On the Fusion of Periocular and Iris Biometrics in Non-ideal Imagery

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Abstract

Human recognition based on the iris biometric is severely impacted when encountering non-ideal images of the eye characterized by occluded irises, motion and spatial blur, poor contrast, and illumination artifacts. This paper discusses the use of the periocular region surrounding the iris, along with the iris texture patterns, in order to improve the overall recognition performance in such images. Periocular texture is extracted from a small, fixed region of the skin surrounding the eye. Experiments on the images extracted from the Near Infra-Red (NIR) face videos of the Multi Biometric Grand Challenge (MBGC) dataset demonstrate that valuable information is contained in the periocular region and it can be fused with the iris texture to improve the overall identification accuracy in non-ideal situations.

1 Introduction

The human iris exhibits a complicated textural pattern on its anterior surface. An iris recognition system exploits the perceived uniqueness of this pattern to distinguish individuals [2]. The key processing steps of an iris recognition system are: (a) acquiring the iris imagery; (b) locating and segmenting the iris; (c) encoding the textural patterns as feature templates; and (d) matching the templates across an existing database for determining identity. A majority of iris recognition systems require a considerable amount of user participation. The iris information captured by the sensor is either processed immediately, or stored in a database for later processing. The biometric cue resident in an iris image depends on at least two factors: (a) the quality of the image; and (b) the spatial extent of the iris present in the captured image. Both these factors can be regulated at the image acquisition stage to achieve reliable accuracy. However, such a regulation is possible only when the iris recognition system is employed in an overt situation involving cooperative subjects.

Acquiring the iris information becomes extremely challenging in covert operations or in situations involving a non-cooperative subject. Several challenges such as moving subjects, motion blur, occlusions, improper illumination, off-angled irises, specular reflection, and poor image resolution adversely affect the biometric content of the iris data. In such situations, the reliability of the iris data could be improved by fusing it with information from the surrounding regions of the eye. Some recent works [9], [11] demonstrate the feasibility of using periocular information as a soft biometric trait in high-resolution images of the face. In this work, the feasibility of using periocular biometrics in *non-ideal conditions*, where iris recognition might not be effective, is studied.

2 Periocular Biometrics

A fixed region surrounding the iris of an individual is referred to as the periocular region[1]. Depending on the size of the image used, this region usually encompasses the eyelids, eyelashes, eyebrows, and the neighboring skin area. Using the periocular region has the following advantages: (a) the information regarding the shape of the eye and texture of the skin around it can vary across individuals; which can be used as a soft biometric trait, and (b) no additional sensors, besides the iris camera, are required to acquire the periocular data.

Periocular skin texture has been used for human identification in various ways. Jain et al. [6] detect

[1]The definition of *periocular region* provided here is specific to this work. Definitions found in the medical literature can differ from this.

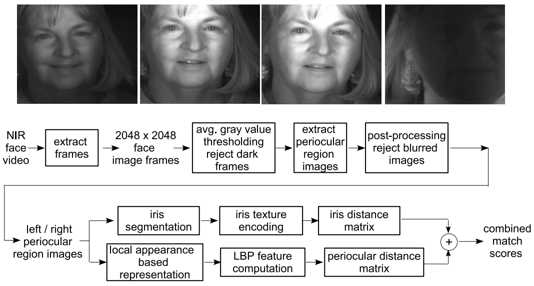

Figure 1. TOP: Four frames from a NIR video of a person. BOTTOM: Overview of the proposed approach.

micro-features such as moles, scars, or freckles and use them as soft biometric traits. Others adopt a more general representation of the overall texture to facilitate recognition using popular texture measures such as Discrete Cosine Transformations (DCT) [4], Gradient Orientation Histograms (GOH), or Local Binary Patterns (LBP) [11, 9]. However, we are not aware of any previous work that attempts to perform human recognition in non-ideal images by combining the information present in the iris and periocular regions.

3 Experimental Dataset

The Near Infra-Red (NIR) face videos of the Multi Biometric Grand Challenge (MBGC) database [12] are used in this work as they represent some of the non-ideal conditions discussed above. The database was constructed by capturing the facial videos of subjects walking through a portal. The videos have a spatial resolution of 2048×2048 pixels recorded in the AVI format with a frame rate of 15 frames per second (fps). Even though the extracted frames are of a very high resolution, the average usable spatial extent of the iris is about 120 pixels. The database contains 149 videos collected from 114 distinct subjects.

All the frames of a given video are extracted and saved in the BMP format without any compression. These frames exhibit large variations with respect to factors such as eye blinking, motion blur, occlusions, specular reflection and illumination. The illumination across the frames is not constant as the external NIR illuminant is activated only for a brief duration of time when the subject walks through the portal. Some of the extracted frames were devoid of any reasonable biometric cue due to lack of illumination. Extracting the iris or periocular information from such images is almost impossible and thus they are rendered unusable (see top row of Figure 1). To exclude such frames, a thresholding process based on the average gray value is used.

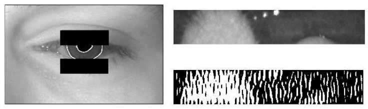

Figure 2. Stages involved in iris recognition. Left: Segmented iris. Top right: Normalized or unwrapped iris. Bottom right: IrisCode.

Although the videos record individuals walking through a portal toward the camera, the effect of scaling in the periocular regions was not significant in the extracted images. Thus, periocular regions of a fixed size, 601×601 pixels, are cropped from the images after marking (manually) the centers of the eyes. Further processing of these cropped periocular region images, based on Fourier energy spectrum [3], is carried out to remove blurred images from the sequence. The resulting database, after the exclusion process, contains: (a) 523 right eye images pertaining to 86 distinct subjects; and (b) 520 left eye images belonging to 88 distinct subjects. From this data, the iris and periocular textural patterns are extracted using the techniques described in Sections 4 and 5, respectively. An overview of the proposed approach is shown in the bottom row of Figure 1.

4 Characterizing Iris Texture

One of the critical steps in an iris recognition scheme is to *localize and segment* the iris in the image. Given an image I, the iris can be localized by detecting its pupillary and limbic boundaries using an integro-differential operator, as described in [2]. Segmentation is then performed to separate the localized iris from the noisy regions such as eyelashes, eyelids, pupil and specular reflection. In this work, segmentation was performed manually, as automatic segmentation on poor quality data may lead to errors. The size of an iris can vary significantly due to its dilation, contraction, and its distance from the sensor. To address such size variations, the segmented iris has to be *unwrapped* onto a normalized polar coordinate system. This *normalization* operation is performed by representing the segmented iris as a rectangular entity, the rows of which correspond to the concentric regions of the unsegmented iris. Simultaneously, the mask denoting the noise regions is also unwrapped into the normalized coordinate system.

To extract the textural features of the iris, a two dimensional Gabor filter is convolved with the unwrapped iris image. The phasor output of this operation is encoded as a matrix of bits known as an *IrisCode*. The Hamming distance between two IrisCodes is used as a measure of dis-similarity between two irises and this value is computed after masking the noisy regions of the irises. Figure 2 shows examples of the stages discussed above. In this work, an open source MATLAB based implementation [8] of Daugman's algorithm [2] was used in the iris recognition experiments.

5 Characterizing Periocular Skin Texture

The periocular skin texture representation is inspired by the idea of local appearance features. To this effect, the periocular images are tessellated into blocks for which the texture features are computed locally. The entire image is then represented by a feature set computed by concatenating the vectors corresponding to each block. Such a representation preserves the spatial relationship of the features, and leads to a fixed length feature vector for each image that can be used directly for matching without any further normalization of the set. To independently evaluate the contribution of the periocular texture toward overall recognition performance, in this work, the interior eye regions are masked with an ellipse of fixed dimensions. This prevents the iris texture being taken into account during periocular recognition. The periocular texture computation steps are shown in Figure 3.

Local Binary Patterns (LBPs) [10] are used as the periocular texture measure. They quantify the commonly observed intensity patterns in a local pixel neighborhood patches such as spots, line ends, edges, corners, and other distinct texture patterns, and have been used in face recognition [1, 7], and iris recognition [13]. The LBP score for a pixel is computed by counting the binary changes of intensity patterns in a p pixel neighborhood along a circle of radius r around that pixel. Let I be the preprocessed input periocular region image (grayscale) that is divided into N blocks of M pixels each with $I^{(i)}$ representing the i^{th} image block. An LBP vector is computed for each pixel in an image patch $I^{(i)}$, which is in turn encoded into a histogram of b_t bins, where $b_t = p(p-1)+3$ (see [9] for details). The overall texture feature representation of the image is given by an ordered set $\mathcal{T}(I) = \{T^{(1)}, \ldots, T^{(N)}\}$, where $T^{(1)}, \ldots, T^{(N)}$ are the texture histograms corresponding to the N blocks. For matching two periocular texture representations, $\mathcal{T}(I)$ is converted to its vectorized form $\overline{\mathcal{T}}(I)$ of $N \times b_t$ dimensions and a distance function $D\left(\overline{\mathcal{T}}(I_1), \overline{\mathcal{T}}(I_2)\right)$ is used to compare the texture features for two images (I_1 and I_2). Of the various commonly used histogram comparison functions, the city-block metric was observed to perform the best in our experiments.

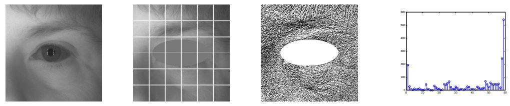

Figure 3. Steps involved in computing the periocular skin texture using LBP: (from left to right) input image, local blocks, LBP scores, and patch histogram.

6 Score Level Fusion

Given two non-ideal images of the iris, the aforementioned processes are invoked in order to generate two match scores: one pertaining to the iris and the other pertaining to the periocular region. The iris and periocular texture scores are first normalized using the min-max normalization scheme [5]. A simple sum rule is then used for score level fusion. In our experiments, the weights associated with the two modalities were varied in the range [0.1, 0.9] in order to determine matching accuracy. In this work, it was noticed that the best matching performance was obtained by assigning the weights 0.4 and 0.6 for the iris and periocular biometrics, respectively. While other sophisticated fusion schemes could have been used, the use of the min-max normalization followed by the the simple sum rule preempts the need to have a large number of training scores. Further, since the goal of this work is to demonstrate the utility of the periocular biometric in non-ideal iris images, current efforts were confined to the feature extraction and matching routines. More sophisticated fusion schemes at the feature and score levels will be investigated in the future.

7 Experimental Results

Two different experiments were conducted to demonstrate the benefits of the proposed scheme. In *Experiment1*, for each modality, the feature vectors associated with the right- and left eyes of an individual are compared against that of the other images (left vs left, right vs right) in order to generate two score matrices - one corresponding to the left eye and the other to the right eye. These scores are then fused to obtain the distance matrices for joint recognition. The ROC curves generated as a result of *Experiment1* along with the equal error rates (EER) are shown in Figure 4 (top). *Experiment2* involves computing cumulative match characteristics (CMC) for a 1 probe, 2 gallery configuration. Since a minimum of three images per subject are required for this experiment, the number of subjects was reduced to 80 right eyes and 79 left eyes. The resulting plot can be seen in Figure 4 (bottom).

In case of the left eye, the rank-1 recognition rates for the iris and periocular regions were observed to be 13.8% and 92.5% respectively, while the combined rank-1 recognition rate was 96.5%. Similarly for the right eye, the rank-1 recognition rates for the iris, periocular regions and their combination were 10.1%, 88.7%, and 92.4% respectively. Although higher iris recognition performance was reported for the MBGC portal chalenge [12], the target images used in the MBGC experiments were still images of relatively higher quality (and of a significatly larger size). In this work, both the target and query images are from the NIR face videos and as described earlier, of highly non-ideal in nature. This is one of the big reasons for the low performance of the iris biometric on its own. The values considered for the various parameters of the LBP scheme are: $N = 36$, $M = 2500$ (50×50 block size), $r = 1$, $p = 8$, and $b_t = 59$.

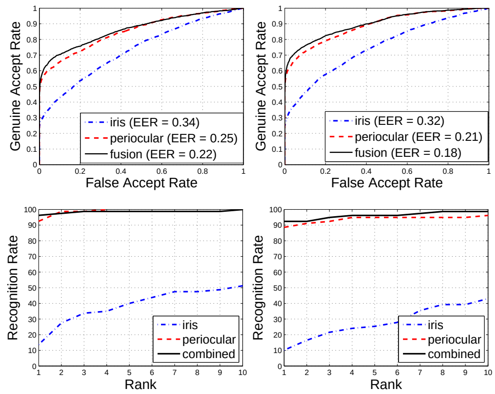

Figure 4. Results for *Experiment1* (top) and *Experiment2* (bottom), for the left and the right eyes (left and right column, respectively).

8 Conclusion

The goal of this paper is to demonstrate the benefits of fusing periocular and iris information for reliable human recognition in non-ideal conditions. Experiments indicate that periocular-based matching outperforms iris-based matching by a large margin thereby indicating an immense potential for its use in non-ideal imagery. The rank-1 recognition accuracy of the biometric system was further improved when both periocular and iris information were used simultaneously by performing score-level fusion. These results bode well for covert applications where the entire iris entity may not be reliably obtained. By using both the iris and the periocular texture simultaneously, the possibility of human recognition in unconstrained environments is significantly improved. Future work includes exploration of additional features such as shape to represent periocular region, extensive experimental validation on a larger dataset (possibly spanning visible spectrum), and using more sophisticated fusion techniques.

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