A Novel Supervised Learning Model for Figures Recognition by Using Artificial Neural Network

Zeyad M. Alfawaer[1(✉)] and Saleem Alzoubi[2]

[1] CCD, Department of Computer Science, Imam Abdulrahman Bin Faisal University, Dammam 31441, Kingdom of Saudi Arabia
zmalfawaer@iau.edu.sa

[2] CSIT, Department of Computer Science, Irbid Private University, Irbid, Jordan

Abstract. Supervised learning has been considered as an important topic as it is used in different fields to exploit the advantages of artificial intelligence. This research introduces a new approach using Artificial neural networks (ANN) to supervise machine learning that enables the machine to recognize a figure via calculating values of angles of the figure, as well as area and length of the line. The research also introduces a processor that would be suitable for the algorithm that uses rotation techniques to specify the best situation in which the figure will be identified easily. This algorithm can be used in many fields such as military and medicine fields.

Keywords: Supervised learning · Figures recognition · Neural network

1 Introduction

Many researchers conducted their work in image recognition of flat regular figure, which was widely used in deferent areas such as robotics, space, communication, telecommunication, medicine, transportation and others [1–8]. Currently, there are plenty of developed methods of image treatment and recognition based on deferent approaches, which have advantages and imperfections [9–16]. The earliest applications of ANNs were published by Pugh [17, 18]. Smith trained an ANN to identify mean and variance shifts [19]. Much of the early research focused on detecting mean and variance shifts using similar approaches to Pugh [17, 18] and Smith [19], including Guo and Dooley [20] and Cheng [21]. Ho and Chang [22] developed an integrated neural network approach for monitoring process mean and variance shifts. Velasco and Rowe [23] demonstrated the potential of ANN application in the analysis of quality control charts. Perry et al. [24] developed two back propagation ANNs for the detection of trends, mixtures, cycles and systematic variation.

Supervised learning has been a great success in real-world applications. This type of learning is analogous to human learning from past experiences to gain new knowledge in order to improve our ability to perform real-world tasks. However, since

M. H. Miraz et al. (Eds.): iCETiC 2018, LNICST 200, pp. 199–208, 2018.
https://doi.org/10.1007/978-3-319-95450-9_17

computers do not have "experiences", machine learning learns from data, which are collected in the past and represent past experiences in some real-world applications.

We identified various mathematical tools to study the figure recognition by using neural network collected from various sources. The mathematical tools identified was implemented using VC++ programming language.

2 Supervised Learning Model for Figures Recognition

2.1 Processing and Recognition of Images

We consider the principle of parallel functioning of devices in processing and recognition the figures in the environments of Cellular neural network (CNN). Process of recognition of flat figure image is carried out by its transformation at the entrance of the device to a form most convenient distinguishing necessary attributes, and formation vector V of attributes from them. The given process is presented by the following model.

$$\boldsymbol{I} \overset{T_0}{\Rightarrow} \boldsymbol{I}_{cp} \overset{T_1}{\Rightarrow} \boldsymbol{I}_M \overset{T_M}{\Rightarrow} \boldsymbol{V} \tag{1}$$

Where $\boldsymbol{I}$ - the initial image at the entrance of the device; $\boldsymbol{I}_{\mathrm{cp}}$ - the initial image, which is written down in electronic multiprocessing matrix environment; $\boldsymbol{I}_{\mathrm{M}}$ - set of images $\{\boldsymbol{I}^1, \ldots .\boldsymbol{I}^{\mathrm{k}}\}$, any of which is intended for obtain of information on the chosen attribute; V – a vector which contains necessary attributes for obtaining the most complete information on the image which is recognized.

$\mathbf{T}_0$ - Operation of transformation of initial image **I** into the image of CNN environment $\boldsymbol{I}_{\mathrm{cp}}$, T_1 – operation of transformation of $\boldsymbol{I}_{\mathrm{cp}}$ (Iav) into set of image $\boldsymbol{I}_{\mathrm{M}} = \{\boldsymbol{I}^1, \ldots .\boldsymbol{I}^{\mathrm{k}}\}$, which form provides the most or that class and within a class is determined. T_{M} – set of operations over the set of images $\boldsymbol{I}_{\mathrm{M}}$, which are oriented on determination of corresponding attribute. Obtained vector V is compared with reference and its identity with this or that class and within a class is determined. Accuracy of recognition depends on a choice of the set of necessary attribute, and also on the accuracy of determination of their quantitative characteristics. The vector of the attributes necessary for recognition of images looks like.

$$V = \left\langle S, N, \alpha_i, l_{1,2}, l_{2,3}, \ldots, l_{N-1,N}, l_{N,1} \right\rangle \tag{2}$$

Where S – the area of the figure at the input of the system; which is measured in corresponding dimensions of individual discrete environments; N – the number of peaks of the figure at the input of the system. It is measured in corresponding dimensions of individual discrete environment; $\mathbf{l}_{\mathrm{i,i+1}}$

The relation between i-th and (i + 1)-th peaks which is expressed by the length, taking into account the geometrical sizes of individual discrete environment; α_{i} - An angle between two neighboring sides in i-th peak i = 1, N. For exact allocation of element of the contour of the figure is used.

$$\boldsymbol{I}_K = \{a^1_{i,j} \,/\, a^1_{i,j}\ \boldsymbol{R}_K\ a^K_{i,j}\} \tag{3}$$

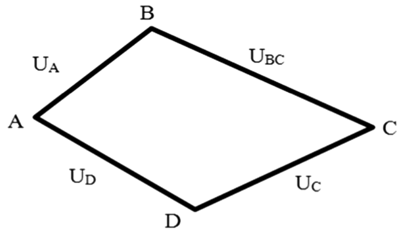
Where $a^k_{i,j}$ – element of the environment, which belongs to limits of the element $a_{I,j}$; R_k - relations which is set between discrete count $a^1_{i,j}$ and element $a^k_{i,j}$. The side is presented as the set of points, which belong to the contour, between two next peaks.

$$\boldsymbol{I}_p(m) = \left\{a^1_{i,j}(m)\right\} \tag{4}$$

Where $a^1_{i,j}(m)$ – points, which belong to the contour of the image between next m-th and (m + 1)th peaks. The peak is presented as

$$\boldsymbol{I}_b(m) = \{\boldsymbol{I}_p(m-1) \cap \boldsymbol{I}_p(m)\} \tag{5}$$

The figure example which is shown in Fig. 1, can be expressed as the set of relations R*i* that represent the contour of the figure in matrix form.



R_l	A	B	C	D
A		l_{AB}		l_{AD}
B	l_{BA}		l_{BC}	
C		l_{CB}		l_{CD}
D	l_{DA}		l_{DC}	

R_α	U_{AB}	U_{BC}	U_{CD}	U_{DA}
U_{AB}		α_B		α_A
U_{BC}	α_B		α_C	
U_{CD}		α_C		α_D
U_{DA}	α_A		α_D	

Fig. 1. Representation of the quadrangle by sides and peak.

The algorithm of determination of image peaks of the figure in CNN, are considered and also the data for determination of peaks at different approaches are studied.

2.2 Supervised System Structure

The structure of the supervised system as shown in Fig. 2 mimic the principle of learning in humans where the nerve cells conduct primary treatment only, and then send it to the processor to supervise and store in main memory if it was the first time you enter into the system, this method is the best and the easiest and least expensive in addition to being supported the principle of parallelism.

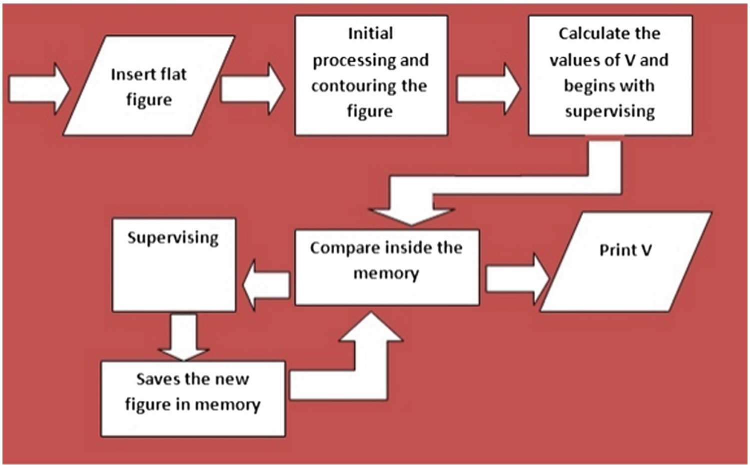


Fig. 2. Supervised system structure

Definition 1. Peak of the image of the flat figure designed in CNN environment is PE, that submits the point of the contour provided that the sum of values of the neighboring PE, which submit internal area of the figure is not equal to the sum of values of the next PE, that do not belong to the image.

$$b_{i,j} = \begin{cases} b^b_{i,j} = 1, & if \sum\limits_{n=1}^{8} \left(a^{1,k}_{i,j}(n) - a^{0,k}_{i,j}(n) - a^{1,k'}_{i,j}(n) \right) \neq 0 \\ b_{i,j} = 0, & \text{in the other case} \end{cases} \tag{6}$$

Where $a^{1,k}_{i,j}(n)$, $a^{0,k}_{i,j}(n)$, - elements of environment which belong to limits of PE and take value accordingly, of logic "1" and "0"; $a^{1,k'}_{i,j}(n)$ - elements of limits $PE_{i,j}$, that belong to the contour; $b^b_{i,j}$ - value $PE_{i,j}$ in the peak. But the given definition is valid in case of presence of two neighboring cells of the contour. For filled figures the following definition is also valid.

Definition 2. Peak of the image of flat figure projected in CNN environment is PE, which submits the point of contour, provided that the sum of values of neighboring PEs, which present internal area of the figure equals 1.

$$b_{i,j} = \begin{cases} b^b_{i,j} = 1, & if \sum\limits_{n=1}^{8} \left(a^{k}_{i,j}(n) - a^{1,k'}_{i,j}(n) \right) \neq 0 \\ b_{i,j} = 0, & \text{in the other case} \end{cases} \tag{7}$$

For definition of convex and concave peaks the following definition are introduced.

Definition 3. The cell in convex peak, if the sum of values of all eight neighboring cells of environment, which belong to Moore's limit is less than 5.

$$b_{i,j} = \begin{cases} b^b_{i,j} = 1, & if \sum_{n=1}^{8} a^k_{i,j}(n) < 5 \\ b_{i,j} = 0, & \text{if in other case} \end{cases} \tag{8}$$

Definition 4. The cell is a concave peak in case when the sum of values of all eight neighboring cells of environment, which belong to Moore's limit is greater than five.

$$b_{i,j} = \begin{cases} b^b_{i,j} = 1, & if \sum_{n=1}^{8} a^k_{i,j}(n) > 5 \\ b_{i,j} = 0, & \text{if in other case} \end{cases} \tag{9}$$

At the account of aliasing for exact allocation of peak the additional layer Fig. 3 is introduced and the following models are used. Cell is a peak which is determined in the second layer in case if the following condition in valid

$$C = \begin{cases} C^b = 1, & if \quad \mathrm{AB}(\mathrm{X}_1(\mathrm{X}_6 + \mathrm{X}_8) + \mathrm{X}_2(\mathrm{X}_6 + \mathrm{X}_7) + \mathrm{X}_{12}(\mathrm{X}_7 + \mathrm{X}_8)) = 1 \\ C^b = 0, & if\ the\ other\ case \end{cases} \tag{10}$$

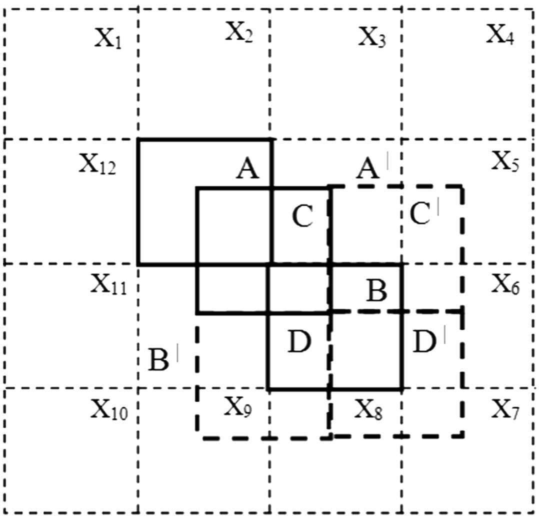


Fig. 3. The example of 2-layered environment with marked all.

The cell B (A) is peak which is determined in the first layer in case if the following condition is valid.

$$C = \begin{cases} \mathrm{B}^b = 1, & if\ C \cdot C' + D \cdot D' + C \cdot D + C' \cdot D' = 1 \\ \mathrm{B}^b = 0, & in\ the\ other\ case \end{cases} \tag{11}$$

The example of allocated peak is presented in Fig. 4 by the result of operations of preliminary processing of images occurrence of jamming cells which are divided into individual. Any of them is presented by logic depending on which is applied. Taking this into algorithm of removal of jamming cells in CNN are presented. Individual jamming cells are eliminated by realization of the following logic expression.

$$\begin{aligned} b_{ij}(t+1) &= b_{i+1,j}(t) \vee b_{i+1,j-1}(t) \vee b_{i+1,j+1}(t) \vee b_{i-1,j}(t) \vee b_{i-1,j-1}(t) \vee b_{i-1,j+1}(t) \\ &\quad \vee b_{i,j-1}(t) \vee b_{i,j+1}(t) \\ &= 0 \end{aligned} \tag{12}$$

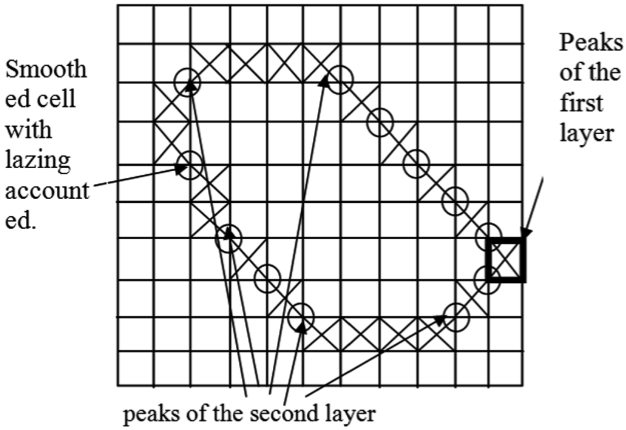


Fig. 4. The example of elimination of peaks in 2-layered structure.

2.3 Determination of Jamming Cells

Removal of the connected jamming cell is determined by the sum of values of the neighboring cells which is described in the following way.

$$b_{i,j}(t+1) = \begin{cases} 0, & \mathit{if} \ \sum_{n=1}^{8} a_{i,j}^{k}(n) = 1 \\ b_{i,j}(t), & \mathit{in\ other\ case} \end{cases} \tag{13}$$

Definition 5. Cell P is the contour jamming cell in case when: it's neighboring to two cells of the contour (one of these cells is activated) vertically and horizontally, and they (two cells of the contour) are neighboring by diagonal between each other, and have other neighbors; It has three neighboring cells that belong to the contour and they are orthogonal; If has three neighbors, one of them is diagonally activated, and two non-diagonal neighbors (they are neighbors by diagonal) are not activated. It has only one neighbor that belongs to the contour. To eliminate such cells the limits of the second order are used, the cells of this limit are the closest neighbors of the cells of the limits of the first order, and the cells that are in the shortest neighborhood are determined.

Definition 6. Three cells which belong to the contour of the image of the figure are in the shortest neighborhood if one of them is neighboring for others which are not neighbors between themselves and have no neighbors that are not neighbors for the common cells processing.

Definition 7. The cell is a jamming cell in case when it's in the neighborhood with cells which are in the shortest neighborhood between themselves. Definitions which characterize relations between the sides consist in development of algorithm s of definition of angles in peaks for this purpose the figure is divided into the triangles, two sides of any of them belong to the contour, and the following formula is applied.

$$\cos\alpha = \frac{(x_2 - x_1)(x_3 - x_1) + (y_2 - y_1)(y_3 - y_1)}{l_1 \cdot l_2} \tag{14}$$

For definition of angles the methods of definition of the neighboring peaks which form the angles is used and the method implies the shift of figure image to the extreme left column, where neighboring peaks are determined. The algorithm is the most effective in case when peaks are known, but their location is unknown.

3 Simulation Result and Discussion

The insertion of the flat figure to the nerve cells in deferent ways to recognize it quickly and accurately by using the algorithm as shown in Fig. 5 then contouring the figure to recognize it easily as shown in Fig. 6. Then rotate the figure to insure that the rotation process did not change the characteristics of the initial figure as shown in Fig. 7 so the changed cells after the rotation will be processed by the 2-layered structure as we mentioned before. In Fig. 8 the rotations was tested after each 5° and then the result table has been printed to choose all possible vector values in the neural network.

Fig. 5. The inserted figure to the network

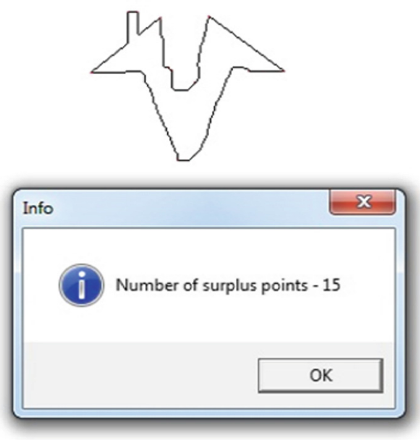


Fig. 6. The figure after contouring process.

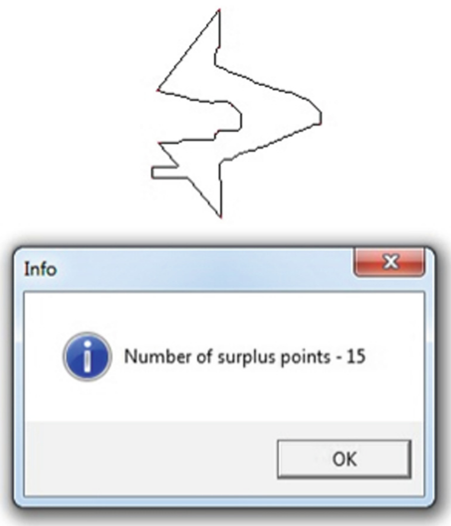


Fig. 7. The figure after rotation process.

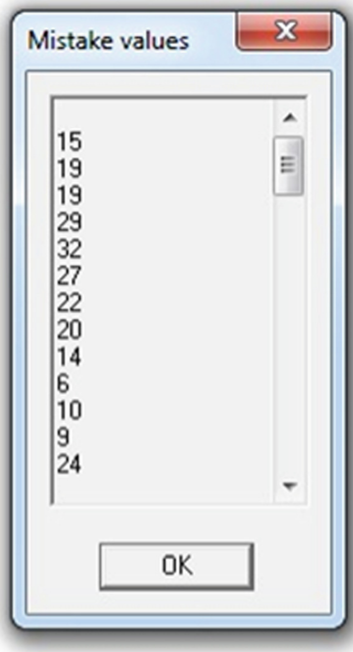


Fig. 8. Rotate the figure 360° after the contouring.

4 Conclusion and Future Enhancements

This research introduces a new approach using neural networks to supervise machine learning that enables the machine to recognize a figure via calculating values of angles of the figure, as well as area and length of the line. The proposed algorithm uses rotation techniques to specify the best situation in which the figure will be identified easily. The proposed algorithm can be used in many fields such as military and medicine fields. The research also introduces a proposed processor that would be suitable for the proposed algorithm. The study is limited by one type of figures and should make enhancement to convert any kind of image to be examined.

References

1. Sylwester, R.: Human and machine intelligence: an intriguing perspective, February 2005
2. Jain, S., Osherson, D., Royer, J.S., Sharma, A.: Systems That Learn: An Introduction to Learning Theory, 2nd edn. The MIT Press, Cambridge (2005)
3. Nilsson, N.J.: Artificial Intelligence: A New Synthesis. Morgan Kaufmann Publishers (2008). ISBN 1558604677
4. Zytkow, J. (ed.): Machine Discovery. Reprinted from FOUNDATIONS OF SCIENCE, 1:2 (1997). 150 p., Hardcover. ISBN 978-0-7923-4406-3

5. Fukushima, K.: Neural network for visual pattern recognition. Computer **21**(3), 65–115 (1983)
6. Hecht-Nielsen, R.: Replicator neural networks for universal optimal source coding. Science **269**, 1860–1863 (1995)
7. Galushkin, A.I., Luskinovich, P.N., Nesmeyanov, S.S., Nikishin, V.I., Frolov, V.D.: The quantum neurocomputer. J. Br. Interplanet. Soc. **47**, 331–333 (1994)
8. Cosman, P.C., Gray, R.M., Olshe, R.A.: Evaluating quality of compressed medical images. In: Proceedings of the IEEE "SNR, Subjective Rating, and Diagnostic Accuracy", vol. 82, no. 6, pp. 919–932 (1994)
9. Dash, L., Chatterji, B.N.: Adaptive contrast enhancement and de-enhancement. Pattern Recogn. **24**(4), 289–302 (1992)
10. Impedovo, S., Dimauro, G., Pirlo, G.: Off-line signature verification by fundamental components analysis. In: Proceedings of the 7-th ICIAP, Bari, Italy (1993)
11. Bartenek, N.: The role of handwriting recognition in future reading systems. In: Proceedings of the Fifth International Workshop on Frontiers in Handwriting Recognition, Univ. of Essex, England, pp. 147–165 (1996)
12. Shumann, J., et al.: Document analysis – from pixels to contents. Proc. IEEE **80**, 1101–1119 (1992)
13. Bilan, S.M., Koval, D.M.: Filling regions on the base of cellular aperiodical neuroautomatons. In: Bulletin of MITI, no. 10, pp. 166–173 (1999)
14. Bilan, S.M., Motornyuk, R.L.: Homogeneous cellular structures for images' segmentation and marking centers of segments out and modelling them into the medium Active –HDL. In: Bulletin of VPI, no. 5, pp. 55–58 (2002)
15. Montessori, M., Gutek, G.L.: The Montessori method: the origins of an educational innovation (2004)
16. Fu, K.: Structural methods in recognition of images. Mir, M., 320 p. (1977)
17. Pugh, G.A.: Synthetic neural networks for process control. Comput. Ind. Eng. **17**(1–4), 24–26 (1989)
18. Pugh, G.A.: A comparison of neural networks to SPC charts. Comput. Ind. Eng. **21**(1–4), 253–255 (1991)
19. Smith, A.E.: X-bar and R control chart interpretation using neural computing. Int. J. Prod. Res. **32**(2), 309–320 (1994)
20. Guo, Y., Dooley, K.J.: Identification of change structure in statistical process control. Int. J. Prod. Res. **30**(7), 1655–1669 (1992)
21. Cheng, C.S.: A multi-layered neural network model for detecting changes in the process mean. Comput. Ind. Eng. **28**(1), 51–61 (1995)
22. Ho, E.S., Chang, S.I.: An integrated neural network approach for simultaneous monitoring of process mean and variance shifts – a comparative study. Int. J. Prod. Res. **37**(8), 1881–1901 (1999)
23. Velasco, T., Rowe, R.: Back propagation artificial neural networks for the analysis of quality control charts. Comput. Ind. Eng. **25**(1–4), 397–400 (1993)
24. Perry, M.B., Spoerre, J.K., Velasco, T.: Control chart pattern recognition using artificial neural networks. Int. J. Prod. Res. **39**(15), 3399–3418 (2001)