NON-COOPERATIVE IRIS RECOGNITION: ISSUES AND TRENDS

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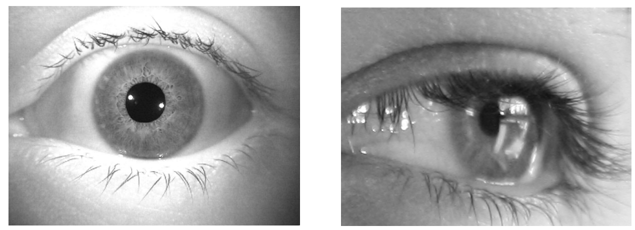
ABSTRACT

To date, no research effort has produced a machine able to covertly recognize human beings. Contrary to popular belief, such automata are confined to science fiction, although itÕs not hard to anticipate the potential impact that they would have in the security and safety of modern societies (forensics and surveillance). Among the research programs that pursuit such type of biometric recognition, previous initiatives sought to acquire data from moving subjects, at long distances and under uncontrolled lighting conditions. This *real-world* scenario brings many challenges to the Pattern Recognition process, essentially due to poor quality of the acquired data. Several programs now seek to increase the robustness to *noise* of each phase of the recognition process (detection, segmentation, normalization, encoding and matching). This paper addresses the feasibility of such extremely ambitious type of biometric recognition, discusses the major issues behind the development of this technology and points some directions for further improvements.



(a) *(b)*

Figure 1: Comparison between the typicall appearance of an (a) iris image acquired in highly constrained conditions in the near-infrared wavelength (WVU database [17]) and an (b) image acquired in the visible wavelength in unconstrained imaging conditions, at-a-distance and on-the-move (UBIRIS.v2 database [16]).

1. INTRODUCTION

The iris is known as one of the most valuable traits to perform the automatic recognition of human beings and growing attention has been paid to the development of iris recognition systems [3]. A number of reasons justify such interest: (1) it is a naturally protected internal organ that is visible from the exterior; (2) it has a near circular and planar shape that turns easier its segmentation and parameterization and (3) its texture has a predominantly randotypic chaotic appearance that is stable over lifetime. The accuracy of the deployed iris recognition systems is remarkable: a study of 200 billion cross-comparisons conducted by Daugman [6] reported false acceptance rates of order 10^{-6} with false rejections of 1% and other independent evaluations ([9] and [11]) confirmed these results.

Regardless a few recent innovations (e.g., the iris-on-the-move project [12]), deployed iris recognition systems are quite constrained: subjects should stop-and-stare close to the acquisition device while their eyes are illuminated by a near infra-red (NIR) light source that enables the acquisition of good quality images. Recently, several initiatives sought to increase acquisition distance and relax constraints by making use of visible wavelength (VW) light imagery, which broads the applicability of this technology to any domain where the subjects cooperation is not expectable and has obvious applications in terms of safety and security of modern societies.

However, as illustrated in figure 1, the use of VW light and the unconstrained data acquisition setup lead to notorious differences in the appearance of the captured data, which justifies the need of specialized recognition strategies to meet the full range of operational requirements.

Why Use Visible Wavelength Light?

Current recognition systems require high illumination levels, sufficient to maximize the signal-to-noise ratio in the sensor and to capture enough discriminating iris features with sufficient contrast. However, if similar processes were used to acquire iris images from longest distances, acceptable depth-of-field values would demand significantly higher f-numbers for the optical system, corresponding directly (squared) with the amount of light required for the process. Similarly, the motion factor will demand very short exposure times, which again will require too high levels of light. The American and European standards councils ([1] and [8]) proposed safe irradiance limits for NIR illumination of near 10 mW / cm^2. In addition to other factors that determine imaging system safety (blue light, non-reciprocity and wavelength dependence), these limits should be taken into account, as excessively strong illumination can cause permanent eye damage. The NIR wavelength is particularly hazardous, because the eye does not instinctively respond with its natural mechanisms (aversion, blinking and pupil contraction).

The pigmentation of the human iris consists mainly of two molecules: brown-black Eumelanin (over 90%) and yellow-reddish Pheomelanin [13]. Eumelanin has most of its radiative fluorescence under the VW, which—if properly imaged—enables the capture of a much higher level of detail, but also of many more noisy artifacts, including spec-

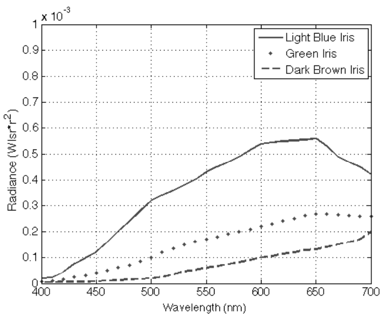


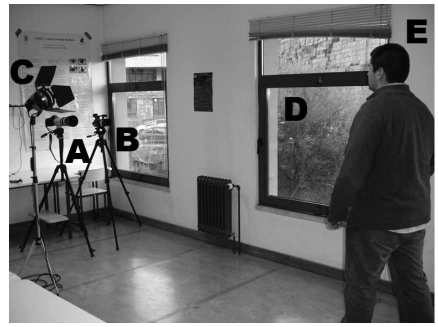
Figure 2: Spectral radiance of the human iris according to the levels of iris pigmentation [10].

ular and diffuse reflections and shadows. Also, the spectral radiance of the iris in respect of the levels of its pigmentation varies much more significantly in the VW than in the NIR (Figure 2). These optical properties are the biological roots behind the higher heterogeneity of the VW iris images, when compared to the traditional NIR data.

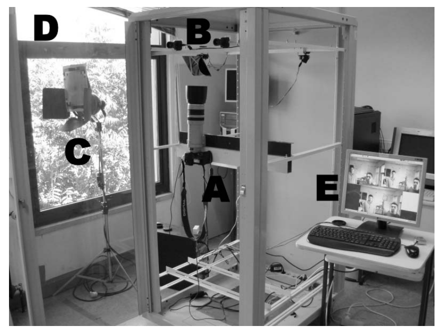
2. NON-COOPERATIVE ACQUISITION FRAMEWORK

The initial task comprised the construction of a data set able to be used in all subsequent experiments. Thus, the major purpose of the UBIRIS.v2 [16] data set is to constitute a tool to evaluate the feasibility of VW iris recognition under non-ideal conditions. The various types of degraded images, imaging distances, subject perspectives and lighting conditions on this database are of strong utility in the specification of the VW iris recognition feasibility and constraints. Figure 3a gives a global perspective of the acquisition framework and of the environment the UBIRIS.v2 data set was collected. In order to disburden the imaging sessions for volunteers and maximize the number of usable images per subject, we decided to perform data acquisition manually. In the meanwhile, a completely automated acquisition framework was devised, being composed by two commercial web cameras, a pan-and-tilt device and an high resolution camera (Figure 3b). The process starts by a software module that performs the detection of human silhouettes, according to the data acquired from one of the web cameras. Using this information and a set of semantic rules, a region of the scene is cropped and given to the real time face detector module (according to the well known method of Viola and Jones [18]). This phase gives the 2D position (x,y) of a face in the scene, which is sent to a stereo vision module that collects data from both web cameras and infer the subject depth in the scene, i.e., the distance z between the acquisition camera and the subject. Using the pan-and-tilt device, the acquisition camera is directed to the 3D scene point at coordinates (x,y,z) and an image that contains approximately the region of the subject's head is captured. Finally, using a set of biologically-based semantic rules, a region that contains the subject's eyes is cropped and used in the biometric recognition phases.

As illustrated in Figures 4 and 5, images of the UBIRIS.v2 data set are degraded by several factors and are highly heterogeneous, regarding the lighting conditions of the environment. Through visual inspection, fourteen different factors were detected and classified into one of two



(a)



(b)

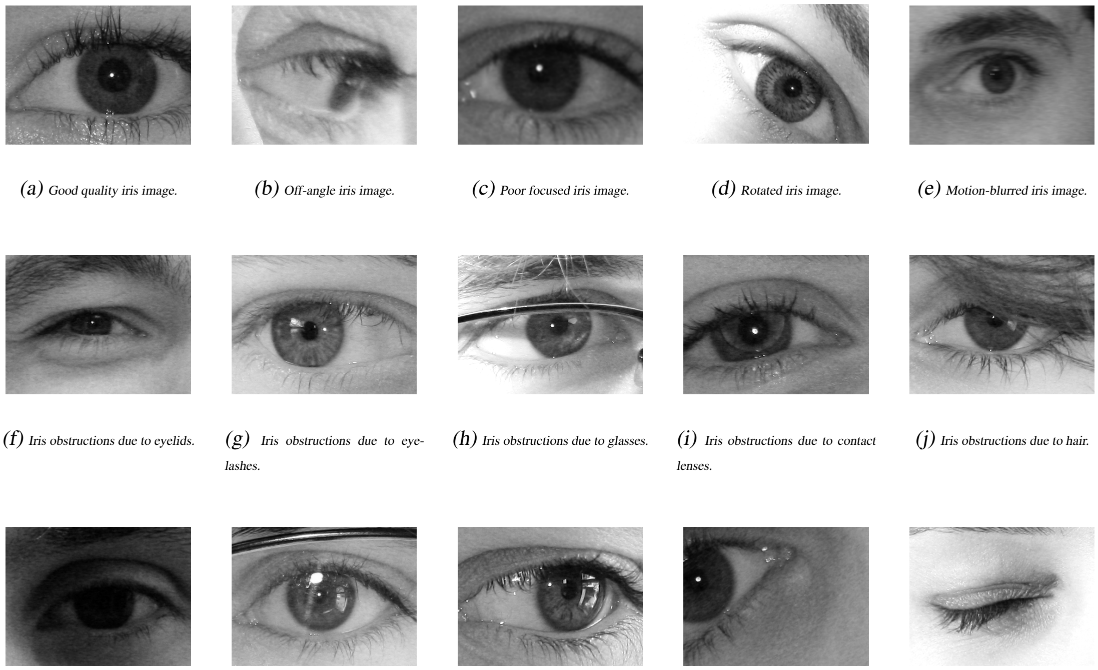
Figure 3: Overview of the image acquisition frameworks (a) used to collect the UBIRIS.v2 data set (A,B: cameras; C,D: light sources; E: subject and (b) used to perform automatic image acquisition, with similar labels to the manual configuration.

major categories: *local* or *global*, as they affect exclusively image regions or the complete image. The *local* category comprises iris obstructions, reflections, off-angle and partial images, while the *global* comprises poor focused, motion-blurred, rotated, improper lighting and out-of-iris images.

Figure 4: Example of a sequence of close-up iris images acquired at different distances (between eight and four meters), on a moving subject and under dynamic lighting conditions.

3. RECOGNITION SPECIFICITY

Previous works had reported an almost infinitesimal probability of producing a false match in comparing signatures extracted from good quality data (e.g., [7], [4], [9] and [11]), which is due to the chaotic appearance of the iris texture and regarded as one of the technology's major advantages, when compared to other biometric traits. This section goes one step beyond and analyzes the probability of producing false matches when comparing degraded iris samples (or from par-



(a) Good quality iris image. (b) Off-angle iris image. (c) Poor focused iris image. (d) Rotated iris image. (e) Motion-blurred iris image.

(f) Iris obstructions due to eyelids. (g) Iris obstructions due to eyelashes. (h) Iris obstructions due to glasses. (i) Iris obstructions due to contact lenses. (j) Iris obstructions due to hair.

(k) Iris imaging in poor lighting conditions. (l) Iris with specular reflections. (m) Iris with lighting reflections. (n) Partial captured iris. (o) Out-of-iris image.

Figure 5: Comparison between a good quality image (Figure 5a) and several types of non-ideal images of the UBIRIS.v2 database. These images resulted of less constrained imaging conditions, under varying lighting conditions, at-a-distance and on-the-move subjects.

tial or non-iris regions due to failures on the eye detection and segmentation modules). This hypothesis was tested using the recognition method proposed by Daugman [7] - composed by iris segmentation, normalization, encoding (bidimensional Gabor wavelets) and matching (Hamming distance) - we extracted 1 000 signatures from UBIRIS.v2 images with good quality. Then, we extracted a set of signatures from 1 000 degraded images, 10 000 non-iris or partial iris images and 10 000 natural and synthetic textures. Finally, using an '*one against all* comparison scheme, we performed a total of 21 000 000 comparisons between signatures. During these tests we didn't get a single dissimilarity value close to the usual acceptance threshold (0.33), which means that not even a single false acceptance was observed if the traditional acceptance thresholds are used. Figure 6 gives the histogram of the obtained dissimilarity values (vertical bars) and the approximated Gaussian distribution (line plot with $\mu = 0.49992$ and $\sigma = 0.02419$). We confirmed that, even on highly degraded data, the used iris encoding and comparison strategies produce a false match with almost null probability. Based on the parameters of the fitted Gaussian distribution, the probability of producing a dissimilarity value lower than 0.33 will be approximately of 1.03923×10^{-12}. Once again, the role of this value for the type of recognition discussed in this paper should be stressed: it can be assumed with extreme confidence that non-cooperative recognition systems will not produce false matches and — thus — any match reported has a full probability of being genuine.

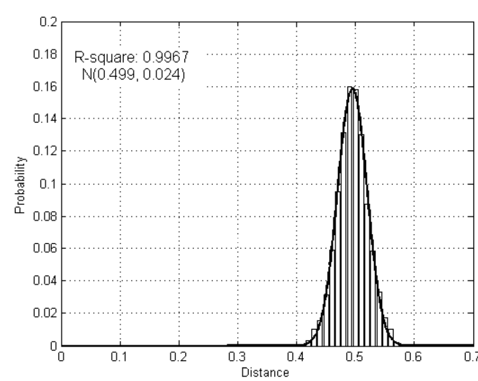


Figure 6: Histogram of the obtained dissimilarities when comparing signatures extracted from 1 000 templates with good quality and 21 000 signatures extracted from iris images with bad quality, partial irises and non-iris data. "R-square" gives the goodness-of-fit of the plotted Gaussian distribution with $\mu = 0.499$ and $\sigma = 0.024$ to the obtained results.

4. RECOGNITION SENSITIVITY

As above stated, the uncontrolled acquisition setup leads to data with heterogeneous quality. In this scope, quality assessment is a fundamental task: the goal is to quantify characteristics and fidelity of the segmented data, particularly in terms of its utility. This is essential, as performing recognition in too much degraded data decreases matching accuracy and increases computational complexity.

According to the afore observations, this section aims at giving an approximation of the recognition rates that non-cooperative iris recognition systems would achieve, according to the quality of the used data. Again, we used the classical Daugman's recognition strategy [7] for our experiments and, according to this choice, the iris boundaries were normalized to dimensionless polar coordinates. Then, a bank of Gabor filters was used to analyze the iris texture and the angle of each phasor quantized to one of four quadrants. Finally, the fractional Hamming distance gave the dissimilarity between two irises. A subset of 10 427 UBIRIS.v2 images was selected, which under visual inspection we verified that the segmentation method has accurately segmented. For comprehensibility, we refer to a *recognition test* when each sample of a data set is matched against all the remaining images of the the same data set, resulting in two types of comparisons: intra-class (genuine) and inter-class (impostor). As suggested by Daugman [5], for two-choice decisions the decidability index d' measures how well separated are the two types of distributions and recognition errors correspond to their overlap area:

$$d' = \frac{|\mu_E - \mu_I|}{\sqrt{\frac{1}{2}(\sigma_I^2 + \sigma_E^2)}} \tag{1}$$

where μ_I and μ_E are the means of the two distributions and σ_I and σ_E their standard deviations.

Figure 7 compares the histograms of the fractional Hamming distances for the genuine (light bars) and impostor (dark bars) comparisons obtained when all images were used in the recognition test (Figure at the far left) and when the poorest quality samples (according to the visual perception of quality) were rejected (Figure at the center). The line plots correspond to the fitted Normal distributions and the upper left corner gives the corresponding decidability index d'. As general considerations, we confirmed that values obtained for the impostor distributions do not significantly vary according to the quality of the data and are almost the same reported for the NIR constrained recognition setups. Oppositely, there is a significant movement of the genuine distributions toward the impostors, substantially decreasing the sensitivity of the system, if traditional acceptance thresholds are used. Due to this, the decidability of the VW recognition systems significantly varied. Figure 7c shows how the true and false matches in our system would change according to different decision thresholds, when no quality is considered (continuous line) and when only samples with good quality are considered for recognition (dashed line). Here, we plot the area under curve (AUC) for both setups, which significantly augments as the poorest quality samples are rejected.

5. CONCLUSIONS AND DIRECTIONS

The possibility of performing automatic recognition of human beings in uncontrolled environments and without requiring them any type of cooperation is of evident interest or forensic and security purposes and represents a *grand-challenge* for the pattern recognition community. This paper discussed the use of VW light to acquire iris images from moving subjects without requiring them any active participation and the potential use of such data to perform biometric recognition. We presented the main characteristics of a data set that is free available for the research community (UBIRIS.v2), and highlighted some of the issues behind the development of this type of recognition.

Due to the evident impact that the type of recognition discussed in this paper would have in modern societies, multiple research efforts are now putted in the development of such technology. Among those, there is an extremely promising new type of biometric recognition called *periocular biometrics* that refers to the regions in the immediate vicinity of the eye (Figure 8) and attempts to perform recognition based not only in the iris but also to its neighborhood.

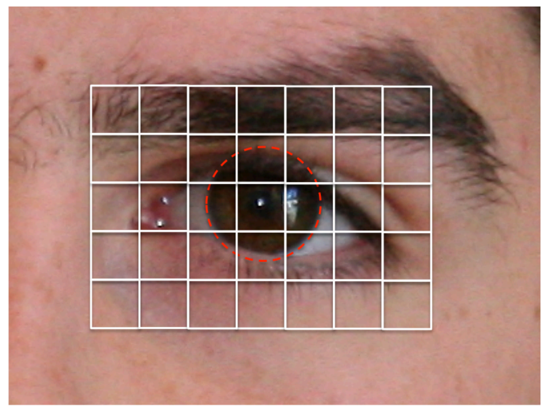


Figure 8: Periocular biometrics refers to the automatic recognition of human beings using not only the information of the iris texture but also of the surrounding information (eyelids, eyelashes, skin, eyebrow). This type of recognition can provide a significant improvement toward the development of recognition methods that perform surreptitiously and in unconstrained environments.

As argued by [15] and [14], periocular recognition is a trade-off between using the entire face region or only the iris: it avoids the resolution problems of iris images captured at long distances and can be used for a wide range of distances. Also, face images acquired from unconstrained environments often suffer from poor illumination, motion blur, low resolution and pose variations. that significantly degrade the effectiveness of face recognition techniques. To the best of our knowledge, few studies have been conducted on the use of the periocular region as a biometric trait. Park et al. [15] used both local and global image features to match periocular images acquired with visible light and established its utility as a soft biometric trait. Miller et al. [14] used Local Binary Pattern (LBP) to encode and match periocular images. Bharadwaj *et* al. [2] proposed the fusion between global and local data encoding and matching strategies, having reported highly promising performance in UBIRIS.v2 images.

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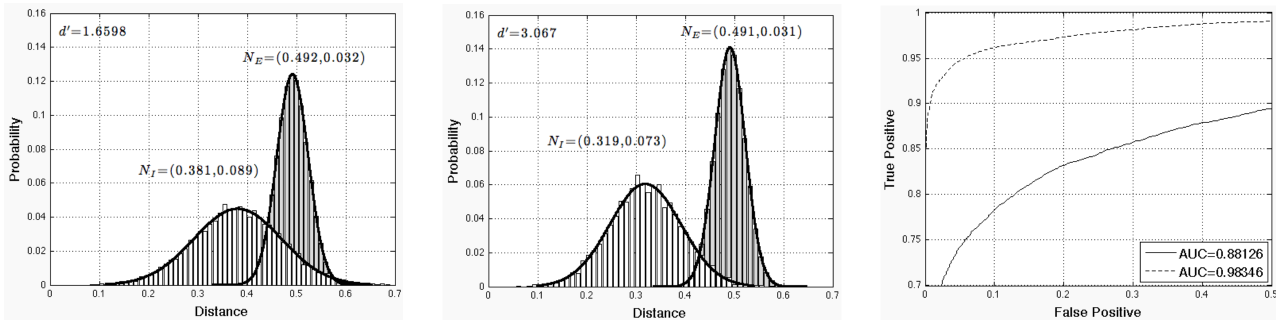

(a) *(b)* *(c)*

Figure 7: Comparison between the histograms of the fractional Hamming distances obtained (a) for a sub-set of 10 427 images of the UBIRIS.v2 database and (b) when samples of poor quality are not considered to the recognition test. Figure at far right gives the corresponding Receiver Operating Characteristic curves.

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