SOM Neural Network as a Method in Image Color Reduction

Amir Maleki Anvar, Alireza Mohammadi, Abdolhamid Pilevar

Department of computer science, BuAli-sina University, Hamedan, Iran

Summary
Accurate and right image partitioning is one of major objectives of the various methods in image processing, specifically in medical images. Methods with full review of image areas could identify and partition available sections in an image. Due to the variety of image gray-levels, consider a method in pre-partitioning level as gray-level reduction could be so helpful. In this paper, for this step of image partitioning a neural network self-organizing map method is introduced. Competitive and single-output properties are the major reason for this self-organizing map method. Self-organizing map color reduction method is tested on human magnetic resonance imaging brain images. Human brain has five distinct areas and this method on color reduction detected all five sections and reduced gray-levels to just five levels.

Key words:
self-organizing map, neural network, color reduction, segmentation, medical image.

1. Introduction

All the times researchers are trying to use more various technologies in medicine in order to recognize their limits and tissues more accurately. One of the most complex body structures is human brain. Its complexity is because of the human brain's neural network and its communication variety.

Because of so much neuronal connections, its concurrency and processing speed this structure is on the way of investigators attentions. In the meantime, apart from the structure and mode of brain function, identify the precise boundaries and brain tissue has always been rather ambiguous, especially when diagnosing patient diseases is among.

For this reason, many studies have been done and the various methods have been proposed. Among the methods discussed, including methods of digital image processing techniques to improve image quality and determine boundary of brain tissues.

Between these methods more than separation the areas of each section, the algorithms are considered on separation of the main tissue not inside them and also less to prepare the image before applying the various methods.

In this paper, introduced a neural network method especially self-organizing map as an introduction to the methods of separating areas of images and obtained very good results from the breakdown of brain tissue image.

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In the second part the self-organizing map neural network is briefly introduced and then in the next part the proposed method is investigated. In the fourth section, the results achieved in the implementation of this method are assessed on human brain images.

2. Self-organizing map

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discredited representation of the input space of the training samples, called a map. SOM networks are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space.

A SOM showing U.S. Congress voting patterns visualized in Synapse. The first two boxes show clustering and distances while the remaining ones show the component planes. Red means a yes vote while blue means a no vote in the component planes (except the party component where red is Republican and blue is Democrat).

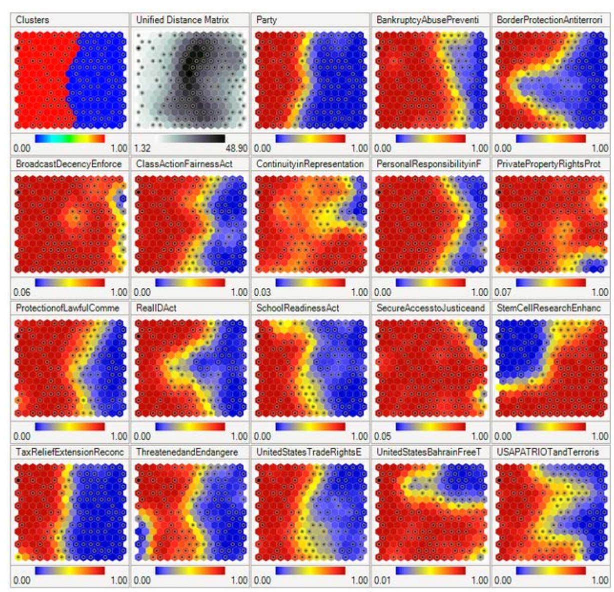
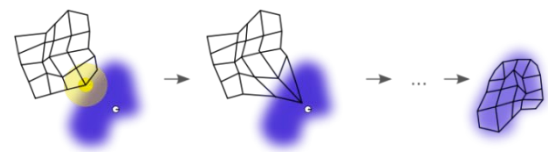


Figure 1: SOM showing US congress voting results. Screenshot from Peltarion Synapse

This makes SOMs useful for visualizing low-dimensional views of high-dimensional data, akin to multidimensional scaling. The model was first described as an artificial neural network by the Finnish professor Teuvo Kohonen, and is sometimes called a Kohonen map [1-3].
Like most artificial neural networks, SOMs operate in two modes: training and mapping. Training builds the map using input examples. It is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector.
A SOM consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a regular spacing in a hexagonal or rectangular grid. The SOM describes a mapping from a higher dimensional input space to a lower dimensional map space. The procedure for placing a vector from data space onto the map is to first find the node with the closest weight vector to the vector taken from data space. Once the closest node is located it is assigned the values from the vector taken from the data space [4].
While it is typical to consider this type of network structure as related to feed-forward networks where the nodes are visualized as being attached, this type of architecture is fundamentally different in arrangement and motivation.
Useful extensions include using toroidal grids where opposite edges are connected and using large numbers of nodes. It has been shown that while SOM networks with a small number of nodes behave in a way that is similar to K-means, larger SOM networks rearrange data in a way that is fundamentally topological in character.
It is also common to use the U-Matrix. The U-Matrix value of a particular node is the average distance between the node and its closest neighbours (ref. 9). In a square grid for instance, we might consider the closest 4 or 8 nodes (the Von Neumann neighbourhood and Moore neighbourhood respectively), or six nodes in a hexagonal grid.
Large SOMs display properties which are emergent. In maps consisting of thousands of nodes, it is possible to perform cluster operations on the map itself [2].

3. Learning algorithm

The goal of learning in the SOM is to cause different parts of the network to respond similarly to certain input patterns. This is partly motivated by how visual, auditory or other sensory information is handled in separate parts of the cerebral cortex in the human brain.[3]
The weights of the neurons are initialized either to small random values or sampled evenly from the subspace spanned by the two largest principal component eigenvectors. With the latter alternative, learning is much faster because the initial weights already give good approximation of SOM weights [4].
The network must be fed a large number of example vectors that represent, as close as possible, the kinds of vectors expected during mapping. The examples are usually administered several times as iterations.



Figue 2: An illustration of the training of a SOM. The blue blob is the distribution of the training data, and the small white disc is the current training sample drawn from that distribution. At first (left) the SOM nodes are arbitrarily positioned in the data space. The node nearest to the training node (highlighted in yellow) is selected, and is moved towards the training datum, as (to a lesser extent) are its neighbours on the grid. After several iterations the grid tends to approximate the data distribution (right).

The training utilizes competitive learning. When a training example is fed to the network, its Euclidean distance to all weight vectors is computed. The neuron with weight vector most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. The magnitude of the change decreases with time and with distance from the BMU. The update formula for a neuron with weight vector Wv(t) is:

$$Wv(t + 1) = Wv(t) + \Theta (v, t)\, \alpha(t)(D(t) - Wv(t)) \qquad (1)$$

Where $\alpha(t)$ is a monotonically decreasing learning coefficient and D(t) is the input vector. The neighbourhood function Θ (v, t) depends on the lattice distance between the BMU and neuron v. In the simplest form it is one for all neurons close enough to BMU and zero for others, but a Gaussian function is a common choice, too. Regardless of the functional form, the neighbourhood function shrinks with time [3]. At the beginning when the neighbourhood is broad, the self-organizing takes place on the global scale. When the neighbourhood has shrunk to just a couple of neurons the weights are converging to local estimates.
This process is repeated for each input vector for a (usually large) number of cycle’s λ. The network winds up associating output nodes with groups or patterns in the input data set. If these patterns can be named, the names can be attached to the associated nodes in the trained net [5-7].
During mapping, there will be one single winning neuron: the neuron whose weight vector lies closest to the input vector. This can be simply determined by calculating the Euclidean distance between input vector and weight vector.

While representing input data as vectors has been emphasized in this article, it should be noted that any kind of object which can be represented digitally and which has an appropriate distance measure associated with it and in which the necessary operations for training are possible can be used to construct a SOM. This includes matrices, continuous functions or even other SOM networks. Training process can be seen in figure below.

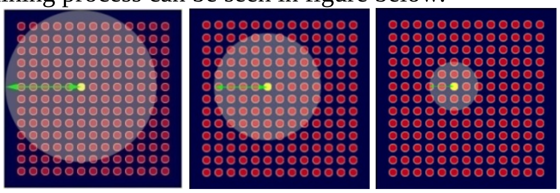


Figure 3: Neighbourhood radius depicted as time goes on.

4. Network structure

A Kohonen layer is an array of single or multi dimension neurons. In the learning phase, units of distance in the vector X are calculated by below formula.

$I_i = D(X, w_i)$ (2)

In which D is distance function. It can be any of typical distance functions such as Spherical arc distance.

$D(u,v) = 1 - \cos(\theta)$ (3)

In which θ is the angle between u and v. Or even Euclidean distance function that is:

$D(u,v) = |u - v|$ (4)

Any units of this calculation is aiming to discover whether or not they have the closet weight to vector x. This is the competitive strength of such networks. The unit with the closest weight to the entering vector wins the completion of this phase. This unit take Z_1 while the rest of Z_i's get 0. Thereafter Kohonen law (5) is applied to update weights [8-10].

$$w_i^{new} = w_i^{old} + \alpha(X - w_i^{old}) z_i \qquad 0 < \alpha \leq 1 \qquad (5)$$

Kohonen law is equivalent of:

$$w_i^{new} = \begin{cases} (1-\propto) w_i^{old} + \propto x \\ w_i^{old} \end{cases} \qquad (6)$$

5. Proposed Algorithm

The current research employs SOM neural networks on images especially medical images (to reduce colourful surfaces) in order to prepare them for separation phase. The proposed approach has been verified on gray surfaces as well as on images with colourful layers. In this approach neural network examines all image pixels and classifies them into different batches. Finally through replication of this process it reaches a generic conclusion and stops the process.

The key issue which requires extra attention in such networks is identifying initial parameters of the network in order to achieve higher precisions in studying different images. Based on experts and scholars opinion, in order to do so, the only way to reach correct parameters in different images is single measuring for parameters with appropriate mutations and thereafter evaluating the results and finally employing them in other similar cases. More specifically, there is no way to identify specific values for parameters which are applicable for all cases.

The proposed algorithm as well as the competitive neural network algorithm is used to compare results. Both algorithms have been tested with different inputs with appropriate mutations. Results obtained in this comparison are described in the next section.

6. Discussion

In order to have a more tangible perception of obtained results, they should be compared to the previously confirmed results. Therefore, the difference between the novel and old approach shows how valuable is the novel idea.

There are several approaches which have been employed to do the comparison with the current approach such as competitive artificial neural networks. In competitive artificial neural networks there is a competition among neural cells and the centre of winner neural cell takes the colour which it receives it the competition in the competition with other neurons. It is a time consuming approach (eleven days of nonstop work to achieve appropriate results in Experimental form). Besides, the obtained results were not accurate enough. Eleven execution took place on a computer with 2 GB RAM, dual processor of 2.4 GHz, Windows OS, and Matlab 2009.

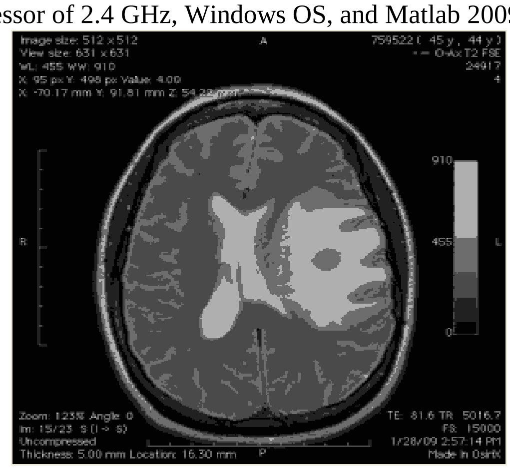
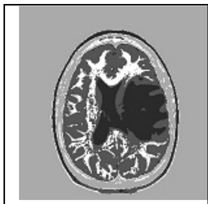
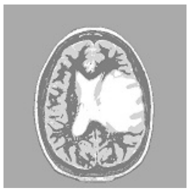
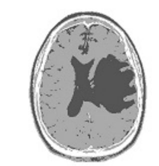
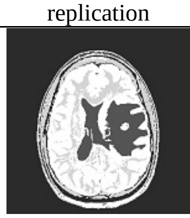
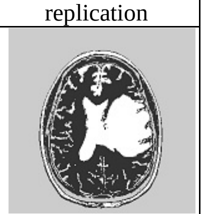
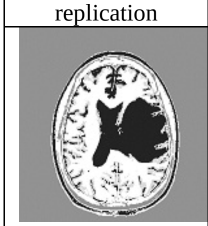
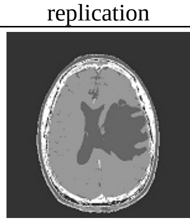


Figure 5: Brain MRI

In the below approach the best case has been selected based on the results under different conditions. The best selected case is an initial image of 300× 300 pixels with competitive neural network and number of 5 neurons in 5 replications. In the next step, in order to compare the influence of number of neurons and replication of neural network, amount of neurons and replication has increased. More specifically in this study the number of neurons increased from 5 to 10 and replications from 5 to 55with mutation of 5. Some of the results of this neural network are presented in below table.

Table 1: results of 5, 6, and 7 neurons in 5, 25, and 55 replications of competitive networks

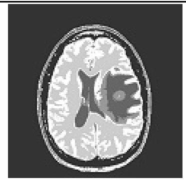
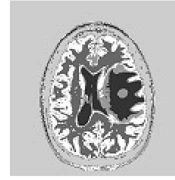
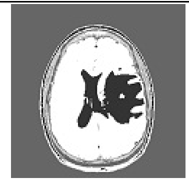
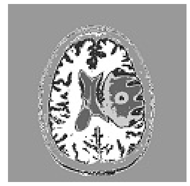
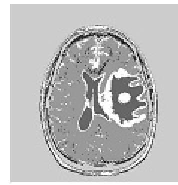
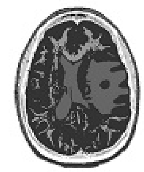
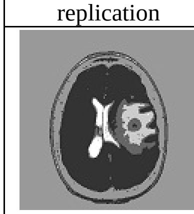
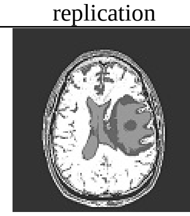
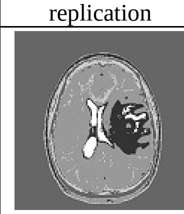
 7 neurons, 5 replication	 6 neurons, 5 replication	 5 neurons, 5 replication
 7 neurons, 25 replication	 6 neurons, 25 replication	 5 neurons, 25 replication
 7 neurons, 55 replication	 6 neurons, 55 replication	 5 neurons, 55 replication

According to table 1, best results were obtained in neural network with 6 or 7 neurons and in 55 replications, although it is still not so clear.

In a competitive neural network each neurons compete with others on each pixel of image in order to win more pixels. In this procedure the overall area of image is shortened to the number of neurons. Apparently, if the number of neurons is less than principal area of the image, some areas will be combined. This point should be respected in such networks.

Competitive neural network is mostly used to decrease image colours or image areas. Although it is a simple approach and it can be easily modified but it is not recommended due to its slowness comparing to other approaches.

Table 2: results of 5, 6, and 7 neurons in 5, 25, and 55 replications of SOM networks

 Block 7 in 7 neuron, 100 replication	 Block 6 in 6 neuron, 100 replication	 Block 5 in 5 neuron, 100 replication
 Block 7 in 7 neuron, 150 replication	 Block 6 in 6 neuron, 150 replication	 Block 5 in 5 neuron, 150 replication
 Block 7 in 7 neuron, 200 replication	 Block 6 in 6 neuron, 200 replication	 Block 5 in 5 neuron, 200 replication

Based on table 2, results of this approach are more accurate and clear comparing to the results of competitive neural networks. Obtained results in blocks in size of 6×6 and 7×7 are preferable comparing to other neural blocks. Apparently, as the size of neural block increases more replication is required to achieve appropriate results.

7. Conclusion

Novelty of approach and trying the approaches which look irrelevant on the first thought may lead to new horizons in artificial intelligence. The current research, strived to improve segmentation approaches by employing SOM and comparing results with competitive neural networks.

8. Future works

In order to achieve parameters' typology of SOM neural networks other researchers can try other approaches such as genetic algorithm instead of Exhaustive that is used in this research.

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