CHAPTER 12

Iris Recognition in Mobile Devices

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CONTENTS

With the popularity of mobile devices (phones, tablets, and other portable devices), people have begun to trust their contraptions with sensitive information. The requirement for security on mobile devices has become prevalent; many devices are marketed on their ability to protect user data. Many phones, such as the Apple iPhone and Samsung Galaxy phones, are also marketed based on their innovative camera technologies. The imaging advancements beg to be the solution to society's security requirement; hence the attractiveness of iris recognition.

12.1 OVERVIEW

12.1.1 History

Daugman (2014) was the first to explore the use of iris as a biometric identification indicator. His work implemented integro-differentials operators to focus on the iris and 2D Gabor filters to extract features from the iris texture. Among the first, Jeong et al. (2005) and Cho et al. (2005) proposed mobile methods for extracting the iris information and localizing the pupil, respectively. There have been many other contributors to the building of a reliable iris identification method.

12.1.2 Methods

Although there are several approaches to iris recognition and identification, the majority of current and new methods can be split into six generic phases. The first phase is simply the *Capturing* of the iris. This is typically accomplished with a camera that operates in the visual (VIS) spectrum, but could possibly be done with a near infrared (NIR) sensor (Jillela and Ross 2015). The second phase is *Image Correction*. Since images can be taken in multiple different lighting environments, corrections need to be made to transport images onto a common baseline. The third phase, *Iris Segmentation*, is the analytical process of separating iris information from the rest of the image. Once the critical information is isolated, *Normalization* converts information gathered from the iris texture into a standard format. From this format, *Feature Extraction* collects essential information into a quantitative form. The final phase is the *Matching* of features to identify the iris. These phases often overlap during the overall process of identification.

12.1.3 Challenges

The majority of mobile iris recognition struggles are rooted in the imperfect imaging process. While the iris is a semiperfect circle, eyelids and eyelashes interfere to allow only a partial view of the iris. *Iris Segmentation* attempts to capture the visible iris despite the interference (Jillela and Ross 2015). Specular reflections and improper illumination (such as shadows and high-intensity lighting) can also interfere with the multiple phases of recognition; *Image Correction* attempts to minimize the effect of such noise. Imaging also finds a dilemma in the use of front-facing and rear-facing cameras. While front-facing cameras are ideal because of their ease of use, the imaging produces lower resolutions on a weaker sensor. In contrast, rear-facing cameras typically have higher resolutions and premium sensors, but require the mobile device to be turned around and tediously aligned for imaging (Jillela and Ross 2015). While imaging of the iris can still be managed, the use of the more common VIS sensor is less accurate than the NIR sensors for imaging iris texture (Jillela and Ross 2015). A final challenge is the consideration of false positives from the imaging of deceptive iris; therefore, liveness detection must be considered during *Capturing*.

12.2 MOBILE DEVICE EXPERIMENT

Barra et al. (2015) experimented iris recognition with modern mobile device while utilizing homogeneity algorithms for segmentation and spatial histograms for matching.

12.2.1 Data

Since Barra et al. (2015) had a focus on use in mobile devices; they created a new database, MICHE-I, that would serve as a rigorous examination of mobile iris recognition. The database contains a collection of images imitating typical attempts of iris recognition from an Apple iPhone 5, Samsung Galaxy S4, and Samsung Galaxy Tab 2. The VIS images were taken both indoors and outdoors with both the rear-facing and front-facing camera at variable distances. (Due to the low quality of the rear-facing camera, the Samsung Galaxy Tab 2's front-facing camera was the only tablet sensor applied for the database.) With a database focused on mobile environment noise, the experiment can be better tested as a realistic form of mobile iris recognition.

Barra et al. (2015) included two additional databases, UPOL and UBIRIS, to understand the performance of their proposed method. UPOL is a collection of VIS images that are under near-perfect conditions; the images are at a high resolution with only the pupil, iris, and portion of sclera visible. UPOL will determine if their method performs as expected without noise. UBIRIS is a collection of noisy VIS images that simulate less constrained capturing but are of higher resolution and cropped properly to the eye area. UBIRIS serves as a viable comparison to the noisier MICHE-I database.

12.2.2 Methods

Barra et al. (2015) applied a series of image corrections on the collected iris images. First, an image is quantified by a grayscale histogram passed through an enhancement filter to remove interference. A "canny" and a median filter are also applied to distinguish the pupil area. Assuming the pupil area is circular, the algorithm developed by Taubin (1991) is utilized to find circular regions. The circular regions are then scored based on the homogeneity and separability of the corresponding pixels to accurately define the iris and sclera boundary. Once the iris circle is defined, the circle region is normalized with polar coordinates. A median filter is used to discard unnecessary sclera inclusion.

To extract features, Barra et al. (2015) utilized a spatial histogram (or spatiogram) calculated from the iris image. The spatiogram is utilized because it preserves the image's geometric orientation without the need for exact geometric transformations. The spatiograms can be used to efficiently calculate differences between two irises for matching.

12.2.3 Results and Conclusion

To first determine the performance of the method, Barra et al. (2015) utilized the UPOL and UBIRIS databases against the MICHE-I image set. The results of the proposed method on UPOL and UBIRIS were mostly effective according to the receiver operating characteristic (ROC) graph (Figure 12.1). MICHE-I with the method proved less effective (Figure 12.2); the database proved too difficult for the method. While the method may benefit from refinement, the results pointed to the need for more controlled conditions of imaging from the user.

12.3 MOBILE DEVICE EXPERIMENT WITH PERIOCULAR INFORMATION

People typically do not recognize others based on their iris texture alone. We absorb the features around the eye also known as the periocular. Since iris is difficult to detect, Santos et al. (2015) utilized the periocular information for recognition. Detecting both the periocular and iris information separately and fusing them together results in powerful recognition.

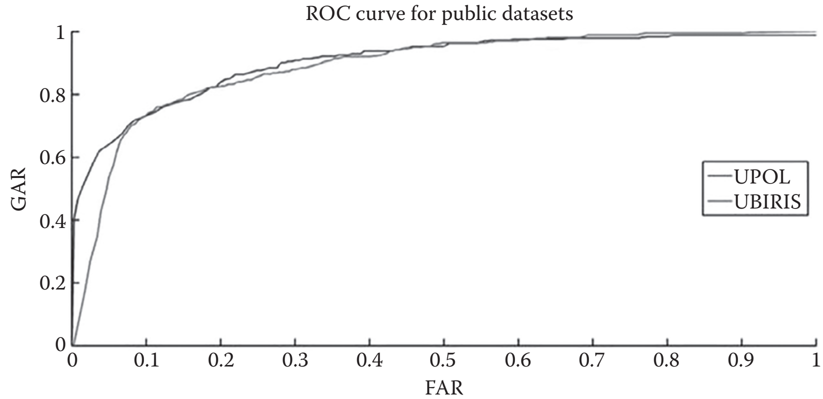

FIGURE 12.1 ROC curve shows effectiveness for UPOL and IBIRIS. (From Barra S. et al. 2015. *Pattern Recognition Letters*, 57, 66–73.)

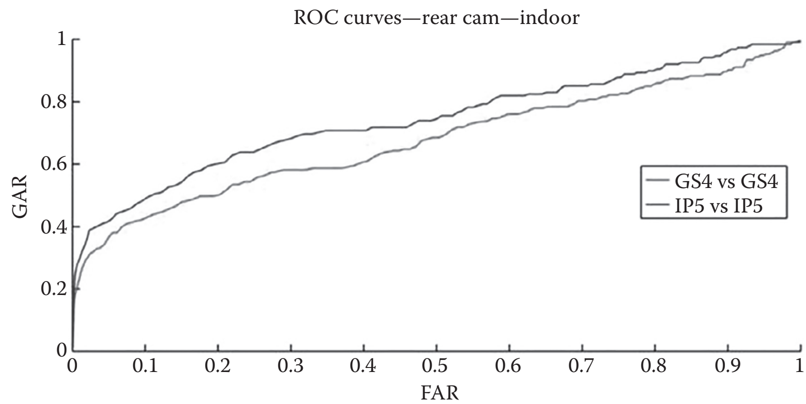

FIGURE 12.2 ROC curve of indoor use of rear-facing cameras prove less effective. (From Barra S. et al. 2015. *Pattern Recognition Letters*, 57, 66–73.)

12.3.1 Data

Santos et al. (2015) created their own iris database for the purpose of incorporating the mobile aspect of the iris recognition. To ensure cross-platform capability, the database consisted of 50 subjects with 4 devices in 10 different setups. These setups included both the rear-facing and forward-facing cameras with both no flash and flash if available. The simulation included multiple lightning situations because mobile use involves iris recognition in a variety of environments. The images also contain significant noise, such as image rotation, deviated gaze, focus issues, and obstructions.

12.3.2 Methods

To split the image for computing iris recognition and periocular recognition separately, a mask is made for capturing the iris. The algorithm from Tan et al. (2010) is utilized to generate a rough location of the iris area. The algorithm presented by Viola and Jones was applied to the captured area to refine and identify the right eye in a binary mask. A reflection filter removes high levels of intensity from the mask.

To normalize the color from different devices, MacBeth ColorChecker® Chart and the algorithm described in Wolf (2003) are combined to create a color correction matrix. The Hough transform is also used to specifically find the iris boundary. Within the boundary, a histogram and Canny edge detector is applied to isolate the pupil boundary. Pixels of the resulting area between the iris and pupil boundaries are mapped to pseudopolar coordinates for normalization.

The iris coordinates are combined with a 2D wavelet bank to produce a binary "iriscode." Features are produced from the periocular image using both distributed and global analysis. The distributed analysis uses three descriptors: HOG, LBP, and ULBP; the global analysis uses two descriptors: SIFT and GIST.

The distributed- and global-extracted features of the periocular were matched through X^2 distance. Binary codes of the iris were matched through a Hamming distance. These scores are fused together through an artificial neural network with two hidden layers. The first hidden layer consists of 11 neurons to represent the 11 scores that result from the scores. The second hidden layer consists of six neurons. The output is a binary computed from the second layer; the binary represents a pass or fail of the inputted image. The training data used to build the neural network were separated from the test data.

12.3.3 Results and Conclusion

Santos et al. (2015) compared the use of the color correction method against no color tampering; color correction proved to enhance detection but decrease clarity of the image's details. Additionally, iris detection was compared with periocular detection and found that the latter performed better than the former. Periocular detection had the ability to work semiconsistently on its own; however, the fusion of periocular and iris detection improves the recognition rate. Certain descriptors, such as GIST, were more successful than others, yet have a lower computational cost.

Santos et al. (2015) compared the performance of recognition between capturing setups. The rear-facing cameras proved to preform best; yet, this was not exclusively the result of higher resolutions. The outcomes also showed that flash-less images had better performance resulting in the best imaging originating from a flash-less, rear-facing camera setup. Images from the same device proved to improve performance, but cross-platform recognition was still effective.

12.4 MOBILE IRIS LIVENESS DETECTION

Since security is the primary focus, the iris recognition must detect false access attacks. Biometric spoofing is addressed by Akhtar et al. (2014) with a liveness detection system to prevent spoof attacks of face, iris, and fingerprint recognition. Iris spoofing can be accomplished by photos, videos, or contact lenses that imitate an accepted iris texture. Many liveness detection focus on involuntary light reactions and reflection analysis; however, these are still risks to spoofing. Akhtar et al. (2014) proposed a level-based security system to eliminate the effectiveness of biometric deceiving including iris spoofing.

12.4.1 Data

Akhtar et al. (2014) utilize the publicly available ATVS-Flr database that includes 8 images of both the eyes of 50 subjects and spoofed versions of each image. The database was split for 40% to be used for training and the other 60% to be used for testing.

12.4.2 Methods

Akhtar et al. (2014) did not use iris detection or segmentation, but instead utilized three-feature analysis algorithms on the entire image. Locally uniform comparison image descriptor (LUCID) calculates order permutations on distributed local information. Census Transform Histogram (CENTRIST) compares pixel intensities to neighboring pixels globally. Pattern of Oriented Edges Magnitude (POEM) uses both global and local information; a gradient image is calculated for all pixels before local histograms are collected on neighboring pixels and encoded together. The security system has three levels: low uses LUCID alone; medium fuses LUCID and CENTRIST; and high incorporates LUCID, CENTRIST, and POEM.

12.4.3 Results and Conclusion

After five deployments of the data through the proposed method, Akhtar et al. (2014) establish success from their system. The system was effective at detecting liveness from spoofing at all three levels. The three analysis processes were isolated for comparison of performance. While LUCID alone proved applicable, CENTRIST had an enhanced performance and POEM resulted in the superlative performance. Together in level high, the effectiveness was drastically increased. The half total error rate percentage was decreased by over 0.7% when using high level over low level.

12.5 LIMITATIONS

While the experimented iris recognition methods proved effective, they have not reached the point of commercial use due to the security priority and rate of false acceptances. Today's mobile security requires virtually flawless recognition systems.

Errors are mainly being produced by the limitations in capturing the environment. The hardware of current mobile devices is not optimized for iris detection because precision cameras are located on the back of devices. While the front-facing cameras are ideal for imaging orientation and ease of use, the resolution and accuracy of these sensors are insufficient in adequately detecting the iris texture. Additionally, users are required to deliver significant effort to image correctly in appropriate lighting. An attempt to circumnavigate imaging constraints would result in too high of computational costs for mobile devices.

12.6 CURRENT TECHNOLOGY

Capabilities are expanding with the improvement of mobile hardware in computational and imaging abilities. Although higher resolutions proved semiirrelevant to iris detection, newer devices are being released with higher resolution sensors. More importantly, the mobile device sensors have reached DSLR-level quality in clarity, color, and low-light sensitivity. The most ideal device will supplement the VIS sensor with a NIR sensor for a better capture of the iris texture.

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