Adaptation of a PCA fusion stage to improve accuracy in a biometric iris recognition system for unconstrained environments

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Abstract. Traditional iris recognition system uses a fixed image acquisition stage which requires a high collaboration of the user to be recognized, a short distance to acquire the fixed image and the correct illumination. All this characteristics are the structure of a controlled environment system. Nowadays, researchers are focused on the development of biometric recognition system which can operate under non-controlled environment, emphasizing the video management within the architectures, optimizing and proposing new stages to improve the recognition rate levels. In this paper we propose a new stage to exploit the biometric information from video-iris, the new stage generate a representative iris biometric template based on the principal component analysis (PCA) which integrates the biometric information of group of frames from a set of templates from a video-iris with optimal coefficients. The resulting representative biometric template should contain more biometric texture information as compared to individual templates that resulting in better recognition performance. The implementation of the new stage generates a new architecture based on video iris biometric recognition for unconstrained environments which achieved a recognition rate of 99.236% with respect to 84.42% of a conventional system. The new system deals with a false acceptance rate FAR=0.3288% and a false rejection rate FRR=0.7634%. The tests were performed with the information of 160 users from the MBGC.v2 database.

Keywords: Iris recognition, Video, MBGC, Fusion, Biometric systems, unconstrained environments.

1 Introduction

The biometric is the study of physical, biological or behavioral traits used to identify and verify a person [1]. Some commonly used biometric features include fingerprints, face, hand geometry, voice, iris, signature, DNA, Palm, Iris, body odor. The biometric recognition systems offer the advantage over information security problem ensuring that only authorized users are able to access the information. Each biometric feature has its strengths and weaknesses. Hugo Proenca [2] conducted a research where analyzed the different biometric identifiers, evaluating them according with 7 properties including: universality, uniqueness, permanence, performance and Measurability. The obtained values were performed by averaging and subjectively weight the classification exposed in at least 10 scientific papers of other authors. According with results obtained by Hugo Proenca, signature and voice have the lower values for the uniqueness property, these biometric identifiers are easy to manage and suitable for low security applications. On the other hand, the more distinctive biometric features such as the retina and iris involve a large number of processes. In his analysis, the iris had the highest average value for the seven properties (84.43 %).

The iris has a diameter of 11 mm approximately, on the outside is surrounded by a white area called sclera. The iris is the pigmented area surrounding the pupil and has a fibrous tissue called stroma, iris connects muscles to contract and dilate the pupil in response at changing light, the fibrous constitution has over 400 features used to recognize a person. The advantages of the iris over others biometric features: It is highly protected, the iris patterns can be captured from distance, encoding and decision analysis not require a computationally complex algorithm and can be made in less of one second, it possesses high degree of randomness (John Daugman [3] probe the uniqueness and randomness of Iris over 200 billion cross comparisons of irises, he reports a theorical false match rate of 1 in $5x10^{15}$). However, the iris is small (approximately 11 mm diameter) which makes it difficult to acquire the biometric information at long distances. Moreover, the iris is a moving object located on a curved surface, wet and reflective, making it difficult to acquire the biometric information.

The traditional iris recognition systems based on still images [4] are designed to work with special or restricted conditions; this means that they require an ideal environment and cooperative user's behavior during the eye image acquisition stage to obtain high quality images. Therefore, if any of these requirements are not met, it can cause a substantially increase of error rates, specially the false rejections. Many factors can affect the quality of an eye image, including defocus, motion blur, dilation and heavy occlusion. Naturally, poor image's quality cannot generate satisfactory recognition because they do not have enough feature information, in this regard; iris recognition is dependent on the amount of information available in two iris images being compared. A typical iris recognition system commonly consists of four main stages [5, 6]; *Acquisition* the aim is to acquire a high quality image. *Preprocessing*, involves the segmentation and normalization processes. The segmentation consists in isolating the iris region from the eye image. The normalization is used to compensate the varying size of the pupil. *Feature encoding,* uses texture analysis method to extract features from the normalized iris image. The significant features of the iris are extracted as a series of binary codes known as digital biometric template. *Matching* compares the user digital biometric template with all the stored templates in the database. The matching metric will give a range of values of the compared templates from the same iris. In recent years, with an increasing of new massive biometric security demands around the world, it seems difficult to fulfill the conditions mentioned above in order to have a reliable iris recognition system [7]. Thus, with the aim of overcoming these drawbacks, news approaches are being developed in an attempt to improve iris recognition performance under non ideal situations i.e. unconstrained environments. These biometric recognition systems are more flexible, the aim has been to achieve automatic acquisition system, where the image acquisition process is transparent to the user, and this has been achieved using the video acquisition system. The development of these systems has involved the redesign of the traditional architecture of a biometric system based on still images. These new architectures are part of the multi-biometric systems which are the current trend in biometric systems. The term multi-biometric denotes the fusion of different types of information (e.g., fingerprint and face of the same person, or fingerprints from two different fingers of a person).

Among these approaches, the video-based eye image acquisition for iris recognition seems to be an interesting alternative [8, 9,21] because it can provide more information through the capture of a video iris sequences. Besides that, it is a friendly system because it is not intrusive and requires few users' cooperation.

In this paper, we propose to exploit the video-iris; it contains information related to the spatio-temporal activity of the iris and its neighbor region over a short period of time. Therefore, the information from individual iris images can be fused into a single composite iris image with higher biometric texture information, resulting in better recognition performance and reducing the error rates. The idea of fusing iris biometric templates to perform biometric recognition has been recently described in the literature. Zhao and Chellappa [10] suggested averaging to integrate texture information across multiple video frames to improve face recognition performance. Hollingsworth et al. [11] improve the matching performance using signal-level fusion, taking advantage of the temporal continuity in an iris video sequence to create a single average image from multiple frames, but they suppose an ideal situation, in which bad segmented iris frames are manually discarded, that may limit its application. There are several methods of fusion, Colores et al. [12] analyzed some fusion methods to determine the most suitable to use in biometric applications. Indeed, the main objective in this work is to determine the effectiveness of including a new stage that implements a fusion method within architecture for a biometric recognition system based on iris. This paper is organized as follows: section 2 explains the basics of the Iris recognition system based on video. Section 3 describes the new stage. In section 4 presents the evaluation of the new architecture, and finally in section 5 presents the conclusions.

2 Iris recognition system based on video

The scheme, shown in figure 1, is based on the conventional iris recognition system [5, 6] modified to operate with video captured on unconstrained environments. Thus, in the modified system firstly the eye frames are captured by a proper video camera in the video acquisition stage.

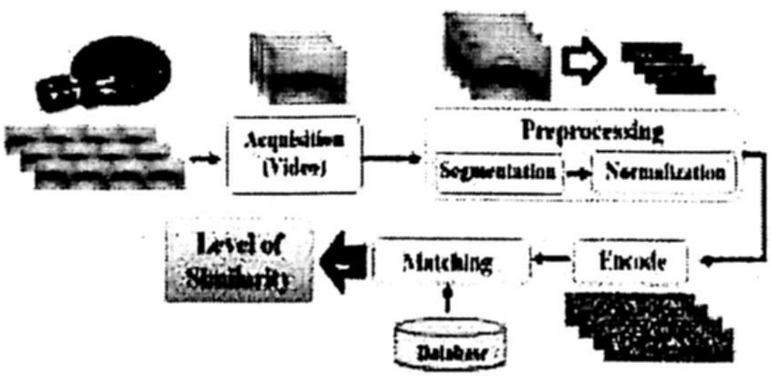


Fig. 1. System 1: Modification of Iris recognition system to use video.

Ideally, the captured eye image should be centered in the frame, free of defocus and aberration errors. It is possible to achieve it by forcing to the user to remain perfectly static and looking to the camera while the video is taken. However, the main purpose of any unconstrained scheme is to be minimally invasive or restrictive with the users. In the case of moving subjects, the images may be of poor quality due to improper illumination, motion blur, occlusions, etc. Moreover, increasing the distance of the subject from the camera causes a decrease in the resolution of the eye recorded in the image; the performance of an iris recognition system is negatively impacted when the spatial resolution of the acquired iris images is low. This fact may result, sometimes, in the introduction of frames with few, or even without any iris's texture information, which can in turn affect the performance of the recognition system. In other cases, even though the image had high quality, may not enough contain information needed to achieve recognition. Therefore, the processing of each of the images will result in a higher processing time. A sample set of all these problems in capturing iris images are shown in figure 2.

Fig.2. Video sequences depicting various problems during capturing iris images.

Some studies report that using high quality image affects recognition accuracy and can improve system performance [7]. Then, it is necessary to select suitable images with high quality from an input video sequence before the next recognition processing. Choosing an eye frame with an appropriate image quality seems to be a challenge. Defocus-blur and motion-blur are the major source of eye frame quality degradation. Indeed, in a less restrictive environment, the users are free to move outside the optimal distance from the camera during video capture process, which means that they may move outside the optimal "depth of field" of the system causing the blurring effects in the captured frames. In general, a focused eye image has a relatively uniform frequency distribution in the 2D Fourier spectrum, while the power spectrum of a defocused or blurred image is concentrated on the lower frequencies. This fact suggests that a spectral analysis of the frequency distribution may be an effective way to estimate the image quality of eye frames for discriminating the distorted frames from the clear ones. Consequently, several discrete formulations have been proposed and that allow obtaining only the power of high frequencies by attenuating the low frequency components of the eye frame and calculating the power spectrum of the high-pass filtered eye image. Colores et al. [13] analyzed four methods used to obtain the high frequency power spectrum of the eye frames for image quality assessment. Evaluation results show that the Kang and Park convolution kernel provides better performance than the other kernels in terms of speed and accuracy [14].Therefore, in the modified scheme (System 1), the acquisition stage employs the Kang and Park convolution kernel.

2.1 Preprocessing video stage

The preprocessing stage of the modified scheme performs the iris segmentation and normalization tasks whose main purpose is to provide a good enough segmentation of the iris region for each frame obtained from video-iris, to enable the encoding and matching stage to perform accurate iris recognition. The *segmentation module* isolates the iris region from the eye frames using the segmentation algorithm proposed by Wildes [6], which is based on the circular Hough transform combined with a Canny edge detector to obtain the iris region. The goal of edge detection algorithms is to produce an image containing only edges of the original image. However, most edge detection algorithms produce an image containing fragmented edges; then in order to turn these fragmented edge segments into useful lines, circles and object boundaries, an additional processing is needed. To this end, the circular Hough transform is used to find circles in eye frame and deduce the radius $[r_p, r_i]$ and centres $[(x_{cp}, x_{cp}), (x_{ci}, x_{ci})]$ corresponding to the pupil and iris regions. This stage plays a very important role because if the segmentation process is not performed with enough precision, the segmentation error will further propagate to the encoding and matching steps. *The normalization module* is used to compensate the size variation of the iris region, in the eye frames, mainly because the stretching of the iris caused by pupil dilatation due to varying illumination levels. This process is done using the linear rubber sheet model proposed by Daugman[5]. This transformation maps each point within the iris region to polar coordinates $(r, \theta)$where r and $\theta$are in the intervals [0, 1] and [0,2π], respectively. The mapping of the iris region from Cartesian representation $I(x, y)$, to the normalized non-concentric polar representation, $I(r, \theta)$ is given by equation 1, $I(x(r,\theta), y(r,\theta))$ is the segmented eye image, (x, y) are the original Cartesian coordinates, (r, θ) are the corresponding normalized polar coordinates.

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta) \quad (1)$$

where

$$x(r,\theta) = (1-r)\big(x_{cp}(\theta) + r_p cos\theta\big) + r\,(x_{cl}(\theta) + r_l cos\theta) \quad (2)$$

$$y(r,\theta) = (1-r)\big(y_{cp}(\theta) + r_p sin\theta\big) + r\,(y_{cl}(\theta) + r_l sin\theta) \quad (3)$$

2.2 Feature encoding video stage

The extracted features are fed into the encoding stage which is used to obtain the digital biometric template [15]. This process has two components: firstly, the filter component is applied in each normalized iris region from video-iris frames using a predefined complex filter or operator to extract the most discriminating information present in the iris region. Secondly, the phase quantization where the resulting complex array is translated into a binary code that constitutes the digital biometric template. The feature encoding stage, then, was implemented by convolving the normalized iris region with a 1D Log-Gabor wavelets, where each row of $I(r, \theta)$ corresponds to a particular circle extracted from the iris rim. Some enhancements are then performed on the extracted signals, such that the intensity values at distorted areas in the normalized iris region are filled with the average intensity of surrounding pixels. Finally, the filter output is transformed into a binary code using the four quadrant phase encoder, with each filter producing two bits of data for each phasor [16].

2.3 Matching video stage

The operation of this stage consists of the comparison of digital biometric templates, producing each a numeric dissimilarity value. In this scheme, the Hamming distance (HD) was employed for Daugman [5]. The HD measure can be used to make a decision whether the digital biometric template is produced by the same or different users.

3 New fusion video stage

The image fusion tries to solve the problem of combining information from several images taken the same object to get a new fusioned [17]. In this paper, each frame of video-iris is first pre-processed in order to obtain the normalized iris region templates. Then, a fusion method is applied to provide a representative fusioned normalized iris region template from these individual templates. The resulting template should be contains more iris biometric texture information as compared to individual templates. We analyzed the image fusion methods to determine the most suitable to achieve greater extraction of iris biometric information [12], the result show that the principal component analysis (PCA) method presents the best performance to improve recognition values according to the Hamming distances. The PCA fusion method transforms the features from the original domain to the new domain (known as PCA domain). Here the features are arranged in order of their variance. Fusion process is achieved in the PCA domain by retaining only those features that contain a significant amount of information. The main idea behind PCA is to determine the features that explain as much of the total variation in the data as possible with as few of these features as possible. Image fusion based on PCA has advantages in maintaining image information, reduce redundant information and highlight the components with biggest influence, can be performed by parallel computing, the spectral information loss is slightly better than others methods of fusion.

Thus, the results suggest that adding a fusion video stage to the architecture of the unconstrained environment iris recognition, it could increase the system performance. Thus, we have a new architecture for a system based on video iris biometric recognition for unconstrained environments. Figure 3 shows the new architecture, the added stage is based on the PCA fusion, operates fusing the normalized templates to generate a single digital normalized template. This new stage will provide to the matching stage a digital template that contains more biometric texture information of the iris region.

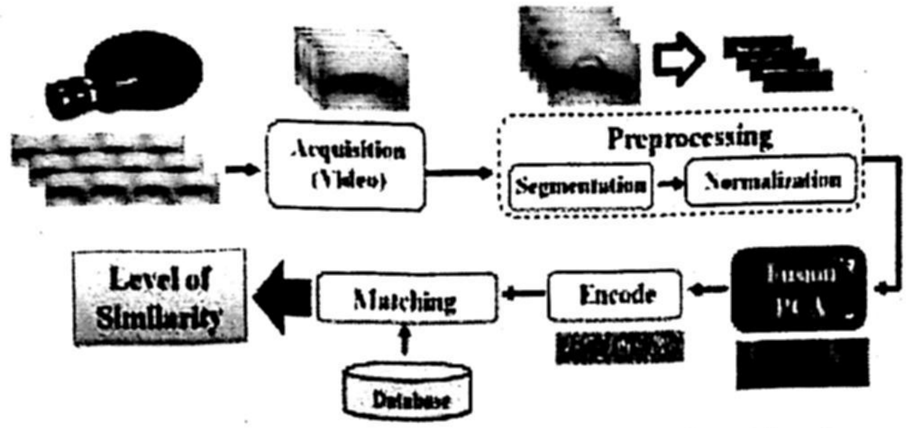


Fig. 3. System 2: Iris recognition system with a fusion video stage.

3.1 Image fusion using principal component analysis

The fusion method based on the principal component analysis [17] is a straightforward way to build a fused image as a weighted superposition of several input images. The optimal weighting coefficients, with respect to information content, can be determined by a principal component analysis of all input intensities. By performing a PCA of the covariance matrix of input intensities, the weightings for each input image are obtained from the eigenvector corresponding to the largest eigen-value.

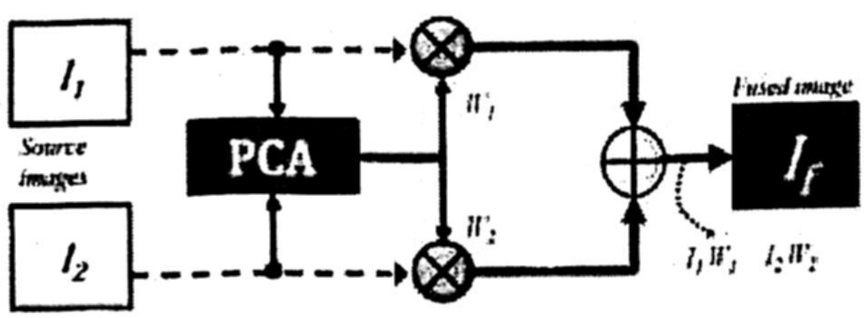


Fig. 4. PCA operation to fuse two images.

Figure 4 shows the basic fusion scheme, where two images I_1 *and* I_2 are fused to obtain a resultant image I_f given by equation 4,$W_1 y W_2$ are the weights coefficients.

$$I_f(x,y) = W_1(x,y)I_1(x,y) + W_2(x,y)I_2(x,y) \quad (4)$$

$$X_k = I_k - \Psi \quad (5)$$

$$C = \frac{1}{2}\,({X_1}^T X_1 + {X_2}^T X_2) \quad (6)$$

$$W_1 = U^T X_1 \quad (7)$$

$$W_2 = U^T X_2 \quad (8)$$

The weights for each source image are obtained from the eigenvector corresponding to the largest eigen-value of the covariance matrix of each source. Arrange source images in two-column vector.

- Organize the data, let S be the resulting column vector.
- Compute empirical mean (Ψ) along each column.

- Subtract Ψ from each column of S, the resulting is a matrix X_k. (eq. 5)
- Find the covariance matrix C of matrix X_k. (eq. 6)
- Compute the eigenvectors and eigen-value and sort them by decreasing eigen-value.
- Consider first column U which correspond to larger eigen-value to compute normalized component W_1 *and* W_2. (eq.7 and eq.8 respectively)

4 Experimental results

To evaluate the performance of the proposed scheme shown in Figure 5, we selected the "MBGC.v2" dataset [4, 18], which presents several noise factors, especially those related to reflections, contrast, luminosity, eyelid and eyelash iris obstruction and focus characteristics. These facts make it the most appropriate to study the iris recognition system for uncontrolled environments. Regarding to the images size, each eye frame is 480 by 640 pixels in 8 bits-gray scale at 30frames per second (fps). This database has been distributed in MPEG-4 format to over 100 research groups around the world. For experiments purposes, iris-videos from the MBGC.v2 database were selected from 131 users to generate the testing dataset. For each user, we select a reference eye frame. The testing eye frames were selected sub-sampling the video-iris at 1/10 frames, although the reference eye frame was chosen according to the characteristics of high-frequency concentration previously described. As shown in Figure 5, the recognition tests were conducted on 3000 eye frames with 131 reference eye frames, allowing the generation of the distributions inter-class and intra-class to compare the performance of proposed and conventional systems. Each frame in the set of test was segmented and normalized using a modified version of the Libor Masek [19] algorithms for iris recognition (based system 1), improvements in the algorithms allow operating with video-iris, obtaining for each frame a normalized template; this template contains only the texture information of the iris region.

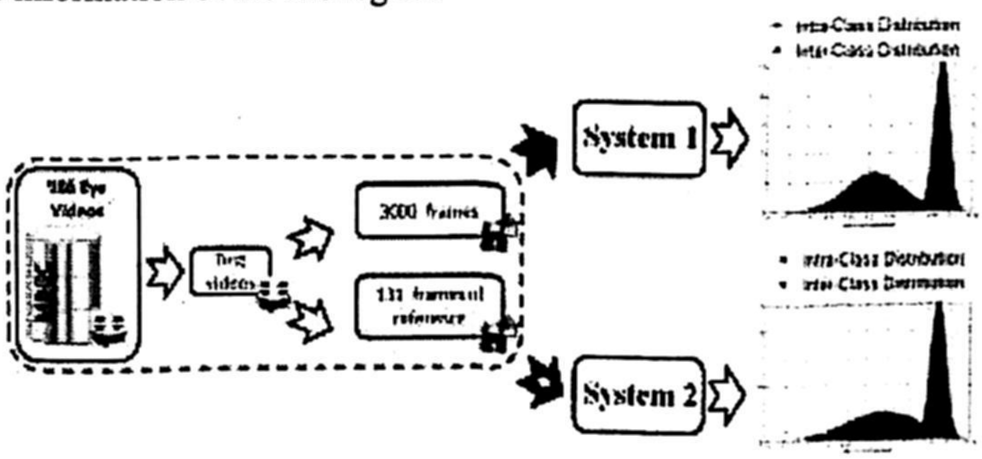
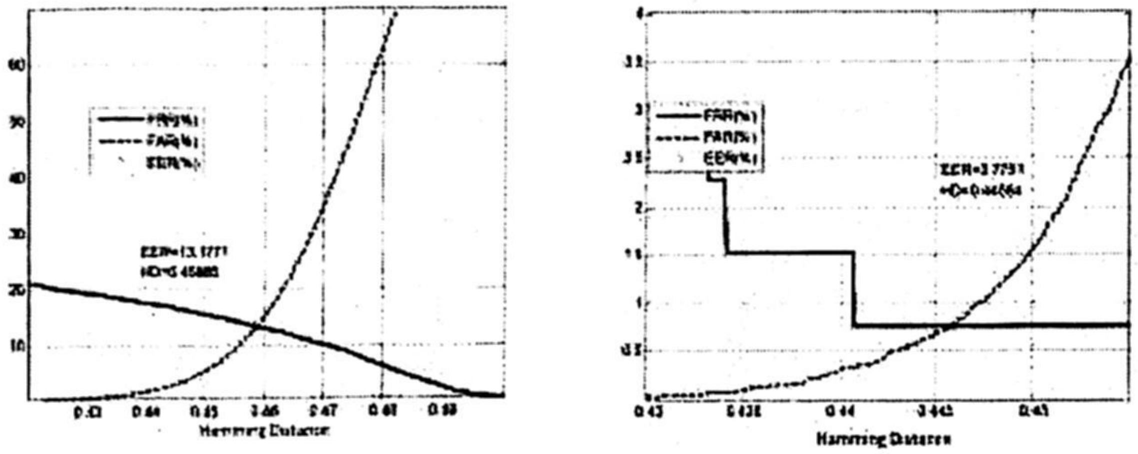


Fig. 5. Scenario of the testing systems.

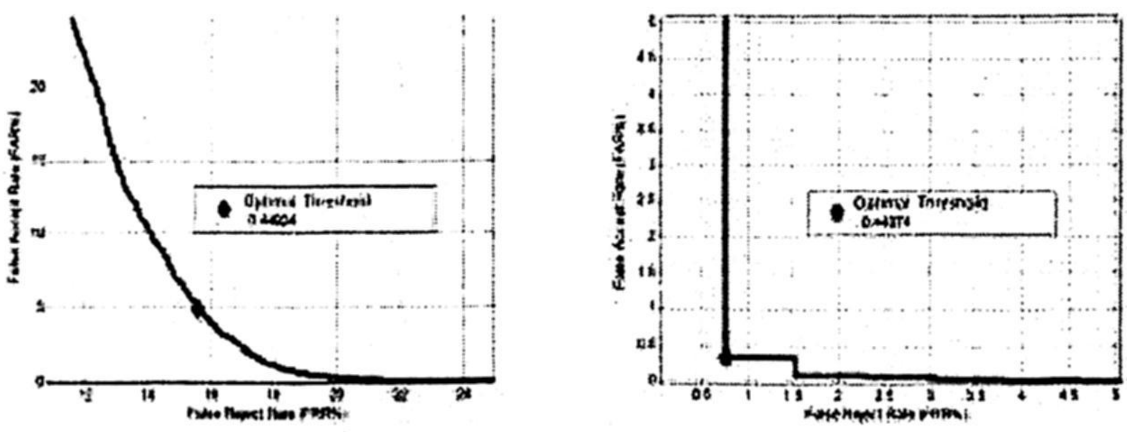
To evaluate the performance of proposed scheme in verification mode, the equal error rate (EER) and the receiver operating characteristics (ROC) curve [20] were used. Figure 1, shows the iris recognition scheme used in unconstrained environments modified to process video (System1) and Figure 3 illustrate the new scheme called System 2 which integrates the fusion stage. Figure 6.a shows the false acceptance rate (FAR) and false rejection rate (FRR) achieved by System 1 which provides an EER equal to 13.1771%, with a threshold (Th) of about 0.4586. Figure 6.b shows the FAR and FRR achieved by the new scheme (System 2) which achieves an EER equal to 0.7751% with a Th equal to about 0.44074.



(a) (b)

Fig. 6. The crossover point between the curves FRR and FAR, EER for systems. a) System 1, b) System 2.

The ROC curves, shown in Figure 7, plot the FAR as a function of the FRR, are useful to compare the performance of proposed and based systems. To confirm the accuracy of iris matching process and to show the overall performance of proposed new scheme, independently of the threshold value, the ROC curves were used. From experimental curves, it follows that the proposed new scheme (system 2) provides a better performance since the ROC curve is much closer to the origin than the proposed based system (system 1). Finally, using properly selected Th, the System 1 may achieve a FAR equal to 4.86%, which is significantly slower than the EER, although in this situation the FRR increases to 15.57% which is much higher than the EER. On the other hand, using the same threshold, the proposed new scheme (system 2) achieves a FAR equal to 0.3288% and a FRR equal to 0.7634%. In addition, in this situation, the genuine acceptance rate (GAR) for System 1 is 84.42% while for the proposed system (system 2) is about to 99.236%.



(a) (b)

Fig. 7. ROC curves (a) Cut-off point optimal, system 1, (b) Cut-off point optimal, system 2.

5 Conclusions

In this work, we propose an improved iris recognition system, integrating a new stage into the iris recognition system modified to use video, in order to increase its adaptability toward less constrained environments. Indeed, under less constrained environments, it is expected that the captured eye frames contain several types of noise and distortion, which affect the segmentation process and consequently impacts the recognition rate. The new stage exploits the biometric texture information from video-iris acquired under non-cooperative scheme, creating a fusioned normalized template through an image fusion technique based on PCA. We used the ROC curves to obtain the optimal decision threshold. The experimental results show that the proposed stage help to reduce the recognition error rates on the new proposed scheme (system 2), contributing to improve the recognition performance. It also decreases the EER by 12.4%; and for a given Th, FAR is reduced by 4.53%, while the FRR is reduced by 14.8% comparing with based iris recognition system (system 1). In addition, the GAR achieved by the proposed scheme (system 2) is 99.236%; while for the based system (system 1) is 84.42%. Thus, the results suggest that adding a fusion video stage to the architecture of the non-cooperative iris recognition, it could increase the system performance. Therefore, we can conclude that our proposal can be integrated as an optimization to the biometric recognition system based on video iris, for an application of iris recognition in uncontrolled environments.

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