A Robust Algorithm for Ear Recognition System Based on Self Organization Maps

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Abstract

This paper presents a robust algorithm for ear identification based on geometrical features of the ear and Kohnen Self Organization Maps (SOM). Using ears in identifying people has been interesting at least 100 years. The researches still discuss if the ears are unique or unique enough to be used as biometrics. Ear shape applications are not commonly used, yet, but the area is interesting especially in crime investigation. In this paper we present the basics of using ear as biometric for person identification and authentication. High resolution ear images are taken by high resolution digital camera. Six images have been taken for twenty three persons. Four geometrical distances were calculated for each image. These geometrical distances are used as an input to the unsupervised Kohonen self organization maps. The accuracy of identification were found to be equal to 98%, for the proposed system .We conclude that that the proposed model gives faster and more accurate identification of persons based on the ear biometrics and it works as promising tool for person identification of persons from the image of their ear for criminal investigation purposes.

1.Introduction

Is this the person who he or she claims to be? Nowadays this question arises incessantly. In different organizations like financial services,e-commerce, telecommunication, government, traffic, health care, the security issues are more and more important. It is important to verify that people are allowed to pass some points or use some resources. The security issues are arisen quickly after some crude abuses. For these reason, organizations are interested in taking automated identity authentication systems, which will improve customer satisfaction and operating efficiency. The authentication systems will also save costs and be more accurate than that a human being [1].

Basically there are three different methods for verifying identity: (i) possessions, like cards, badges, keys; (ii) knowledge, like userid, password, Personal Identification Number (PIN); (iii) biometrics like fingerprint, face, ear. Biometrics is the science of identifying or verifying the identity of a person based on physiological or behavioral characteristics. Biometrics offer much higher accuracy than the more traditional ones. Possession can be lost, forgot or replicated easily. Knowledge can be forgotten. Both possessions and knowledge can be stolen or shared with other people. In biometrics these drawbacks do exist only in small scale [2].

The ear has been proposed as a biometric. The difficulty is that we have several adjectives to describe e.g. faces but almost none for ears. We all can recognize people from faces, but we hardly can recognize anyone from ears.

Ear biometrics are often compared with face biometrics (e.g. [4], [3]).

Ears have several advantages over complete faces: reduced spatial resolution, a more uniform distribution of color, and less variability with expressions and orientation of the face. In face recognition there can be problems with e.g. changing lightning, and different head positions of the person.

There are same kinds of problems with the ear, but the image of the ear is smaller than the image of the face, which can be an advantage because of the reduced number of features that is available in ear than face. In practice ear biometrics aren't used very often. There are only some cases in the crime investigation area where the earmarks are used as evidence in court. However, it is still inconclusive if the ears of all people are unique.

Researchers have suggested that the shape and appearance of the human ear is unique to each

individual and relatively unchanging during the lifetime of an adult [5].
Therefore, the ear has been proposed for use in biometrics [4,5, 6, 7]. In fact, the ear may already be used informally as a biometric. For example, the United States Immigration and Naturalization Service (INS) has a form giving specifications for the photograph that indicates that the right ear should be visible [INS Form M-378 (6-92)]. Moreno et al. [8] experiment with three neural net approaches to recognition from 2D intensity images of the ear. Their testing uses a gallery of 28 persons plus another 20 persons not in the gallery. They find a recognition rate of 93% for the best of the three approaches. They consider three methods of combining results of the different approaches - Borda, Bayesian, and weighted Bayesian.

2. Ear biometrics

In proposing the ear as the basis for a new class of biometrics, we need to show that it is viable (i.e., unique to each individual, and comparable over time). In the same way that no one can prove that fingerprints are unique, we cannot show that each of us has a unique pair of ears. Instead, we will assert that this is probable and give supporting evidence by examining two studies from Iannarelli [5].
It is obvious that the structure of the ear does not change radically over time. The medical literature reports [9] that ear growth after the first four months of birth is proportional. It turns out that even though ear growth is proportional, gravity can cause the ear to undergo stretching in the vertical direction. The effect of this stretching is most pronounced in the lobe of the ear, and measurements show that the change is non-linear. The rate of stretching is approximately five times greater than normal during the period from four months to the age of eight, after which it is constant until around 70 when it again increases.

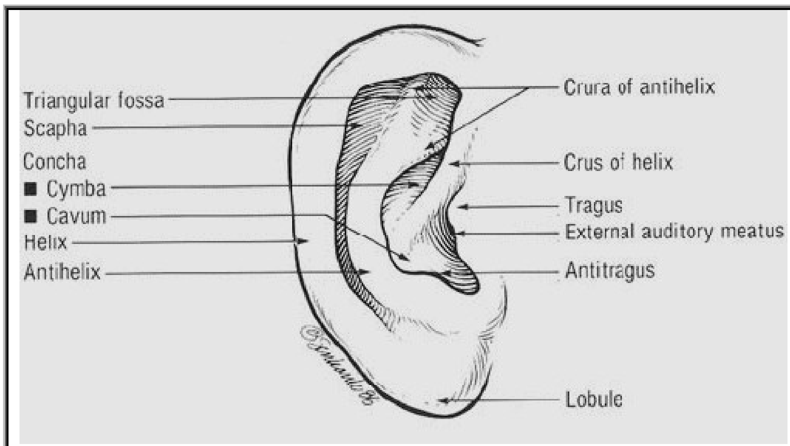

Figure (1) Anatomy of the ear

It have been shown that biometrics based upon the ear are viable in that the ear anatomy is probably unique to each individual and that features based upon measurements of that anatomy are comparable over time. The anatomy of the ear is shown in fig. 1. Given that they are viable, identification by ear biometrics is promising because it is passive like face recognition. Instead of the difficulty to extract face biometrics, robust and simply extracted biometrics like those in fingerprints can be used.
The purpose of this study was to develop ear identification system based on four geometrical distances measured from the ear images and SOM.

3. Self organization maps theory

Kohonen networks or self-organizing feature maps are networks, which consist only of two layers, an input and an output layer. The output layer of Kohonen networks can be two-dimensional. The most important difference is that the neurons of the output layer are connected with each other. The arrangement of the output neurons plays an important role. Sensorial input signals, which are presented to the input layer, cause an excitation of the output neurons, which is restricted to a zone of limited extent somewhere in the layer. This excitation behavior comes from the back coupling of the neurons. It is essential to know how the interconnections of the neurons have to be organized in order to optimize the spatial distribution of their excitation behavior over the layer. Neurons with similar tasks can communicate over very short pathways.

The optimization produces topographic maps of the input signals, in which the most important relationships of similarity between the input signals are converted into relationships among the neuron positions. This corresponds to an abstracting capability which suppresses unimportant details and maps the most important features along the map dimension. In summary, one can say that Kohonen networks seek to transpose the similarity of sensorial input signals to the neighborhood of neuron positions [9] [10].

A sketch of a SOM topology is shown in fig. 2. The SOM algorithm for classification is summarized below:

1. Initialize input nodes, output nodes, and connection weights: Use the top (most frequently occurring) N terms as the input vector and create a two-dimensional map (grid) of M output nodes. Initialize weights wij from N input nodes to M output nodes to small random values.
2. Present each set in order: Describe each set as an input vector of N coordinates..
3. Compute distance to all nodes: Compute Euclidean distance dj between the input vector and each output node j:

$$d_j = \sum_{i=0}^{N-1} (x_i(t) - w_{ij}(t))^2 \qquad (1)$$

where xi(t) can be 1 or 0 depending on the presence of i-th term in the document presented at time t. Here, wij is the vector representing position of the map node j in the document vector space. From a neural net perspective, it can also be interpreted as the weight from input node i to the output node j

4. Select winning node j* and update weights to node j* and its neighbors: Select winning node j*, which produces minimum dj. Update weights to nodes j* and its neighbors to reduce the distances between them and the input vector xi(t):

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)(x_i(t+1) - w_{ij}(t)) \qquad (2)$$

Where η(t) is the learning parameter. After such updates, nodes in the neighborhood of j* become more similar to the input vector xi(t). Here, h (t) is an error-adjusting coefficient (0 < h (t) <1) that decreases over time.

For the neurons that lose the competition as:

$$w_{ij}(t+1) = w_{ij}(t), \qquad (3)$$

Kohonen's SOM or a feature map provides us with classification rules. SOM combines competitive learning with dimensionality reduction by smoothing clusters with respect to an a priori grid. With SOM, clustering is generated by having several units compete for (training) data The unit whose weight vector is closest to the data becomes the winner so as to move even closer to the input data, the weights of the winner are adjusted as well as those of the nearest neighbors. This is called Winner Takes All (WTA) approach. SOM assumes some topology among the input data. The organization is said to form a SOM map because similar inputs are expected to put closer position with each other. The flow chart of SOM algorithm is shown in fig. 3 [11].

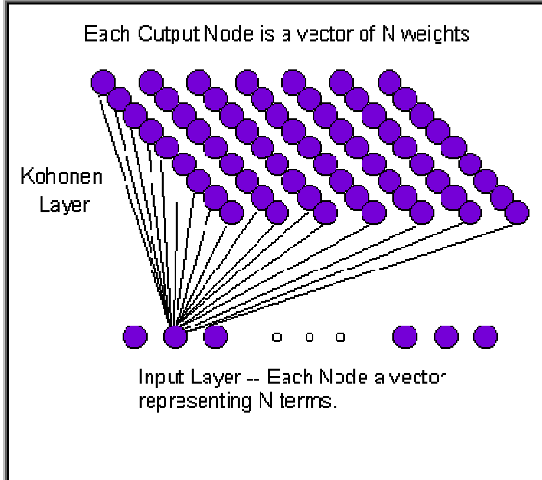

Figure (2) Kohonen SOM topology

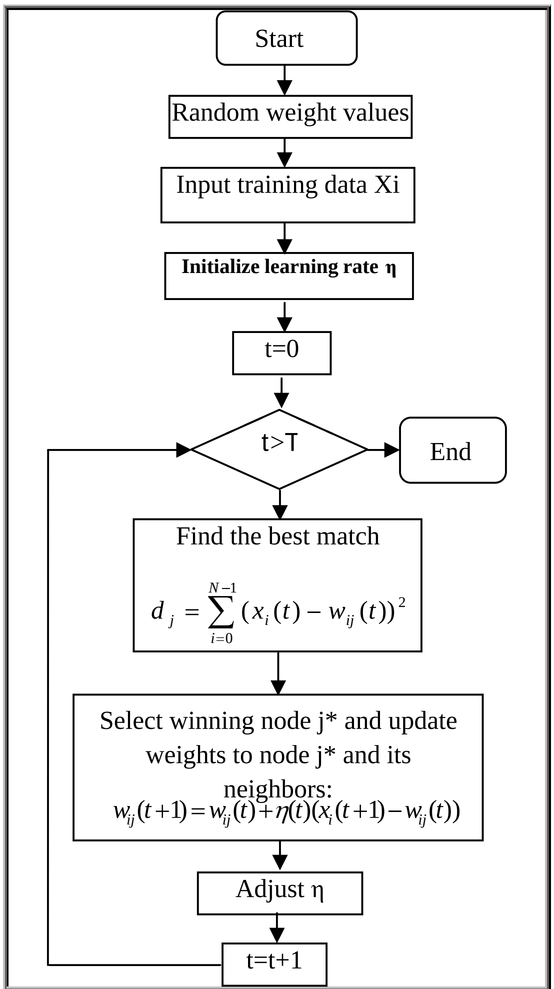

Figure (3) Flow chart of SOM algorithm

Figure (4) Images of the ear for six subjects

4. Data Acquisition

All the images used in this paper were acquired by Sony Cyper-shot camera (model W35, resolution 7.2 M pixel). In each acquisition session, the subject sit approximately 16 cm away from the camera with the left side of the face facing the camera. Twenty three subjects are chosen from persons in the department of Biomedical Engineering-Al-Khawarzmi College of Engineering-Baghdad University. Six images for each subject with resolution of 480x640 color image are obtained.

The earliest good image for each of 23 persons was enrolled in the gallery. The gallery is the set of images that a “probe” image is matched against for identification. The latest good image of each person was used as the probe for that person. A subset of 138 images of data was used to explore algorithm options in some initial experiments.

Figure (5) Two gray level images after gray level separation

The acquired images are transferred to the computer via USB cable. The images were read by MATLAB software package version 7. At first, the colored images are transfered into gray scale image (Black and white) see fig. 4 and fig. 5. The algorithm for gray level separation for ear images into single gray level is shown in fig. 6.

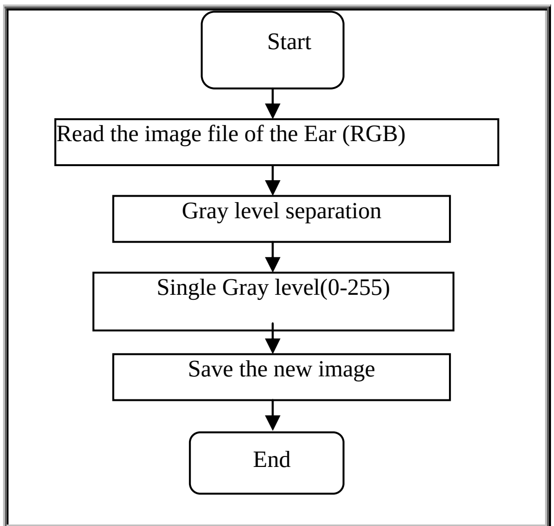

Figure (6) The algorithm for gray level separation for ear images into single gray level

5. Landmark Selection

It have been investigated four different geometrical distances. These distances are :

1- The total length of the ear lobule (L1).
2- Small length (L2).
3- Radius of the upper half circle of the air lobule (R).
4- Width of the Helix (WH).

The four geometrical distances are shown in fig. 5. These 4 distances were measured for 138 images (23 persons each one had six images). These 4 distances are used as input to the SOM neural network to train and to test the network.
Table 1. shows the four distances of six subjects. The 138 images were divided into two groups, one for the training set and the other for testing by SOM.
The training set consists from 4 images for each person (92 images).
The remaining two images are used to test the efficiency of the SOM. The testing data consists from 46 images.

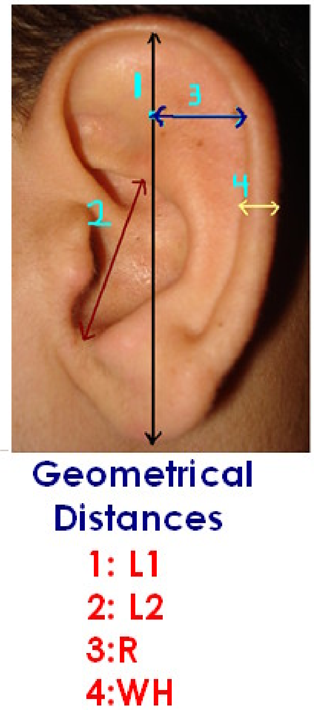

Figure (7) Geometrical distances measured for each ear

The training set is grouped in one matrix with dimension of (92x4). This matrix is fed to the input layer of SOM. Output weight was stored after the training for the testing process.
The network tested with the 46 data set.

Table (1) The four geometrical distances for six persons

No.	case no.	L1	L2	R	WH
1	subject 1	332	129.07	44.667	22.67
2	subject 1	308	123.54	39.333	29.33
3	subject 1	302.67	122.38	40	29.33
4	subject 1	281.33	113.92	40	25.33
5	subject 2	316	104.52	53.333	20
6	subject 2	301.33	93.571	50.667	25.33
7	subject 2	320	103.6	50	28
8	subject 2	304	98.097	54	22.67
9	subject 3	278.67	102.46	54.667	20
10	subject 3	282.67	99.849	64	24
11	subject 3	296	105.87	60.667	22.67
12	subject 3	289.33	98.378	60.667	21.33
13	subject 4	261.33	77.345	42.667	30.67
14	subject 4	258.67	82.935	44.667	28
15	subject 4	277.33	87.28	46.667	34.67
16	subject 4	280	92.154	42.667	32
17	subject 5	321.33	96.894	64.667	28
18	subject 5	353.33	100.96	60	30.67
19	subject 5	337.33	100.63	67.333	29.33
20	subject 5	368	120.57	70.667	29.33
21	subject 6	309.33	88.534	58.667	29.33
22	subject 6	324	96.563	63.333	30.67
23	subject 6	305.33	89.899	54.667	25.33
24	subject 6	293.33	82.149	54.667	25.33

6. Results and discussion

The performance of the ear identification algorithm was evaluated by computing the percentage and Accuracy of Identification of Subject (AIS), the definition of Accuracy of identification algorithm is [12]:

$$AIS = \frac{\text{Correct identification}}{\text{Totlal no. of images}} * 100\% \qquad (4)$$

The obtained accuracy of identification with the time to run the algorithm is shown in table. 1

In our study, the use of SOM has been proposed for person identification from ear images by means of calculating the geometrical distances for ear the ear images. The obtained accuracy of identification was found to be 98%. This mean that only there was only one misidentification. and to be used for criminal identification This is regarded a very robust and the system is reliable and can be a very robust. The results showed that the algorithm can be reliable purposes in the police departments.

Table (2) The results after training of the network

	No. of cases	Accuracy of Identification	Time
SOM	46	98%	2.3 S

7. Conclusions

In this paper, it have implemented a robust algorithm for person identification system based on SOM and geometrical distances. 138 images were taken for 23 persons. These images are transferred to personal computer and read by MATLAB software package version 7. Four geometrical distances were calculated to 138 images collected. These distances were carried out to generate training data for the SOM and to identify persons. These distances are fed to the SOM.

The accuracy is calculated to evaluate its effectiveness. The obtained accuracy of identification was 98%. We conclude that that the proposed system gives faster and more accurate identification and acts as promising tool for person identification for the identification purposed in the security field.

8. References

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خوارزميةقوية لنظام تمييزالاذن معتمداً على الخرائط الذاتية التنظيم

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الخلاصة

يقدم البحث خوارزميةقوية لنظام تمييز الاذن ومن ثم التعرف على الشخص من خلال الاذن. تم اخذ صور ست صور ل٢٣ شخص من طلاب وطالبات قسم هندسة الطب الحياتي-كلية هندسة الخوارزمي-جامعة بغداد. تم قياس اربعة اطوال لكل صورة، هذه الاطوال استعملت كمدخلات للخرائط الذاتية التنظيم. لاختبار كفاءة الخوارزمية، تم حساب نسبة التمييز للشبكة ووجد انها ٩٨% ومن هذا البحث نستنتج ان النظام المقترح يعطي تنبؤ سريع ودقيق للاشخاص من خلال الاذن ويمكن ان يستعمل في التعرف على الاشخاص في التحقيقات الجنائية.