A NEW MULTIMODEL APPROACH FOR HUMAN AUTHENTICATION: SCLERA VEIN AND FINGER VEIN RECOGNITION

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Abstract

The vein structure is stable over time and can be manipulated for identifying human. The sclera portion of the human eye has blood vessel pattern which is unique for each human being. So, the sclera vein pattern can be used for a useful biometric feature. A few research works has been done over finger vein pattern recognition. Finger vein is an important biometric technique for personal identification and authentication. The finger vein is a blood vessel network under the finger skin. The network pattern is distinct for each individual, unaffected by aging and it is internal i.e. inside human skin which can always guarantee more security authentication. Sclera vein pattern recognition can face a few challenges like: the vein structure moves as the eye moves, low image quality, multilayered structure of the sclera vein and thickness of the sclera vein changes with the excitement level of the human body. To overcome this limitation, the multimodel biometrics is proposed through which the user can be authenticated either sclera vein or finger vein recognition. Sclera vein recognition used Y-shape descriptor and finger vein recognition used repeated line tracking based feature extraction method to effectively eliminate the most unlikely matches respectively. According to the available work in literatures and commercial utilization experiences, sclera vein and finger vein multimodality ensures higher performance and spoofing resistance. Thus building the multimodel biometric system increases the population coverage and improves the accuracy of the human recognition.

Keywords: *Sclera Vein Recognition, Sclera Feature Matching, Sclera Matching, Sclera Segmentation, Feature Extraction, Finger Vein Recognition, Multimodel Biometrics.*

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1. INTRODUCTION

User authentication is extremely important for computer and network system security. Currently, knowledge-based methods (e.g., passwords) and token based methods (e.g., smart cards) are the most popular approaches [1]. However, these methods have a number of security flaws. For example, passwords can be easily shared, stolen, and forgotten [2], [3].Similarly, smart cards can be shared, stolen, duplicated, or lost. To circumvent these issues, a number of login authentication methods, including textual, graphical passwords [4] and biometric authentication [5], have been utilized. All of the above login methods share a common problem, namely, they authenticate a user only at the initial log-in session and do not reauthenticate a user until the user logs out. Anyone can access the system resources if the initial user does not properly log out or the user leaves the workstation unattended to take a short break without logging out.

To resolve this problem, the system must continuously monitor and authenticate the user after the initial login session. In order to achieve this objective, we need to develop robust, reliable, and user-friendly methods for continuous user authentication. It is desirable that the resulting system has good usability by authenticating a user without his active cooperation. Continuous Authentication is essential in online examinations where the user has to be continuously verified during the entire session. It can be used in many real time applications, when accessing a secure file or during the online banking transactions where there is need of highly secure continuous verification of the user. A number of biometric characteristics exist and are used in various applications. Each biometric has its own strengths and weaknesses, and the choice depends on the application. Some of the commonly used hard biometrics are Face, Hand geometry, Fingerprint, Iris. Soft biometrics include Keystroke, Voice, Colour of the clothing, Facial colour etc [2,4].

A single biometric trait (unimodal technique) is not sufficient to authenticate a user continuously because the system sometimes cannot observe the biometric information. To address the limitations of single biometrics, using multimodal biometrics is a good solution. It is the combination of two or more biometric traits to raise systems security and reliability. Multimodal has several advantages over unimodal. Combining the results obtained by different biometric traits by an effective fusion scheme can significantly improve the overall accuracy of the biometric system. Multimodal system increases the number of individuals that can enroll. It provides resistance against spoofing. The proposed work includes Sclera and Fingerprint as their Multimodal biometric traits for continuous authentication of the user. The blood vessel structure of the sclera is unique to each person, and it can be obtained using Y-shape descriptor.

The rest of the paper is organized as follows: related work is discussed in Section 2. The proposed system is explained in Section 3. The experimental result and discussion is explained in Section 4. In section 5, the conclusion and future work is described.

2. RELATED WORK

Some research studies have been reported on continuous authentication. Many of them use multimodal biometrics, but none of them can identify the user in the absence of biometric observation. Zhi Zhou, Eliza Yingzi Du, and N. Luke Thomas [6] proposed sclera recognition method which can achieve comparable accuracy (EER = 1.34% and 3.83%) with that of the two iris recognition methods using visible-light acquired images (EER = 2.38% and 3.72%). In particular, note that the iris patterns in dark eyes are hard to extract under visible light illumination. Therefore, these results show that sclera recognition could have some advantage over iris recognition in the visible wavelengths. F. Pernus, S. Kovacic, and L. Gyergyek defined the Fingerprint is one of the most important biometric technology as it is more distinct, persistence and ease of acquisition. Fingerprint recognition is a process of determining whether two sets of fingerprint ridge detail are from the same person [7]. There are multiple approaches that are used in many different ways for fingerprint recognition which are minutiae, correlation, ridge pattern. These types of approaches can be broadly categorized as minutiae based or texture based recognition [8]. Minutiae are the most popular approach that is used for fingerprint representation. It is based on local landmarks. The minutiae-based systems locate the points firstly. These points are called minutiae points which represent the fingerprint ridges either terminate or bifurcate in the fingerprint image, and then these minutiae points are matched in a given fingerprint and the stored template.[9] Minutiae points perform fairly high accurate fingerprint matching. Sim and Zhang [10, 11] proposed a continuous authentication technique using face and fingerprint biometrics. They used a mouse with a built-in fingerprint sensor, which made fingerprint authentication a passive method for authentication. Sim and Zhang's technique had the same limitations as [12]; when no biometric observations are available, the authentication certainty must go down rapidly with time in order to protect the security, irrespective of whether the user is in front of the console or not. On comparing, the proposed method uses the same fingerprint biometric mouse for verification since sclera is more accurate biometric than face, it is used as initial login. Similar to Sim and Zhang [10, 11], Azzini and Marrara [13,14] also proposed a continuous authentication technique using face and fingerprint biometrics. Their system checked the identity of the user only on the basis of face recognition. If the authentication certainty of face recognition falls below a threshold, then a new fingerprint acquisition is required. Again, the authentication certainty in this approach must go down rapidly with time in order to ensure the security, regardless of whether the user is in front of the console or not. Kang and Ju [15] proposed a continuous authentication technique using face and behavioural biometrics. They used face trajectory and its pose as behavioural features. Because behavioural biometrics was used only for assisting face and the features are not consistent throughout the session, and also it is soft biometric so less reliable when compared to proposed method where we have used hard biometrics. Finally, only limited works were carried out which paves way for the researchers to invent new methods to reduce the error rates and to improve the accuracy and speed of the systems.

3. PROPOSED METHODOLOGY

The design of a multimodal biometric system is strongly dependent on the application scenario. A number of multimodal biometric systems have been proposed but they are differ from one another in terms of their architecture, the number and choice of biometric modalities, the level at which the evidence is accumulated, and the methods used for the integration or fusion of information. The proposed system adopts multiple biometric traits of an individual, to establish the identity. From the Fig.1 the proposed system architecture shows initially in enrollment, input data eye image and finger vein image have to register. Then the eye image and the finger image are segmented to obtain the enhanced vein patterns. Then feature extraction takes place to drive the vein features of sclera and finger vein and stored into database with respect to account number. Required proof details are registered with personal details of the user.

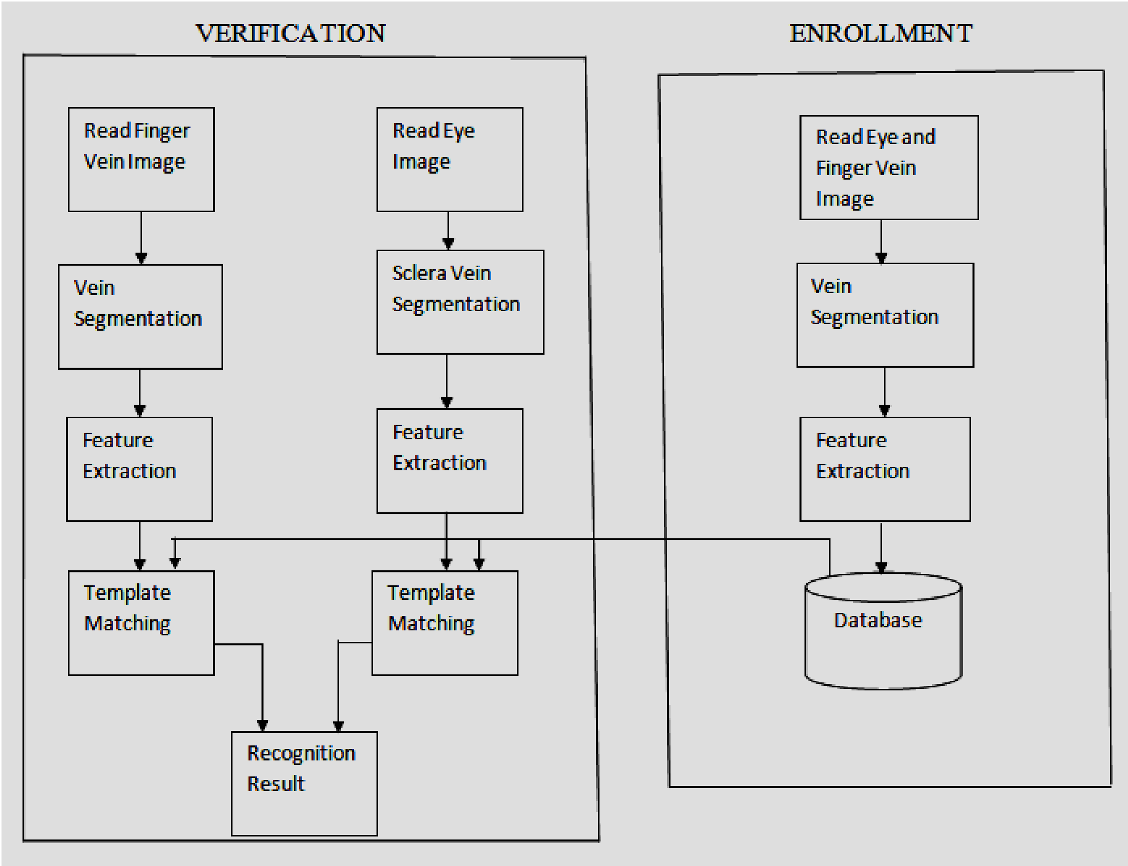

Fig.1. System Architecture

3.1 Finger Vein Recognition

Finger vein biometric system can verify a person's identity by recognizing the pattern of blood veins in the Finger. Finger vein authentication uses the vascular patterns of an individual's Finger as personal identification data. Like fingerprints, the pattern of blood veins in the Finger is unique to every individual, even twins have different patterns and apart from size, this pattern will not vary over the course of a person's lifetime. The Finger is an ideal part of the body for this technology; it normally does not have hair which can be an obstacle for photographing the blood vessel pattern, and it is less susceptible to a change in skin color, unlike a finger or the back of a hand.

3.2 Line Tracking Algorithm

The method is based on line tracking, which starts at various positions. Local dark lines are identified, and line tracking is executed by moving along the lines, pixel by pixel. When a dark line is not detectable, a new tracking operation starts at another position. All the dark lines in the image can be tracked by repeatedly executing such local line tracking operations. Finally, the loci of the lines overlap and the pattern of finger veins is obtained statistically. As the parts of the dark lines are tracked again and again in the repeated operations, they are increasingly emphasized. Although noise may also be tracked, noise is emphasized to a smaller degree than the dark lines. This makes line extraction robust.

3.3 Iris Recognition

The iris is the coloured ring around the pupil of every human being and like a snowflake, no two are alike. Each is unique in its own way, exhibiting a distinctive pattern. The iris remains stable over time as long as there are no injuries and a single enrolment scan can last a lifetime. Even blind people can use this scan technology since iris recognition technology is iris pattern dependent not sight dependent. Today's commercial iris cameras use infrared light to illuminate the iris without causing harm or discomfort to the subject. Localization of the iris is an important step in iris recognition because, if done improperly, resultant noise (i.e.: eyelashes, reflections, pupils and eyelids) in the image may lead to poor performance.

3.4 Sclera Recognition

The sclera is the part of the eye commonly known as the "white". It is the outer and protective covering of the eye. It is made up of four layers of tissue i.e. the episclera, stroma, laminafusca and endothelia. The blood vessel structure of the sclera is unique to each person, and it can be remotely obtained non intrusively in the visible wavelengths. The structure of blood vessels is visible and stable over time in sclera. With increasing age collation and elastic fibers deteriorates, sclera dehydration occurs and calcium and lipid salts accumulate but the blood vessels do not deteriorates. Therefore, it is well suited for human identification. Sclera recognition is a challenging research problem because images of sclera vessel patterns are often defocused and/or saturated and, most importantly, the vessel structure in the sclera is multilayered and has complex nonlinear deformations.

3.5 Sclera Vein Segmentation

Segmentation is the one of the steps in image processing; it divides an image into multiple parts so that we can extract more accurate image attributes. In this project the input eye image have to segment for getting the sclera vein pattern for authentication.

3.6 Estimation of Sclera Area

First the pre-processing step includes task to convert the input color image to gray scale image for easy computation. Then there are two classes in an input eye image, foreground (object) and background, which can be separated into two classes by intensity. The hue of the sclera area should have low hue (about bottom 1/3), low saturation (bottom 2/5), and high intensity (top 2/3). Therefore, the following heuristic is developed:

$$Result\ (x,y) = \begin{cases} 1 & if\ H(x,y) \le th_h\ and\ S(x,y) \le th_s\ and\ I(x,y) \le th_i \\ 0 & else \end{cases}$$

With the thresholds calculated using:

$$th_h = arg\left\{t|min|\sum p_h(x) - T_h\right\}$$

$th_s = arg\{t|min|\sum p_s(x) - T_s\}$ and

$$th_i = arg\left\{t|min|\sum p_i(x) - T_i\right\}$$

Here, $p_h(x)$ is the normalized histogram of the hue image, $p_s(x)$ is the normalized histogram of the saturation image, $p_i(x)$ is the normalized histogram of the intensity image, and result(x, y) is the binary sclera map. The thresholds T_h, T_s and T_i are 1/3, 2/5, and 1/3 respectively. This way, we eliminate non-sclera areas and detect the sclera area in Fig.2.

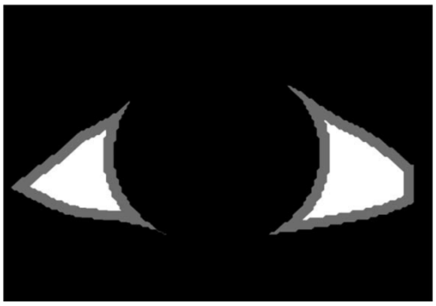

Fig.2. Weighted Image

3.7 Sclera Vessel Pattern Enhancement

As a result, the sclera vascular patterns are often blurry and/or have very low contrast. Because the vascular patterns could have multiple orientations, in this paper, a bank of directional Gabor filters is used for vascular pattern enhancement.

$$(x,y,\vartheta,s) = e^{-\left(\frac{(x-x_0)^2+(y-y_0)^2}{s_2} \times e^{-2\pi i(\cos\theta(x-x_0)+\sin\theta(x-x_0))}\right)}$$

Where (x_0, y_0) is the center frequency of the filter, s is the variance of the Gaussian, and ϑ is the angle of the sinusoidal modulation. Here, only the even filter was used for feature extraction of the vessels, since the even filter is symmetric and its response was determined to identify the locations of vessels adequately. The image is first filtered with Gabor filters with different and scales

$$I_F(x,y,\vartheta,s) = I(x,y) \times G(x,y,\vartheta,s)$$

where *I(x, y)* is the original intensity image, *G(x, y, ϑ, s)* is the Gabor filter, and *I(x, y, ϑ, s)* is the Gabor-filtered image at orientation θ and scale s. All the filtered images are fused together to generate the vessel boosted image *F(x, y)*;

$$F(x,y) = \sqrt{\sum_{\vartheta\in\theta}\sum_{s\in S} I_F(x,y,\vartheta,s)^2}$$

Gabor filtered image

$$B(x,y) = \begin{cases} 1 & F(x,y) > th_b \\ 0 & else \end{cases}$$

$$th_b = \arg\left\{|min|\sum_{x=1}^{t} p_{edge}(x) - T_b\right\}$$

where *B(x, y)* is the binary vessel mask image, *F(x, y)* is the vessel-boosted image, and *p(x)* is the normalized histogram of the nonzero elements of *F(x,y)*. The morphological operations are applied to the binary maps to remove isolated pixels, and small regions of contiguous pixels. Sclera Vein Pattern is shown in Fig.3.

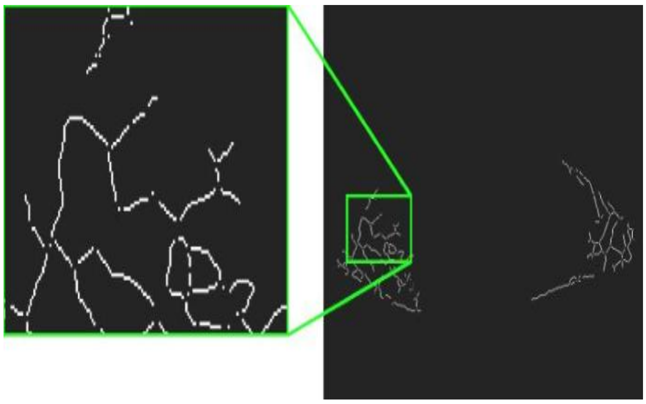

Fig.3. Sclera Vein Pattern

3.8 Sclera Vein Feature Extraction

Within the sclera, there can be several layers of veins. The motion of these different layers can cause the blood vessels of sclera show different patterns. But in the same layers, blood vessels keep some of their forms. As present in Fig.4, the set of vessel segments combine to create Y shape branches often belonging to same sclera layer.

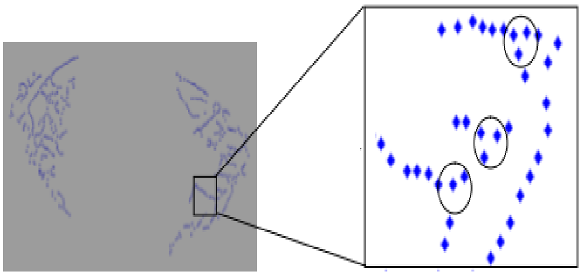

Fig.4. Y-Shape Vessel Branch in Sclera

When the numbers of branches is more than three, the vessels branches may come from different sclera layers and its pattern will deform with movement of eye. Y shape branches are observed to be a stable feature and can be used as sclera feature descriptor. To detect the Y shape branches in the original template, we search for the nearest neighbors set of every line segment in a regular distance, classified the angles among these neighbors. If there were two types of angle values in the line segment set, this set may be inferred as a Y shape structure and the line segment angles would be recorded as a new feature of the sclera. Even when the head tilts, the eye moves, or the camera zooms occurs at the image acquisition step, ϕ1, ϕ2, and ϕ3 are quite stable. To tolerate errors from the pupil center calculation in the segmentation step, we also recorded the center position (x,y) of the Y shape branches as auxiliary parameters. So in our rotation, shift and scale invariant feature vector is defined as: Y(ϕ1, ϕ2, ϕ3, x, y). The Y-shape descriptor is generated with reference to the iris center. Therefore, it is automatically aligned to the iris centers. It is a rotational- and scale-invariant descriptor.

3.9 Y-Shaped Descriptor

Within the sclera, there can be several layers of veins. The motion of these different layers can cause the blood vessels of sclera show different patterns. But in the same layers, blood vessels keep some of their forms. The set of vessel segments combine to create Y shape branches often belonging to same sclera layer. When the numbers of branches is more than three, the vessels branches may come from different sclera layers and its pattern will deform with movement of eye. Y shape branches are observed to be a stable feature and can be used as sclera feature descriptor. To detect the Y shape branches in the original template, we search for the nearest neighbors set of every line segment in a regular distance, classified the angles among these neighbors. If there were two types of angle values in the line segment set, this set may be inferred as a Y shape structure and the line segment angles would be recorded as a new feature of the sclera. The Y-shaped descriptor is very fast to match because no registration was needed. The matching result in this stage can help filter out image pairs with low similarities.

3.10 Sclera Vein Matching

The feature vector for all images that are in the databases are pre-computed and stored during enrollment stage. When coming to verification stage y_{tei} and y_{taj} are the Y shape descriptors of test template T_{te} and target template T_{ta} respectively. d_{ϕ} is the Euclidian distance of angle element of descriptors vector defined. d_{xy} is the Euclidian distance of two descriptor centers. n_i and d_i are the matched descriptor pairs' number and their centers distance respectively. t_{ϕ} is a distance threshold and t is the threshold to restrict the searching area. We set t_{ϕ} to 30 and t_{xy} to 675 in our experiment. Here

$$d_{\phi}(y_{tei}, y_{taj}) = \sqrt{(\varphi_{i0}-\varphi_{j0})^2 + (\varphi_{i1}-\varphi_{j1})^2 + (\varphi_{i2}-\varphi_{j2})}$$

And

$$d_{xy}(y_{tei}, y_{taj}) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

To match two sclera templates, searched the areas nearby to all the Y shape branches. Here, α is a factor to fuse the matching score which was set to 30 in our study. N_i and N_j is the total numbers of feature vectors in template i and j separately. The decision is regulated by the threshold t: if the sclera's matching score is lower than t, the sclera will be discarded.

$$matching\_score = \frac{2\sum n_i - \alpha \sum d_i}{\max(N_{te}, N_{ta})}$$

4. EXPERIMENTAL RESULT AND DISCUSSION

The metrics used for evaluation are False Acceptance rate (FAR) and False Rejection Rate (FRR).

$$FRR(n) = \frac{No.of\ all\ rejection\ attempts\ for\ a\ qualified\ person\ n}{No.of\ all\ verfication\ attempts\ for\ a\ qualified\ person\ n}$$

$$FAR(n) = \frac{No.of\ successful\ independent\ fraud\ attempts\ for\ a\ qualified\ person\ n}{No.of\ all\ independent\ fraud\ attempts\ for\ a\ qualified\ person\ n}$$

The FRR is the frequency that an authorized person is rejected access. The evaluation of sclera recognition was carried out with 100 images taken from UBIRIS database were grouped into ten users and the results are tabulated for FAR and FRR.

Table I and Fig.5 shows the resulted (FRR) as obtained for the proposed sclera vein and existing iris technique. From the result, it can be observed that the proposed technique results in lesser False Rejection Rate when compared to the existing techniques. The FAR is the frequency that a non-authorized person is accepted as authorized. The result is shown in Fig.6.

Table 1 FRR and FAR results

Number of Users	FRR (%)		FAR (%)	
	Existing Fingerprint + Iris	Proposed Finger vein + Sclera Vein	Existing Fingerprint + Iris	Proposed Finger vein + Sclera Vein
1-20	87.7	84.3	0.36	0.12
21-40	88.1	83.9	0.33	0.17
41-60	88.9	84.8	0.31	0.12
61-80	89.6	85.4	0.39	0.14
81-100	88.8	84.5	0.36	0.13

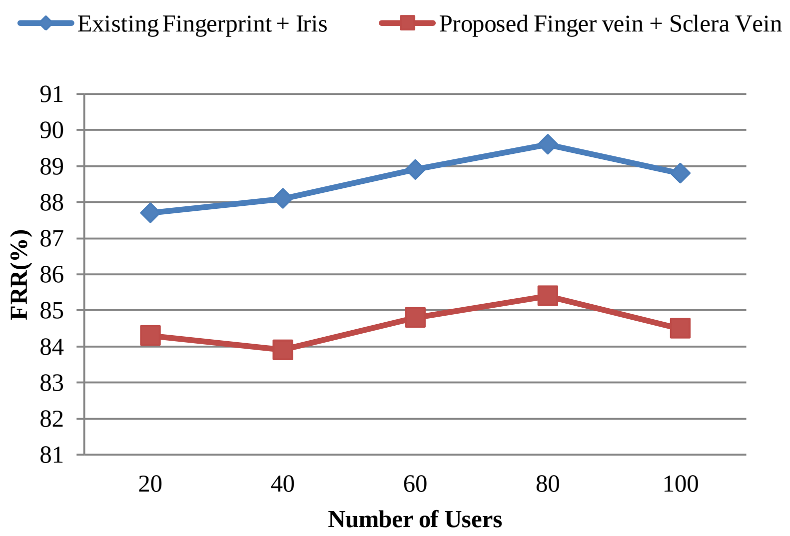

Fig.5 FRR comparison result

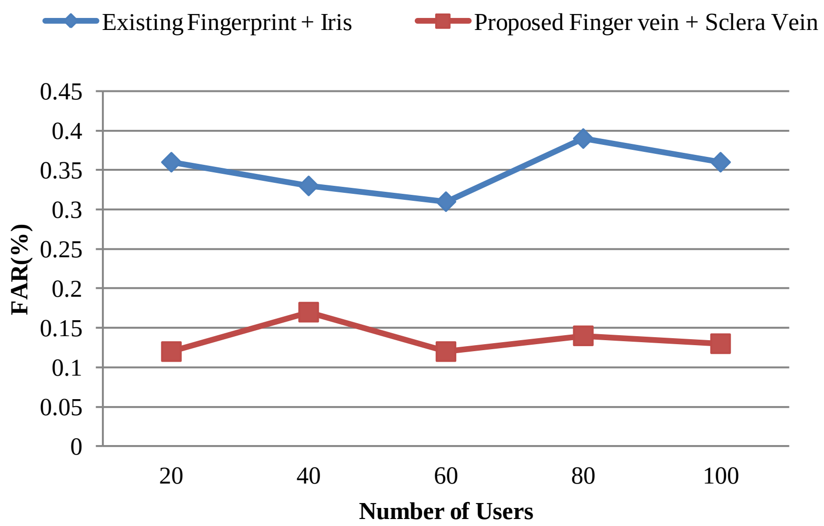

Fig.6 FAR comparison result

5. CONCLUSION AND FUTURE WORK

In this paper we have presented a secured multimodal biometric system by fusing eye vein and Finger vein images. In this system of fusion, we have considered both of the eye vein and finger vein features for verification. In proposed work the user can be authenticated through sclera vein recognition by using a rotation and scale-invariant Y-shape descriptor based feature extraction method efficiently eliminate most unlikely matches. The proposed model has improved the security of the system as verified using FAR and FRR curves. Automatic authentication is possible with state of art technologies like sclera recognition on the move and finger vein scanner on the steering of car. As future improvements the cryptographic key of multimodal biometrics like sclera and iris can be developed and issued for enhancing security. Thus the performance and accuracy of human authentication was increased by the proposed sclera vein biometric recognition.

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