Proc. 2nd Saudi Sci. Conf., Fac. Sci., KAU, 15-17 March 2004, **Part I**, pp. 175-183 (2005 A.D./1425 A.H.

Person Recognition by the Ear Image Using Compressed Artificial Neural Networks

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ABSTRACT. An artificial neural network model is used for recognizing a person based on the image of his ear. Specifically, an ear image is presented to multi-layers neural network during the training phase of the net. To achieve compression, the number of the neurons used in the hidden layer is less than the number of the neurons in the other layers. The weights developed during the training phase are used in the testing phase to compress ear images and to examine the ability of the net to identify the person to whom a certain pattern belongs. After decompression, the second order correlation coefficient between the unknown ear pattern and each member of a library of known ear images is computed to find the value of the maximum correlation, and consequently, to yield the most similar pattern to the unknown pattern. The ability of the neural net to generalize based on patterns not used during the training is also tested. In general, the results showed a successful identification of the decompressed unknown ear sample at high compression ratios.

Keywords: Image compression, Neural networks, Pattern recognition, Biometrics, Correlation coefficient, Person identification.

Introduction

Person identification is one of the most common means practiced everyday. In most cases the human face is the main identifying feature of the people. Biometrics use fingerprints, iris scanning or complete face images to recognize people (Moreno *et al.*, 1999). Modern means of person identification are using DNA-finger-printing (Fridell 2001).

The process of human identification can be automated for the use in some applications in order to speedup the processing and to reduce the recognition error rate for more reliability. For this reason, many researchers tackled this problem from different angles and they used different schemes. Some researchers suggested using the face for people identification (Kerin & Stonham, 1990). Others used partial face images (e.g. eye, nose, and ear images) for identification (Sato *et al.*, 1998). Others suggested the use of outer ear images for personal identification (Carreira, 1995; Moreno *et al.*, 1999). Still others combined the ear and face for biometric recognition using principle component analysis (Chang *et al.*, 2003).

It has been shown that the outer ear images have more identification richness than some other part of the human body (except for the fingerprints or the iris), and they do not change significantly from the moment in which the suhject reaches adult age (Moreno *et al.*, 1999). From the point of view of image processing the ear has some advantages over eomplete faee; its surfacc is smaller, having a more uniform distribution of color while a faee can ehange its appearance with varied expressions of the subjeet (Moreno *et al.*, 1999).

In this paper, a human recognition system based on the image of the ear using a back-propagation neural network model is presentcd. The neural net is trained to compress the ear images at differcnt comprcssion ratios. The effect of this eomprcssion on the rccognition of humans, bascd on their car images, is studied. The rohusrness of the net is investigated by presenting strange, noisy, or rotated ear patterns.

Materials and Methods

Artificial Neural Network

An artificial neural network is an information-processing system that has certain performance characteristics in common with biological neural networks (Fausett 1994). These ncural networks are used in many applications among them pattern classification, rccognition, and as gcneralizations of mathematical models of human cognition or neural biology (Fausett 1994).

A ncural network can be set and trained to classify and rccognize a set of patterns. Then, the trained net can be used in classification and recognition by presenting the patterns used during the training phase, as well as, patterns not used during the training in order to examine the memorization and generalization capahilities of the net.

In this study, a multilayer neural network structure with one input, one hidden, and one output layer is used. The back-propagation algorithm (the algorithm can be looked-up in many texts such as Fausett, 1994; Freeman & Skapura, 1991; Haykin, 1999) is used for training the nct. The training input patterns are fed to the neurons of the input layer and the output responses of the net corresponding to the input patterns are computed. The training is continued for many epochs until the net converges by reaching to a stage where no more weights updating are noticeable.

Neural Network Model for Ear Identification

Artifieial Neural networks (*ANN*) are suitable for data compression because there are some *ANN* architeetures that can be trained to map a set of patterns from an n-dimensional space to a p-dimensional space then back to n-dimensional space, where $p < n$. The weights developed by the nct at the neurons of the hidden layer represent a eoded version of the input data. This weight vector can be either stored for later processing, or transmitted from one location and decompressed at auother location. In both cases there is a gain of using the neural network to aehieve compression.

In this research, a set of ear images that belong to 17 different individuals are presented to the neural net during the training phase. The eonnection weights between the net layers are updated accordingly. The procedure is repeated until the network converges aecording to a preset stopping condition.

The recognition is performed by loading the weights between the net layers which are developed during the training phase. Then, the unknown pattern is loaded to the input layer. The output responses of the net (Y) are eomputed and reshaped to reeonstruet an approximation of the input image. The seeond correlation eoefficient (SC) is computed between the resulted pattern and each template of the known ear images in the library (T). This can be written as

$$SC = Y \circ T \tag{1}$$

The nearest mateh to the input pattern can be yielded by computing the maximum output correlation coeffieient (mc) value

$$mc = \max(SC) \tag{2}$$

The deeision rule (D) for recognition or rejection of an unknown input pattern can be set by using a recognition threshold value (η). The rule that we can use here can be written as

$$D = \begin{cases} mc \geq \eta & \textit{recognition} \\ mc < \eta & \textit{rejection} \end{cases} \tag{3}$$

The setup used for this teehnique is illustrated in Fig. (1).

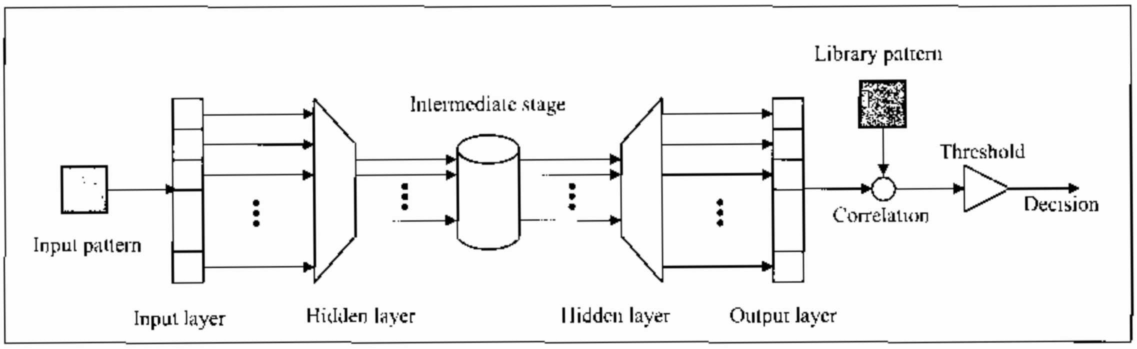

Fig. (1). Setup used for the recognition of the ear patterns using a compressing neural net.

In this study, a database that contains 22 ear images is used. Each image is of size 64×64, and of 256 gray-levels. **Error! Reference source not found.** illustrates the database of the ear images (the original database was taken from Carreira, M. 1995). A subset of ear images from the available database is used in the training. Another subset is used as training-testing patterns during the training for the purpose of keeping a balance between the memorization and generalization capabilities of the net.

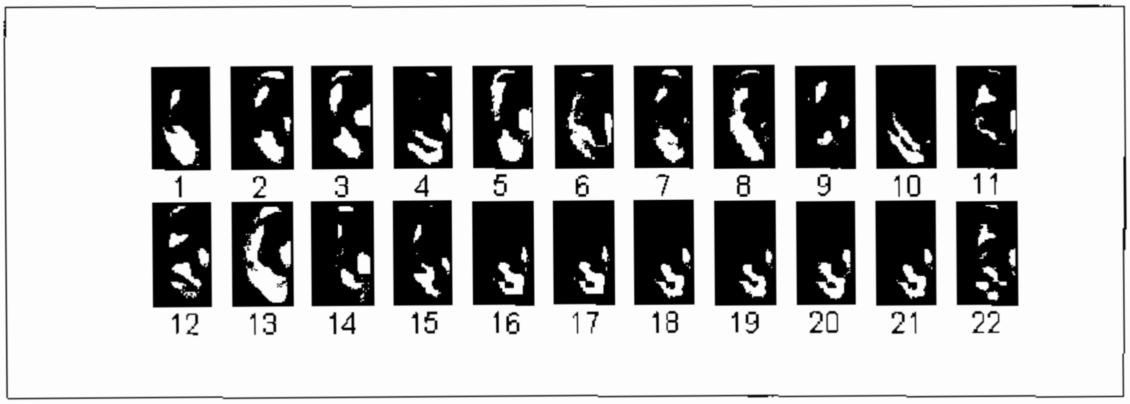

Fig. (2). Set of ear images used in the training and testing phases of the neural net.

The database is divided into five sets. The first used for training. It eontains the ear images #1-5. The second (images #6-10) is used as training-testing patterns. The third set is used during the testing phase. It contains ear images #1-16. The fourth set (images #16-21) represents the same individual's ear image with slight changes in the head positiou from image to image. Finally, the fifth set contains image #22 and it is used as a strange pattern.

Results and Discussion

The technique demonstrated in the previous section was used to examine the effect of the recognition of humans based on the image of the ear. The training of the neural net was performed using a net with 64 input, and 64 output neurons. The hidden neurons was set and changed to: 16, 12, 8, 4, and 1; this is corresponding to compression ratios of: 4:1, 5.33:1, 8:1, 16:1, and 64:1 respectively. The recognition threshold (η) was set to a value of: 0.92.

The identification of the ear pattern #1 using a net with a compression ratio of 4:1 is shown in Fig. (3). It is noticeable from the figure that the pattern is identified successfully and almost there is no significant difference in the identification between the original ear pattern and its decompressed version at this compression ratio.

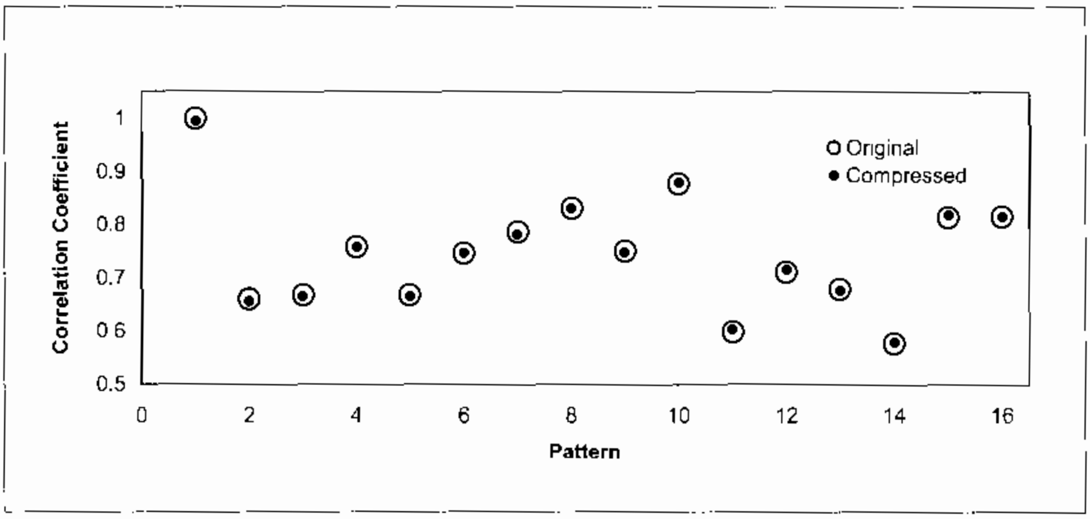

Fig. (3). Identification of the ear pattern #1 at a compression ratio of 4:1.

The net generalization capability was tested. Pattern #9 was used for this purpose. The results, as can be depicted from Fig. (4), show the ability of the neural net in identifying the input pattern. The correlation coefficient value after compression is a little bit lower in this case.

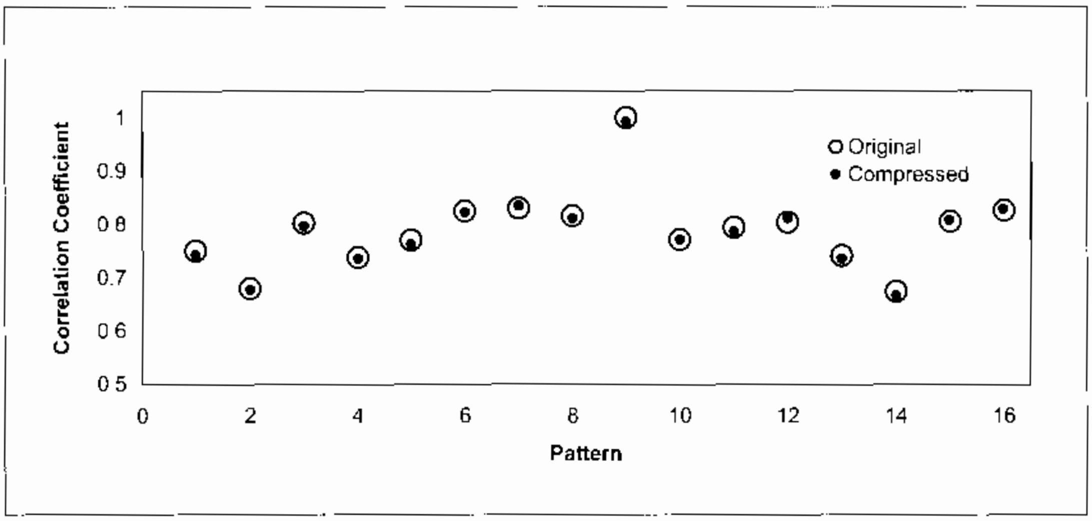

Fig. (4). Identification of the ear pattern #9 at a compression ratio of 4:1.

The system was also presented with a strange pattern (#22). By applying the recognition threshold, Fig. (5) illustrates the rejection of this pattern which is not considered among the 16 known patterns.

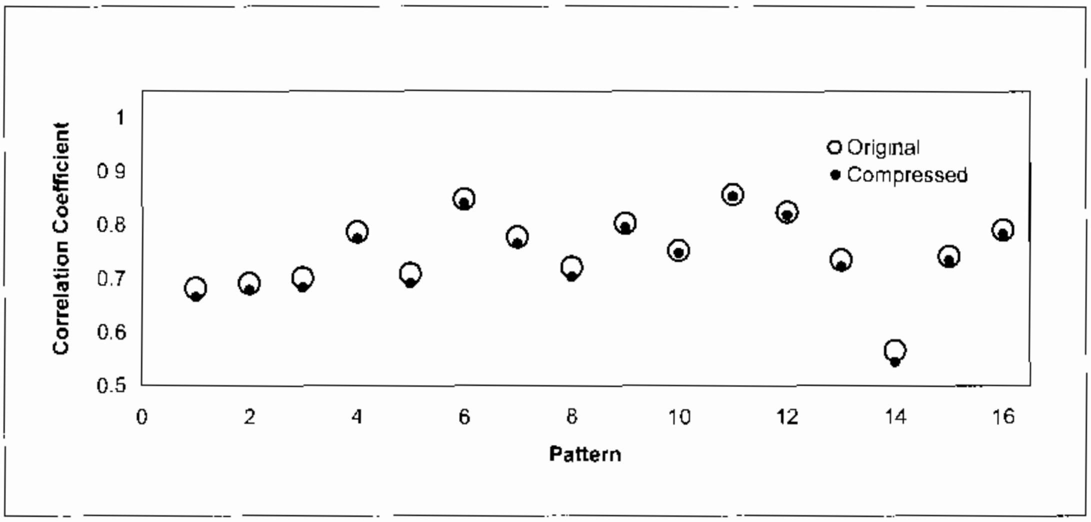

Fig. (5). Identification of a strange ear pattern #22 at a compression ratio of 4:1.

The results of compressing the unknown test pattern were compared to the results of compressing the known templates instead and keeping the test pattern uncompressed. For these two cases, Table 1 shows the correlation coefficient for the test pattern #7 with the templates. It is apparent that there is no significant distinction in the recognition in both cases. This situation can be used in cases where there is a large set of library patterns. In such case, all known patterns can be compressed and stored in the intermediate stage (see Fig. (1). The unknown pattern will be correlated with each of the decompressed versions of the library patterns. This situation is ideal when there is a need to store a large database of patterns for later recognition of an unknown input pattern to the system. The unknown pattern is kept uncompressed.

Table 1: Comparing the compressing the test pattern (#7), and compressing the templates.

Pattern	Original	Correlation Coefficient		Pattern	Original	Correlation Coefficient	
		Test	Templates			Test	Templates
1	0.7850	0.7750	0.7818	9	0.8304	0.8348	0.8347
2	0.8474	0.8463	0.8498	10	0.7587	0.7554	0.7453
3	0.7980	0.7963	0.7987	11	0.7725	0.7778	0.7709
4	0.8038	0.7969	0.8051	12	0.8371	0.8411	0.8340
5	0.8055	0.8021	0.8041	13	0.8438	0.8399	0.8513
6	0.8516	0.8573	0.8562	14	0.7153	0.7149	0.7133
7	1.0000	0.9934	0.9934	15	0.8337	0.8309	0.8299
8	0.9098	0.9073	0.9093	16	0.8399	0.8379	0.8368

The effect of the compression ratio on the identification is tested. As a typical case Fig. (6) illustrates this relationship for pattern #7. As can be noticed from the graph, for compression ratios from 1:1 to 16:1, the identification is above the recognition threshold. This means that the system responds correctly when hidden neurons are greater or equal to 4.

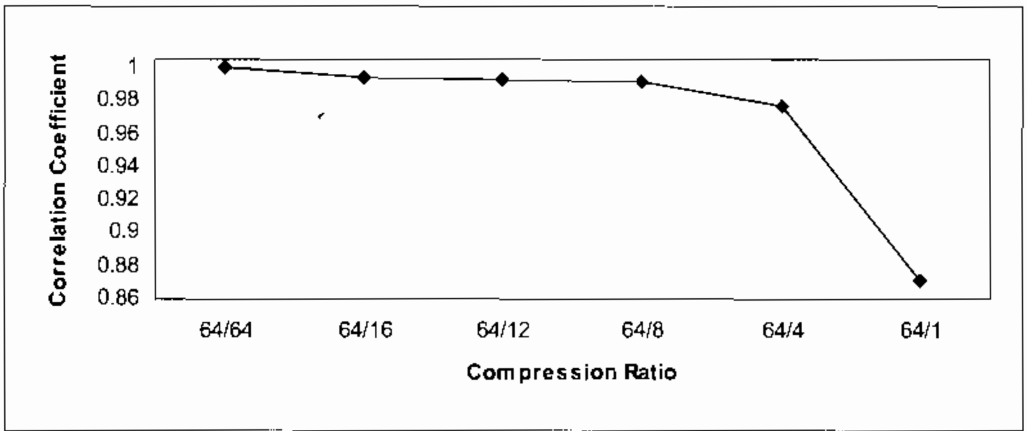

Fig. (6). Effect of the compression ratio on the identification of the pattern #7.

Using ear pattern #16 with its similar patterns 17, 18, 19, 20, and 21, Table 2 summarizes the results. It can be noticed, with the exception of the case at compression ratio 64:1, that each pattern responds almost the same regardless of the compression ratio.

Table 2: Results of identifying pattern #16 and its five-similar patterns.

Pattern	Compression Ratio				
	1:1	4:1	8:1	16:1	64:1
16	1.0000	0.9946	0.9924	0.9823	0.9062
17	0.9693	0.9670	0.9673	0.9599	0.8941
18	0.9488	0.9470	0.9477	0.9433	0.8895
19	0.9678	0.9658	0.9663	0.9605	0.8954
20	0.9704	0.9676	0.9673	0.9592	0.8955
21	0.9826	0.9773	0.9747	0.9657	0.8933

The effect of the noise on the identification of the input patterns was also considered. In these experiments, a Gaussian white noise with zero-mean and a standard deviation of σ were used to corrupt the input patterns. The relation of the correlation coefficient to the noise added with different standard deviations is depicted in Fig. (7).

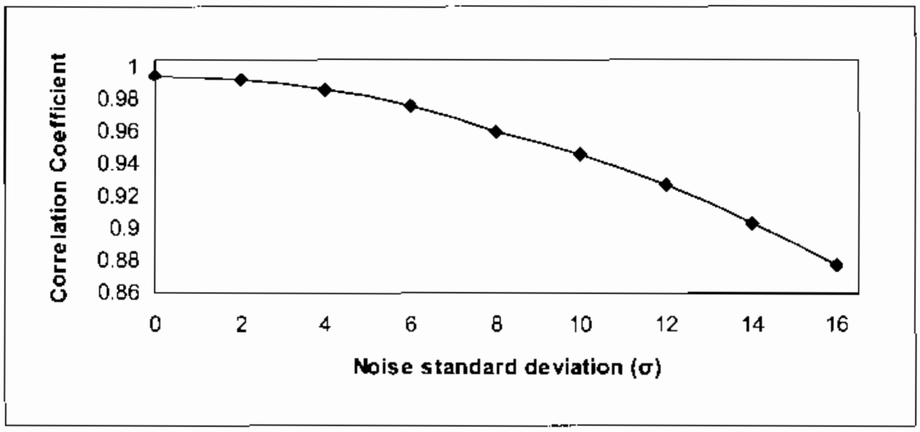

Fig. (7). Noise effect on the identification of ear pattern.

Finally, the effect of rotating the input pattern at different orientations is also investigated. This relation is depicted in Fig. (8). Using a recognition threshold of 0.92, it can be concluded from the figure that the pattern can be identified successfully up to a rotation angle of 5°.

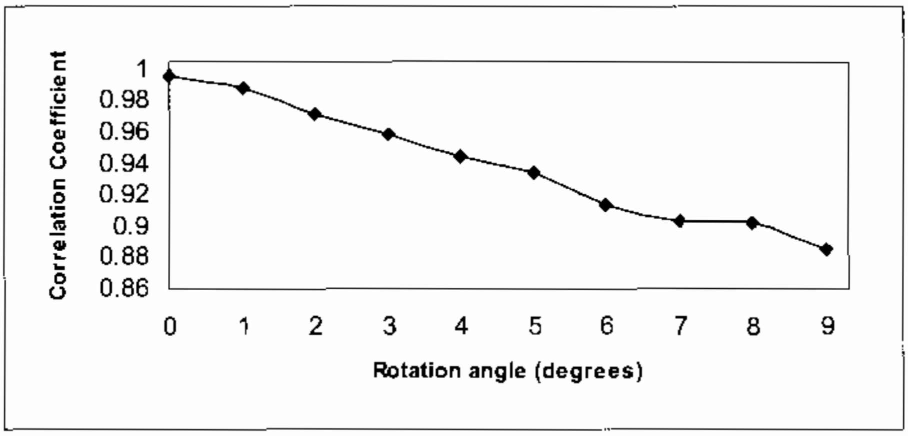

Fig. (8). Correlation coefficient as a function of the pattern orientation.

Conclusion

In this paper, the identification of a person using the image of the external ear and based on a compressed neural network is investigated. The results showed the ability of the proposed technique to identify an unknown pattern used or not used during the training phase of the net. Using a neural network with a compression ratio up to16:1, the recognition rate for the patterns used from a given database was almost 100%. The results also showed the ability of the system to reject strange patterns. The robustness of the system was also tested. This situation was performed by identifying similar, noisy, and rotated patterns. The results showed acceptable recognition responses.

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التعرف على هوية الشخص من صورة الأذن المضغوطة باستخدام الشبكات العصبية الاصطناعية

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المستخلص. توضح هذه الدراسة طريقة لاستخدام الشبكات العصبية الاصطناعية كنموذج رياضي للتعرف على هوية الأشخاص من خلال صورة الأذن الخارجية. حيث تم بناء شبكة عصبية تقوم بضغط صورة للأذن وذلك بتقليل عدد العصبونات في الطبقة الخفية للشبكة. بعد ذلك استخدمت الأوزان الشبكية المضغوطة الناتجة من مرحلة التدريب في مرحلة الاختبار لتقييم قدرة الشبكة على التعرف على هوية الشخص. واستخدم لهذا الغرض معامل الارتباط الثاني الذي يتم حسابه بين شكل أذن مجهولة ومجموعة أشكال الآذان المعروفة. وقد أظهرت النتائج مقدرة كبيرة للشبكة العصبية على تمييز هوية الشخص من خلال صورة الأذن بعد ضغطها.