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Geometrical and Eigenvector Features for Ear Recognition

Fajri Kurniawan[1,2], Mohd. Shafry Mohd. Rahim[1]
[1]Faculty of Computing
Universiti Teknologi Malaysia
Skudai 83110, Johor Bahru, Malaysia
fajri.email@yahoo.com

Mohammed S. Khalil[2]
[2]Center of Excellence in Information Assurance
King Saud University
Riyadh, Saudi Arabia
sayimkhalil@gmail.com

***Abstract*—Unconstrained ear biometric means an ear image that has variance in view and pose. This situation is challenging in ear recognition because one ear has various presentation. In this study, two features are considered to handle unconstrained ear image. The features called geometrical feature and eigenvector features. In eigenvector feature, the ear is extracted from six regions then the eigenvector is computed from each of those regions. Each region has capability to represent particular part of the ear image. Another feature is called geometrical feature that reflecting the shape of ear image. The widely used classifier is utilized and it trained with both features. Proposed method outcome is measured to evaluate the recognition rates among single features and fused features. The experiment is carried out on benchmark database collected by University of Science and Technology Beijing (USTB). It shows the proposed method can achieved promising result.**

Keywords; ear recognition; feature extraction; geometrical; eigenvector; region-based

I. INTRODUCTION

Physical and behavioral property that belongs to individual personality, known as biometrics, can be used for self identification or verification purpose. Moreover, biometrics can be utilized as identity of particular person rather than utilizing traditional identity such as password or ID card, which might forgotten or left somewhere.

Nowadays, numerous automated biometrics systems has been used such as fingerprint, facial, palm, finger-vein, ear recognition and gait analysis. These systems would significantly improve and support forensic task, which is important for police forces or military departments.

This study will focus on ear recognition. In the literature, utilizing the ear for personal identification offers some benefits. Iannarelli [1, 2] has demonstrated the ear property is anatomically steady since it does not change significantly during human life. In addition, normally the ear is detectable and does not enclosed to let better hearing. Choras [3] mentioned people are more relaxed when the officer taking their ear photograph rather fingerprint and iris. The reason is a person does not required to contact with any machine such as for fingerprint scanner, which might not hygiene. Besides that, the person has a tendency worry with their expression when acquiring the photographs. Such circumstances will affect performance of biometric systems. In contrast, a person cannot control his/her ear as it does not have expression.

Numerous ear recognition methods have been proposed as found in the literature. One of the studies presented geometrical-based method originated by Burge and Burger [4]. It was based on constructed neighborhood graph by transforming the detected edges into Voronoi diagrams. Hurley et al. [5] developed another approach by extracting the energy features. False positive might happen when some object presence around the ear. It is because of the principal elliptical shape unable to determine outer ear perfectly.

The geometric measurements that motivated by standard operation of forensic expert have been utilized to extract the ear feature and perform automatic ear recognition [4, 6]. Wang et al. [7] proposed block-based method that considers wavelet transform and binary pattern. The main drawback is their method generate deceive features when occlusion present (i.e.: hair, jewelry or cap). Choras [8] introduced geometrical information by considering the most significant contours. Choras claimed this new method outperform his previous method [9].

Another method reported by Chang et al. [10], in the experiment comparing ear and face properties in order to successfully identify humans in various conditions, was based on PCA. Besides that, feature extraction based on macro features extracted by compression networks was presented by Moreno et al. [11]. Recently, the possibility of human identification on the basis of 3D images has been extensively researched. Various approaches towards ear recognition with multimodal biometrics and 2D and/or 3D ear images have been developed and published [12, 13]. Chen and Bhanu proposed ear recognition for 3D image based on local profile descriptor as well as ICP algorithm. Their results of ear detection, matching and identification achieved good recognition rate [12]. Yan and Bowyer developed three methods for recognition of 3D ear image, which are edge-based, ICP and 3D-PCA. They designed fully automated ear recognition system [13].

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Additionally, some study also introduced ear recognition techniques that included problems such as different lighting conditions and unconstrained poses, which reported obtain varying performances [14, 15]. They reported uncontrolled lighting conditions and unstable camera viewpoints tend yield unsatisfied performances. Several study adopted robust pattern representation techniques such as PCA, LDA, and wavelet to handle those problems. The SIFT (Scale-Invariant Feature Transform) technique are proposed in [14, 16]. Bustard and Nixon [14] proposed SIFT features that fused from different poses of ear image and Euclidean distance is utilized to match the ear. Dewi and Yahagi [16] introduced 16 key points for each ear image that can be matched with respect to the closest distance. They [14, 16] claimed it works not only for ear image with background clutter and occlusion, but also with pose variations. Rathore et al [17] introduced fused template that built from SIFT feature. In the Principal Component Analysis (PCA) based [12], the ear recognition performance is achieved promising result but under semi-controlled conditions. Liu et al. [15] proposed the combination of Linear Discriminant Analysis (LDA) and kernel techniques to defeat restrictions due to PCA approach. Nevertheless, the eigenvalues still not generalized. Finally, a real-time method is introduced by Jeges and Mate. [18]. Initially, Jeges and Mate performed pattern matching based on edge orientation with an active contour. Their method is sensitive to occlusion in the pattern matching localization, which generating bad active contour fitting.

Even various ear recognition methods have been reported but recognition problem on unconstrained ear images still challenging and open. Hence, this study proposed a novel method to identify ear biometric, which has pose variance issue.

In this paper, the proposed feature extraction method based on geometry and eigenvector are presented in Section 2. Afterward, in Section 3 results and discussion are given. Finally, conclusion is presented in last section.

II. PROPOSED FEATURE EXTRACTION METHOD

A. Overview of Proposed Method

In this paper, author presented a region-based technique that is robust with respect to pose variance. An overview of the proposed method is given in Figure 1.

The considered input image is an ear image that has been cropped from face profile. For example an ear detection method can be used to localize the ear [19]. Moreover, unconstrained ear images considered have various captured angle, some occlusions (for example: cap, long hair, earring or eyeglasses frame) and illumination varies. Nevertheless, the image of ear that captured from backside is avoided because the backside of ear does not prove contains a unique feature yet [2]. Some samples from USTB ear database [20] is presented in Figure 2.

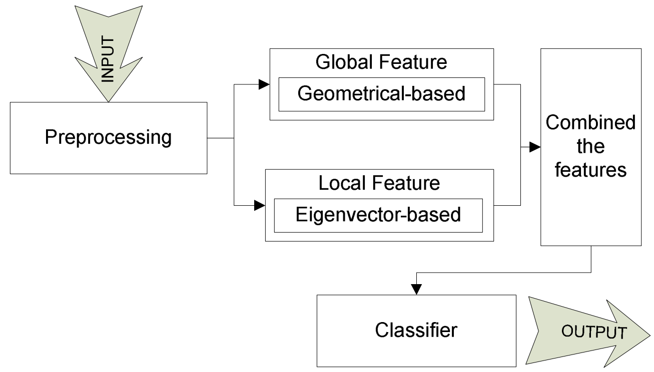


Figure 1. Overview of the proposed region-based method.

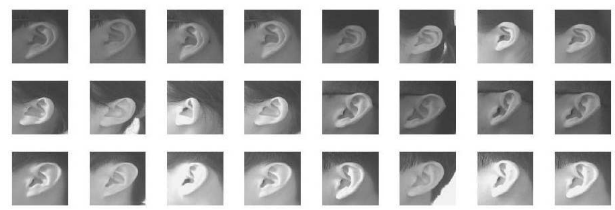


Figure 2. Some examples of ear image in USTB database.

Preprocessing method is adopted to enhance quality of the source image. Image with high illumination will produce too bright image. It such situation, the edge of ear does not strong enough. Hence, the contrast variance should be stabilized prior to attain clear ear edges [21].

In the literature, proposed feature extraction that available mostly are intended for side pose of ear image. On the other hand, this paper introduced a region-based approach that can handle pose variation issue. Two features called geometrical and eigenvector features are adopted in this study.

The shape of ear biometrics is measured based on geometrical feature as proposed by Choras [8]. In this paper, the features called triangle ratio method (TRM) and shape ratio method (SRM) are adopted as proven yield promising performance [8]. Since shape information has limitation due to occlusion and pose variance hence this study introduces eigenvector feature, which is extracted based on defined ear regions. The ear image is broke into six regions then eigenvector feature are extracted. The slices included 6 regions of the ear as depicted in Figure 3.

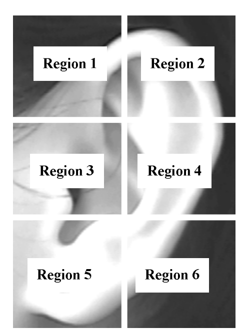


Figure 3. Six regions that considered in proposed method.

The defined regions are allowing the feature extracted part by part to tackle pose issues. Pose variance makes a number of ear's part become hidden or the edge information was not completely acquired. In such pose variance issue, if we treated the ear into region by region then it shows that some regions would have better features than the others.

Finally, the generated features are utilized as input for the classifier. The robust and well-known artificial neural network (ANN) will be adopted. The ANN is trained with various pose of ear image. Then some samples, which not included as data train, considered as testing data. Output of the ANN is classified in two states, which are identified ear or not identified ear.

B. Preprocessing

The ear image has various contrast that need histogram equalization in order to enhance the image. The equalization method is work by transforming intensity values of the image [22]. The conventional histogram equalization method is only suitable for image with similar global contrast. Conventional histogram method is not suitable for ear image that need to maintain the ear texture. The ear texture contains sensitive information that acts as a unique feature to identify the person.

Zuiderveld [21] proposed a method named the Contrast Limited Adaptive Histogram Equalization (CLAHE). CLAHE was reported can locally adapt the contrast variance. The idea is CLAHE restricts the gradient of grayscale to circumvent the over-saturation. It was considering a factor called clip limit to achieve stable saturation. Particularly it useful when dealing with the image that has equivalent areas and has elevated peaks in the gray-level histogram. A sample in preprocessing step is presented in Figure 4. The ear shape (Figure 4.a) becomes clearer after applied CLAHE method (Figure 4.b).

The size image of USTB ear database is already equal. Thus, in this paper the input image is not needs to be normalized. The size image is 300x400 pixels.

(a) original image (b) after preprocessing

Figure 4. Ear image in preprocessing step.

C. Slicing Image into Region

The crucial step in the proposed method is slicing ear image into several regions. Proposed method makes use of a region-based approach for the following reasons:

- Texture information on separated regions can represent rich textures and consequently can improve performance of the recognition system.
- Unclean and noisy regions can be treated independently thus it able to produce clean texture information.
- Local information taking from the region and combine with geometrical feature can provide robust texture and shape features.

The slicing procedure is explained as follow:

1) *The input image A is denoted by* m x n *matrix.*

$$A = \left[a_{i,j} \right] i = 1,...,m; j = 1,...,n \tag{1}$$

Where, m is image width and n is height of image. Afterward, the region matrix (m_{slice} and n_{slice}) is determined using Equation 2 & 3 as below:

$$m_{slice} = \left\lfloor \frac{m}{2} \right\rfloor \tag{2}$$

$$n_{slice} = \left\lfloor \frac{n}{3} \right\rfloor \tag{3}$$

2) *Six regions are computed with respect to matrix A based on reference's size as defined before, m_{slice} and n_{slice}. The regions are defined below (Equation 4-9):*

$$B_1 = \left[a_{i,j} \right] i = 1,...,m_{slice}; j = 1,...,n_{slice} \tag{4}$$

$$B_2 = \left[a_{i,j} \right] i = m_{slice},...,m; j = 1,...,n_{slice} \tag{5}$$

$$B_3 = \left[a_{i,j} \right] i = 1,...,m_{slice}; j = n_{slice},...,2 \times n_{slice} \tag{6}$$

$$B_4 = \left[a_{i,j} \right] i = m_{slice},...,m; j = n_{slice},...,2 \times n_{slice} \tag{7}$$

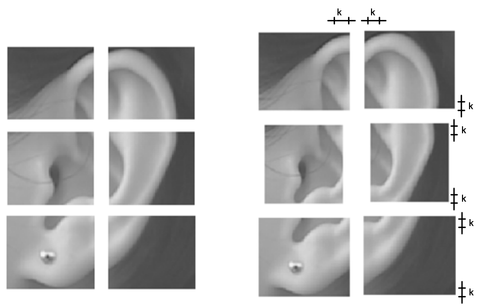
$$B_5 = \left[a_{i,j} \right] i = 1,...,m_{slice}; j = 2 \times n_{slice},...,n \tag{8}$$

$$B_6 = \left[a_{i,j} \right] i = m_{slice},...,m; j = 2 \times n_{slice},...,n \tag{9}$$

3) *Lastly, the region's size is extended with factor k where k < m,n. This step will produce an overlapped matrix as defined in Equation 10.*

$$\begin{aligned} &B_b = \left[a_{i,j} \right] i = p-k,...,q+k; j = r-k,...,s+k \\ &b = 1,...,6; p,r > k \text{ and } q,s < n \end{aligned} \tag{10}$$

Figure 5 presented the ear image after applying slicing procedure. Figure 5.b. depicted the 6 regions of ear image before apply step 3. Figure 5.b. depicted 6 regions after expanded the region with factor k=10. It shows how the regions now include the partly cover area of its neighborhood. This six regions are later on utilized to extract the eigenvector features.



(a) Regions (b) Expanded regions (k = 10)

Figure 5. Six regions of the ear image.

D. *Feature Extraction*

The geometrical and eigenvector features are extracted from the input image in order to perform ear's identification. First, the geometrical feature is basically computed from the edges information. Edge information is obtained by applying any well-known edge detector approach. Once the edges are generated then the unique information regarding shape properties and geometrical shape of certain ear can be calculated [8]. Second, the eigenvector features are generated after sliced the ear image using slicing procedure as described in section C above. Both features are explained separately as follows:

1) Geometrical Feature. Two geometrical features that adopted from Choras [8] are shortly presented as below:

a) Triangle Ratio Method: it used to represent the peak edge in ear image by taking the stable geometrical information. In this regard, the longest edge from ear's edges are selected. Such selection is very critical and can affect the recognition accuracy. Once the longest edge's are selected then using Equation 11 the triangle ration is computed.

$$tr = \frac{h_m w_1}{h_d w_2} \tag{11}$$

where, hm and hw are both represent height of triangle, w1 and w2 are both define sum of length from 2 side of the triangle.

b) Shape Ratio Method: It calculated shape ratio of main edges. The ratio kk is calculated using Equation 12:

$$kk = \frac{L_c}{d_{kp}} \tag{12}$$

where, Lc is the length of edges given by (Equation 13), dkp is the line length that connecting the end-points of each edge given by (Equation 14).

$$L_c = \sum_{q=1}^{Q-1} \sqrt{\left(x_{q+1} - x_q\right)^2 + \left(y_{q+1} - y_q\right)^2} \tag{13}$$

$$d_{kp} = \sqrt{\left(i_k - i_p\right)^2 + \left(j_k - j_p\right)^2} \tag{14}$$

where, Q defined the amount of contour points, c defined the amount of contours, for c = {1, . . .,C}, (x, y) presented the coordinates of edge points, q is index for the current contour point.

2) Eigenvector Feature. Eigenvector has been widely used in the field of face recognition [23]. This feature reported used in various systems [24-26] and can obtained promising accuracy. That success has bring a motivation to utilize the eigenvector as robust feature for proposed region-based feature extraction approach. The eigenvector offers a feature in lower dimension rather high dimension that greatly suitable for the classifier. The reason is eigenvector provide a measureable and clear vector space. Equation 15 presented the basic correlation between eigenvectors and eigenvalues.

$$Cu = \lambda u \tag{15}$$

Notation C stored the average of covariance matrix, λ is eigenvalues of C and u is the eigenvectors. The adopted eigenvector feature is calculated as below:

a) Firstly, the ear image on training data is divided into 6 slices. Later the slice in same region will be grouped into one class. Hence, the training data will have 6 classes, each class must consist the subject's ear with same region.

b) After grouping the region in a vector, Equation 16 is used to calculate the average of the vector. The entire column of vector is summed then it divided by M number of image.

$$\psi = \frac{1}{M} \sum_{k=1}^{M} \tau_i \tag{16}$$

c) Then normalized mean □ is calculated using Equation 17. The τi is represent the dissimilarity among the vector set and each image in training data. Afterward, C is computed using Equation 18.

$$\phi_k = \tau_k - \psi \tag{17}$$

$$C = \frac{1}{M} \sum_{k=1}^{M} \phi_k \phi_k^T \tag{18}$$

The eigenvectors that consider from highest eigenvalues is representing the important features of the vector. Such that it can be used to approximate the image outside the training set. The eigenvector of each slice has six eigenvalue.

E. *Ear Recognition*

One of the most important in recognition step is to select a suitable classifier. The recognition accuracy is depend on classifier performance. The back-propagation algorithm has been proved very successful in many real word applications. Therefore, a feed forward artificial neural network (ANN) with a single hidden layer using back-propagation algorithm is implemented in recognition stage.

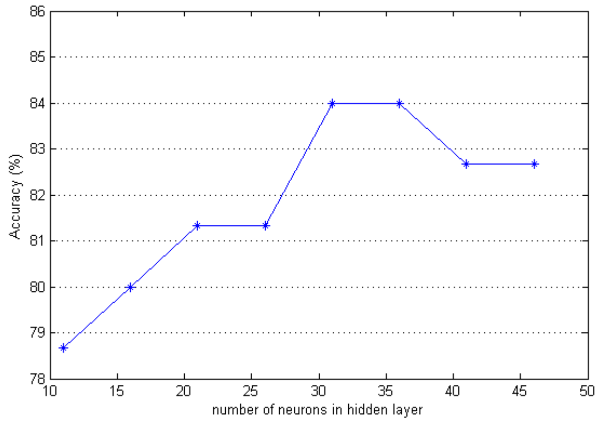


Figure 6. Optimizing the neural netwoks I

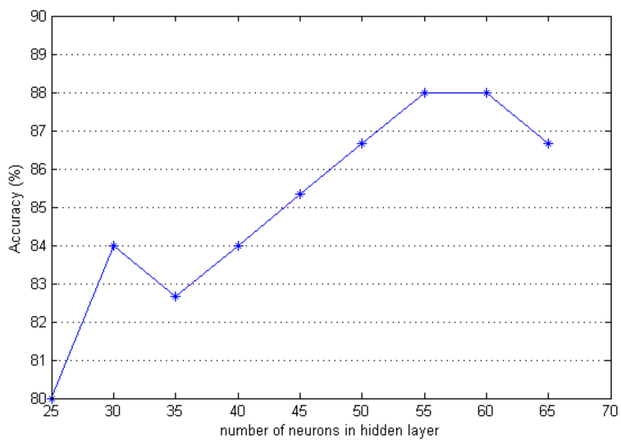


Figure 7. Optimizing the neural netwoks II

The extracted features of ear image in training set are normalized. Afterward, it is fed to artificial neural network for training phase. A number of experiments are conducted with training dataset to obtain optimal ANN structure. The optimal structure of ANN is presented in table 1. Two ANN with different structure are developed for single feature and fused features.

Optimal number of neuron in hidden layer should be derived after several attempts. In the experiment, hidden neurons of NN is optimized by starting a network with a small number of hidden neurons and keep adding hidden neurons until the neural networks indicates over-fitting. Figure 6 shows the highest accuracy achieved when number of neuron set with 31 neurons. Increasing number of neuron in hidden layer cannot improve the accuracy because error of fitting the weight also increasing.

Similar with above, the neural network II is also configured to obtain optimal accuracy. Number of hidden neurons is change within range 25-65 neurons. Figure 7 demonstrates the best result can be obtained when hidden neurons set to 55. Comparing NN I and NN II, the NN II needs more hidden neuron rather than NN I. It is because, number of input neuron in NN II greater than NN I.

TABLE I. OPTIMAL STRUCTURE FOR THE ANN

No	Input layer	Hidden layer	Output layer	Momentum/ learning rate
I	64 neuron	31 neuron	8 neuron	0.05
II	100 neuron	55 neuron	8 neuron	0.05

III. RESULT AND DISCUSSION

Ear database collected by the University of Science and Technology Beijing (USTB) [20] is utilized to analyze performance of the proposed method. This database covered pose variance problem that composed from 32 subjects. The pose variance occurs due to the ear image is acquired by placing the camera in two positions within range {-30o, 30o} with respect to the human ear. In addition, the dataset has lighting variance. In this experiment, the 104 ear images consist of 25 individuals are extracted from USTB database. Those images then divided into two sets for training and testing data. The first 75 ear images are considered for training data. Then the remaining image is utilized during testing. Sample ear images are shown in Figure 1. The comparison is carried out to evaluate robustness of geometrical feature and eigenvector feature. In this regards, first experiment only extracted geometrical feature and second experiment is combined geometrical and eigenvector features.

TABLE II. NEURAL NETWORK OPTIMAL STRUCTURE

Extracted features	ANN Structure	Number of features	Accuracy
TRM-SRM	I	64	82.76 %
TRM-SRM-Eigenvector	II	64 + 36	93.10 %

Table 2 depicted that the geometrical feature does not work well when the tested data images vary greatly in pose. One possible reason is that data samples in this experiment were small and it too sensitive to the geometrical feature. The fusion features, geometrical and eigenvector features, achieved better recognition rate because the eigenvector features uses a more flexible way to determine significant features thus can better reveal the essential structure.

Combination geometrical and eigenvector features outperforms rather than single feature. It can achieved promising recognition rate. But, increasing number of features will also burden the computation cost. However, recent processing unit are mostly capable to perform complex calculation with reasonable computation time. According to the results, eigenvector can capture overall variances in ear images and minimize the error when the ear has pose variant. While geometrical feature shows able to maximize the statistical feature in whole ear image. The results also show that both features are effective for ear recognition.

IV. Conclusion and Future Works

In this paper, a method for feature extraction based on geometrical and eigenvector features are presented. The eigenvector features are generated after applying slicing region. The experiment shows geometrical feature unable to handle pose variance. Hence, the simple slicing procedure is introduced to allow extract eigenvector feature from each region rather than from whole image. Geometrical feature is obtained from edges information on ear image. This feature is included triangle ratio method (TRM) and shape ratio method (SRM). Classification is based on the ANN output between the input feature vectors, and all the feature vectors from the database. Fused geometrical and eigenvector features shows can obtain promising results.

For future works, feature vectors should be enriched with more geometrical features in order to better distinguish ear identity. It should followed by testing some new geometrical parameters describing shapes of ear contours and compare their effectiveness in ear identification. Moreover, further study should consider exploring another transform-based feature such as statistical, energy and texture parameters. It will be challenging to discover which features are the most significant in determining ear identity. Additionally, a benchmark database that consists of large ear image with occlusion problem should be considered.

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