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# Retinal identification system based on Optical Disc Ring extraction and new local SIFT-RUK descriptor

**Abstract:** Personal recognition based on retina has been an attractive topic of scientific research. A common challenge of retinal identification system is to ensure a high recognition rate while maintaining a low mismatching FMR rate and execution time. In this context, this paper presents a retinal identification system based on a novel local feature description. The proposed system is composed of three stages, firstly we enhance the retinal image and we select a ring around the optical disc as an interest region by using our recently proposed Optical Disc Ring ODR method. Secondly, in order to reduce the mismatching rate and speed up the matching step, we propose in this paper an original alternative local description based on the Remove of Uninformative SIFT Keypoints, that we call SIFT-RUK. Finally, the generalization of Lowe's matching technique (g2NN test) is employed. Experiments on the VARIA database are done to evaluate the performance of our proposed SIFT-RUK feature-based identification system. We show that we obtain a high performance with 99.74% of identification accuracy rate without any mismatching (0% of False Matching Rate FMR) and with a low matching processing time compared to existing identification systems.

**Keywords:** Biometric, Retinal identification systems, Optical Disc Ring (ODR) method, Scale Invariant Feature Transform (SIFT), Remove of Uninformative Keypoints (RUK), Speeded Up Robust Features (SURF).

## 1 Introduction

Biometric recognition is a challenging topic in pattern recognition area based on distinguishing and measurable "morphological and behavioral" characteristics such as face, retina, iris, ADN, etc [1]. Retinal recognition has received increasing attention in recent years as it provides promising solution to security issues [2]. Hence, nowadays,

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retina is one of the most secure and valid biometric trait for personal recognition due to its uniqueness, universality, time-invariance and difficulty to be forged. Indeed, retinal patterns have highly distinctive characteristics and the features extracted from retina identify effectively individuals, even among genetically identical twins [1]. In addition, this pattern will not change through the life of the individual, unless a serious pathology appears in the eye.

Existing retinal recognition systems include two modes: Identification which compares each pattern to all others (1:N) and Verification which compares the pattern to other patterns from the same individual (1:1). Both of these identification and verification systems aim actually to find the best compromise between the good retinal recognition accuracy and the processing time. In this context, we proposed recently an original ring selection as a region of interest around the optical disc that we called "ODR". Two new ODR-based retinal recognition systems were developed. Our SIFT [4]-based identification system [11] gives a high identification rate (99.8%) but still suffers from an important execution time (10.3s). The recently proposed SURF [6]-based verification system [12] offers a high verification rate (100%) and a low processing time thanks to the verification mode that compares one pattern to only the other ones belonging to the same individual. However, it suffers from mismatching and slowness in the identification mode. Consequently and to solve these problems, we present in this paper a new retinal identification system. In which, we use firstly the ODR method [11], then we employ the SIFT description [4] since its accuracy and finally the g2NN matching. In order to reduce the mismatching rate and speed up the matching step, we propose in this paper an original alternative local description based on the Remove of Uninformative SIFT Keypoints. Our new local feature descriptor is named SIFT-based Removal Uninformative Keypoints (SIFT-RUK). It allows an important identification rate while reducing the number of mismatching keypoints and speed up the execution time.

The remainder of this paper is organized as follows: next section presents the related works of retinal recognition systems based on local features. Our proposed identification system is detailed in section 3. Section 4 illustrates the obtained experimental results. Finally, conclusions are discussed in section 5.

## 2 Biometric recognition systems based on local feature descriptors: Related works

Image geometric transformations, illumination changes, mismatching and processing time are the most challenging problems in retinal biometric recognition. Local feature descriptors [4] [6] are distinctive and robust to geometric changes, contrary to global generic algorithms [8]. In this context, many different local descriptor-based biometric system have been developed in the literature [7] [11].

The most known and performant local feature descriptor is the Scale Invariant Feature Transform (SIFT), developed by David Lowe [4] in 1999. Thanks to its distinctiveness to translation, rotation and scale changes, it is widely used in object recognition. For instance, it was employed in adaptive optics retinal image registration by Li et al [18]. Indeed, it extracts corner points and match corresponding ones in two frames by correcting the retina motion. However, its main defect is that it may suffer from a huge keypoints number which leads to eventual mismatching and a consequent high matching processing time. In order to overcome this drawback, recent extensions of SIFT algorithm [5] have been proposed, as well as some preprocessing and matching topologies which reduce the number of extracted local features. In 2008, Herbert Bay [6] proposed a speed local descriptor named Speeded Up Robust Features (SURF) which is similar to SIFT but faster with 64 dimensional descriptor. This algorithm is used on biometric recognition [7] in 2009 and proved its efficiency in term of processing time. So, to further speed up the local feature extraction, Israa Abdul et al. [10] applied in 2014 the Principle Component Analysis (PCA) to the SIFT descriptor. The PCA reduced the dimensionality of SIFT feature descriptor from 128 to 36, so that the PCA-SIFT minimized the size of the SIFT feature descriptor length and speeded up the feature matching by factor 3 compared to the original SIFT method [4]. In [19], sub-segments around the pupil (left, right and bottom of the iris), are used as input for SIFT feature extraction instead of the whole iris image. In retinal recognition, we proposed in 2015 a new ROI selection based on Optical Disc Ring (ODR) extraction [11]. It aims to maintain the most dense retinal region in order to improve the SIFT-based identification rate and further decrease the execution time. In 2016, we exploited the SURF descriptors in retinal verification system [12]. This system is faster than some existing ones, but it still suffers from some individual mismatching in identification mode. In order to reduce the mismatching rate and speed up the matching step, we propose in this paper a retinal identification system based on the Remove of Uninformative SIFT Keypoints. Next section details the proposed system based on SIFT-RUK descriptor.

### 3 Proposed local feature SIFT-RUK descriptor-based retinal identification system

In this work, we propose a novel retinal identification system based on the Remove of Uninformative SIFT Keypoints. This proposed system uses firstly the ODR method [11], then employs the new proposed SIFT-based Remove of Uninformative keypoint (SIFT-RUK) description and finally the g2NN matching. The flowchart of the proposed system is illustrated in the Fig. 1.

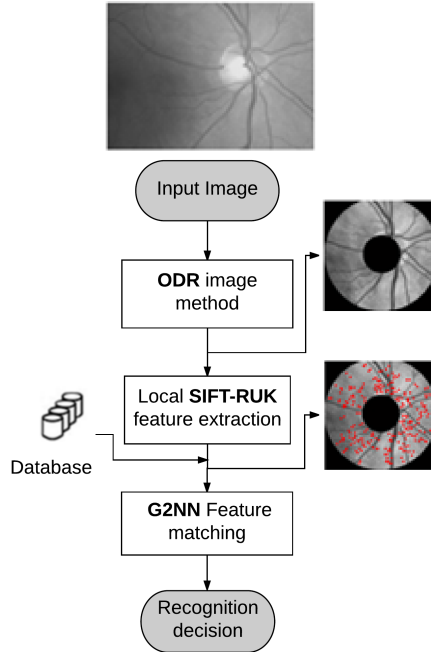


Fig. 1: Flowchart of our proposed retinal identification system.

### 3.1 Ring extraction around the optical disc

On the one hand, the presence of noise, the low contrast between vasculature and background, the brightness, and the variability of vessel diameter, shape and orientation are the main obstacles in retinal images. On the other hand, SIFT characterization is sensible to the intensity variation between regions, which requires the elimination of the brightest area (the optical disc). In order to overcome these problems, we use our recently proposed Optical Disc Ring (ODR) extraction [11]. The CLAHE technique [20] is used to improve the quality of the retinal image. Then a ring around the optical disc is selected as an interest region. The output of this first step in our identification is shown on the Fig. 2.

### 3.2 SIFT-RUK feature descriptor

In this step, we improve the Scale Invariant Feature Transform (SIFT) [4] local image descriptor. We apply for that an original Remove of Uninformative Keypoint (RUK) method. It allows to reduce the number of redundant SIFT keypoints while

maintaining the quality of description. The SIFT-RUK local descriptor algorithm is detailed in the following subsections.



**Fig. 2:** The Optical Disc Ring (ODR) extraction step: (a) the input retinal image and (b) the extracted ring around the optical disc.

### 3.2.1 The standard SIFT description

The standard SIFT description is stable and robust to some imperfections acquired by retinal image process such as scale, rotation, translation and illumination changes. The SIFT algorithm includes four stages [4]: scale-space peak detection, keypoint localization, orientation assignment and keypoint description.

#### Scale-space peak detection

This first stage aims to recognize those locations and scales that are identifiable from different views of the same object. The scale-space is defined by this equation 1.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

Where:  $L(x, y, \sigma)$ ,  $G(x, y, \sigma)$  and  $I(x, y)$  are respectively the scale-space function, the variable scale Gaussian function and the input image.

In order to detect the most stable keypoint locations in the scale-space, we compute the distance of Gaussians  $D(x, y, \sigma)$  in different scales, as given by the equation 2.

$$D(x, y, \sigma) = L(x, y, s\sigma) - L(x, y, \sigma) \quad (2)$$

Where  $s$  is a scale factor.

In order to detect local scale-space extrema, we compare each point with its 8 neighbors in the same scale, and its 9 neighbors in respectively the immediate upper

and downer one scale. If this point is representing the minimum or the maximum of all compared ones, it is considered as an extrema.

### Keypoint localization

In this second stage, we compute the Laplacian value for each founded keypoint in stage 1. The location of extremum  $E$  is given by the equation 3.

$$E(x, y, \sigma) = (\partial\partial D^{-1}(x, y, \sigma) / \partial^2(x, y, \sigma)) * (\partial D(x, y, \sigma) / \partial(x, y, \sigma)) \quad (3)$$

### Orientation assignment

This third stage identifies the dominant orientations for each selected keypoint based on its local region. The assigned orientation(s), scale and location for each keypoint enables SIFT to construct a canonical view for the keypoints that are invariant to similarity transforms.

### Keypoint description

This final stage builds a representation for each keypoint by generating its local image descriptor that is a 128 elements vector because the best results were achieved with a  $4 \times 4$  array of histograms with 8 orientation bins in each keypoint ( $4 \times 4 \times 8$ ).

## 3.2.2 Removal Uninformative SIFT Keypoint method

As known huge number of local keypoints increases the matching run time and the mismatching rate. In addition, by our study carried out after the extraction of SIFT keypoints, we note that local keypoints extracted from the same region in the retinal image may suffer from redundancy and similar description. For that, our proposed SIFT-based the Remove of Uninformative Keypoint method called SIFT-RUK aims to limit the number of interest keypoints used to characterize the retinal image. To detect and reject the redundant keypoints, we use the locations  $(x, y)$  and the orientation  $O$  of these local features. The algorithm of our proposed RUK method is presented as follows.

We assume that the retinal image is characterized by  $n$  local SIFT Keypoint set  $K = \{k_1, \dots, k_i, \dots, k_n\}$  and each local keypoint  $k_i$  is presented by a vector composed by location vector  $L$  and the orientation  $O$ . The Remove of Uninformative SIFT keypoint method is detailed as follows.

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**Algorithm 1:** The algorithm of our RUK method

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Data: Local SIFT keypoint set  $K = \{k_1, k_2, \dots, k_i, \dots, k_n\}$ 
 $k_i : (L(k_i), O(k_i)), i \in \{1, \dots, n\}$ 
 $L(k_i) = (x_i, y_i)$ : localisation vector.
 $O(k_i)$ : orientation vector
Result: Local SIFT-RUK keypoint set  $K'' = \{k_1'', k_2'', \dots, k_i'', \dots, k_m''\}$ 
/* Compute the localisation distance  $D_l(L(k_i), L(k_j))$  of feature pairs */
1  $D_l(L(k_i), L(k_j)) = \|(x_i - x_j) + (y_i - y_j)\|, i, j \in \{1, \dots, n\}$  and  $i \neq j$ 
/* Compute the OTSU-based localisation distance threshold  $T_l$  */
2  $D_{lmax} = \max(D_l)$ 
3  $D_{lmin} = \min(D_l)$ 
4  $Dif_l = D_{lmax} - D_{lmin}$ 
5  $Otsu_l = Otsu_{graythresh}(|D_l|)$ 
6  $T_l = (Otsu_l * Dif_l) + D_{lmin}$ 
/* Localisation condition (1) */
7  $K' = []$ 
8 if  $D_l(L(k_i), L(k_j)) < T_l, i, j \in \{1, \dots, n\}$  and  $i \neq j$  then
9    $K' = \{K', k_i\}$ 
10  $l = \text{length}(K'), l < n$ 
/* Compute the orientation distance  $D_o(O(k'_i), O(k'_j))$  of feature pairs */
11  $D_o(O(k'_i), O(k'_j)) = \|O(k'_i) - O(k'_j)\|, i, j \in \{1, \dots, l\}, i \neq j$ 
/* Compute the OTSU-based orientation distance threshold  $T_o$  */
12  $D_{omax} = \max(D_o)$ 
13  $D_{omin} = \min(D_o)$ 
14  $Dif_o = D_{omax} - D_{omin}$ 
15  $Otsu_o = Otsu_{graythresh}(|D_o|)$ 
16  $T_o = (Otsu_o * Dif_o) + D_{omin}$ 
/* Orientation condition (2) */
17  $K'' = []$ 
18 if  $D_o(O(k'_i), O(k'_j)) < T_o, i, j \in \{1, \dots, l\}$  and  $i \neq j$  then
19    $K'' = \{K'', k_i\}$ 
20  $m = \text{length}(K''), m < l < n$ 

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### The SIFT keypoint location condition

Firstly, we employ the manhattan distance, due to its simplicity and speed, to compute the location distances  $D_l$  between all extracted keypoint pairs in the considered image (algorithm 1, line 1). Secondly, based on the OTSU thresholding [14], the optimal value of the location distance threshold  $T_l$  is automatically determined for each retinal image. The  $T_l$  value (algorithm 1, line 6) is found by multiplying the  $Otsu_l$  thresholding level value (algorithm 1, line 5) [14], by the difference  $Dif_l$  (algorithm 1, line 4) between the maximum manhattan distance

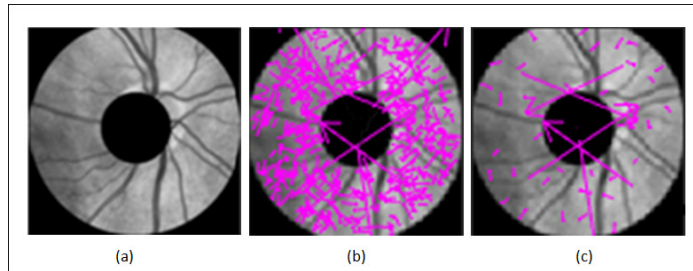


$D_{lmax}$  and the minimum one  $D_{lmin}$ . Indeed, the  $Otsu_l$  level is found by using the Otsu thresholding of the normalized location distance  $D_l$  in order to classify it into two classes: small and large distances. So, the resultant product maximizes the variance between the near local keypoints and the distant ones. After that, we add the minimum manhattan distance  $D_{lmin}$  between all extracted keypoint pairs in the considered image. Thirdly, we check the location distance of each keypoint pairs (algorithm 1, line 8). We consider that  $k_i$  is neighbor of  $k_j$ ,  $i, j \in 1, \dots, n$  and can describe the same interest region if the manhattan location distance between  $k_i$  and  $k_j$  is less than the threshold  $T_l$ .

### The SIFT keypoint orientation condition

After identifying local neighbor keypoint set  $K'$  (algorithm 1, line 9) which verified the first location condition, we compute, first, the manhattan orientation distance between these pairs (algorithm 1, line 11). Second, we compute the optimal orientation distance threshold  $T_o$  (algorithm 1, line 16) based on the same process as OTSU-based localisation distance thresholding. Consequently, if  $k'_i$  and  $k'_j$  verify the orientation condition (algorithm 1, line 18), the local keypoint  $k'_j$  is removed from the keypoint candidate list and we design the new distribution  $K''$  (algorithm 1, line 19) as input for matching process. This SIFT keypoint set  $K''$  contains a reduced number of keypoints  $m$  for each image (algorithm 1, line 20) where  $m < l$ .

Indeed, the standard SIFT description suffer from huge number of uninformative keypoints, as shown in Fig. 3-b, that leads to mismatching. It may also be very time-consuming. Hence the interest of using the new local descriptor SIFT-RUK which seriously eliminates the uninformative SIFT keypoints, as illustrated in Fig. 3-c.



**Fig. 3:** The SIFT-RUK description: (a) The input retinal ring around the optical disc (ROI) image, (b) the SIFT-characterised ring of interest and (c) the ring of interest characterised by SIFT-RUK keypoints.

### 3.3 Feature matching strategy

This step of matching is performed on the SIFT-RUK space among the feature vectors of each keypoint to identify similar retinal images. According to Lowe [11], we use a matching technique called g2NN [11] to find the best candidate which is based not only on the distance with the first most similar keypoint, but also with the second one; in particular, we use the ratio of computed distance with the candidate match  $d_i$  and the 2nd nearest candidate distance  $d_{i+1}$ . The two considered keypoints are matched only if this ratio is low (e.g. lower than 0.6). Finally, by iterating over all keypoints, we can obtain the set of matched points, that describe identical retinal images.

## 4 Experimental results

To evaluate our proposed retinal identification system based on the new SIFT-based Removal Uninformative Keypoint (SIFT-RUK) descriptor, we use the publicly available VARIA database [15]. This database includes 233 retinal images of 139 different subjects with a resolution of  $768 * 584$ . The images have been acquired over several years with a TopCop NW-100 model non-mydratic retinal camera. These images are optic disc centered and have a high variability in contrast and illumination. All the experiments are implemented in MATLAB, and performed on a PC with a 3.2 GHz CPU and 4 G Byte memory.

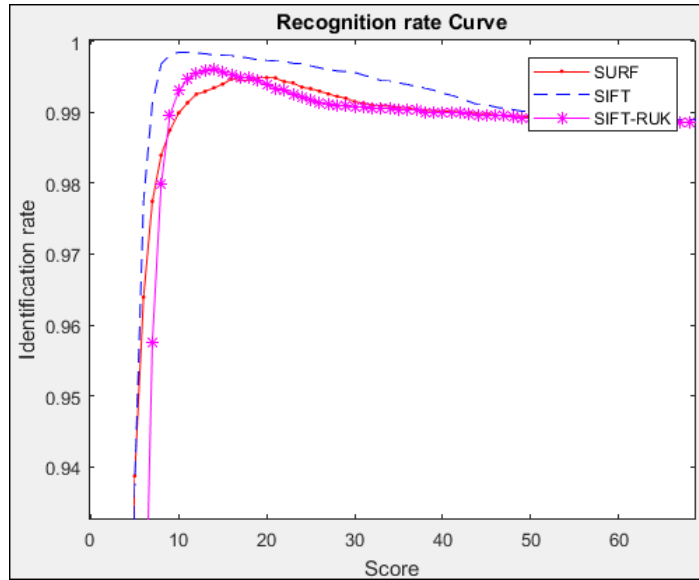
**Tab. 1:** The Removal Uninformative SIFT keypoint analysis on images of the used VARIA database.

Local description	Extracted keypoint number per image (average)
SIFT	2012
SIFT-RUK	1501

Table 1 reflects the impact of our proposed SIFT-RUK method on the number of standard SIFT keypoints. We note that the average number of maintained keypoints in each retinal image based on SIFT is seriously dropped by 25.4%, from 2012 to 1501 keypoints.

As shown in Tab. 2, this huge numbers of uninformative SIFT keypoints can lead to a much more time consumption and to individual mismatching. On the one hand, our SIFT-RUK based proposed system ensures almost the same identification rate

99.74% as SIFT-based identification system (99.8%) [12] and seriously more than the SURF-based identification rate (99.4%), as shown in Tab. 2. The Identification Rate curves for these retinal identification systems using the VARIA database are illustrated in the Fig. 4. We can see clearly that our system identifies a higher rate compared to the others ones, to reach the optimal identification by 99.74%.



**Fig. 4:** The Identification Rate Curves of retinal Human identification systems based on local feature descriptors.

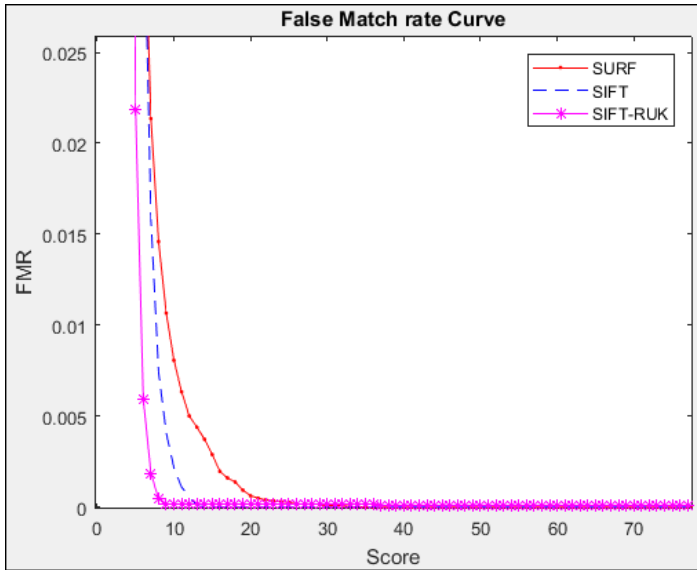
Moreover, matching execution time has been severely reduced from 9.8s in SIFT-based identification system [12] to only 6.6s in our SIFT-RUK system. This reached execution time is essentially due the Remove of SIFT Uninformative Keypoint strategy. It helps to keep the most informative keypoints in order to maintain a high performance (99.74%) and decrease the processing time of the matching step. However, this execution time still slower than SURF-based system due the low 32- SURF descriptor dimension.

On the other hand, the mismatching, in biometric identification system, is illustrated by the False Match Rate (FMR) error. It measures the percent of invalid input identities which are incorrectly assigned to one person. So, the evaluated system is more efficient [16], when this error is lower. Table 2 shows that our novel proposed system allows reducing the FMR error from  $6.2 \cdot 10^{-4}\%$  with the SURF-based system and  $4.3 \cdot 10^{-5}$  with the SIFT-based one to 0% with the new proposed SIFT-RUK-based identification system. Therefore, thanks to the

**Tab. 2:** The identification rate, the FMR error and the processing time of our proposed retinal identification system compared to SIFT and SURF-based systems

Identification system	Identification rate (%)	FMR (%)	Matching run time average (s)
<b>SIFT-RUK-based system</b>	99.74	<b>0</b>	<b>6.6</b>
SIFT-based system	99.8	$4.3 \cdot 10^{-5}$	9.8
SURF-based system	99.4	$6.2 \cdot 10^{-4}$	3

elimination of uninformative SIFT keypoints, the SIFT-RUK-based identification system lets identifying all individuals without any error. Figure 5 illustrates this performance of matching. It shows that the SIFT-RUK based identification system has the lowest FMR rate (0%) compared to the two other ones.



**Fig. 5:** The False Match Rate (FMR) Curves of retinal Human identification systems based on local feature descriptors.

## 5 Conclusion

In this paper, we present an automatic retina identification system based on a new local image descriptor extended from SIFT, named SIFT-RUK. Firstly, we extract an interest ring around the optical disc to be an input for the feature extraction phase. Secondly, we employ our new proposed feature SIFT-RUK to well describe the selected region. Indeed, SIFT-RUK allows detecting redundant SIFT keypoints and then eliminates uninformative ones while maintaining a relevant quality of description. Finally, the test g2NN is applied to compute the number of matched keypoint pairs and classify identical retinal images. We show in this paper that our proposed system reduces the matching processing time (6.6s), compared to the standard SIFT-identification system (9.8s) while leading to get a high identification performance (99.74%) with 0% of FMR error.

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## Biographies



**Takwa Chihaoui** is currently a PhD student the National Engineering School of Tunis (ENIT) and at ESIEE Paris since 2013 and 2014 respectively. She received her degrees of Engineer and Master from the National Engineering School of Tunis (ENIT) in 2012 and 2013 respectively. Her research focuses on Image and Signal processing (Pattern recognition, Forgery detection, Biometric). Particularly, In her Master degree project, she worked on Image Forgery Detection Systems for Digital Forensics Investigations. Currently, her doctoral research is about Biometric based on retina.



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