification systems

Identification Systems	Accuracy Rate
Zhitao Xiao[4] system	93.3%
Fahreddin Sadikoglu [5] system	97.50%
Ritesh Kumar Gharami[16] system	95%
The proposed system	100%

6. Conclusions

In this paper, a hybrid matching algorithm that is used in identification system is proposed in order to solve the classical detection and description algorithm problems. The experimental results are compared with those of SURF, BRISK algorithms, the BRISK algorithm is 22.5% less time than SURF, Also the BRISK shows more robustness against transformation than SURF. As result the combination between them give as an excellent results reach 100% accuracy rate and the time is reduced by 78.3% as compared with SURF because the number of octaves and layers in the scale space has been reduced and 72.01 % as compared with BRISK . As a future work retinal identification system can be modified by considering some technique to enhance the feature extraction stage such as FAST corner detector or using binary detector like Binary Robust Independent Elementary Features (BRIEF) detector.

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