Automatic Segmentation and Classification of Computed Tomography Brain Images: An Approach Using One-Dimensional Kohonen Networks

Ricardo Pérez-Aguila

Abstract - **This work is devoted to describe a potential use of the 1-Dimensional Kohonen Networks in the automatic non-supervised segmentation and classification of computed tomography brain slices. Possible perspectives of application include the automatic delineation of areas on the cerebral map and the automatic correlation between new clinical cases with previous boarded and closed cases. The classification is proposed in two phases. First, the images are segmented via a 1D Kohonen Network. One of the main aspects considered in this phase is related to the fact that tissue classification is achieved by taking in account the tissue and its associated neighborhood. By this way, it is possible to argue that the obtained tissue characterizations are sustained in the topology and geometry of the human cranium. The second phase is given by the classification of the whole set of segmented images via a second Kohonen Network. It is discussed how the final classes contain images which share specific properties.**

Index Terms - **Artificial Neural Networks, Kohonen Networks, Automatic Image Classification, Automatic Image Segmentation, Pattern Recognition.**

I. Introduction and Problem Statement

Automatic classification of normal and pathological tissue types, using brain slices images generated by computed tomography, has great potential in clinical practice. Possible areas of application include the automatic delineation of areas to be treated prior to invasive procedures [2], and the correlation between new clinical cases with previous boarded and closed cases. However, as Abche et al [1] point out, the automatic segmentation and classification of medical images is a complex task for two reasons:

- The variability of the human anatomy varies from a subject respect to other. Hence, it is restricted the use of general knowledge in order to achieve the segmentation. Therefore, the absence of a general model that describes this variability introduces impediments to the tissue classification process [1].
- The images' acquisition process could introduce noise and artifacts which are difficult to correct. For example, the grayscale intensities of a given tissue could be non-uniform.

This work is devoted to describe a potential use of 1-Dimensional Kohonen Networks in 1) the automatic non-supervised characterization of tissue in the human brain, and 2) the automatic classification of segmented images corresponding to computed tomography brain slices. It is well known the application of Kohonen Networks for classification when a high level of redundancy is present in the input space [4]. Via non-supervised classification, images presenting similar features are grouped in classes. Many processing tasks (as description, object recognition or indexing) are based on such preprocessing ([12] & [14]). For example, in [8] and [9], Kohonen Networks are used for classifying color images corresponding to the Popocatépetl Volcano (located in the State of Puebla, México, active and monitored since 1997). Currently, the classified volcano images are going to be correlated with other experiments in the research center where the study was carried out.

The idea to be described in this work considers the use of two 1D Kohonen Networks (see **Fig. 1**). A first network will be used to characterize brain tissue in the human head. Such characterizations are then used for segmenting brain images. The whole set of segmented images is then used as a training set for a second 1D Kohonen Network whose objective is to group them in classes in such way it is expected the members of a class share common and useful properties.

This work is organized as follows: **Section II** describes the theoretical frame behind 1-Dimensional Kohonen Networks. **Section III** describes the methods, criteria, and results obtained from the characterization of tissue in computed tomography brain slices through Kohonen Networks. The **Section IV** describes how a set of segmented images was used as training set for a 1D Kohonen Network in order to group such images in classes. There are summarized the obtained results. Finally, the **Section V** discusses some observations identified when the classes and their members were analyzed, and some conclusions and future perspectives of research are presented.

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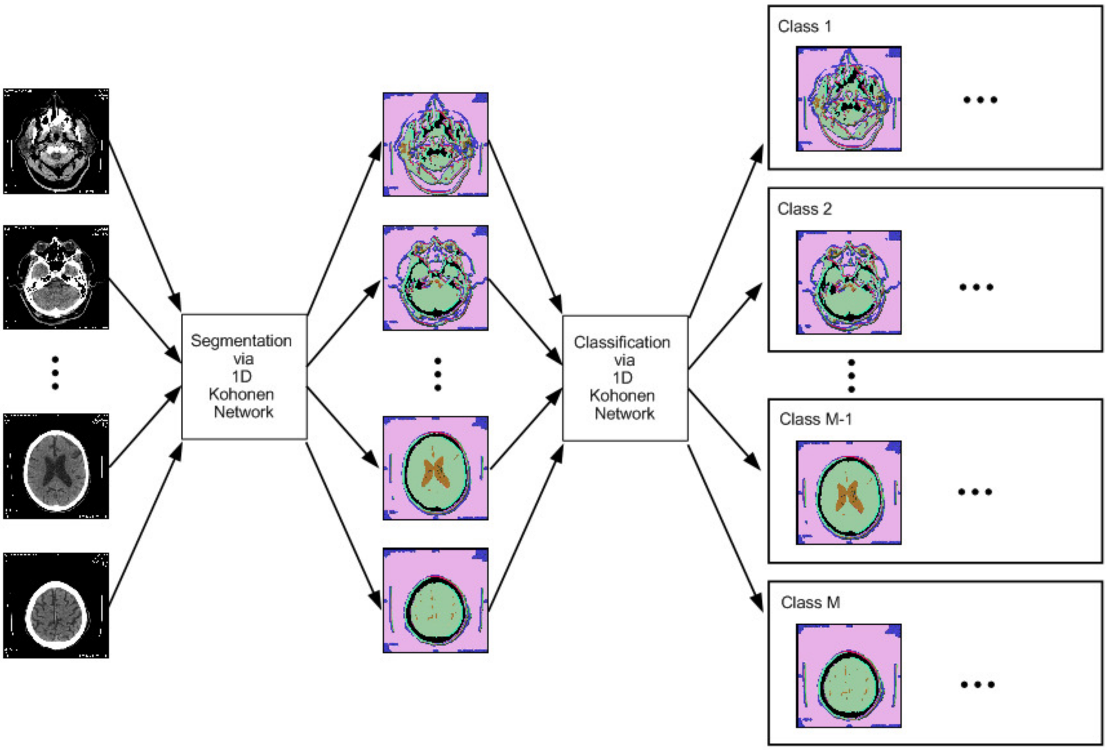


Fig. 1. Classifying computed tomography brain slices in two phases. First, the images are segmented via a 1D Kohonen Network. The second phase is given by the classification of the whole set of segmented images through a second 1D Kohonen Network.

II. Fundamentals of the 1-Dimensional Kohonen Networks

A Kohonen Network with two layers showing L input neurons and M output neurons may be used to classify points embedded in an L-Dimensional space into M categories ([3], [11]). Input points have the form $(x_1, \ldots, x_i, \ldots, x_L)$. The total number of connections from input layer to output layer is $L \times M$ (See **Fig. 2**). Each output neuron j, $1 \le j \le M$, will have associated an L-Dimensional weights vector which describes a representation of class C_j. All these vectors have the form:

$$\text{Output neuron 1: } W_1 = (w_{1,1}, \ldots, w_{1,L})$$
$$\vdots$$
$$\text{Output neuron M: } W_M = (w_{M,1}, \ldots, w_{M,L})$$

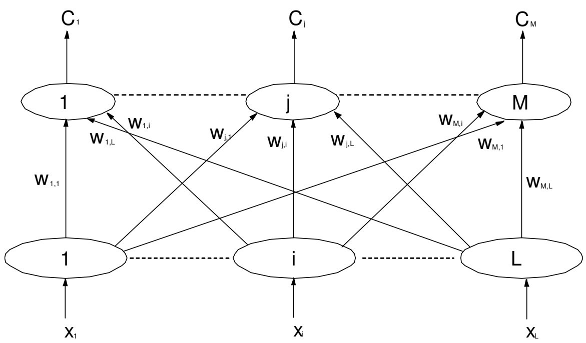


Fig. 2. Topology of a 1-Dimensional Kohonen Network.

A set of training points are presented to the network T times. According to [4], all values of weight vectors should be initialized with random values. The neuron whose weight vector W_j, $1 \le j \le M$, is the most similar to the input point P^k is chosen as winner neuron, for each t, $0 < t < T$. In the model proposed by Kohonen, such selection is based on the squared Euclidean distance. The selected neuron will be that with the minimal distance between its weight vector and the input point P^k:

$$d_j = \sum_{i=1}^{L} \left(P_i^k - W_{j,i} \right)^2 \qquad 1 \le j \le M$$

Once the j-th winner neuron in the t-th presentation has been identified, its weights are updated according to:

$$W_{j,i}(t+1) = W_{j,i}(t) + \frac{1}{t+1}\left[P_i^k - W_{j,i}(t) \right] \qquad 1 \le i \le L$$

When the T presentations have been achieved, the values of the weights vectors correspond to coordinates of the 'gravity centers' of the points, or clusters of the M classes.

III. Automatic Non-Supervised Tissue Classification

As commented in the introduction of this work (**Section I**), the first part of the problem to be boarded is the automatic non-supervised classification of cerebral tissue. It is expected that the proposed Kohonen Networks identify, during its training processes, the proper representations for a previously established number of classes of tissue.

There are some situations to be considered respect to the training sets to be used. One first approach could suggest that the grayscale intensity of each pixel, in each brain slice, can be seen as an input vector (formerly an input scalar). However, as discussed in [8], the networks will be biased towards a classification based only in grayscale intensities. It is clear that each pixel has an intensity which captures, or is associated, to a particular tissue; however, it is important to consider the pixels that surround it together with their intensities. The topology around a given pixel is to be taken in account because it complements the information about the tissue to be identified. Two pixels A and B with the same grayscale intensity but with distinct neighborhood should belong to distinct classes. For example, if pixel A has a neighborhood composed by bone tissue while the corresponding neighborhood of pixel B is composed by gray matter, then the characterization should be performed by considering that the type of tissue they belong also depends on the head's location and their surrounding tissue (A network classifying by taking in account only intensities, and ignoring neighborhoods, could determine that pixels A and B belong to the same class and hence they are the same type of tissue).

Let p be a pixel in a given image. Through p, it is possible to build a sub-image by taking those pixels inside a square neighborhood of radius r and center at p. Pixel p and its neighborhood will be called a mask. The size of the mask is given by the length (number of pixels) of its sides. For example, it is possible to build, in a 100 × 100 pixels image, 96 × 96 = 9,216 masks of size 9 (See **Fig. 3**). It is assumed that those pixels at the borders of the image can not form a mask. In the above example, it is the case of pixels in the first four rows and columns, and the pixels in the last four rows and columns.

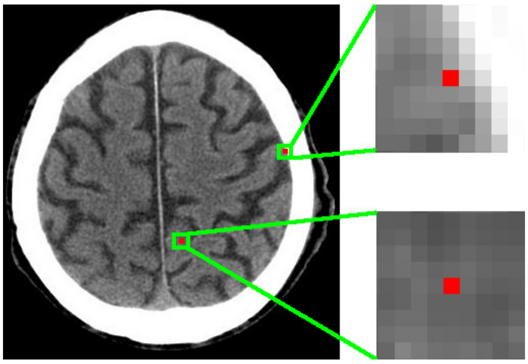
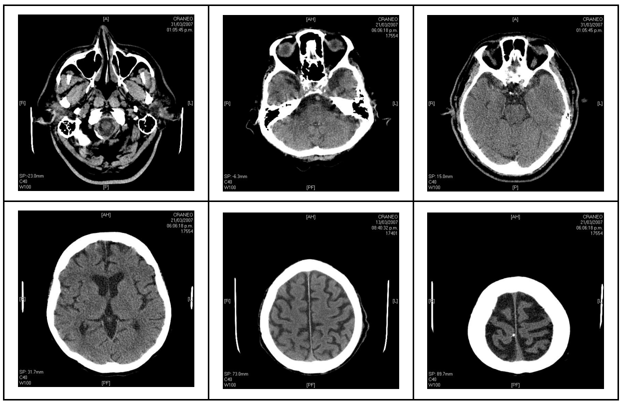


Fig. 3. Two masks of size 9 pixels in a brain slice image. They describe a neighborhood around the corresponding pixels in red.

The experiments were performed using a set of 340 grayscale images corresponding to computed tomography brain slices (see **Table 1**). They are series of axial images of the whole head of 5 patients (each one labeled as patient **a**, **b**, **c**, **d**, and **e**). All the 512 × 512 pixels images were captured by the same tomography scanner and they have the same contrast and configuration conditions.

Table 1. Some samples from the image set used for characterization of cerebral tissue.



The networks' training sets are composed by all the masks that can be generated in each one of the 340 selected brain slices. As commented in **Section II**, a Kohonen Network expects as input a vector, or point, embedded in the L-Dimensional Space. A mask can be seen as a matrix, but by stacking its columns on top of one another a vector is obtained. In fact, this straightforward procedure *linearizes* a mask making it a suitable input for the network.

There were implemented three 1D Kohonen Networks with different topologies and training conditions. In fact, the topology of each network depends of the selected mask size:

- Network Topology τ_1:
  - Training set's cardinality: 260,100 masks
  - Mask size: 5 pixels
  - Input Neurons: $L = 5 \times 5 = 25$
  - Output Neurons (classes): $M = 10$
  - Presentations: $T = 6$
- Network Topology τ_2:
  - Training set's cardinality: 260,610 masks
  - Mask size: 4 pixels
  - Input Neurons: $L = 4 \times 4 = 16$
  - Output Neurons (classes): $M = 20$
  - Presentations: $T = 40$
- Network Topology τ_3:
  - Training set's cardinality: 255,025 masks
  - Mask size: 15 pixels
  - Input Neurons: $L = 15 \times 15 = 225$
  - Output Neurons (classes): $M = 20$
  - Presentations: $T = 80$

The **Table 2** presents the segmentation obtained for three brain slices at distinct positions of the head. According to the network topology, a different color was assigned to each class. The segmentations are then presented as false color images. In fact, the whole set of 340 images was segmented using the networks described above in order to obtain three training sets for the Kohonen Network to be used in the experiment to be described in the following section.

IV. Automatic Non-Supervised Computed Tomography Images Classification

Let TS(τ_1), TS(τ_2), and TS(τ_3) be defined as the sets of segmented images generated by Kohonen Networks τ_1, τ_2, and τ_3, respectively. Now, each one of these sets will be used for training a Kohonen Network. The idea is that such network classifies the images in a given number of classes. Each training set is then composed by 340 images whose size is 512 × 512. The segmented images (presented in false color) are codified under the color model 24-bits RGB.

A. Representing Images through Vectors in $\mathbb{R}^L$

Let l_1 (rows) and l_2 (columns) be the dimensions of a two-dimensional segmented image. Let $L = l_1 \cdot l_2$. Each pixel in the image will have associated a 3-Dimensional point (x_i, y_i, RGB_i) such that $RGB_i \in [0, 16777216)$, $1 \le i \le L$, where RGB_i is the color value associated to the i-th pixel. The color values of the pixels will be normalized such that they will be in [0.0, 1.0) through the transformation:

$$normalized\_RGB_i = \frac{RGB_i}{16777216}$$

Basically, it is defined a vector in the L-Dimensional space by concatenating the l_2 columns in the image considering for each pixel its normalized color RGB value. By this way, each image is now associated to a vector in the L-dimensional Euclidean space. Therefore, the training images to be applied in a Kohonen Network are mapped in order to be embedded in a unit L-Dimensional hypercube.

Table 2. Tissue Characterization of Three selected Brain Slices

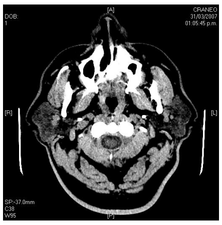
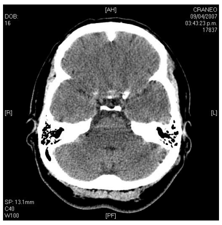
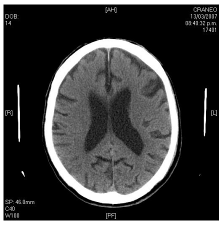
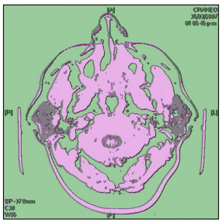
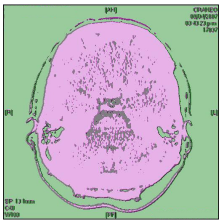
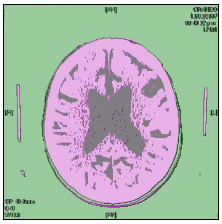
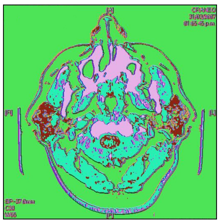
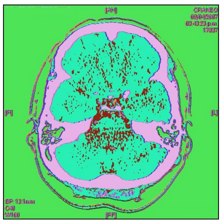
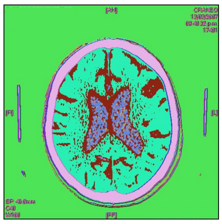
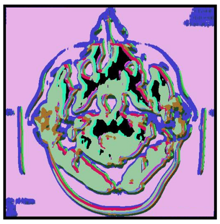
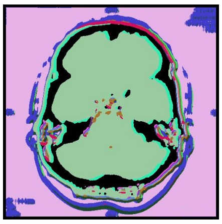
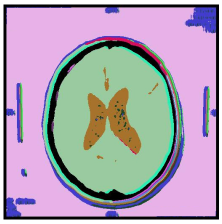
	Brain Slice 1	Brain Slice 2	Brain Slice 3
Original Brain Slice			
Segmentation by Network Topology τ_1			
Segmentation by Network Topology τ_2			
Segmentation by Network Topology τ_3			

Table 3. Classification of 340 training segmented images according to a Kohonen Network with 262,114 input neurons, 30 output neurons, and 45 presentations.

	Using TS(τ_1)		Using TS(τ_2)		Using TS(τ_3)	
Class	Images	Patients	Images	Patients	Images	Patients
1	43	c	15	a, d	6	d
2	2	a	19	a	18	b, c
3	8	e	8	c	27	a, b, c, d
4	8	b	14	c	4	c
5	33	d	9	b, e	23	a
6	9	c	12	a	11	a, d
7	8	a	4	c	7	a
8	3	e	9	d	10	d
9	17	b	12	b, e	20	b, e
10	31	a	4	c	12	c
11	22	b	5	d	3	c
12	18	d	12	e	18	b, c, e
13	7	b	14	b	14	a
14	29	d	13	c	12	d
15	15	a	11	c, e	8	a
16	11	e	13	b, c, e	4	a
17	2	c	9	a, d	7	c
18	21	c	16	b	12	e
19	27	a	4	c	12	c
20	25	b	7	d	22	b, e
21	1	e	4	b	12	a
22	0	-	20	d	16	c
23	0	-	7	b	21	b
24	0	-	10	d	29	d
25	0	-	14	b, c	12	d
26	0	-	3	c	0	-
27	0	-	28	a	0	-
28	0	-	9	d	0	-
29	0	-	15	b, c	0	-
30	0	-	20	a, d	0	-

B. Classifications Results

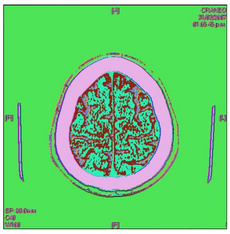
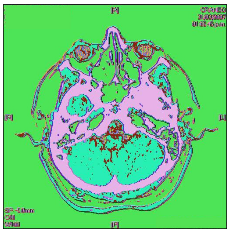
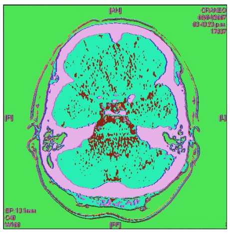
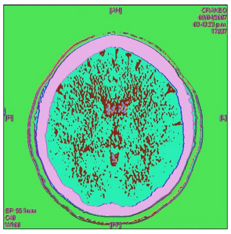
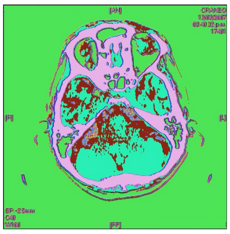
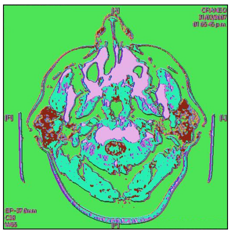
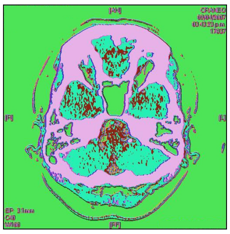
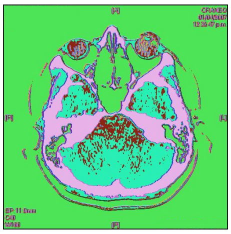
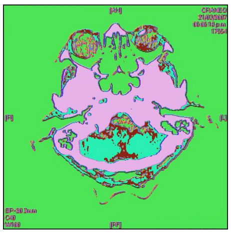
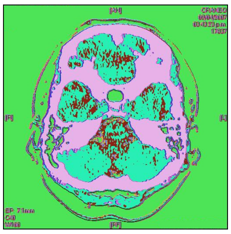
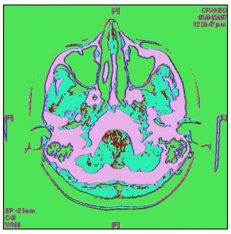
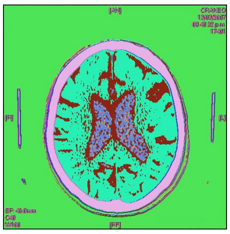
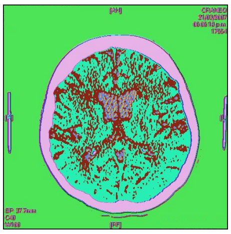
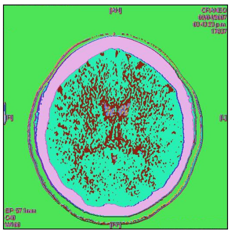
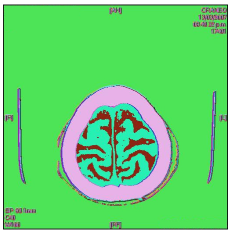
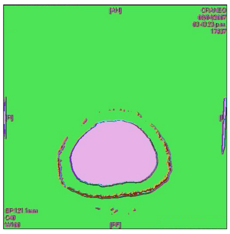
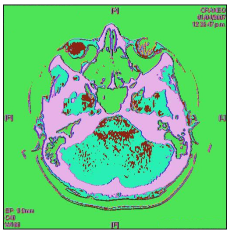
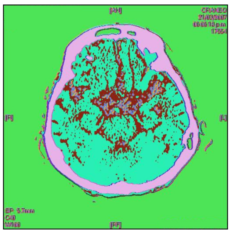
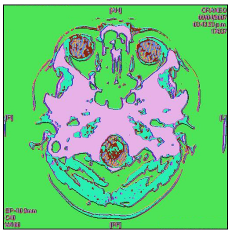
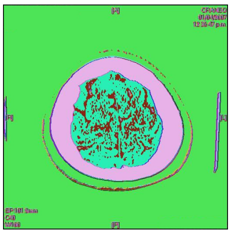
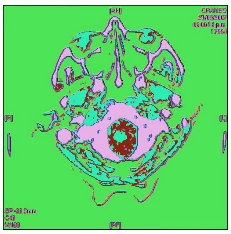
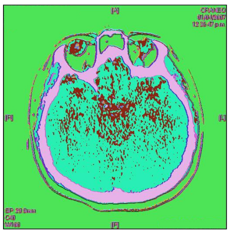
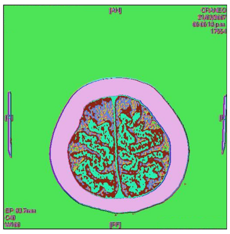
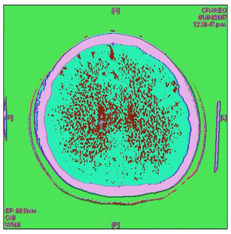
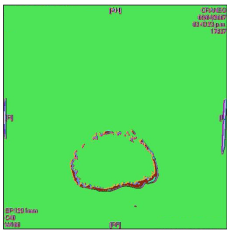
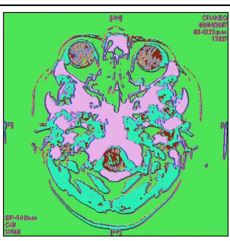
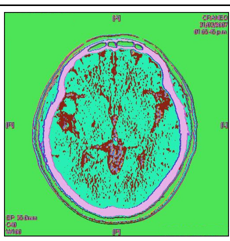
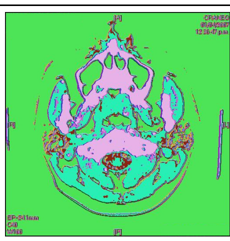
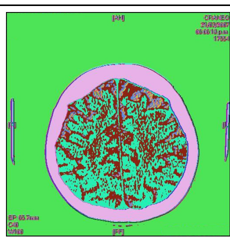
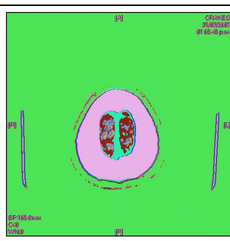
The 1D Kohonen Network used for classifying the segmented images was composed by L = 512×512 = 262,114 input neurons and m = 30 output neurons (classes). Each set of 340 training points (segmented images) was presented T = 45 times. The training procedures were applied according to **Section II**. All the weights vectors' were always initialized to 0.5.

Table 3 shows the obtained classification of the segmented images using the three proposed training sets. In the **Table 3** is also presented the distribution of the 340 training segmented images in each one of the classes.

Table 4 presents some images that are representative of each class when using training set TS(τ_2) (these images were selected from each class in an arbitrary way).

According to **Table 3**, the network trained with TS(τ_2) distributed the 340 images in its 30 classes. When the network is trained with the segmented images in TS(τ_1) and TS(τ_3) only 21 and 25 classes are respectively used.

Table 4. Classes' representative images when using the training set TS(τ_2) (See Section III).

 Class 1	 Class 2	 Class 3	 Class 4	 Class 5
 Class 6	 Class 7	 Class 8	 Class 9	 Class 10
 Class 11	 Class 12	 Class 13	 Class 14	 Class 15
 Class 16	 Class 17	 Class 18	 Class 19	 Class 20
 Class 21	 Class 22	 Class 23	 Class 24	 Class 25
 Class 26	 Class 27	 Class 28	 Class 29	 Class 30

C. Classification Based On Other Distance Functions

In **Section II** was commented during the training of the network the neuron whose weight vector W_j, $1 \le j \le M$, is the most similar to an input point P^k is chosen as winner neuron. Kohonen established that such selection is based on the Squared Euclidean Distance [11]. In the experiments summarized in **Table 3**, the selected winner neuron was always that with the minimal squared Euclidean distance between its weight vector and the input point P^k:

$$d_j = \sum_{i=1}^{L} \left(P_i^k - W_{j,i} \right)^2 \qquad 1 \le j \le M$$

In fact, other distance functions can be considered for the purpose of identifying a winner neuron. The use of a function different than the Squared Euclidean Distance usually obeys to the needs of the application ([6] & [13]). Clearly, when using a distinct metric, it must express the amount of similarity between an input point and a weight vector and, hence, it is reasonable to expect some impact in the way the network classifies and distributes the elements in the training set.

Distances that can be used for the purpose of determining winning neurons are:

- The Manhattan Distance [10]:

$$d_j = \sum_{i=1}^{L} \left| P_i^k - W_{j,i} \right| \qquad 1 \le j \le M$$

- The Sup Distance (a special case of the Minkowski Distance also known as Chebyshev Distance) [5]:

$$d_j = \max_{1 \le i \le L} \left| P_i^k - W_{j,i} \right| \qquad 1 \le j \le M$$

- The Canberra Distance [13]:

$$d_j = \sum_{i=1}^{L} \frac{\left| P_i^k - W_{j,i} \right|}{\left| P_i^k \right| + \left| W_{j,i} \right|} \qquad 1 \le j \le M$$

Now consider the following function:

$$d_j = \begin{cases} 1 - \dfrac{\sum_{i=1}^{L} P_i^k}{\sum_{i=1}^{L} W_{j,i}} & if \quad \sum_{i=1}^{L} P_i^k < \sum_{i=1}^{L} W_{j,i} \\ 1 - \dfrac{\sum_{i=1}^{L} W_{j,i}}{\sum_{i=1}^{L} P_i^k} & if \quad \sum_{i=1}^{L} W_{j,i} < \sum_{i=1}^{L} P_i^k \\ 0 & if \quad \sum_{i=1}^{L} W_{j,i} = \sum_{i=1}^{L} P_i^k \end{cases} \qquad 1 \le j \le M$$

Such function is in fact a distance over $\mathbb{R}^+$ and it is called the *Pérez-Aguila Metric* ([8] & [9]).

The three training sets generated by networks τ_1, τ_2, and τ_3, namely $TS(\tau_1)$, $TS(\tau_2)$, and $TS(\tau_3)$, are used again for training Kohonen Networks in the same fashion as described in the above subsections: there are defined 1D Networks with $L = 512 \times 512 = 262{,}114$ input neurons and $m = 30$ output neurons. Each set of 340 training points (segmented images) is presented $T = 45$ times. However, in these new experiments the Squared Euclidean Distance is substituted by the Manhattan, Pérez-Aguila, Canberra, and Sup distances. The idea is to determine the classifications obtained when these functions are used during the training process. The results are then compared with those generated when the traditional squared Euclidean distance was used.

Charts in **Figs. 4.a**, **4.b** and **4.c** show the distribution of the input segmented images, according to the distance under consideration, when the training sets $TS(\tau_1)$, $TS(\tau_2)$, and $TS(\tau_3)$ are respectively applied.

The **Table 5** shows when using the Pérez-Aguila Metric and the Manhattan Distance both functions produce distributions that lead to identify than less than 11 of the 30 available classes are used. The Pérez-Aguila Metric groups all the training images in only 2 classes while the Manhattan Distance groups them in 11 classes, when using $TS(\tau_1)$, and 5 classes when using training sets $TS(\tau_2)$ and $TS(\tau_3)$. Although the Sup distance distributes respectively to all the elements in $TS(\tau_1)$, $TS(\tau_2)$ and $TS(\tau_3)$ in the networks' 30 defined classes, it is observed that just one class has more than 300 elements, approximately the 85% of the training sets' cardinality, while the remaining classes have associated at least one input segmented image.

By applying the Canberra Distance under $TS(\tau_1)$ it is observed a distribution of the 340 training images between 15 classes, with an average of 22.6 members per class. However, by considering training sets $TS(\tau_2)$ and $TS(\tau_3)$, there were used 7 and 6 classes respectively. In the first case there is a class with 201 associated images, 59% of $Card(TS(\tau_2))$, while in the second case just one class groups 125 elements, that is, 36% of $Card(TS(\tau_3))$.

By experimental way, it can be concluded that the squared Euclidean distance produces much better and consistent classifications of the elements in $TS(\tau_1)$, $TS(\tau_2)$, and $TS(\tau_3)$ than those shared by the other considered functions. The **Tables 3** and **5** shows a good distribution of the 340 training images between the available classes when Euclidean distance is used. The number of used classes in this case is located between 21 and 30. The median/mean of the number of images associated to a class is 15/16.2, 11.5/11.3, and 12/13.6 when training with $TS(\tau_1)$, $TS(\tau_2)$, and $TS(\tau_3)$, respectively. Hence, the results presented in **Fig. 4** and **Tables 3** and **5** lead to establish the squared Euclidean distance seems to be an adequate choice for the particular classification problem being under attack.

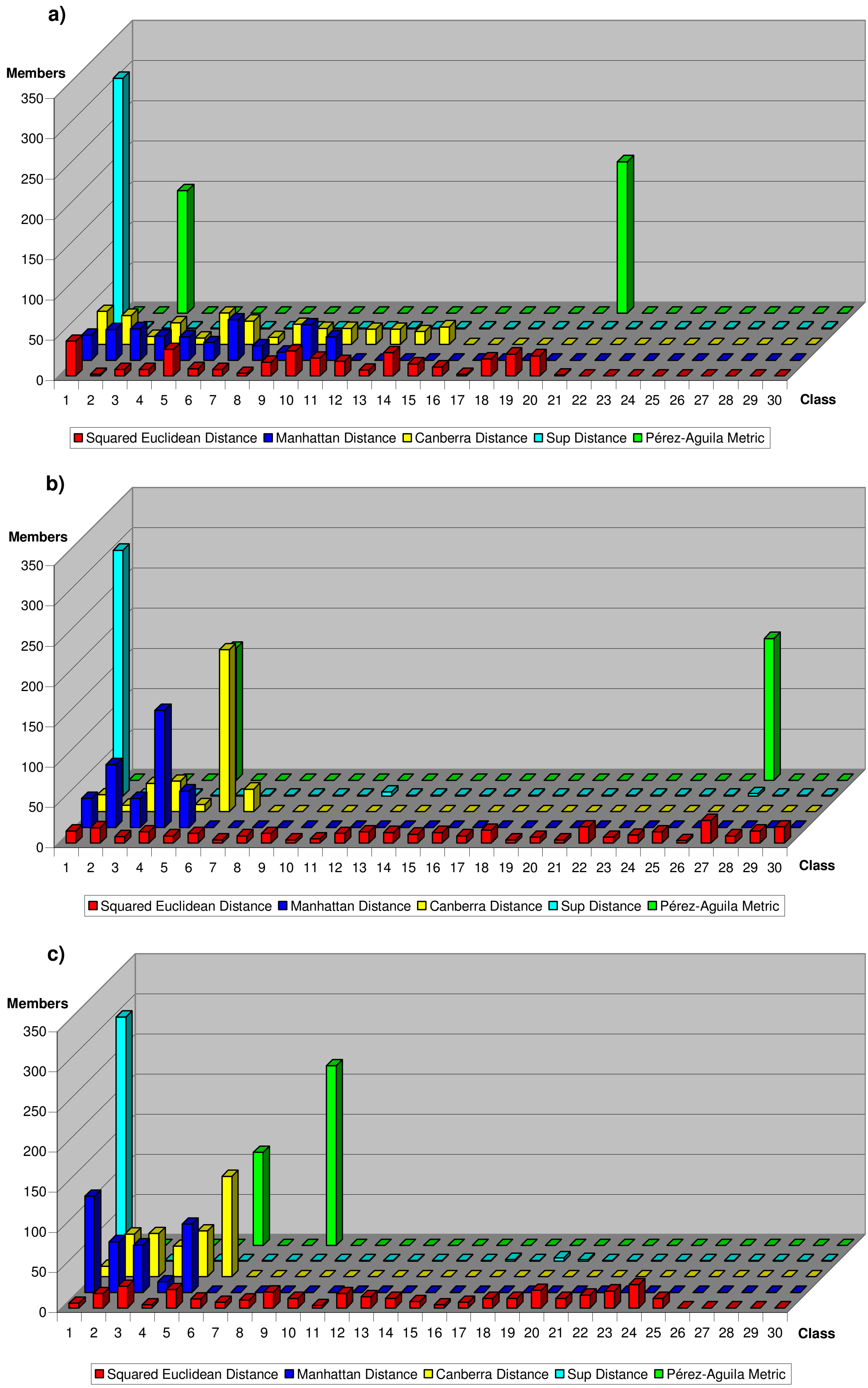


Fig. 4. Distributions of segmented images by using a Kohonen Network based on different distance functions. Results obtained by application of training sets a) TS(τ_1), b) TS(τ_2), and c) TS(τ_3).

Table 5. Statistics associated to classifications provided by a Kohonen Network when different distance functions are used.

Training Set		Squared Euclidean Distance	Pérez-Aguila Metric	Manhattan Distance	Canberra Distance	Sup Distance
TS(τ_1)	Used Classes	21	2	11	15	30
	Maximum number of members in a used class	43	188	50	41	311
	Minimum number of members in a used class	1	152	10	8	1
	Median	15	170	30	20	1
	Mean	16.2	170	30.9	22.6	11.3
TS(τ_2)	Used Classes	30	2	5	7	30
	Maximum number of members in a used class	28	176	145	201	305
	Minimum number of members in a used class	3	164	36	8	1
	Median	11.5	170	45	28	1
	Mean	11.3	170	68	48.5	11.3
TS(τ_3)	Used Classes	25	2	5	6	30
	Maximum number of members in a used class	29	224	120	125	304
	Minimum number of members in a used class	3	116	13	13	1
	Median	12	170	63	53.5	1
	Mean	13.6	170	68	56.6	11.3

V. Discussion, Conclusions, and Future Work

In previous sections was commented the original set of brain slices were obtained from 5 patients (**a**, **b**, **c**, **d**, and **e**). When training the networks no information was passed about the ownership of each image because only vectors containing intensities were used as input. In this way, the networks had no information about which image belongs to which patient. Once the members of each class were obtained, it was determined the ownership of each image. The network trained with the segmented images in TS(τ_1) is an interesting case. It grouped the images in only 21 of the 30 classes, but each class contains images that belong to just one patient (See **Table 3**). The other two cases also exhibit these characteristic in the majority of their classes, but some of them have images that belong to two or more patients.

One path of future research considers determining the criteria followed for each network in order to form the representation of each class. On one hand, the idea is to identify the number of classes required for classifying all types of tissue in the human brain. The size of the masks to use is important because they determine the quantity of information that is related to a given pixel. There must be identified an optimal mask size such that no redundant or lacking information is given to the network.

On the other hand, there have been identified some interesting results when a set of segmented images is used for training. Moreover, there are clear, at least from an experimental point of view (**Section IV.C**), the advantages of using the squared Euclidean distance for measuring the correspondence between an input point and a weight vector during the training phase. It is possible to argue that the network is capable of identifying specific similarities between segmented images in such way it grouped in a same class only brain slices corresponding to the same patient. Moreover, the network was also capable of differentiating the variations between the head anatomy associated to each patient. This leads to study the different "similarity metrics" generated by each network. In the future phases of research, physician advisory is going to be taken in account. The optimality in terms of the best parameters to use in a Kohonen Network will be considered in function of the medical usefulness of the segmentations and classifications obtained.

Another objective, respect to future work, refers to indexation of previously boarded clinical situations. It is well known that medical reasoning is mainly based in the information and knowledge acquired from previous cases [7]. By forming a training set of images that correspond to patients with well specified diagnosis and the procedures followed, it could be possible 1) to index, via a Kohonen Network, an image corresponding to a new case in an appropriate class, and 2) to use the associated closed case of each member in such class in order to build a suggestion of the diagnosis and procedures to apply. Moreover, it is clear that by analyzing the cases associated to each member of each class it could be possible to count with more elements to determine in a more precise way the patterns followed during the training procedures and therefore, to understand the criteria followed for the network that lead to the training images' final groupings.

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