Image Segmentation with Kohonen Neural Network Self-Organising Maps.

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Abstract

Kohonen [1,2] has developed an algorithm with self-organising properties for a network of adaptive elements. These elements receive signals from an event space and the signal representations are automatically mapped onto a set of output responses in such a way that these responses acquire the same topological order as that of the primary events.

Images can be processed to become the input signals for the Self-Organising Maps (SOM) and the output neurones that have adapted to the image, present interesting features such as contour-extraction and edge detection.

In this work the Kohonen algorithm was programmed and medical images were used as input to prove the convergence of the algorithm.

Keywords: Neural Networks, Image Segmentation, Self - Organising Maps.

1. INTRODUCTION

Image Processing has been an important area of research for some time. Even since the 1920's when newspaper photographs were transmitted through transatlantic cables there has been interest in upgrading the pictorial information for human interpretation as well as the data processing for machine perception. The problem of Image Processing has been subdivided into several research areas, Hall [3] classifies the major problems into several applications: Image Enhancement and Restoration, Three Dimensional Reconstruction, Digital Television and Image Compression, Segmentation and Description and Scene Matching and Recognition.

The medical research has been quite receptive of image processing in applications like X-ray, Computer Aided Tomography, Ultrasound and Magnetic Resonance. The output of these techniques, an image of the patient's body, allows the physician to examine and diagnose without the need of surgery [4,5,6]. Some applications have evolved up to Image Guided Surgery [7] where Magnetic Resonance images are acquired during the surgery in order to guide the surgeon.

In order to perform these complex medical processes, some operations over the images have to be completed. One of these, and perhaps the most important and complex, is image segmentation [8,9,10]. Segmentation, as defined by Kapur, [8] is "*a labelling problem in which the goal is to assign to each voxel in an input gray-level image, a unique label that represents an anatomical structure*". Therefore, the ultimate objective would be to properly identify some structures such as a tumour, the brain tissue or the skull.

The segmentation of an image can be carried out by different techniques that are based mostly on the discontinuity and similarity of the grey levels of an image. Gonzalez and Woods [11] propose several edge detection and segmentation techniques and Felzenszwalb and Huttenlocher [12] propose yet different methods. In this paper, a neural network approach is used to segment medical images.

Neural Networks try to simulate a structure similar to the one that is believed the human brain has. Two-dimensional layers of cellular modules, that are densely interconnected between them, model most neural networks in the brain, especially in the cortex. This area of the brain is organised into several sensory modalities such as speech or hearing. The engineering approach of neural networks develops hardware or software inspired by the brain's structure. For an anatomical treatise concerning neurones S. Ramón-Cajal [13] is a classic.

The Self-Organising Maps [1,2] will consist on a series of nodes or "neurones" that will act upon a series of inputs. Each cell is densely interconnected, receives a primary input and a great number of lateral interconnections from the outputs of other units. The lateral coupling of the neurones is thought of as a function of the distance in two ways: excitatory and inhibitory. The excitatory is in a short range up to a certain radius, and the inhibitory surrounds the excitatory area up to a bigger radius. Outside the inhibitory range, a weaker, and much bigger excitatory zone exists. A cluster or bubble around one particular node of the network is formed because of the lateral coupling around a given cell. The primary input determines a "winner" node, which will have a certain cluster, and then, following the input, the winner node with its surrounding cluster or neighbourhood will adapt to the input. The process continues for a number of iterations until a certain degree of adaptation is reached. When the input is an image, certain features can be extracted from the final adaptation of the neurones.

The remaining part of the paper is organised as follows: in Section 2 the implementation of the neural network interface for segmentation is described. In Section 3 some results on human brains are presented. Finally, conclusions are summarised in Section 4.

2. IMPLEMENTATION

The Self-Organising algorithm proposed by Kohonen is follows two basic equations: matching and finding the winner node determined by the minimum Euclidean distance to the input (1) and the update of the position of neurones inside the cluster (2).

$$\|x(t)-m_c(t)\| = \min_i \|x(t)-m_i(t)\| \qquad (1)$$

$$\begin{aligned} m_i(t+1) &= m_i(t)+\alpha(t)[x(t)-m_i(t)] & i \in \mathrm{N_c} \quad (2)\\ m_i(t+1) &= m_i(t) & i \notin \mathrm{N_c} \end{aligned}$$

Where, for time *t*:
- x is the input
- m_i is any node,
- m_c is the winner,
- α is the gain sequence, and
- $\mathrm{N_c}$ is the neighbourhood of the winner.

It should be noted that only the excitatory region would be considered for the update with satisfactory results. The decrease rate of the neighbourhood and the initial value of the parameters are studied in [14].

The updating process is a variation of the location of the node, proportional to the Euclidean distance from the node to the input multiplied by the gain sequence if the node lies inside of the neighbourhood. If it is not inside the neighbourhood, its position remains unaltered.

The definition of the neighbourhood presents two different cases, one if the network of nodes accepts that the neighbourhood is limited by the edges of the network itself, and the other in case that the neighbourhood is not limited by the edges of the network. If the network consists of n*1 neurones, the first case results in a linear network and second an annular network. Figure 1 shows both cases for 10 neurones and neighbourhood of size 2 around a winner node and the output to a given input. The neighbourhood for linear network consists only of four neurones on one side of the network, contrary to the annular network that includes a fifth neurone on the other side.

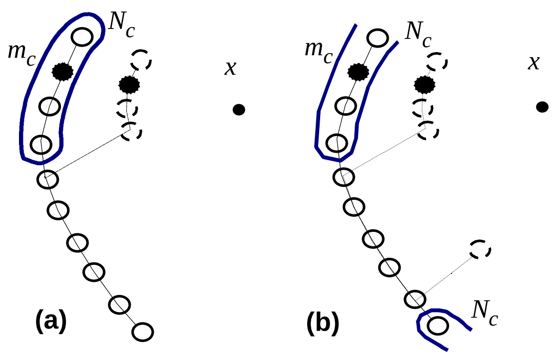


Figure 1. Differences in update regions: (a) Linear Network, (b) Annular Network.

If the network is a two-dimensional array of neurones, the network itself generally limits the neighbourhood. Figure 2 presents the results for neurones organised as a linear, annular and grid network, all of them having a triangular input region. Both linear and annular networks consist of 50 neurones and the grid of 20*20 neurones and the results were obtained after 10,000 iterations. It should be noted that no initial conditions for the network are required. In fact, the neurones start at random positions.

The input signal can be defined either as a test set a geometrical region like a square, triangle, cube, or it can be read from an image. The geometrical regions are widely used to test algorithms.

When an image is used as input, it is first transformed into an *i*j*l* matrix, where *i*j* is the dimension in pixels of the image and l, the number of layers of the image. For colour images l = 3 and for a grey scale images l =1. For each (i, j, l) position there exists a $k_{i,j,l}$ value in the range 0-255 depending on the intensity of the colour or grey level. Let R_{ijl} be the region of existence of k.

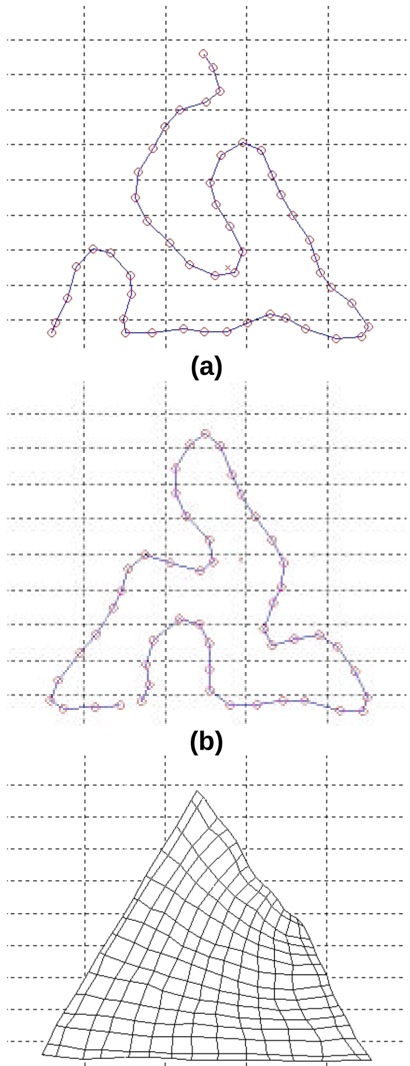


Figure 2. Output for triangular input: (a) Linear Network, (b) Annular Network, (c) Rectangular Grid Network

Figure 3 shows a grey level Magnetic Resonance (MR) image of a transaxial slice of a human head transformed into a matrix. The i and j axis follow the original image, and the value of the k-axis is proportional to the intensity, darkness/brightness, of the pixel in the x, y position of the original image. The bones from the skull appear with a higher k value while the brain and other elements have different lower values.

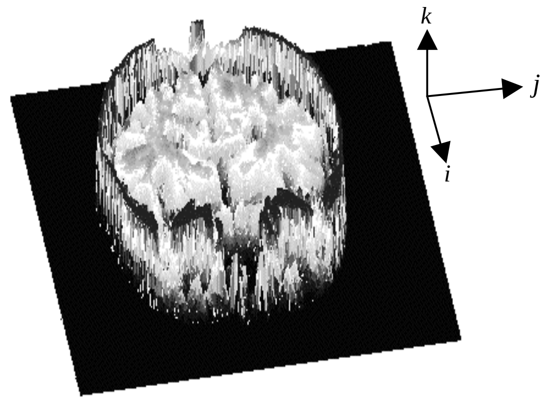


Figure 3. Matrix 3D display of a brain slice image.

This format of the image allows several transformations. Since the k value represents the grey level, selecting a certain range of k can segment the image. With two different thresholds one lower, LT, and one higher, HT, the values of k can be transformed according to:

$$\begin{array}{lll} \forall i, j, l & 0 \le LT < HT \le 255 & \\ 0 < k_{i,j,l} \le LT & \rightarrow & k_{i,j,l} = 0 \\ LT < k_{i,j,l} \le HT & \rightarrow & k_{i,j,l} = k_{i,j,l} \\ HT < k_{i,j,l} < 255 & \rightarrow & k_{i,j,l} = 0 \end{array}$$

As an example, Figure 4 presents a segmentation with LT = 200 and HT = 255, the higher k values which correspond to bone of the skull.

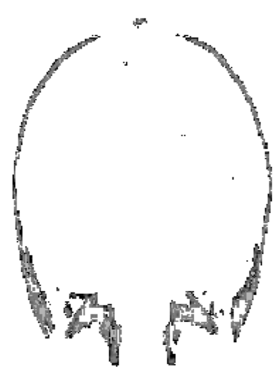


Figure 4. Segmentation of Human Head MR.

Once the image has been transformed into a matrix, and segmented if needed by grey level selection, the algorithm for the SOM will have as input region the non-zero values of the matrix.

$$\exists\ k_{i,j,l} \in R_{ijl} : [k_{i,j,l} \neq 0 \Leftrightarrow \exists\ x_{i,j,l}]$$

The x value is used for the Self-Organising algorithm that runs until a certain parameter of α is reached. Then, the final network is compared with the original image to identify the segmented regions. The process is shown graphically in Figure 5.

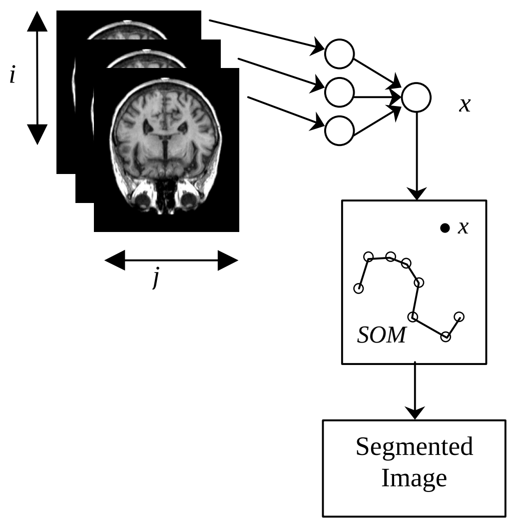


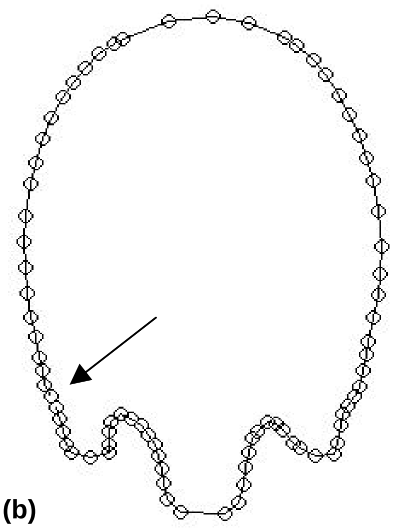
Figure 5. Segmentation Algorithm

3. RESULTS

The Self-Organising Maps were run with different images as input signals. Figure 6 shows the result of an 80-neurone network after 10,000 iterations run over the MR slice previously segmented with grey levels. In this case a network with ring topology, instead of a grid or linear can provide the best results in order to extract the contour and "thin" the bone as well as to give continuity to the shape of the skull. In Figure 6 (a) The black diamonds show the position of the neurones connected with virtual lines. In Figure 6 (b) only the neurones are presented with circles, note how the region of the nose is completed with a virtual line between neurones and also in the occipital region. A slight discontinuity can be noted between the first and the last neurones in the parietal region on the left side of the network.

One application of the algorithm is the volumetric object reconstruction: a collection of images produced by contiguous slices of MR of a human head can be segmented and for each slice, an n-neurone network will represent points in the positions of the human skull. A Volumetric algorithm can be used to produce the 3D model based on the point in a three dimensional space.

(a)



(b)

Figure 6. 80-neurone network adapted over figure 4. (a) Neurone positions (black) and skull (grey) and (b) Neurones only, arrow points discontinuity between first and last neurones.

For images that have not been previously segmented through grey levels, a grid network is preferred over a linear or annular network. Figure 7 shows a 20*20 network that adapted after 10,000 iterations over figure 3, below on the k-axis, is the original image.

The position of the neurones will depend on the density of pixels, note for example how letter A points a higher density of neurones along the skull, while letter *B* shows an unfilled region between the skull and the brain. Through this Euclidean distance between neurones certain elements can be identified like the bone labelled by *A*.

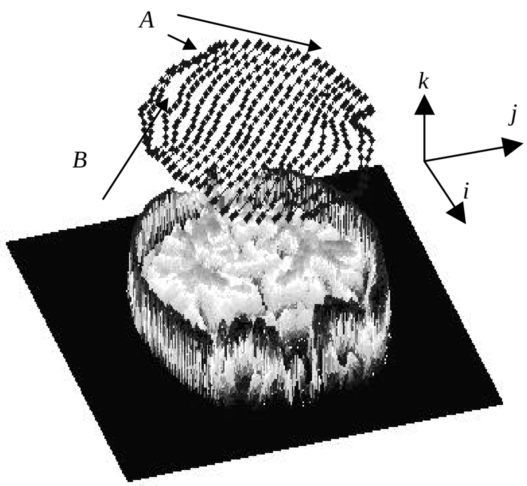


Figure 7. Output of 20*20 network. Letters A and B show different distributions of the neurones.

4. CONCLUSIONS

A Self-Organising Map network was programmed to receive images, as input signal regions. For this work, medical images were used and different segmentations were obtained with annular and grid networks without the requirement of initial conditions. These types of results allow extracting important features like the skull from a human head and representing its position through *i*, *j* co-ordinate points. The limitations of the algorithm depend now on computational complexity of the images and the amount of neurones for the networks. Also, different kind of networks can be programmed like a hexagonal grid.

Current research is focused in applying the algorithm with different images and trying other segmentation problems with more complex shapes and identifying different elements such as the ventricles for a human head MR.

The results encourage further research in the application of SOMs for image segmentation.

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