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Iris Recognition based on Local Mean Decomposition

Wei-Yu Han[1], *Wei-Kuei Chen*[1,*], *Yen-Po Lee*[1], *Kuang-shyr Wu*[1] *and Jen-Chun Lee*[2]

[1] Department of Computer Science and Information Engineering, Chien Hsin University, Taoyuan, Taiwan
[2] Department of Electrical Engineering, Chinese Naval Academy, Kaohsiung, Taiwan

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Abstract: The increasing need for information security has led to more attention being given to biometrics-based, automated personal identification. Among existing biometric approaches, the human iris is the most promising technique. In general, an iris recognition algorithm includes four basic steps: image quality assessment, image preprocessing, image feature extraction, and image matching. This paper proposes an iris image matching and recognition method based on local mean decomposition (LMD). The LMD is a multi-resolution decomposition technique employed as a low-pass filter and utilizes discriminating features for iris recognition. To evaluate the performance of this novel approach, several similarity measures were used to assess the results based on experiments using both the CASIA and ICE iris image databases. The results showed promising performance using any of the three measures. Therefore, the LMD method is a useful tool for iris feature extraction and recognition.

Keywords: Iris recognition, Local Mean Decomposition (LMD), Multi-resolution decomposition

1 Introduction

Biometrics [1] deals with unique characteristics of an individual that can be used for personal identification. Biometric recognition systems may be based on various human physiological features or behavior including the face [2], hand vein geometry, fingerprints, palmprint texture, retinal image, handwritten signature, and gait and can improve the security of personal identification. Iris recognition has been developed to resolve problems inherent in other methods [3,4,5]. Daugman's algorithm uses 2D Gabor filters for iris image feature extraction to demodulate the iris image phase information [6]. Each phase structure is quantized into one of four quadrants in the iris image phase information, with the Hamming distance employed for feature matching. Wildes et al. proposed Laplacian pyramids to decompose iris image texture and combined features from four different resolutions, followed by a normalized correlation to decide whether the input image and the database image belong to the same class [7]. Lee et al. [8] proposed a novel texture analysis method to extract local edge patterns (LEPs) for iris recognition. Chang et al. [9] employed empirical mode decomposition (EMD) as a low-pass filter for iris recognition. Ma et al. proposed a novel method to characterize the iris image based on local intensity variation analysis, and adopted Gaussian-Hermite moments and a dyadic wavelet for iris recognition [10,11]. Generally speaking, an iris recognition system consists of four stages: 1) iris image quality assessment, 2) image preprocessing, 3) iris image feature extraction, and 4) iris image feature matching decision. Because poor quality images can significantly degrade the performance of iris recognition systems, the first step, iris image quality assessment, is an important step in any iris recognition system. The goal of this step is to acquire a high quality image to support iris recognition. Next, an image-processing algorithm is designed to localize the inner and outer boundary of the iris area. In addition, areas obscured by specular reflections, eyelids, eyelashes should be detected and discarded in order to improve the performance of iris recognition. Third, the Gabor or wavelet transform is used to extract the iris features. Finally, a decision on whether to verify the individual is made based on whether the iris features match those of an image in the database. In this paper, an iris recognition method is employed which adopts a local mean decomposition (LMD) method as a low-pass filter for iris image feature extraction. LMD is a fully data-driven method and does not have any predetermined filter or wavelet function. Experimental results have shown that this novel method is effective for iris

* Corresponding author e-mail: wkchen@cyu.edu.tw

recognition. The rest of paper is organized as follows. We will briefly introduce the proposed method for iris recognition in Sec. 2. Experimental results are presented and discussed in Sec. 3. Finally, concluding remarks are given in Sec. 4.

2 Proposed Method

2.1 Iris Image Quality Assessment

In the iris image database, not all iris images are high quality and suitable for recognition. We found that the low quality images can be divided into two types, namely, blurred images and occluded images which are affected by eyelids or eyelashes. In our earlier work [12], we proposed and described in detail a novel and rapid method to automatically evaluate the quality of iris images. That method is employed in this work to select high quality iris images. Briefly, based on Eq. (2.1), we can choose images of high quality from the input iris image sequence.

$$Q = Q_1 \& Q_2, \begin{cases} Q_1 = \begin{cases} 0, q_1 < C_{lowq_1} \\ 1, q_1 \geq C_{lowq_1} \end{cases} \\ Q_2 = \begin{cases} 0, q_2 < C_{lowq_2} \\ 1, q_2 \geq C_{lowq_2} \end{cases} \end{cases} \quad (2.1)$$

where q_1 and q_2 are the two values of the in-focus image and the unoccluded image, respectively; C_{lowq_1} and C_{lowq_2} are the lower confidence limits of confidence intervals for the two values (q_1 and q_2), respectively, and & indicates the logical AND operation.

2.2 Iris Image Preprocessing

The eye image has different structures such as sclera, iris, pupil, eyelids, eyelashes, etc. Iris image preprocessing extracts only the iris features from the whole eye image. There are three steps in this extraction process. First, the iris area is segmented from the rest of the image. Second, the segmented iris is normalized to a rectangular window of a fixed size in order to achieve approximate scale invariance. Finally, irrelevant parts are removed from the normalized iris image by selecting an appropriate region of interest (ROI).

The iris image preprocessing method used in this work is described by Lee et al. [8]. It uses three points for locating the iris image, rather than finding all the points on the inner and outer iris boundaries. This reduces the computation cost of the method [8]. Fig. 1 illustrates the steps in iris image preprocessing.

2.3 Iris Image Feature Extraction

The local mean decomposition (LMD) was proposed by Smith [14] for analysis of natural signals into a set of product functions. The LMD method can be used to analyze any data, and is relevant to the analysis of unstable natural signals. It can decompose a signal into components called product functions (PFs), and the decomposition procedure continues until the remaining signal shows no more oscillations. This method extracts the highest local frequency of the original signal for each mode. The LMD signal is achieved by smoothing the signal using moving averaging. This moving averaging is weighted by the distance between the successive extrema of the signal.

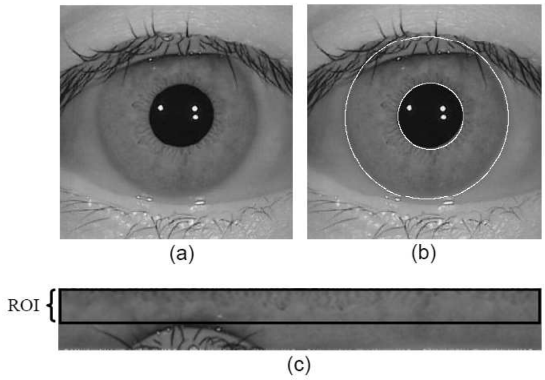

Fig. 1: Iris image preprocessing (a) the eye image, (b) the eye image with iris image located, and (c) the normalized image and the ROI.

For the iris signal $x(t)$, the PFs process is described as follows:

1. To calculate the mean of the maximum and minimum points of the signal, the i-th mean value m_i of each two successive extrema n_i and n_{i+1} is given by

$$m_i = \frac{n_i + n_{i+1}}{2} \quad (2.2)$$

The local means are shown by blue lines in Fig. 2(a).

2. The local magnitude of each half-wave iris signal is calculated by

$$a_i = \frac{|n_i - n_{i+1}|}{2} \quad (2.3)$$

The local means are smoothed using moving averaging to form the local mean function $m(t)$ (the red line in Fig. 2(a)) and the envelop function $a(t)$ (Fig. 2(b)).

3. The signal obtained is represented by a corresponding mean, then the original data is subtracted from the mean signal to give the resulting signal, shown by $h_{11}(t)$, and divided by $a_{11}(t)$. If $a_{12}(t) \neq 1$, the procedure needs to be repeated for $s_{11}(t)$. The iteration process repeats n times until the

frequency-modulated signal $s_{1n}(t)$ is obtained.

$$\begin{aligned}
&h_{11}(t) = x(t) - m_{11}(t),\\
&h_{12}(t) = s_{11}(t) - m_{12}(t),\\
&\vdots\\
&h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t),\\
&\text{where} \qquad (2.4)\\
&s_{11}(t) = h_{11}(t)/a_{11}(t),\\
&s_{12}(t) = h_{12}(t)/a_{12}(t),\\
&\vdots\\
&s_{1n}(t) = h_{1n2}(t)/a_{1n}(t),
\end{aligned}$$

4.The corresponding envelop is described by

$$a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q-1}^{n} a_{1q}(t) \quad (2.5)$$

5.A product function $PF_1(t)$ is the envelop function $a_1(t)$ multiplied by $s_{1n}(t)$,

$$PF_1(t) = a_1(t)s_{1n}(t) \quad (2.6)$$

6.The original data $x(t)$ is subtracted from the product function to form a new function $u_1(t)$ that represents the original data since the highest frequency oscillations.

$$u_1(t) = x(t) - PF_1(t) \quad (2.7)$$

7.The process is repeated k times until $u_k(t)$ is a constant or there are no more oscillations. Finally, the original signal can be reconstructed as

$$x(t) = \sum_{p=1}^{k} PF_p(t) + u_k(t) \quad (2.8)$$

Here, k is the number of PFs, and $u_k(t)$ describes the final residue that can be regard as the DC component of the signal.

By the decomposition procedure, the natural signals are decomposed into k fundamental components. This is to say that the first component is associated with the smallest time scale, which corresponds to the fastest time variation of the signal. When the signal executes the decomposition process, the mean frequency of the mode decreases, and the time scale increases. Finally, we can design a time-space filter as

$$x_{pq}(t) = \sum_{i=p}^{q} PF_i(t) \quad (2.9)$$

where $p, q \in [1, \ldots, n], p \leq q$. When $p = 1$ and $q < n$, it can be used as a high-pass filter; when $p > 1$ and $q = n$, it can be used as a low-pass filter; when $1 < p \leq q < n$, it can be used as a band-pass filter. In this paper, we use the low-pass filter.

The goal of LMD is to derive the basic functions dynamically from the signal itself. The irregular blocks of the iris are darker than their surrounding areas, as can be seen by observing the iris images from the CASIA database. Therefore, suppose the residual signal presents

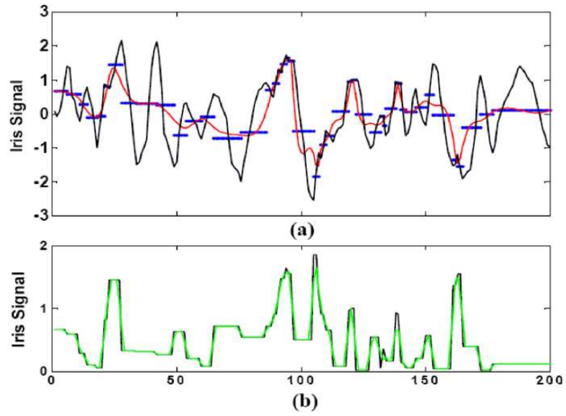

Fig. 2: (a) An iris signal is described as the black line. Local means, shown by blue lines, are computed from two successive extrema. The local means are then used to generate a moving average (red lines). (b) Local magnitudes are calculated from the iris signal (green line).

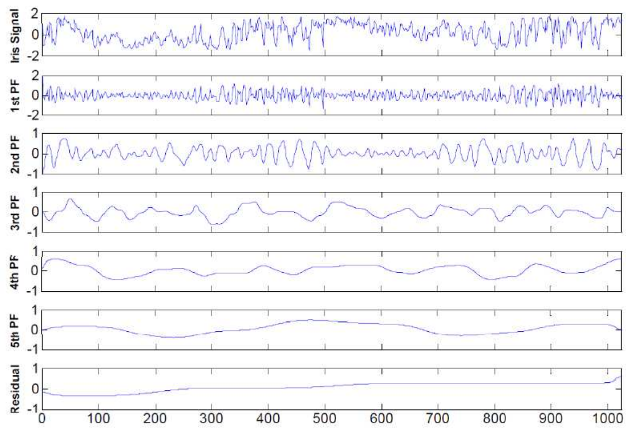

Fig. 3: Five PF components from the original signal and the residual signal obtained by the LMD method.

the basic features of the iris and the detail indicates the noise signal represented by the highest frequency. The LMD was used as a low-pass filter so the distinctive iris characteristics could be used as discriminating features for accurate iris recognition. The LMD method produces five PF components and a final residual as shown in Fig. 3.

As described above, the features of the iris image can be considered to be instantaneous signals. Local variations are generally used to describe the main structures of instantaneous signals. Therefore, we made a set of 1-D signals which preserve the sharpest variations in the iris image. For the normalized iris image I, the 1-D vector V can be achieved by concatenating the pixel series from different rows.

$$V = \{I_1 \cdots I_x \cdots I_k\} = \{v_1, v_2, \cdots v_j, \cdots, v_n\} \quad (2.10)$$

where I_x indicates the values of the row in the image I, v_j defines the j-th position of the vector V, and n is the number of total components. The detailed procedure has been described in [9]. Finally, the feature vector of each LMD iris residual signal can be described as follows:

$$R^m = \{R_1^m, R_2^m, \ldots, R_j^m, \ldots, R_n^m\} \quad (2.11)$$

where R^m denotes the m-th residual iris signal from LMD and R_j^m indicates the feature value from the j-th of the R^m. This work used LMD as a low-pass filter to extract iris features for iris recognition. In other words, we remove the first PF iris signal and retain the first residual signal as the feature vector for iris recognition.

2.4 Matching

The matching process matches features of the unknown image with known feature classes in the iris image database to determine whether the unknown feature comes from an authenticated person or an imposter. The matching process can be calculated using different metrics. In this work, the different similarity measures used as criteria are as follows:

1. The Euclidean distances measure (MED):

$$d_1(p,q) = \sqrt{\tfrac{1}{M}\sum_{i=1}^{M}(p_i - q_i)^2} \quad (2.12)$$

Where M is the number of the feature vector, p_i is the i-th component of the feature vector, and q_i is the i-th component of the unknown feature vector.

2. The cosine similarity measure:

$$d_2(p,q) = 1 - \tfrac{p}{\|p\|} \bullet \tfrac{q}{\|q\|} \quad (2.13)$$

where p and q are two feature vectors and $\|\bullet\|$ indicates the Euclidean norm. The range is $[0,1]$.

3. The binary Hamming distance (HD) measure:

$$d_3(p,q) = \tfrac{1}{M}\sum_{i=1}^{M}(p_i \oplus q_i) \quad (2.14)$$

where $\oplus$ indicates Exclusive-OR, M is the number of the feature vector, p_i is the i-th component of the feature vector, and q_i is the i-th component of the unknown feature vector.

3 Experimental Results

In order to evaluate the performance of the proposed method, two public iris databases, CASIA [15] and ICE [16], were used to obtain test iris images. Both identification and verification mode tests were conducted to evaluate the performance of the proposed method. In identification mode, the proposed method can be measured by correct recognition rate (CRR). In verification mode, the receiver operating characteristic (ROC) curve is employed to analyze the performance of the proposed method. The ROC curve, which compares the false match rate (FMR) to the false non-match rate (FNMR), shows the overall performance of the proposed method [5]. A false match is a sample in which an imposter is falsely declared to match the template of an authorized subject and a false non-match is a sample in which an authorized subject is falsely declared not to match his template. In our experiments, all three measures methods are used for performance evaluation. The experiments and results are described as follows:

Table 1. The number of high quality iris images chosen from the CASIA and ICE databases using different confidence intervals and iris recognition rates using different similarity measures

Iris database			confidence intervals 90%	95%	99%
CASIA	The number of High quality iris images		6454	6705	6998
	Correct recognition rate (%)	MED	100	100	99.5
		Cosine	100	99.5	99.1
		HD	100	99.3	98.6
ICE	The number of High quality iris images		2431	2564	2658
	Correct recognition rate (%)	MED	100	100	100
		Cosine	100	100	99.2
		HD	100	100	99.5

3.1 Performance Evaluation of the Proposed Method

A confidence interval [17] was employed to estimate the performance of the image quality assessment method. High quality iris images were selected from the two databases based on three lower confidence limits, as shown in Table 1. The iris recognition results achieved by our proposed method based on Eqs. (2.12)-(2.14) are shown for each of the three confidence intervals. When high quality iris images are obtained with the statistical method the CRR can be as high as 100% for both iris image databases at the 95% confidence intervals. Table 1 also shows that recognition in the ICE iris database was better than the CASIA iris database. In addition, the performance differences are relatively small when different confidence intervals are used. In the identification tests, only a slightly lower recognition rate of 98.8% was obtained by using iris images at the 99% confidence level. Thus, the experimental results demonstrate that the method [12] is effective for iris recognition.

3.2 Comparison and Discussion

The experimental results show that the LMD method is an effective algorithm for feature extraction and that the

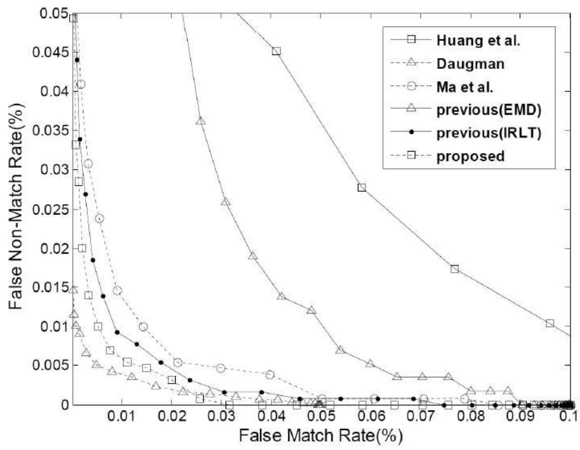

Fig. 4: ROC curves of six methods.

MED similarity measure achieves a CRR up to 100% for both the CASIA and ICE iris databases, as shown in Table 1. The Fourier wavelet feature [18], 2-D Gabor filters [6], and Gaussian-Hermite moments [10] are famous existing methods for iris recognition. We evaluated these, along with the IRLT and EMD methods [8,9] for extraction of the iris features in comparison with the LMD method. The six iris recognition methods were tested on 244 classes of the ICE iris database. The proposed method can fulfill the demand of high accuracy iris recognition, as shown in Fig. 4. The experimental results show that our proposed method is better than three methods: Huang et al. [18] and previous work [8,9], and is similar in performance to two other approaches, Daugman [6] and Ma et al. [10]. Based on the experimental results, we can conclude the following.

1. In the iris image preprocessing phase, we recognized that the iris image boundaries are not concentric, and used the ROI to eliminate distracting features. The experimental results demonstrated outstanding performance. Furthermore, we noted that the accuracy of iris recognition could be improved by using noncircular models for the iris image boundaries. Future work will examine noncircular models.
2. The proposed method can achieve a high accuracy of personal identification. This indicates that the LMD technique is effective at extracting important features for iris recognition.

4 Conclusions

In this paper, we report the design of a novel approach for personal identification based on the iris image database. On the basis of a texture analysis method, a novel feature extraction method for iris recognition is presented using the Local Mean Decomposition (LMD) technique. The experimental results demonstrate the effectiveness of the proposed method on the two public iris image databases. The performance of iris recognition has been evaluated using the LMD approach with three different similarity measures. The MED measure provided the best metric for similarity, but the other two measures also performed correctly more than 99% of the time. Thus, the proposed method is an outstanding technique for iris recognition, and LMD is useful for feature extraction.

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Wei-Yu Han received his PhD degree in Computer and Information Science from Chiao Tung University in 1997. From 1997 to 2004, he worked as an associate researcher at Chung-Shan Institute of Science and Technology. In August 2004, he joined the Department of Computer Science and Information Engineering at Chien Hsin University, where he is currently an assistant professor. His recent research interests include image processing, pattern recognition and information hiding.

Wei-Kuei Chen received his M.S. and Ph.D. degrees in Department of Computer Science and Information Engineering from National Chiao Tung University, Taiwan, in 1995, and 2001, respectively. In 2001, he joined the faculty of the department of information management, Ching-Yun University, Chung-Li, Taiwan, and now is an associate professor in Department of Computer Science and Information Engineering. Furthermore, he had been the chairman of Department of Computer Science and Information Engineering from 2002 to 2008 and the dean of secretariat affairs of Chien Hsin University from 2008 to 2010, respectively. His current research interests include network and communication security, electronic commerce, data hiding, pattern recognition and electronic voting, and he has published over 30 papers in journals, books, and conference proceedings.

Yen Po Lee received his PhD degree in Computer Science and Information Engineering from Chiao Tung University in 2002. From 1984 to 2003, he worked as an associate researcher at Chung-Shan Institute of Science and Technology. In August 2003, he joined the Department of Computer Science and Information Engineering at Chien Hsin University, where he is currently an assistant professor. His current research interests include data mining, data hiding, pattern recognition and classification.

Kuang-Shyr Wu was born in Hsin-Chu, Taiwan, Republic of China on February 17, 1963. He received his Ph. D. in Computer Science from National Chiao-Tung University, Hsin-Chu, Taiwan, in 1997. He is currently an assistant professor in the Computer Science and Information Engineering Department of Chien Hsin University, Chung-Li, Taiwan, Republic of China. His research interests include image processing and wireless communication.

Jen-Chun Lee received the MS degree in Information Science from National Defense University, Taiwan, in 2003, and the PhD degree in Electrical and Electronic Engineering from the National Defense University in 2009. Currently, he is an assistant professor in the Department of Electrical Engineering, Chinese Navel Academy, Taiwan. His research interests include digital image processing, biometric identification, and statistical pattern recognition.