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Development of Efficient Iris Identification Algorithm using Wavelet Packets for Smartphone Application

Teddy Surya Gunawan[1], Nurul Shaieda Solihin[1], Malik Arman Morshidi[1], Mira Kartiwi[2]
[1]Department of Electrical and Computer Engineering, International Islamic University Malaysia
[2]Department of Information Systems, International Islamic University Malaysia
Jalan Gombak 53100 Kuala Lumpur, Malaysia
e-mail: tsgunawan@iium.edu.my

Abstract

Nowadays, iris recognition is widely used for personal identification and verification based on biometrical technology, especially in the smartphone arena. By having this iris recognition for identification and verification, the smartphone will be secured since every person have their own iris type. In this paper, we proposed an efficient iris recognition using Wavelet Packets and Hamming distance which has lightweight computational requirements while maintaining the accuracy. There are several steps needed in order to recognize the iris which are pre-processing the iris image consists of segmentation and normalization, extract the feature that available in the iris image and identify this image to see whether it match with the person or not. For comparison purposes, different types of wavelet bases will be compared, including symlets, discrete meyer, biorthogonals, daubechies, and coiflets. Performance of the proposed algorithm was tested on Chinese Academy of Sciences Institute of Automation (CASIA) iris image database. The optimum wavelet basis function obtained is symlet. Results showed that the accuracy of the proposed algorithm is 100% identification rate.

Keywords: *Iris identification; wavelet packets; Hamming distance; CASIA database*

1. Introduction

Biometrics is a unique characteristic of an individual that can differentiate one person with another [1]. There are many advantages of using iris as a biometric recognition system. Firstly, the iris is cannot easily affected by diseases or injuries since it is protected by the eyelid and the cornea. Secondly, the stability of iris remains constant throughout the individual's entire life. Thirdly, in order to obtain the iris image, there is no contact with the human body.

Figure 1. An Example of Iris Verification in Galaxy Note 8

In the smartphone, there is growing interest in the iris scanner that could replace or complement the current popular fingerprint scanner. In 2015, Fujitsu developed Arrows NX F-04G smartphone which includes the first iris scanner. Subsequently, other smartphones used some forms of iris scanner, including Microsoft 950 XL, Vivo X5Pro, ZTE Grand S3, Alcatel Idol 3, and most recently Samsung Galaxy Note 8 as shown in Figure 1. The iris verification is

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not only used for unlocking the smartphone, but it could use as well for banking transactions as the popularity of mobile payments,such as Android pay, Apple pay, Samsung pay, have grown over time.

Figure 2 shows the typical iris identification system. The image pre-processing includes iris localization, eyelid detection, eyelashes detection, iris normalization and image enhancement. Many methods have been developed for iris localization, including Integro-differential operator, hough transform [2], discrete circular active countour, bisection method, and black hole search method [3-5]. In this research, we used Hough transform

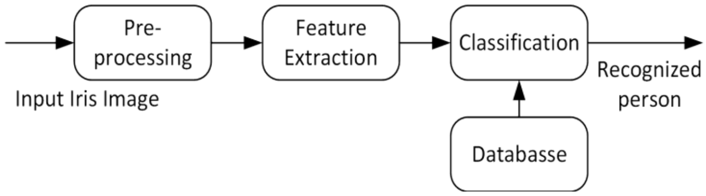

Figure 2. Typical Iris Identification System

Many features have been developed for iris identification, including Gabor filters, wavelet packet, Laplacian of Gaussian filter, key local variation, discrete cosine transform [6], and advanced correlation filter [4, 5, 7]. For the classification, there are many methods have been utilized, including Hamming distance, weighted Euclidian distance, nearest features line, peak to correlation energy, and peak to sidelobe ratio [5, 8].

Although many researchers have been conducted on the iris recognition system, but not so many researches have been conducted to find an efficient iris identification algorithm suitable for smartphone application. There is a tradeoff between the recognition rate and computational time. The objective of this research is to develop an efficient algorithm for iris identication using wavelet packets and hamming distance. Various wavelet bases will be evaluated and hamming distance will be used due to its simplicity but higher accuracy.

2. Proposed Iris Identification System

In this paper, iris recognition system consists of three main stages in order to identify the iris image. Firstly, iris image will undergo pre-processing process which are segmentation and normalization. Segmentation method that this system used is Hough transform which is used to determine the edge of iris image [9]. Moreover, it also can determine the eyelids, eyelash and reflection areas which called as noise [8]. For the normalization process, Daugman's rubber sheet model is chosen in order to reduce dimensional inconsistencies between iris regions [8, 10]. For feature extraction process, wavelet packet analysis is chosen since it can decompose high frequency signals more details and overcome the low frequency signals problem [1, 2]. Then, for the classifier, Hamming distance method is chosen because it requires simple calculation formula which can save the time taken to process the iris image [5]. Figure 3 shows our proposed iris identification system.

Wavelet packes (WP) were introduced in [11] by generalizing the link between multiresolution and wavelets If iris images approximated at the scale 2^L, to the root of the quad-tree, we can associate the approximation space $V_L^2 = V_l \otimes V_L \subset L^2(R^2)$. The two-dimensional wavelet packet quad-tree is composed of separable wavelet packet spaces. Each node of this quad-tree is labeled $\{j, p, q\}$, where 2^j represents the scale and the two integers $0 \leq p \leq 2^{j-L}$ and $0 \leq q \leq 2^{j-L}$ correspond to the separable space:

$$W_j^{p,q} = W_j^p \otimes W_j^q \tag{1}$$

that can be written as the direct sum of the four orthogonal subspace corresponding to the four children nodes in the quad-tree as follows:

$$W_j^{p,q} = W_{j+1}^{2p,2q} \oplus W_{j+1}^{2p+1,2q} \oplus W_{j+1}^{2p,2q+1} \oplus W_{j+1}^{2p+1,2q+1} \quad (2)$$

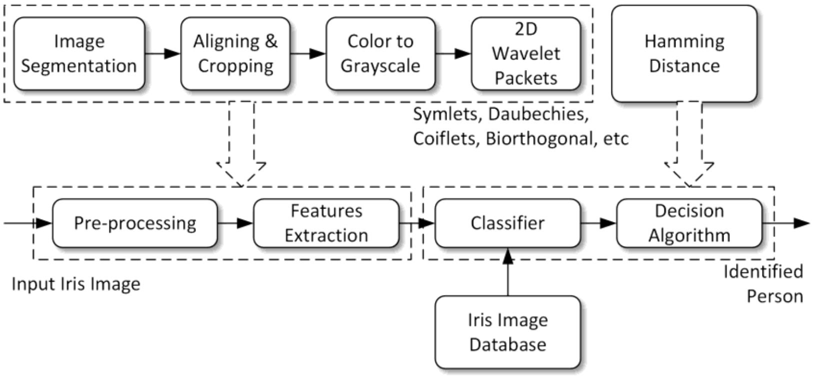

Figure 3. Proposed Iris Identification System

The filter bank implementation of the 2D WP is straightforward, the decomposition coefficients being computed by iterating Eq uation (3) to (6) along the branches of the quad-tree.

$$d_{j+1}^{2p,2q}[n_1, n_2] = d_j^{p,q}[n_1, n_2] * h_d[n_1]h_d[n_2] \quad (3)$$

$$d_j^{2p+1,2q}[n_1, n_2] = d_j^{p,q}[n_1, n_2] * g_d[n_1]h_d[n_2] \quad (4)$$

$$d_{j+1}^{2p,2q+1}[n_1, n_2] = d_j^{p,q}[n_1, n_2] * h_d[n_1]g_d[n_2] \quad (5)$$

$$d_{j+1}^{2p+1,2q+1}[n_1, n_2] = d_j^{p,q}[n_1, n_2] * g_d[n_1]g_d[n_2] \quad (6)$$

The reconstruction image is then calculated as shown in Equation (7).

$$d_j^{p,q}[n_1, n_2] = d_{j+1}^{2p,2q}[n_1, n_2] * h[n_1]h[n_2] + d_{j+1}^{2p+1,2q}[n_1, n_2] * g[n_1]h[n_2] + d_{j+1}^{2p,2q+1}[n_1, n_2] * h[n_1]g[n_2] + d_{j+1}^{2p+1,2q+1}[n_1, n_2] * g[n_1]g[n_2] \quad (7)$$

The original image $x[n_1, n_2] = d_L^{0,0}$ is reconstructed from the wavelet packet coefficients stored at the leaves of any admissible quad-tree by repeating the partial reconstruction Eq. (7) in th inside nodes of the quad-tree. The decomposition and reconstruction scheme is illustrated in Figure 4.

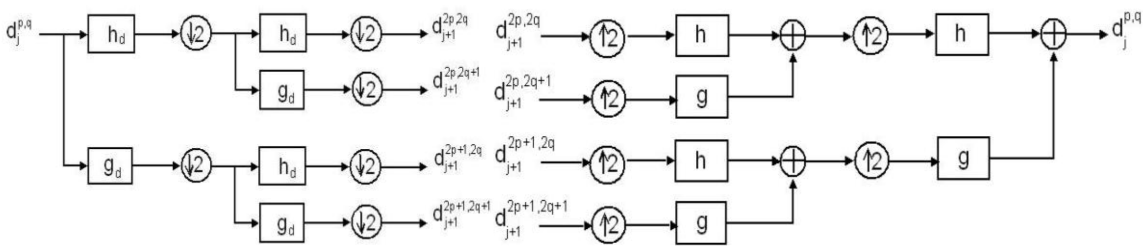

Figure 4. WP Decomposition and Reconstruction

The wavelet packet basis in iris identification system can be selected by experimentation, in which the best recognition rate will be used as the selection critera. There are many commonly used wavelet bases as shown in Figure 5. Haar wavelet is one of the oldest and simplest wavelet. Daubechies wavelets are the most popular wavelets as their frequency responses have maximum flatness at frequencies 0 to π which is a very desirable properties in some applications. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets and Meyer wavelets are capable of perfect reconstruction.

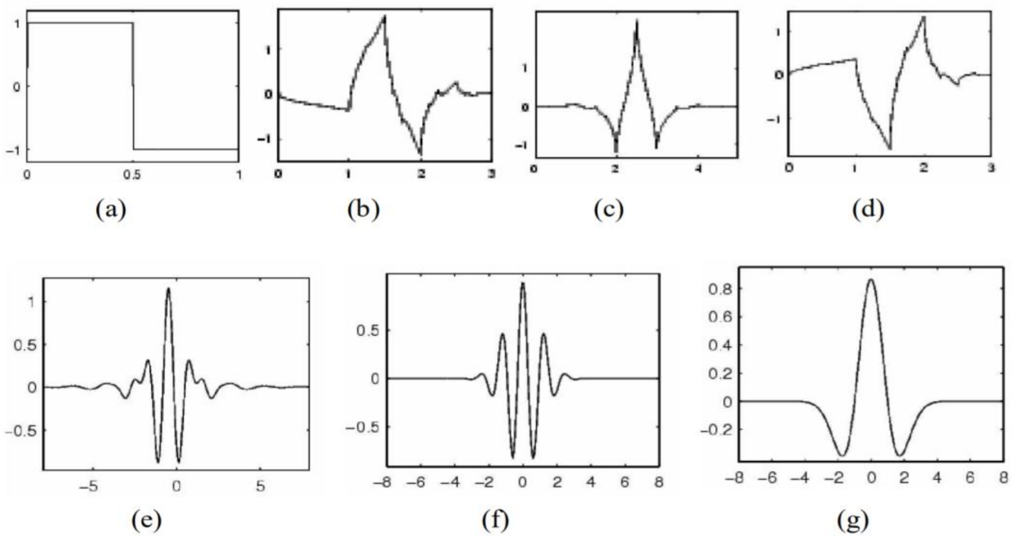

Figure 5. Samples of Wavelet bases: (a) Haar, (b) Daubechies, (c) Coiflet, (d) Symlet, (e) Meyer, (f) Morlet, (g) Mexican Hat

Hamming distance is the fractional measure of dissimilarity between two binary templates [5], and the computational requirement is very minimal and therefore it is suitable for smartphone application. A Hamming distance of zero would represent a perfect match. Moreover, a Hamming distance of 0.5 means that the two templates are completely independent. A threshold is set to decide whether the two templates are from the same iris or not. Hamming distance can be calculated as follows [5]:

$$\mathrm{HD} = \frac{\|(TemplateA \otimes TemplateB) \cap maskA \cap maskB\|}{\|maskA \cap maskB\|} \quad (8)$$

Hamming distance has fast classification speed due to the templates are in binary format and is suitable for comparisons of million of templates in large database.

3. Results and Analysis

In this section, the experimental setup, iris database, iris segmentation and normalization will be discussed. Furthermore, experiments on various wavelet bases will be conducted to find the optimum wavelet basis function for iris detection algorithm.

3.1. Experimental Setup and Iris Database

A high performance system was used for processing, i.e. a multicore system with Intel Core i7 6700 K 4.00 GHz (4 cores with 8 threads), 32 GBytes RAM, 256 GBytes SSD and 2 TBytes hard disk, installed with Windows 10 operating system and Matlab 2017b with Image Processing, Signal Processing and Neural Network Toolboxes.

There are many Iris databases available, such as CASIA, BATH, MMU, ICE, WVU, UPOL, and UBIRIS as explained in [12]. In this paper, we used CASIA iris database due to its popularity and availability. The database captured the right and left eye image with various position and lighting conditions.

3.2. Iris Segmentation and Normalization

The iris image must undergo segmentation and normalization step in order to localize the iris region from an eye image and isolate eyelid, eyelash and reflection areas. For the normalization step, it is important in order to reduce dimensional inconsistencies between iris regions. Then, the iris pattern is extracted into polar template before obtaining the grey code. The results from segmentation and normalization part is shown in Figure. 6.

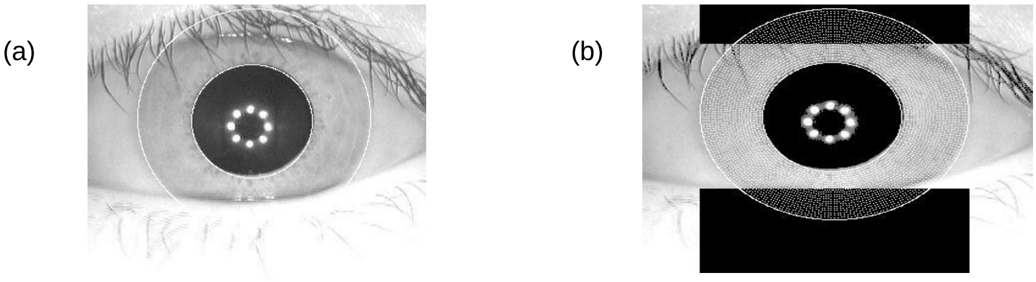

Figure 6. An iris image after (a) segmentation, (b) normalization

3.3. Experiments on Optimum Wavelet Bases

After segmentation and normalization, the iris image is tested using different wavelet packet bases families. There are three experiments conducted using this project to test whether the result can be obtained correctly or not. For the first experiment, the experiment is tested on 10 different person of iris images from the database. Next, these iris images is tested using different wavelet bases families using Matlab function wfilter() configure for 'bior1.3', 'db2', 'dmey', 'coif2', and 'sym3'.

Table 1 to 5 shows comparison of using different wavelet bases among 10 different persons. ('U' represents for uncertainty, 'X' represents for unmatched iris and '√' represents matched iris). If it is the same iris, the hamming distance value will between 0 and less than or equal to 0.2. If it is different iris, the hamming distance value is between 0.4 and 1. Meanwhile, if the value between 0.3 and 0.4, it shows uncertainty. Based on the results, it shows that Symlets wavelet packet bases have high accuracy compare to another wavelet bases since the percentage of uncertainty is low. Other wavelet bases mostly have uncertainty between 5% until 46%. From this experiment the optimum wavelet bassis function is Symlets as it provides higher identification rate and lower uncertainty. Symlets combined orthogonal and biorthogonal bases so that it could be the reason why Symlets has low number of uncertainty percentage.

Table 1. Iris Identification Experiment using Symlets Wavelet Base

Person/ Person	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	√	X	X	X	X	X	X	X	X	X
S2	X	√	X	X	X	X	X	X	X	X
S3	X	X	√	X	X	X	X	X	X	X
S4	X	X	X	√	X	X	X	X	X	X
S5	X	X	X	X	√	X	X	X	X	X
S6	X	X	X	X	X	√	X	X	X	X
S7	X	X	X	X	X	X	√	X	X	X
S8	X	X	X	X	X	X	X	√	X	X
S9	X	X	X	X	X	X	X	X	√	X
S10	X	X	X	X	X	X	X	X	X	√

Table 2. Iris Identification Experiment using Biorthogonal Wavelet Base

Person/ Person	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	√	X	X	X	X	U	X	U	U	U
S2	X	√	X	X	U	U	U	U	X	X
S3	X	X	√	X	U	U	U	U	X	X
S4	X	X	X	√	U	U	U	U	X	X
S5	X	U	U	U	√	X	X	X	X	X
S6	U	U	U	U	X	√	X	X	U	U
S7	X	U	U	U	X	X	√	X	U	U
S8	U	U	U	U	X	X	X	√	U	U
S9	U	X	X	X	X	U	U	U	√	U
S10	U	X	X	X	X	U	U	U	U	√

Table 3. Iris Identification Experiment using Meyer Wavelet Base

Person/ Person	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	√	X	X	X	X	X	X	X	X	X
S2	X	√	X	X	X	X	X	X	X	X
S3	X	X	√	X	X	X	X	X	X	X
S4	X	X	X	√	U	X	X	X	X	U
S5	X	X	X	U	√	X	X	X	X	X
S6	X	X	X	X	X	√	X	X	X	X
S7	X	X	X	X	X	X	√	X	U	X
S8	X	X	X	X	X	X	X	√	X	X
S9	X	X	X	X	X	X	U	X	√	X
S10	X	X	X	U	X	X	X	X	X	√

Table 4. Iris Identification Experiment using Daubechies Wavelet Base

Person/ Person	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	√	X	X	X	X	X	X	X	X	X
S2	X	√	X	X	X	X	X	X	X	X
S3	X	X	√	X	X	U	X	X	X	X
S4	X	X	X	√	X	X	X	X	X	U
S5	X	X	X	X	√	X	X	X	X	X
S6	X	X	U	X	X	√	X	X	X	X
S7	X	X	X	X	X	X	√	X	U	X
S8	X	X	X	X	X	X	X	√	X	X
S9	X	X	X	X	X	X	U	X	√	X
S10	X	X	X	X	X	X	X	X	X	√

Table 5. Iris Identification Experiment using Coiflets Wavelet Base

Person/ Person	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	√	X	X	X	X	X	X	X	X	X
S2	X	√	X	X	X	X	X	X	X	X
S3	X	X	√	X	X	U	X	U	X	X
S4	X	X	X	√	X	X	X	X	U	X
S5	X	X	X	X	√	X	X	X	X	X
S6	X	X	U	X	X	√	X	X	X	X
S7	X	X	X	X	X	X	√	X	X	X
S8	X	X	U	X	X	X	X	√	X	X
S9	X	X	X	U	X	X	X	X	√	X
S10	X	X	X	X	X	X	X	X	X	√

Table 6 summarizes the identification rate for experiments on various wavelet bases function. To simplify, the uncertainty will be counted as false identification. Therefore, it can be concluded that the proposed iris recognition system with the optimum wavelet basis, i.e. symlet, using fast Hamming distance, is suitable for smartphone implementation. This is due to its 100% accuracy with low processing demand, i.e. lightweight.

Table 6. Identification Rate for Various Wavelet Bases

Wavelet Basis	Identification Rate (%)
Symlet	100
Biorthogonal	54
Discrete Meyer	94
Daubechies	95
Coiflets	94

4. Conclusion

This paper has presented an efficient iris identification algorithm suitable for smartphone implementation. The pre-processing of iris images including segmentation using Hough transform and normalization using Daugman's rubber sheet model. For feature extraction, 2D wavelet packet is used with various wavelet bases. Hamming distance was used as classifier due to its simplicity yet high accuracy. CASIA iris image database was used for performance evaluation. Experiments on various wavelet basis function revealed that symlet which combined both orthogonal and biorthogonal bases was the optimum wavelet basis as it provides 100% accuracy when tested with 10 different iris image. Further research includes real implementation on Android or iOS for real life applications.

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