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Application of hopfield network in improvement of fingerprint recognition process

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ABSTRACT

Hopfield Network is able to convert noisy data provided to the network because it can act as content addressable memory. Hopfield Network can convert images of noisy fingerprint to the noiseless images or the images with the minimum noise by training through receivable models set. In this research, fingerprint recognition process has been performed through Hamming Distance and effect of use of Hopfield network on fingerprint recognition process has been mentioned. In case those Hamming Distance operations are performed after Hopfield Networks processing, error of fingerprint recognition will be reduced.

Introduction

Hopfield Network is one of the neural networks which have been used in the present research. Hopfield network in images can have useful applications. Fingerprint images which are used for identification may have noise. For example, it may be injured. In the present research, we study to what extent Hopfield Network can improve noisy or defective fingerprint images and be applied in fingerprint recognition process. Fingerprint images become binary after recalling to be calculated for Hopfield network studies. Hamming Distance is regarded as the best option due to application for binary data. Hamming Distance will find the closest similar image by studying differences between each image of input fingerprint and other images.

Images of fingerprint

Fingerprint of each person is a unique biological trait and can have effective applications for identification. Identification system based on biological traits should be distinguished and can be gathered and stable and bolometric trait of fingerprint has the mentioned specifications so that it has been regarded as valid evidence in judicial authorities (Daliri et al, 2007). Images of fingerprint are fingertips tissue pattern which have unevenness. Unevenness of the fingertip is due to wrinkles (Jean et al, 1997). According to analysis and study of wrinkles in fingertip, we can adjust identify recognition system based on this biological trait.

Preprocessing operations on images of fingerprints images:

In the present research, 40 fingerprints images have been used as model set for Hopfield Network learning. All images of fingertips are converted to black and white format and then size of all images is equal. Primary images of fingertip are in large dimensions which are difficult to calculate. For this reason, images will be calculated in smaller sizes. Background of fingertips is removed and contrast of the images is increased so that images of fingertips are made more evident. Stages of preprocessing operations on one of the fingerprint images are shown in Figure 1. After performing preprocessing on the model set images, Hopfield operations will be performed.

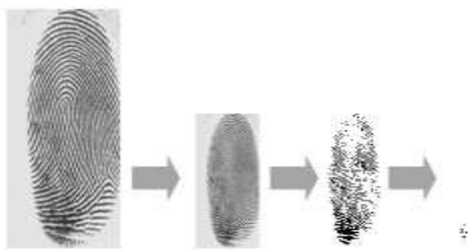

Figure 1: Preprocessing operations on the fingerprint images

Recall of fingerprint images

In the present research, all operations on images have been done in MATLAB software. In this software, the related matrix will be specified after recall of the images. Matrix elements of fingerprint images are determined on the basis of gray spectrum zero to 255 belonging to each one of the image pixels. In the next stage , images are binary and because the studied method is Hopfield network and all studied elements in Hopfield network should be +1 and -1, therefore, all zeros are converted to -1 and +1s remain unchanged. In the following Figure, matrixes of fingerprint image are shown. In the first stage, all elements of matrix are between zero and 255 and are zero and 1 in the next stage and finally between -1 and +1.

Figure 2: Fingerprint images matrices

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Hopfield Network

Hopfield network is a kind of recurrent artificial neural networks have been invented by John Hopfield. Hopfield network can play role of a system with dependent memory including two mode components. Hopfield Network has been composed of some nodes each connected to other nodes. Therefore, with regard to the shown figures, among two Hopfield networks, this network is a related network.

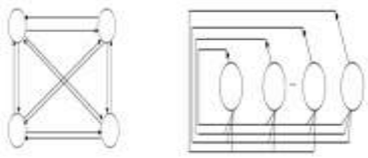


Figure 3: Different images of Hopfield Network

Components of Hopfield network are two state components. It means that they can be in two defined states and that their position is determined dependent on the fact that input set of the related component is less or more than the threshold value. In Hopfield Network, all neurons act like each other and there is no classification of input and output neurons. In fact, Hopfield network is a recurrent network in which output of each neuron is connected to input of other neurons. This action is repeated to the extent that output of the network converges to a fixed point.

Hopfield Network Algorithm

In this section, the algorithm which determines function of Hopfield network has been mentioned. The mentioned algorithm is derived from book "introduction to neural networks''. (Translated by Alborzi, 2001)

Stages of algorithm:

weight coefficients are determined with the following formula:

(1)

$$\sum_{S=0}^{M-1} X_i^s X_j^s$$

$$i = j, 0 < i, j < M-1$$

w_{ij} is weight coefficient from node I to node j and x_i^s is ith member of sample model s. value of x_i^s is +1 and -1. The number of models is M from zero to M-1 and threshold value of all nodes is zero.

We give unknown model to the network. $\mu_i(t)$ is, i node output at t time.

$\mu_i(0) = x_i$,0 < i < N-1

We iterate it to perfect convergence.

$$\mu_i(t+1) = f_h \sum_{i=0}^{N-1} w_{ij} \mu_j(t)$$

$\mu_i(0) = x_i$, 0 < i < N-1

Function f_h is a Heaviside step function of Figure 4. Heaviside step function behaves in such a manner that output is one in case of positive input and output is zero in case of negative input.

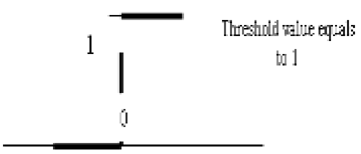


Figure 4: Heaviside step function

Weight coefficients between neurons are determined with use of selective sample algorithm of all classes with the formula which is given in algorithm. This stage is stage of network education so that each model is made similar to it. In stage of identification, output of the network is put against the unknown model by imposition, and then the network is released to change in discrete time intervals as long as it reaches stability and its output is fixed. In such case, the network converges to final answer. If an entangled pattern is given to the network, the network will produce its correct pattern, therefore, the network acts as a content addressable memory. In Hopfield Network, patters are not supplied to the network one by one but they are fed to the network with use of the above stage by calculating weight coefficients. In fact, network education is done only in one step. Function of the Hopfield Network can be summarized as follows:

- *We commission the network*
- *We supply the unknown pattern*
- *We iterate it until final convergence*

- Noisy fingerprint images processing with Hopfield network:

In order to process images of fingerprint with Hopfield network, a set of fingerprint images has been given to the network. Then, images of noisy fingerprint are supplied to the network. In this research, images of fingerprint have been studied by adding line or point as noisy fingerprint image. After the images are noisy, they become binary and matrix of noisy images is studied with noiseless images and then elements of the matrix change after being noisy. Noisy elements in images matrix which have been studied as unknown pattern range from 0 to 6. In the following table, the number of images with noisy elements has been studied:

Matrix of unknown pattern images faces different results after convergence. In this following table 4, noisy images are given with primary matrixes of noiseless images, noisy images matrix and final matrix after convergence.

Matrix of fingerprint images will have different results after convergence. The best result which is obtained from Hopfield networks is similar to the first line of the above table. In this case, image matrix is noiseless like the primary image matrix. As shown in the above table, all noisy elements of the matrix may not change correctly and sometimes some fixed elements of matrix may change after convergence. Generally, results obtained from Hopfield operations can be divided into four groups as follows:

First answer group: final matrix is similar to the primary matrix and is noiseless after convergence and all noisy elements have been similar to the primary matrix after convergence. For matrixes with zero noisy elements, first answer group has not changed after operations of Hopfield network of the studied matrix.

Second answer group: in the final matrix, some elements are noiseless after convergence and some elements of the noisy matrix have not changed.

Third answer group: in the final matrix, some elements which were fixed after being noisy changed after convergence.

Fourth answer group: noisy elements have not changed in the final matrix after convergence.

In some cases, results of Hopfield network are combination of two answer groups. Group's combination is as 1 and 3, 2 and 3 and 3 and 4.

Answer 1 and 3 group: noisy elements have changed correctly but some elements of the main matrix have changed by mistake.

Answer 2 and 3 group: noisy elements have changed correctly but some have not changed. Some elements of the main matrix have changed by mistake.

Answer 3 and 4 group: noisy elements have not changed after convergence but some have changed by mistake.

As mentioned above, 40 images of fingerprint images have been stored in system. Different images of these 40 images have been noisy with different noises randomly. With regard to the fact that there are some images with different noises, number of these fingerprint images is 100. 100 matrixes of fingerprint image with zero to 6 noisy elements have been studied with Hopfield network.

After study of the fingerprint image matrixes with Hopfield network, matrixes resulting from these operations are studied in fingerprint recognition process according to Hamming distance method. 100 images of the fingerprint image are studied again in fingerprint recognition process to define effect of Hopfield in fingerprint recognition process.

Hamming Distance:

Hamming distance is obtained by calculating difference of each element in a vector and its corresponding element in another vector and sum of absolute magnitude of differences. Hamming Distance is applied for calculating vectors zero and one. With regard to the obtained numbers in calculations and matrices of fingerprint images, Hamming distance is the best option for fingerprint recognition process.

$$H = \sum (| x_i - y_i |)$$

With the above formula, the minimum sum of absolute magnitude of differences is found and the closest vector similar to the input vector is obtained.

- Fingerprint recognition process according to Hamming distance

In the present research, images of fingerprint are studied with or without Hopfield network according to Hamming distance. In study of fingerprint recognition process, effect of Hopfield network is specified. As mentioned in the previous section, image of fingerprint has been considered. Matrixes of the mentioned images have 0 to 6 noisy elements. Fingerprint images group which have been studied with Hopfield network in fingerprint recognition process have got closer to the primary noiseless image after operations of Hopfield network.

As mentioned above, 40 images of sound fingerprint have been stored in the system. Different images of these 40 images have been randomly noisy with different noises. With regard to the fact that some images are available with different noises, the number of these images group is 100. In fingerprint recognition process, one image out of 100 images is regarded as input according to Hamming distance and compared with 40 images saved in the system. Hamming distance is studied in such a manner that elements of input matrix are compared with elements of 40 matrixes saved in the system and finally the closest similar matrix of the input fingerprint image is mentioned. The announced results in fingerprint recognition process can be classified into four classes of answer.

In case that only one matrix similar to input matrix is announced which is input matrix, result of fingerprint recognition process has been correct in this case.

○ In case that two matrixes are similar to input matrix provided that there is matrix of the primary image similar to the input image, result of fingerprint recognition process is announced for two images similar to input image.

○ In case that three matrixes are similar to input matrix provided that there is matrix of the primary image similar to the input image, result of fingerprint recognition process is announced for three images similar to input image.

○ In case that the announced matrixes are not the matrixes corresponding to input image, the announced result is incorrect in fingerprint recognition process.

○ Therefore, 100 images of fingerprint are studied (with and without Hopfield Network) according to Hamming Distance in two stages and the obtained results are shown in table 4.

With regard to Table 4, there are more correct results with Hopfield Network and fewer incorrect results. That the noise applied to the images is high range; one can make correct comparison on the basis of noisy elements in fingerprint images. With increase in images, it is unlikely that the image similar to the first image will be obtained without noise with Hopfield network.

- Study of hamming distance results with regard to noise of the images

In this part of the article, results obtained from fingerprint recognition process with or without Hopfield network are compared with each other on the basis of noise of the images. In table 5, the obtained results are shown. The upper number in each cell of table is the result with Hopfield network and the lower number is the result without Hopfield Network.

As shown in Table 5, results of fingerprint recognition process with Hopfield network is averagely more correct. The important point in this table is images without noise or one noisy element and in this case, more correct results have been obtained without Hopfield network. In images with average noise rate, there has been more correct recognition with Hopfield network and less incorrect recognition. In images with 5 and 6 noisy elements in each fingerprint matrix, there has been no correct recognition with and without Hopfield network but there is recognition for some similar images and there are fewer results with Hopfield network than those without Hopfield network in incorrect recognitions. In diagrams 3 to 9, percentage of correct results and recognition of two similar images (2?) and recognition of three similar images (3?) and incorrect results are shown on the basis of noise in images.

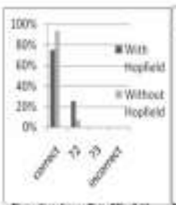


Figure 5: study on effect of Hopfield network on results of Hamming distance in images set with 2 noisy elements

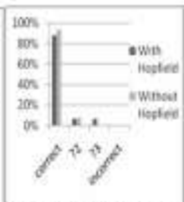


Figure 4: Study on effect of Hopfield network on results of Hamming distance in images set with 1 noisy element

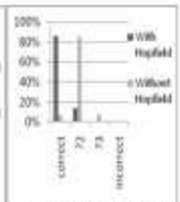


Figure 3: Study on effect of Hopfield network on results of Hamming distance in images set with zero noisy elements

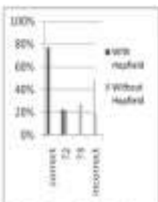


Figure 8: Study on effect of Hopfield network on results of Hamming distance in images set with 5 noisy elements

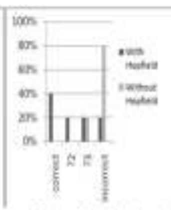


Figure 7: Study on effect of Hopfield network on results of Hamming distance in images set with 4 noisy elements

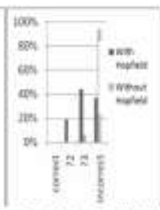
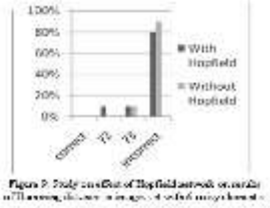


Figure 6: Study on effect of Hopfield network on results of Hamming distance in images set with 3 noisy elements



Conclusion

In this article, effect of Hopfield network on improvement of fingerprint recognition process was mentioned. Hopfield network could convert images of fingerprint with average noise to images without noise or the least noise. In case of performance of Hopfield network before recognition process, effect of error will be reduced. Hopfield network can act as a content addressable memory and is able to convert noisy images to noiseless images or images with the least noise. In case those operations of Hopfield network are performed on images of fingerprint with average noise and the obtained images are studied in the fingerprint recognition process, error rate will be reduced. Therefore, Hopfield network is able to improve fingerprint recognition process.

References

[1] Alborzi, M. 2001. Introduction to neural networks. Second edition. Tehran, Sharif University of Technology Publication Institute.

[2] Daliri, A., Osarerh, A. 2007. Biometric security system. Bioelectronics Seminar of Biomedical Engineering Faculty of Amir Kabir University of Technology.

[3] Abd Allah, M. 2005. Artificial neural networks based fingerprint authentication with clusters algorithm. Informatica. 29 , PP .303–307

[4] Baldi, P., Chauvin, Y. 1993. Neural Networks for Fingerprint Recognition. Massachusetts Institute of Technology, Neural Computation 5, PP. 402-418

[5] Choudhary, P. 2009. Human recognition using multiple fingerprints. B. Tech. Project Report. Department of Computer Science and Engineering, Indian Institute of Technology, Kanpur, India

[6] Hopfield J. J. 1982. Neural networks and physical systems with emergent collective computational abilities. Proceedings of the National Academy of Sciences of the USA. vol. 79 no. 8 pp. 2554-2558.

[7] Jain. A.K, Hong.L, Pankanti.S and Boll.R. 1997. An identity authentication system using fingerprints. Proc. IEEE vol 85, no .9, pp. 1365-1388.

[8] Weber, D.M. 1992. A cost effective fingerprint verification algorithm for commercial applications. IEEE. Unknown.

[9] Yang J., Govindaraju, V. 2005. A minutia-based partial fingerprint recognition system. The journal of Pattern Recognition society 38. pp 1672 – 1684

[10] Yi,S., Jie-Ge, L., Sung, Y . 1995 .Improvement on performance of modified Hopfield neural network for image restoration. IEEE transaction on image processing vol. 4, No. 5 , pp. 688-693

Table 1: Noisy images and rate of noisy elements in fingerprint images

Number of noisy elements equivalent to 6	Number of noisy elements equivalent to 5	Number of noisy elements equivalent to 4	Number of noisy elements equivalent to 3	Number of noisy elements equivalent to 2	Number of noisy elements equivalent to 1	Number of noisy elements equivalent to 0 0	Noise rate / Matrix
10	16	10	18	14	16	16	Number of matrix

Table 2: Results of the studied images matrixes with Hopfield network

		T1= $\begin{matrix}1&1&1&1&1\\1&0&0&1&1\\1&0&0&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$		M1(1)= $\begin{matrix}0&1&1&1&1\\1&0&0&1&1\\1&0&0&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$		M1(3)= $\begin{matrix}1&1&1&1&1\\1&0&0&1&1\\1&0&0&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$
		T2= $\begin{matrix}1&1&1&1&1\\1&0&0&0&1\\1&0&0&0&1\\1&0&0&0&1\\1&0&0&0&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$		M2(1)= $\begin{matrix}1&1&1&1&1\\1&0&0&0&1\\1&0&1&0&1\\1&0&1&0&1\\1&0&0&0&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$		M2(3)= $\begin{matrix}1&1&1&1&1\\1&0&0&0&1\\1&0&1&0&1\\1&0&0&0&1\\1&0&0&0&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$
		T3= $\begin{matrix}1&1&1&1&1\\1&1&0&1&1\\1&1&0&0&1\\1&1&1&0&1\\1&1&0&0&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$		M3(1)= $\begin{matrix}1&1&1&1&1\\1&1&0&1&1\\1&0&0&0&1\\1&1&0&0&1\\1&1&0&0&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$		M3(3)= $\begin{matrix}1&1&1&1&1\\1&1&0&1&1\\1&1&0&0&1\\1&1&0&0&1\\1&1&0&0&1\\1&1&1&1&1\\1&1&1&1&1\end{matrix}$
		T4= $\begin{matrix}1&1&1&1&1\\1&0&1&1&1\\1&0&1&1&1\\1&0&1&1&1\\1&0&0&1&1\\1&0&0&1&1\\1&1&1&1&1\end{matrix}$		M4(1)= $\begin{matrix}1&1&1&1&1\\1&0&1&1&1\\1&0&1&1&1\\1&0&1&1&1\\1&0&0&0&1\\1&0&0&0&1\\1&1&1&1&1\end{matrix}$		M4(7)= $\begin{matrix}1&1&1&1&1\\1&0&1&1&1\\1&0&1&1&1\\1&0&1&1&1\\1&0&0&0&1\\1&0&0&0&1\\1&1&1&1&1\end{matrix}$

Table 3: Analysis of Hopfield network results and noisy elements in fingerprint image matrix

Number of noisy elements equivalent to 6	Number of noisy elements equivalent to 5	Number of noisy elements equivalent to 4	Number of noisy elements equivalent to 3	Number of noisy elements equivalent to 2	Number of noisy elements equivalent to 1	Number of noisy elements equivalent to 0	noise / Result
0%	0%	0%	16%	64%	37%	44%	Matrixes which have reached first answer group.
0%	0%	0%	11%	14%	37%	56%	Matrixes which have reached first and third answer group
0%	12%	30%	44%	21%	0%	0%	Matrixes which have reached fourth answer group
90%	81%	60%	22%	0%	0%	0%	Matrixes which have reached second and third answer group.
0%	6%	1%	0%	0%	6%	0%	Matrixes which have reached third and fourth answer group
10%	0%	0%	5%	0%	0%	0%	Matrixes which have reached fourth answer group

Table 4: Study on effect of Hopfield network by comparing results obtained from Hamming distance

Without Hopfield Network	With Hopfield Network	
100	100	Total number of images according to Hamming distract
31	57	The number of results showing that Hamming distance is correct.
18	16	The number of results of 2 similar images of Hamming distance
10	11	The number of results of 3 similar images of Hamming distance
41	16	The number of results showing that Hamming distance is not correct.

Table 5: Study of noise and effect of Hopfield network on fingerprint recognition process according to hamming distance

The number of noisy elements in fingerprint image matrix equivalent to 6	The number of noisy elements in fingerprint image matrix equivalent to 5	The number of noisy elements in fingerprint image matrix equivalent to 4	The number of noisy elements in fingerprint image matrix equivalent to 3	The number of noisy elements in fingerprint image matrix equivalent to 2	The number of noisy elements in fingerprint image matrix equivalent to 1	The number of noisy elements in fingerprint image matrix equivalent to 0	
0% 0%	0% 0%	40% 0%	77% 0%	86% 7%	88% 93%	75% 93%	Recognition of correct Hamming distance
10% 0%	19% 0%	20% 0%	23% 22%	14% 85%	6% 7%	25% 7%	Recognition of two similar images hamming distance
10% 10%	44% 6%	20% 20%	0% 27%	0% 8%	6% 0%	0% 0%	Recognition of three similar images hamming distance
80% 90%	37% 94%	20% 80%	0% 49%	0% 0%	0% 0%	0% 0%	Recognition of incorrect Hamming distance