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Image Quality Evaluation for Video Iris Recognition in the Visible Spectrum

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Abstract

Video-based eye image acquisition in the visible spectrum for iris recognition has taken great importance in the current context of the extensive use of video surveillance cameras and mobile devices. This modality can provide more information from the video capture of the eye region, but it is essential that the images captured have a quality that allows an effective recognition process. In this work, an approach for video iris recognition in the visible spectrum is presented. It is based on a scheme whose novelty is in the possibility of evaluating the quality of the eye image simultaneously with the process of video capturing. A measure of image quality that takes into account the elements defined in the ISO / IEC 19794-6 2005 standard and its combination with automatic detection methods is proposed. The experiments developed on three international databases and own video database demonstrate the relevance of the proposal.

Keywords: Iris Recognition; Quality Measure; Video

Introduction

Near-Infra-Red (NIR) light (in the range of 780 nm to 840 nm) is capable of effectively capturing the iris pattern since light in this range is scattered in the internal structures of the iris regardless of the color it is, or the possible low contrast between the iris and the pupil in those individuals with dark irises. However, most commercial sensors, such as video surveillance cameras, do not have NIR sensors to perform this type of capture. On the other hand, the rise of mobile devices such as smart phones and their integrated cameras are already used for various biometric applications. Nevertheless, in the case of iris biometry this can be hampered by the limiting factor of not having NIR sensors. Therefore, if you intend to use a sensor that works in the visible spectrum (in the range of 380 nm to 720 nm) to capture iris patterns, the success could be limited only to those instances of light color iris and that are captured in a controlled scenario. In view of the growing popularity of iris biometry based on this type of sensor [1], it is important to address this problem due to the wide spectrum of applications that can be developed. The acquisition of video-based eye images for iris recognition is an interesting alternative in the current context of the extensive use of mobile devices and video surveillance cameras [2,3]. This modality can provide more information from video capture of eye region.

The problem in these systems is the generated large amount of information from the video capture and how to decide what information will be passed to the system in order to perform the recognition process. A metric for evaluating the quality of eye images combined with automatic image detection can be an alternative. In this work, an approach for video iris recognition is proposed; it is based on a scheme whose novelty is in the possibility of evaluating the quality of the eye image in real time simultaneously with process of video capture. For this purpose, a measure of eye image quality is proposed, it takes into account the elements defined in the ISO/ IEC 19794-6: 2005 standard [4]. The combination of the proposed measure with automatic eye detection method ensures that eye images are extracted so that they do not have elements that negatively influence the identification process such as closed eyes and out-of-angle look. The work is structured as fallows. Section 2 discuss the related works, section 3 presents the proposed approach, in section 4 the experimental results are presented and discussed, and finally the conclusions of the work are set.

Related Works

Evaluating the quality of iris images is one of the recently identified topics in the field of iris biometry [5,6]. In general, quality metrics are used to decide whether the image should be discarded or processed by the iris recognition system. The quality of iris images is determined by many factors depending on the environmental and camera conditions and on the person, being identified [5]. Some of the quality measures reported in literature [6] focus on the evaluation of iris images after the segmentation process, which makes the systems in their capture stage, allow the processing of poor and good quality images. The main lack of these approaches is that the evaluation of the iris image quality is reduced to the estimation of a single or a couple of factors [3], such as out-of-focus blur, motion blur, and occlusion. Other authors [6,7] use more than three factors to evaluate the quality of the iris image: such as the degree of defocusing, blurring, occlusion, specular reflection, lighting, out of angle. Its main lack is they consider that the degradation of some of the estimated parameters below the threshold brings to zero (veto power) the measure that integrates all the evaluated criteria. This may be counterproductive in some systems where the capture conditions are not optimal.

The ISO / IEC 19794-6: 2005 [4] standard identified several properties of the iris image that influence the recognition accuracy. These factors include the distance of the acquisition system from the user, the pixel density of the iris texture and the degree of image blurring. In practice, some of these factors can be controlled by the correct selection of the camera, the correct analysis of the Depth of Field (DOF) and the Field of Vision (FOV). A quality measure that considers the parameters established in the standard [4] and evaluates detected eye image before the segmentation can produce a reduction in errors in the next steps of the system with a consequent increase in recognition rates.

The Proposed Approach

Figure 1 shows the general scheme of the proposed approach. The novelty of the proposed approach lies in the proposal of a new quality metric and it combination with a previous stage of eye image detection. This approach will ensure that the detected eye images do not have elements that negatively influence the identification related with: illumination, sharpness, blurring, gaze, occlusion, pixel density of image.

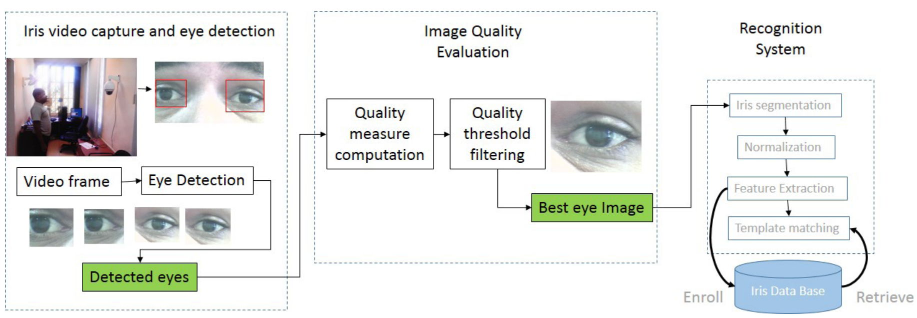

Figure 1: General scheme of the proposed approach.

Iris Video Capture and Eye Detection

In [9] the authors perform an analysis of the implication of using iris images in the Visible Spectrum (VS). They demonstrated how the use of a white LED light source positively influences the recognition rates of an iris recognition system. In our proposal, these precepts using a similar design to capture the video were assumed in this work. Detection of eye images is achieved through the classical Viola and Jones algorithm [10]. A detector was trained to detect open eyes containing pupils and iris with or without specular light reflection. The training set consisted of 1000 labeled eye images taken from the MobBio [11], UTIRIS [12] databases and our own dataset (see section 4). As positive samples were taken images of open eyes looking forward and as negative samples images of blurred, closed or occluded eyes.

Image Quality Evaluation

Among the parameters established by the standard [4], the FOV and the focal length are two parameters required to determine the distance between the subject and the camera. The FOV indicates the optimal distance between the subject and the camera for a given pixel density and the focal length is the zoom of the subject in the image. The FOV can be calculated by equation 1.

$$FOV = \frac{n}{d} \tag{1}$$

Where (n) are the pixels through the sensor and (d) is the desired pixel density. The standard [4] states that the pixel density (diagonal of iris image) of an iris image should be at least 200 pixels and contain at least two lines per millimeter (2 lppmm). If from detected eye images we can know their pixel density (EDens), it is possible to establish a percentage relation between the eye region and the iris region. It will allow us to estimate the iris pixel density (IDens) in the image captured, for this, it can be assumed that the iris represents 25 -30% of an eye image. Therefore, if the concept of pixel density is extrapolated from the iris to the eye using the classical Pythagorean Theorem, it is possible to determine the pixel density of an eye image (equation 2). Where w and h are the width and height of the detected eye image. Then it is possible to estimate the value of IDens by equation 3.

$$EDens = \sqrt{w^2 + h^2} \qquad (2)$$

$$IDens = \frac{EDens * ciris}{100} \qquad (3)$$

Where, ciris is the approximate percentage (25-30) of the detected eye image representing the iris.

Quality Measure for Eye Images

When an image is blurred or out of focus, it loses the details of the edges. In [3], the Kang & Park method was used to evaluate the quality of NIR iris images. This method applies a high-pass filter in the spatial domain and then calculates the total power using Parseval's theorem, which states that the total power has been conserved in the spatial and frequency domains. The method proposes a convolutional kernel of 5x5 pixels and consists of three square box functions, one of 5x5 size with amplitude -1, one of 3x3 size and amplitude +5, and four of 1x1 size and amplitude of -5. Theoretically, the operator can detect the high frequency of the iris texture much better and the processing time is reduced due to the small size core. It is possible that this behavior can be similar in different conditions of iris image capture and in images captured in the VS. Taking into account, that the sensor pixel density of an iris is a very important element that influences the quality of the images, we propose its combination with the Kang & Park method to obtain a quality measurement of the iris image (Qindex) that is calculated by equation 4.

$$Qindex = \frac{IDens * kpm}{UDens * Ukpm} \qquad (4)$$

Where kpm is the average value of the image pixels obtained as a result of the convolution of the input eye image with the Kang and Park kernel. UDens is the threshold established by the standard [4] for the minimum IDens with which it will be possible to obtain a quality image. Ukpm is the estimated threshold of kpm with which it will be possible to obtain a quality image, in [3] it is recommended from experimental results that it be =15. The values that Qindex can reach will depend on the thresholds selected for IDens and kpm. Thus considering the threshold UDEns= 200 for IDens that establishes the standard and Ukpm=15 experimentally obtained in [3], the minimum value of Qindex to obtain a quality eye image would be 1, higher values would denote images of higher quality and values less than 1 images with a quality below the standard:

If Qindex <1, the image has a quality below the parameters established by the standard.

if Qindex = 1, the image complies with the quality parameters established by the standard.

If Qindex> 1, the image has a higher parameters set by the standard quality.

One aspect to explore in this case would be to determine under what minimum values of Qindex it is possible to obtain acceptable recognition accuracies for a given configuration of a system.

Experimental Results and Discussion

In order to validate the proposal, our experimental design was divided into two parts. The first part was oriented to verify the validity of the proposed quality measure by evaluating it using three benchmark iris databases. The second part was oriented to the validation of the proposed approach using several quality thresholds (Thqindex) of eye images, from the video capture of 51 people eye regions using a video surveillance camera.

Implemented Pipeline for Experiments

Four basic modules compose the implemented pipeline for experiments. Iris image acquisition: The Iris image acquisition module is based on the approach described in the previous sections. Image segmentation: Segmentation algorithm based on Weighted Adaptive Hough and Ellipsopolar Transforms is a method implemented in the USIT system [13]. By combining the polar and the ellipsolar transforms, the limbic boundaries can be uniformly detected for VS and NIR. Iris texture feature extraction. For the purpose of experiments in this work, we used Scale-Invariant Feature Transform extracts SIFT-based key points [14]. Comparison (feature matching): Taking into account that we use SIFT method for feature extraction, for the comparison it is also necessary to use this method which estimates dissimilarity score by matching two sets of SIFT key points trimming false matches [14]. The average time it takes to analyze a frame of 1920 x1080 pixels, in a PC with an Intel Core i5-3470 processor at 3.2 GHz and 8 GB of RAM, is 20-30 milliseconds. This allows it to be used in any video iris recognition application.

Iris Datasets

The experiments were carry out on three benchmark iris databases and in our own dataset. MobBio [11] is a multi-biometric dataset including face, iris, and voice of 105 volunteers. The iris subset contains.16 images of each individual at a resolution of 300 × 200 (see an example in figure 2). The database contains images of people with light skin of Caucasian origin, dark skin of African origin. UTIRIS dataset [12] is an iris biometric dataset containing iris images of the same persons in VS and NIR. The database is constructed with 1540 images from 79 individuals and 158 classes. For our experiments, we used the VS set (806 images of 2048 x 1360, see an example in figure 2). UBIRIS-v1. VS Iris database [15]. For the acquisition, a Model Nikon E5700 camera with a 2/3-inch was used. In our experiments, we used a subset composed by 1500 images from all the subjects. (See an example in figure 2). The database contains images of light-skinned people of Caucasian and Asian origin. Our database consists of 102 videos of 51 people taken in two sessions of 10 seconds each at a distance of 1.55 m. The camera used was a SIQURA HSD820H2-E. It is a camera designed for video surveillance indoors and outdoors. The HSD820H2-E has a 20x zoom with 8x digital zoom, high definition 1080p resolution. In order to guarantee a high-resolution iris image, the videos were captured at resolution of 1920 x1080. The videos were taken in indoor conditions with ambient lighting and presence of specular reflections to achieve an environment closer to the poorly controlled conditions of a biometric application. The database contains images of people of clear skin of Caucasian origin, dark skin of African origin and mestizo skin (mulattos).

Experimental Results

The evaluation of accuracy of the proposed approach was assessed by the degree of influence of the eye image quality on verification accuracy. It was estimated by Equal Error Rate (EER) at False Acceptance Rate (FAR) ≤0.001%. The EER is the location on ROC or DET curve, where the False Reject Rate (FRR) and FAR are the same, or is computed as the point where False Nonmatch Rate = False Match Rate (FNMR = FMR). Table 1 shows the comparison of the EER obtained by the implemented system on MobBio, UTIRIS and UBIRIS v1 databases, taking 3 different values of Thqindex to reject or accept the eye images to be processed, equal to 0, 1 and the Qindex average value of the experimented database.

Database	Thqindex	% of images processed	EER
MobBio	0.0	100	36.15
	1.0	32.9	35.40
	1.09	10.5	30.53
UTIRIS	0.0	100	32.35
	1.0	77,8	31.99
	1.32	30.1	30.84
UBIRIS-v1	0.0	100	12.93
	1.0	96.6	11.65
	2.29	70.2	0.33

Table 1: Experimental results on MobBio, UTIRIS and UBIRIS v1 datasets.

The results in the three experimented databases show that the UBIRIS v1 contains higher quality images than the UTIRIS and MobBio, since the number of images with a Qindex value > = 1 represents 96.6% in UBIRIS v1, 77.8 % in UTIRIS and only 32.9% in MobBio. It is observed that as the value of the Thqindex increases, the system supports high quality images and rejects low quality images (See examples in figure 2). This increase in quality, results in a decrease in the EER, with the most significant result in UBIRIS-v1 where an EER = 0.33 is achieved with the 70% of the database and Thqindex=2.29. However, in the other two databases (MobBio and UTIRIS), increase in the Thqindex threshold results in a significant decrease in the number of images to be compared.

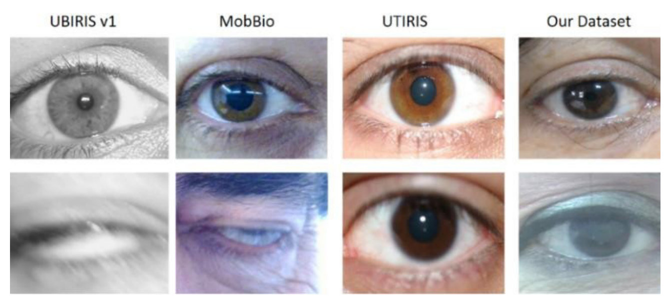

Figure 2: Samples of eye images with Qindex>=1(above) and Qindex<1(below).

Figure 3 shows the DET curve obtained on our own database from the processing of video sequences with different values of Thqindex. The use of the proposed approach in video processing allows maintaining the same number of images to be compared (1000 from all individuals) as the Thqindex threshold is increased with a consequent decrease in the EER.

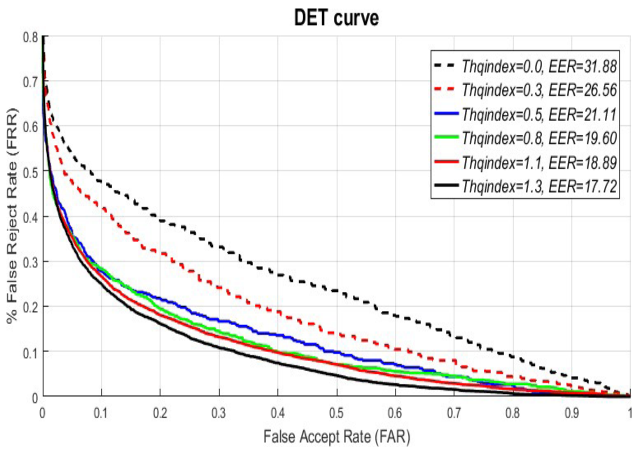

Figure 3: DET curves obtained in the experiment for the own video dataset capturing 1000 images containing all classes.

Conclusions

In this paper, we propose a new eye Image Quality Evaluation Approach for Biometric Iris Recognition in the VS. It combines automatic detection methods and a new image quality measure, based on the elements defined in the ISO / IEC 19794-6: 2005 standard, to ensure the high quality of eye images to be processed. We analyzed the relevance of the image evaluation stage as a fundamental step to filter the information generated from the iris video capture. The experimental results showed that the inclusion of the proposed approach within an iris recognition system limits the passage of low quality images to the system, which results in an increase of recognition rates.

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