Hybrid Ear Segmentation Based on Morphological Analysis and RBF Network for Unconstrained Image

Mohammed J. Alhaddad and Dzulkifli Mohamad

King Abdul-Aziz University, Department of Information Technology
Saudi Arabia, Jeddah
{*malhaddad*, dyakoob}@*kau.edu.sa*

Abstract

Biometric has been implemented on numerous public facilities to enhance the security system. Fingerprint and face are the most popular biometric. Emerging technology has introduced potential biometric such as palm print, lips, teeth, vein and ear. However, most of this biometrics requires a special device to capture it. Thus, the implementation of such system will be costly. Iannarelli [1, 2] has proved that ear biometric is having a great potential for identifying a person. In this research work, an attempt is made to improve the detection and finally to segment the human ear from the whole image of human's head. The success of this stage is very important for achieving the later goal, such as recognition and classification. This paper introduces a novel method for ear segmentation. Proposed method is based on morphological analysis fused with RBF neural network. Experiment shows that the proposed method has delivered a promising result.

Keywords: *Biometric, Ear Biometric, Ear Detection, Ear Segmentation, Morphological Operation, RBF Neural Network*

1. Introduction

Biometrics corresponds to self verification or identification by considering some personality such as behavioral or physical, which related to the individual. Therefore, the person can be identified based on self personality, rather than by external identity such as ID card or password. Nowadays, numerous automated biometrics systems has been used including facial recognition, fingerprint recognition, hand identification, ear identification, height determination and gait analysis. These systems would significantly improve the effectiveness of forensic work, in which adopted by police forces or other military departments.

In the literature, using the ear for human identification can provide some advantages. Iannarelli [1, 2] has proved that the ear is a stable anatomical because it does not vary significantly throughout human life. Numerous ear recognition or identification methods have been proposed and available in the literature. A lot of studies have been done for ear detection and recognition but only some techniques proposed in ear segmentation [2–7].

According to literature reviews above, research on ear segmentation for unconstrained ear image is still lacking. Hence, this study attempts to provide robust segmentation method for unconstrained human ears. The automatic ear segmentation process is desired in recognition system. The main problem here is, how does the contour line of ear can be segmented from ear image with different side views?

2. Proposed Hybrid Segmentation Method

In this research work, the RBF technique is explored to study its eligibility to be used in ear segmentation. Prior to this, morphological operations are used in preprocessing stage to generate a sharp contour or edge of the ear. A study regarding parameter and characteristic of the morphological analysis should be conducted to obtain the best result.

The hybrid ear segmentation is analyzed to measure its performance. A comparison conducted to observe whether proposed method can improve recognition accuracy or not. The segmentation performance is judged based on human vision. It is because no standard metric available to measure the ear segmentation accuracy. The research objectives are to enhance the quality of ears image from its source, to detect the contour or edge of the ear and to segment the ears portion from the unconstrained ears image. The research design and methodology, presented in figure 1, is divided into five (5) main phases:

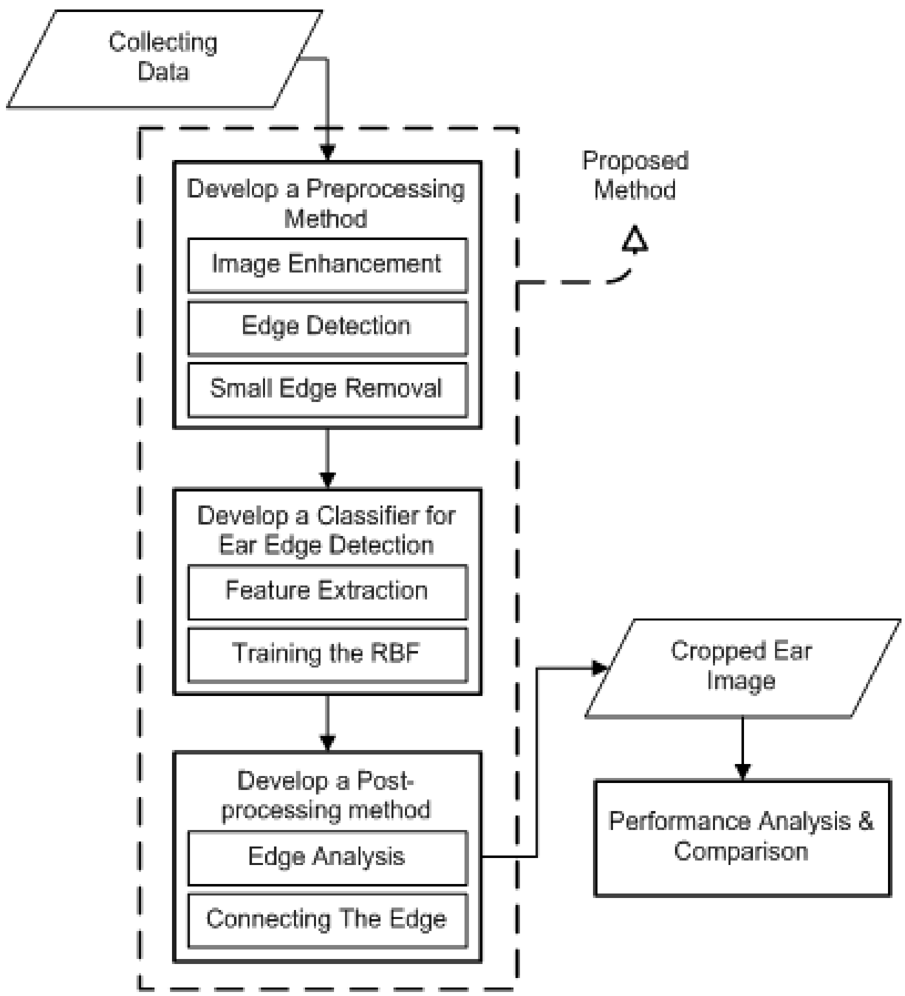

Figure 1 Research Framework

3. Development of a Pre-processing Method

Morphological analysis is used as a top hat transformation, where edge detection and elimination of unwanted edges are performed in the preprocessing stage. The purposes of preprocessing stage are:

1. to emphasize the edges of ear
2. to remove small component based on predefined threshold value, and
3. to examine the remaining components based on geometric characteristic.

The first objective of preprocessing stage is to emphasize the ear contour in grayscale image and to smother the dark grayscale. A transformation method namely opening top hat transformation is utilized for detecting bright pixels that adjacent by dark pixels. This method can emphasize the ear including the ear that surrounded by hair or cheek, enhancing the edge of ear itself. The top-hat transformations denoted by $\mathrm{TH_w}$ and $\mathrm{TH_b}$ are defined as follows [1]:

$$TH_w = f(x,y) - f \circ B(x,y)$$

$$TH_b = f \blacksquare B(x,y) - f(x,y)$$

$$f \circ B(x,y) = (f \oplus \Delta B) \circledast B$$

$$f \blacksquare B(x,y) = (f \circledast \Delta B) \oplus B$$

Where, ° indicates opening operation and ■ indicates closing operation. The above equations indicate that structuring elements B is considered to generalize the background of the image and improve the potential target areas.

Following image enhancement based on top hat transformation, an edge detector is applied using Canny operator [17]. The suitable parameter for Canny operator is derived after numerous experimental study. However, spurious edges that disturb edges of the ear, cannot be avoided. In this regard, analysis on edge length and curvature are proposed. First, the edges with length less than predefined threshold should be detached. New edges set after edge length analysis can be defined as follows

$$X_l = \{e \mid e \in X \; and \; length(e) > T_l\}$$

Where, $\mathrm{length(e)}$ calculates the length of edge e. Then, $\mathrm{T_l}$ is a predefined value of the edge length threshold. This criterion used to eliminates short spurious edges which commonly occur because of hair, earring or bad lighting. $\mathrm{T_l}$ should be defined in proper way because too large value will eliminate most of ear edges and if too small will give insignificant result.

Secondly, it is known that spurious edges do not have curvature shape. In other words, the edge that has weak curvature should be eliminated. The average absolute curvature proposed by [18] is adopted to eliminate weak curvature. Suppose $\mathrm{e = \{v_i \mid i = 1, 2, \dots, n\}}$ is an edge having n pixels and $\mathrm{v_i = (x_i, y_i)}$ be the $\mathrm{i^{th}}$ pixel. The continuous curve denoted by $\mathrm{y: [a, b] \rightarrow \mathbb{R}^2}$. The average absolute curvature [18] is given as follows:

$$AAC = \frac{total\ absolute\ curvature}{total\ length\ of\ curve} = \frac{\int K_s}{\int d_s}$$

Then, the absolute curvature is described as follows:

$$k(i) = |(v_{i-1} - v_i) - (v_i - v_{i+1})|^2$$

Hence, the average absolute curvature for an edge e can be calculated using the equation below:

$$e_{AAC} = \frac{1}{n}\sum_{i=1}^{n} k(i)$$

Where, number of pixels in edge e is denoted as n. Finally, the edge set following remove weak edge is denoted by:

$$E^c = \{e \mid e_{AAC} > T_c\}$$

Where, $e \in E^l$ and T_c are described as a predefined threshold for AAC. However, this preprocessing phase unable to eliminate edge that is very similar with ear edge. Therefore, a classifier is employed to tackle this problem.

4. Development of a Classifier for Ear Edge Detection (s)

Morphological analysis is unable to decide whether an edge is either belongs to ear or non-ear. It is because those edges have similar shape, size and length. Thus, hybrid method is desired to tackle such problem. The main problem is how to formulate criterion to classify edge of ear. There is some solution for this problem such as heuristic method or classifier-based method. Unfortunately, formulation of a heuristic method with a set of rules is very much complicated. Simpler option is greatly desired. In this regards, a robust neural networks is adopted to create a complex function that capable to differentiate edge of ear and non-ear. The neural networks consist of numerous transfer functions and weights in which they are adjustable according to the nature of the problems. This work utilizes a RBF networks because it does not require the setting of the network parameter, structure or neuron weight.

RBF networks allow viewing input and target as a curve-fitting problem. The value of RBF function depends on the Euclidean distance from origin to some other point [19]. Like other neural networks, such as Back Propagation Neural network (BP), RBF has also feeding forward mechanism. RBF networks can learn arbitrary mappings with only using its hidden layer. The hidden layer units have a receptive field, which centralized on a particular input value at which they have a maximum output. Their output tails off as the input moves away from this point with maximum output. The mathematical formula for RBF is denoted as follows:

$$Z(x) = \emptyset(||x - \mu||)$$

Where, n-dimensional vector is denoted by x. The average of n-dimensional vector is called the center of the radial basis function denoted by μ, and Euclidean distance is then calculated between x and μ. The RBF networks are constructed by a linear combination of N radial basis functions along with N distinct centers. Given an input vector x, the output of the RBF network is the activity vector $\hat{y}$ given by

$$\hat{y}(x) = z\sum_{j=1}^{N} \beta_j Z_j(x)$$

Where β_j is the weight associated with the jth radial basis function, centered at μ_j, and $Z(x) = \emptyset(||x - \mu||)$. The output $\hat{y}$ approximates a target set of values denoted by y.

The simple but robust features are introduced further for input of the RBF networks. Three features are combined to represent the edge of ear and non-ear. It concludes centroid, bounding box, orientation and area of the edge.

Centroid is defined as the midpoint of mass of the region. It has two values represent x and y coordinates. A zone-based method is desired to normalize the point of centroid. In this regards, the input image is divided into 12 (twelve) zones or 3x4 zones. A point fall on corresponding zone is recorded as zone i^{th} (where i^{th}: 1, 2, . . ., 12). Most of ear edges fall within zone 4th to 9th. On the other hand, non-ear always appear in outer zones. The centroid is calculated as follows [18]:

A set of k points $(x_1, y_1), (x_2, y_2), \dots, (x_k, y_k)$ has centroid (C_x, C_y):

$$C_x = \frac{\sum_{i=1}^{k} \mathrm{x_k}}{k}$$

$$C_y = \frac{\sum_{i=1}^{k} \mathrm{y_k}}{k}$$

The second feature is bounding box. Bounding box is the smallest rectangle that should localize the edge. Two features are desired from bounding box which are height and width of the bounding box itself.

The orientation of the ear edge is within the same range as compared to non-ear. Thus, this feature is used to distinguish between ear and non-ear. Similar with the centroid feature; a normalization of feature orientation is required. Orientation will round up or down within [+0o, +15o, +35o, +45o, +90o] .

Area of the edge is simply a count number of pixels in the edge. This feature is used to classify small edge that belongs to non-ear or large edge that belongs to ear. The area should be normalized by dividing it with bounding box of the edge.

The RBF is trained using numerous edges of ear and non-ear to generalize the networks. Firstly, proposed preprocessing method is utilized to produce the edges. These edges should be manually classified into ear or non-ear by human inspection. In training data, it consists of 846 edges for ear class and 731 edges for non-ear class. The features of those edges are extracted then the feature vectors are fed into RBF networks.

5. Development of a Post-processing Method

Post-processing steps is required to generate connected graph from the edges of ear. In this situation, convex hull is the most suitable tool to produce connected graphs [12]. Firstly, let V is defined as the vector of ear's edge. Number of edge is denoted by n and each edge has its own index. Moreover, the edge can also be represented by a single point. This point is defined as P where it consists of p1, p2, ... , pn.

Initially, convex hull is computed from edge ei,; denoted as CH(ei). Two intersect convex hulls will be treated as the new relation points to be connected as a new graph G, G = (V,E). Where, V is a set of vertices and E is a set of edges, as follows:

$$V = \{p_i \mid p_i \in P\}$$
$$V = \{(p_i, p_j) \big| CH(e_i)\ intersects\ CH(e_j)\}$$

Naturally, whole ear will be covered by a single big edge that include all inner edges. Using convex hulls, all detected edges should intersect one to another. Thus, it can ensure that convex hull of an edge cutting will minimize one convex hull of another edge. This convex hull-based method is capable to identify the connectivity among the vertices without being influenced by variance of scale. Final output of this stage is a segmented ear and its extracted edges.

6. Experimental Results and Analysis

The proposed method for ear segmentation is benchmarked with standard database that is available on the internet. This database should cover various problems in ear segmentation. In this regards, a database collected by University of Science and Technology Beijing (USTB) [15] is used to analyze the performance. This database considers such problems:

1. The images taken from different subjects, angle views and variant heights.
2. It also has variant background and illumination conditions.
3. The ear images take into account man and woman, skin color, presence of occlusion such as earrings, hair, and glasses.

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Once image has been enhanced, edge detection is performed. The edge is exploited to represent the border of ear. The Sobel operator with defined parameter is able to produce clear edge. An overlapped ear edge and original image describe how edge detection properly extracts the edge. It is known that some small edges are do exists. In addition, edges from hair, earrings or glasses frame are also present. Thus, a method named small edge removal is proposed. This method is straightforward removes the small edge. It properly preserves all ear edges and removes the unwanted edges. Nevertheless, this method is unable to eliminate edges from earrings, frame glasses or hairs. In this regards, the proposed RBF networks are employed to overcome such problems. Earlier, the RBF-networks are trained with 2 classes of edges. From figure 2, it is clearly seen that the proposed method has managed to eliminate various false edges. The performance of RBF-based ear edge detection is presented in table 1. The RBF performance is evaluated based on human inspection. The consensus decision has been made by 5 people of judges or evaluators. The result shows that RBF has correctly classified ear edges, and 92.55% achievement is obtained. While the false classification is only 7.35%. The RBF also mistakenly classify some ear edges as non-ear due to the similarity of both shape. However, this misclassification is in remote cases and does not affect the overall performance.

Table 1 Performance of RBF-based Ear Edge Detection

Edges Classification	Range of angle		Average
	$[-10^o, 40^o]$	$[41^o, 75^o]$	
Correct	93.32%	91.78%	92.55%
Wrong	6.59%	8.11%	7.35%
Miss	0.2%		0.2%

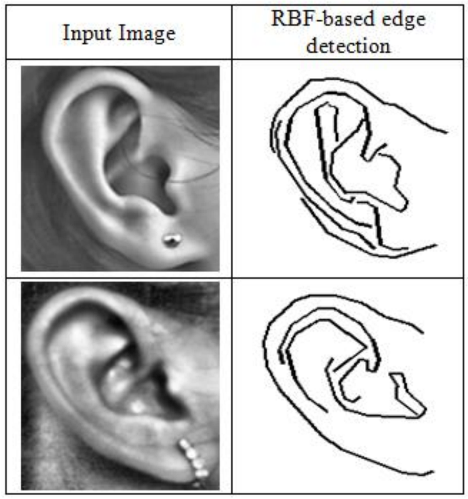

Figure 2 Result of RBF-based Ear Edge Detection

Finally, a comparison is made by benchmarking with the recent method [14]. Both methods are evaluated using same set of data, i.e. USTB's dataset. The evaluation is completed on five subclasses as mention before. Table 2 presents the comparative performance between the proposed method and recent method [14]. In normal case, where an ear's image is taken in the range of [-10o, 40o], both methods are able to produce good result. However, recent method has failed to handle ear's image captured in the range of [41o, 75o]. It is because the ear was occluded by the hair. Also, the structure of ear turns into indistinguishable because of rotation. On the other hand, RBF-networks are still capable to distinguish between edge of ear or non-ear based on its training data. Hence, the proposed method is proven to be robust and does achieve promising result to handle unconstrained ear image.

Table 2 Comparison of the Proposed Method with the Recent Method [14]

Method Name	Range of angle	
	$[-10^o, 40^o]$	$[41^o, 75^o]$
Proposed method	93.32%	91.78%
Method [14]	92.89%	75.32%

7. Conclusions

This paper introduces a robust method for automatic ear segmentation based on morphological operations and RBF networks. The proposed method is used to segment the ear's region/edge from the side view of human face automatically. The experimental results show that the proposed method is invariant to scales, poses, and shapes. USTB is the most frequently used database in this research's communities to benchmark their works due to substantial image's conditions are taken into account. Based on the undertaken performance analysis, the proposed method has delivered promising results in ear segmentation's problem. This stage is a role key to have a successfully system of ear recognition in later process.

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Author

Dr. Mohammed J. Alhaddad received his Master from Essex University in 2001, and he obtained PhD school of Computer Science and Electronic Engineering, University of Essex in 2006, UK. He became Vice Dean of Admission & Registration of Northern Borders University, and Chairman of Information Technology Department at King Abdul-Aziz University. His research interests are: Artificial Intelligence, Robots, Brain Computer Interface BCI, and Radio Frequency Identification RFID, Data Mining, Semantic Query Optimization, co-operative query answering, distributed databases and Deductive databases.