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# Neural Method Based on Kohonen Topological Maps Applied to the Whole-body Scintigraphy Image

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**Abstract:** *Objective:* The aim of this study was to describe the stages of learning Kohonen's self-organizing maps applied to scintigraphy imaging in order to perform classification for medical diagnostic aid. *Method:* To achieve these goals, the neurons, arranged on a regular grid, are connected to each other by a neighbor relationship, which creates the topology of the map. The input layer consisted of pixels from the scintigraphy images. *Results*: During the iteration rounds of learning, we have seen a deployment of neurons on the nodes of the map that becomes more and more important. And it is the same for the winning neurons. After 750 iterations, the Davies Bouldin index attests to the end of the training with a quantization error that goes from 0.175 at the beginning of the training to 0.0225 at the end of the training. After this study, we find that neurons 41, 62, 121, 101 and 145 have captured most of the data with a peak uptake achieved by neuron 41 which has captured 1048 data. This individualizes the class of high intensities undoubtedly corresponding to metastatic hyperfixations. *Conclusion*: This innovative method could undoubtedly be integrated into the link in the chain highlighting periarticular metastases in developing countries, most of which do not have a SPECT-CT.

**Keywords:** Artificial Neural Networks, Kohonen Self Organizing Maps, Bone Scintigraphy

## 1. Introduction

The advances in medical imaging are closely linked to the development of mathematical algorithms and the digitization of medical images. With the advent of artificial intelligence, we are increasingly seeing collaboration between doctors and engineers in the semi-quantification of images through the use of algorithmic methods. Thus, learning models that can go as far as deep learning undoubtedly allow the automatic detection of lesions, thus opening the way to the diagnostic of metastases of osteophilic cancers, in particular that of prostate cancer. Because of the lower specificity of the scintigraphy, these methods are interesting. The nuclear medicine physcians often misses "super bone scan" lesions and even more the peri-articular hyperfixations of metastatic origin [1-2]. Nowdays, we have not found an application of scintigraphic images as input into the use of Kohonen's self-organizing maps.

The objective of this study was to present a neuronal learning technique in the image of the human brain using Kohonen topological maps with the pixels of the scintigraphic image as input for a partition to individualize the class of metastases.

## 2. Material and Methods

### 2.1. Material

To achieve the learning process through artificial intelligence, we used Kohonen's self-organizing maps. They do the research, by data learning, to partition all of the available observations into similar groupings. These groupings have a neighborhood structure which can be materialized by means of a discrete space called a "topological map". This is most often a low-dimensional lattice on which the neighboring structures are taken into account by the model. The neurons are arranged on a regular grid and are connected to each other by a neighbor relationship, which creates the topology of the map [3]. The input layer is used to present the observations to be classified, which in this case are the pixels of the scintigraphic image. The output layer is made up of the lattice of neurons that make up the map. Each neuron is connected to all elements of the input layer. The reference vector Wc is the weight vector associated with neuron c of the self-organizing map as indicated in Figure 1 [4].

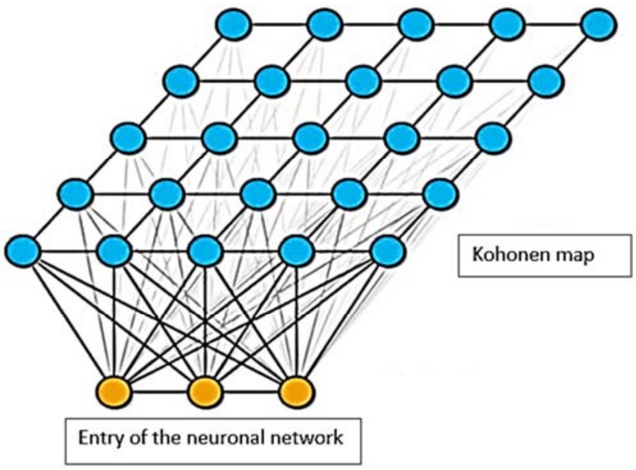


***Figure 1.*** *Architecture of a 2-D topological map [4].*

### 2.2. Methods

During learning, the self-organization process makes it possible to take into account the adaptation of the weights of the connections essentially on the region of the map that is the most "active". This active region is considered to be the neighborhood associated with neurons in the most active state. We are talking about a winning neuron. The criterion for selecting the winning neuron is the neuron whose weight vector is closest in the sense of a Euclidean distance. It is this notion of neighborhood that introduces topological constraints into the final geometry of Kohonen maps. Thereby, the neuron of the card, after having captured a data, can move, thus modifying its position and its neighborhood. Indeed, the closer a neuron is to the selected neuron, the more it is influenced. The extent to which the modification of the weight vector of a neuron affects it is determined by the neighborhood function. This plays a key role in the adaptation of the network to its inputs and varies according to the number of cycles performed [5]. Before starting the training, the algorithm first performs a random initialization of the values of each neuron. During this process, there is hardly any iteration, most of the data is located to the right of the SOM map. As no training has been done, there is no correlation between the concentration of data in this area and the distribution of neurons as shown in Figure 2.

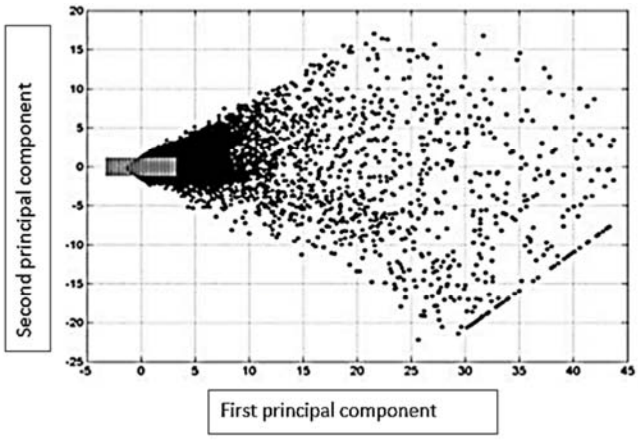


***Figure 2.*** *Initial stage of learning the artificial neural network.*

## 3. Results and Discussion

### 3.1. During the Learning of the Artificial Neuron Network

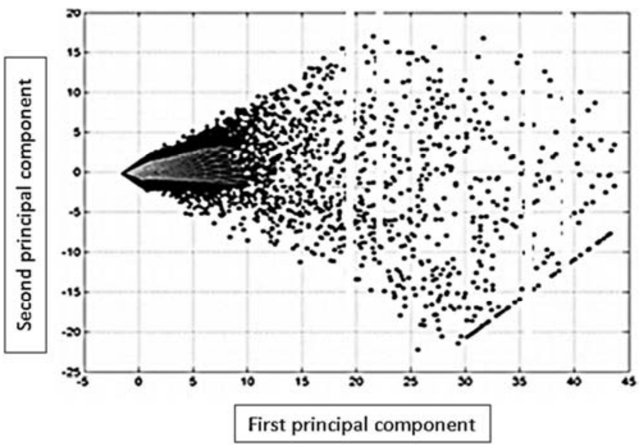


***Figure 3.*** *Deployment of neurons during learning.*

Figure 3 represents the deployment of neurons on the nodes of Kohonen's self-organizing map. And we see that as the number of iterations increases, this deployment gets bigger and bigger and the winning neurons get bigger and bigger. They observe a change in value in order to be able to respond better to stimuli of the same nature as the previous one. It is the same for the neighboring neurons of the winner but with a gain multiplying factor of less than one. There is a neighborhood coefficient whose role is to determine a neighborhood radius around the "winning" neuron. The neighborhood function forces the neurons that are in the neighborhood of the winning neuron to bring their referent vectors closer together. The closer a neuron is to the winner in the grid, the less its displacement is important and vice versa. This allows specialization of the entire region of the map located around the winning neuron. Thus, the map described by the referent vectors of the network evolves from a random state to a state of stability in which it describes the topology of the input space while respecting the order relations in the grid. Hence the progressive self-organization of this card.

### *3.2. Towards the End of Learning the Artificial Neuron Network*

In Figure 4, we used the Davis Bouldin index to estimate the quantization error, which goes from 0.175 at the very start of training in the absence of iteration to 0.0225 after 750 iterations. Beyond this number of iterations, the quantization error becomes and remains stable, thus signaling the end of learning.

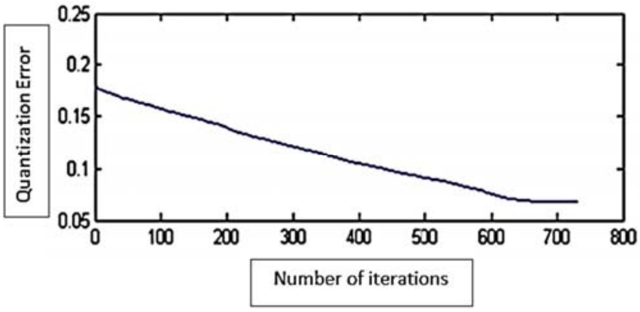


***Figure 4.*** *Quantization Error as a function of the number of iterations.*

### *3.3. At the End of the Learning of the Artificial Neuron Network*

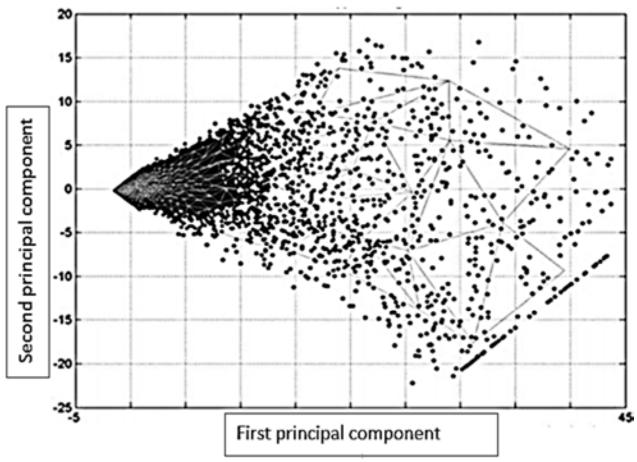


***Figure 5.*** *End of learning the neural network.*

At this stage of learning, the neurons do not move or move very little. And with each iteration, the self-organizing map covers the entire data topology. Just like the cortex, artificial neurons are connected to each other. There is a link between the data (pixels) in the scintigraphic image and neurons. Which is in favor of a good organization of the map. Throughout the training, the deployment of the network on the data is dynamically schematized by figure 5. It can be seen, along the training, neurons which are distributed as and when on the data in blue represented. by the figure below. At the same time, there is a synchronized evolution of the quantization error during this learning process. The completion of the training results into 400 neurons whereas each is the representative of a class whose elements are pixels of the scintigraphic image. So once the learning is completely finished, the algorithm establishes a cardinality map made up of the 400 neurons where each has picked up a set of pixels.

At the end of this test, we found that the neurons 41, 62, 121, 101, 145, 18, 15, 200, 180, 398 respectively captured 1048, 772, 734, 594, 464, 54, 52, 43, 31, 30 data. From these results, we note that the neurons 41, 62, 121, 101, and 145 have captured most of the data with a peak of capture effected by the neuron 41. This maximum intensity undoubtedly corresponds to the hyperfixation of metastatic origin in the clinical-biological context. One of the classes being found, the cardinality map shown in Figure 6 makes it possible to highlight the existence of 2 other classes of intermediate intensity which may be linked to the arthritis phenomenon and a low intensity which may correspond to a normo-fixing zone.

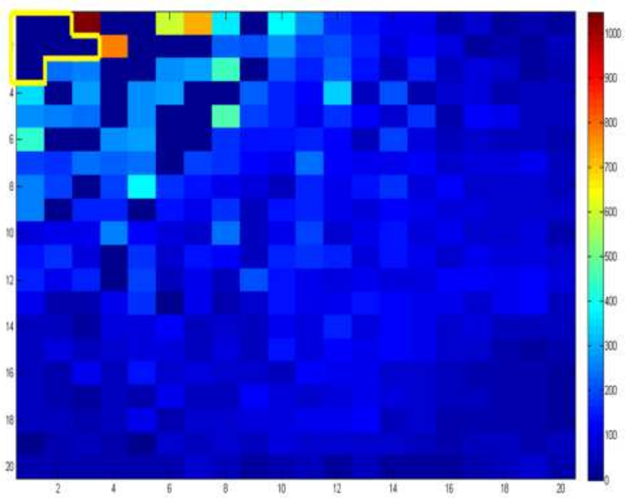

***Figure 6.*** *Cardinality map (number of data captured by each neuron).*

We have not found any state of the art studies based on artificial neural networks having as input the bone scintigraphic image. Supervised learning where the data to be discriminated is known in advance and seems to be more popular. So most of these studies have used this method. Indeed, according to Chiu et al. [6- 8] Multilayer Perceptrons give the best model. They found that the best final architecture of the neural network model is the four-layered perceptrons. For other authors the use of these Multilayer Perceptrons poses a lot of difficulties especially for the resolution of problems using neurons of discontinuous types. This is how the determination of the optimal architecture is done using statistical theories concerning the choice of a model like that of [9]. These authors tested the combination of several classifiers of the Multilayer Perceptrons type. This combination improves performance by aggregating several classifiers together to build a more efficient one. Other algorithms such as the Feed-Forward network [10], a supervised three-layer network using a normally Gaussian non-linear transfer function for hidden neurons and a linear transfer function for output neurons. In the literature, we have found other supervised learning neurons like the "Feedback network" where it is possible to have signals traveling in both directions by the introduction of loops. And their condition continually changes until they reach a point of equilibrium. Next to it we find a Hopfield network [11] which is a specific type of Feedback network designed to act as a form of associative memory, in a manner similar to parts of the human brain. The purpose of associative memory is to converge to a remembered state of learning when part of the state is presented as an input. For unsupervised learning neural networks with the use of Kohonen's self-organizing maps, the algorithm process depends only on inputs and does not require the intervention of a supervisor. In the context of data analysis, which interests us, Kohonen's algorithm is presented as a generalization of a popular algorithm which is the mobile center algorithm or Forgy's algorithm [12-13]. Indeed, the data to be analyzed consist of observations (pixels of the scintigraphic image) whose structure we seek to understand and to learn the corresponding dependencies which seem not to be known yet [14].

# 4. Conclusion

Supervised learning methods are more used in artificial intelligence to aid in the diagnosis of medical pathologies. But since the advent of the discovery of Kohonen's self-organizing maps in 1982, applications in medicine of artificial neural networks have become increasingly popular. We hope this present work to be innovative as we did not encounter such a paper in the literature which used as input the pixels of the scintigraphic image to establish a classification for an aid in the differential diagnosis of medical pathology after realization of the ascending hierarchical classification and reconstruction of the scintigraphic image.

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