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Detection of Cluster in Self-Organizing Maps for Controlling a Prostheses using Nerve Signals

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Abstract. In order to control a prostheses by means of biological nerve signals, a self-organizing map (SOM) has been used to classify nerve signals recorded by a regeneration type neurosensor. The trained SOM contains the information about the relation between the recorded nerve signal and the winning neuron of the SOM. Classes of nerve signals fired by defined axons can be found in cluster on the SOM. For controlling a prostheses, the clusters on the SOM must be assigned to an action of the prostheses. Since the medical stuff is usually not experienced to identify the clusters within the SOM we have developed Clusot, an algorithm that defines automatically clusters within SOMs.

After a short introduction to the project of controlling a prostheses by nerve signals, we present the signal processing of the project. In this paper, we focus on the automatic detection of clusters within a trained SOM using Clusot. Clusot will be explained within the context of the project in question.

Introduction

A global overview of the idea for a peripheral nervous system (PNS) remoted limb prostheses [4] is shown in figure 1. Nerve signals will be recorded and amplified by a regeneration-type neurosensor [8, 2]. Then, an artificial neural net (ANN) is applied which classifies the resulting signals in order to assign certain limb movements to the signal classes. A control unit uses the resulting information to regulate the movement of the prostheses.

Ideally, the prostheses is equipped with sensors. Signals from the sensors will be processed by an ANN and transmitted via a signal generator and the neurosensor to the PNS. This means, the prostheses will be completely controlled from the PNS like a natural limb.

Up to now, the first part of the feedback loop is realized. The Signalprocessing is done by different ANNs, such as INCA [6] for the separation of the nerve signals out of the recorded mixtures, Kohonens self-organizing map (SOM) [7]

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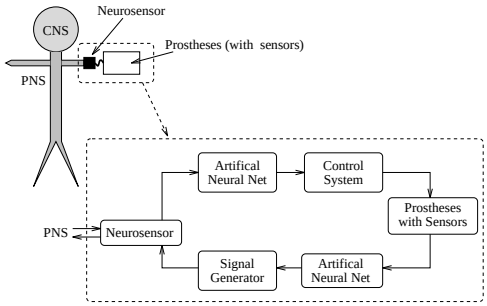

Figure 1: Scheme Configuration of a bio-neural controlled prostheses

and Clusot for the classification of the identified nerve signals. The whole description of the system including the data preprocessing, the signal processing as well as the characterization of the nerve signals is given in [2, 3].

In this paper we focus on the detection of cluster within a trained SOM. In order to explain the algorithm and its use, we are using the example of the nerve controlled prostheses described above.

Automatic detection of cluster in SOM

An important problem during classification using SOMs is the definition of the clusters within the trained SOM. The detection of clusters within Kohonen's SOM requires an experienced user. Since the medical staff (which will be responsible for the implant of the nerve controlled prostheses) is usually not experienced with the detection of clusters in Kohonen's SOM and the whole system still must be easy to handle for them, we have developed a tool called Clusot [2] to detect the clusters of a trained map automatically.

Clusot can be applied for one- and two-dimensional SOMs. In this paper we focus on the algorithm for the two-dimensional SOM. The algorithm is explained within the context of the nerve controlled prostheses, but it can be applied for other classification problems as well [2].

Data set

The data set, which is used here for the classification, has been recorded by the Institut für Biomedizinische Technik (IBMT)[1]. IBMT has chosen the stomatogastric nervous system (STNS) of the crab *Cancer pagurus* which contains about 30 nerve cell bodies [3].

A typical recorded sequence of the signals of these cells are shown in figure 2. The durations of the recordings are 24 respectively 40 seconds. The data set were recorded using a sample frequency of 5 kHz.

[1]The authors like to thank J.-Uwe Meyer, Cornelia Blau and their team from IBMT at St. Ingbert, for giving the data at our disposal.

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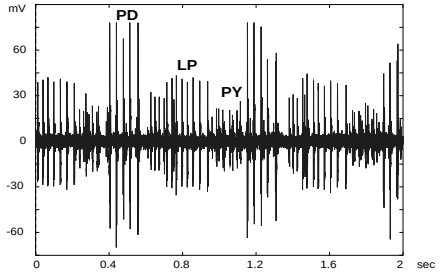

Figure 2: One detail out of the recordings from the gastric nerve of a crab. Nerve signals from PD, LP and PY motoneurons are labeled.

This system has been chosen since the STNS is probably the only nervous system which contains a reasonable small number of neurons which almost all have been identified. Thus, the results obtained by the definition of the clusters of the trained SOM using Clusot can be verified by neurologists for their correctness.

Training of Kohonens SOM

For the classification of the data set a two dimensional SOM with 10 neurons in both dimension have been applied. The training data set consists of 2667 vectors with six components. The computation of the training vectors has been described elsewhere [2, 3].

The SOM, which has been obtained after the training, is very well disposed and has no topological defects. This can be confirmed using the topographic Waber-product [1] which returns a value of -0.0024 for the trained map [2].

Clusot

After obtaining a well ordered map, what is required for the use of Clusot, it is important to identify the clusters within the trained SOM since every cluster represents specific nerve signals from an axon respectively from a group of axons (e.g. PD or PY cells) which will be assigned to an action of the prostheses.

There are different methods assisting the experienced user finding the clusters in self-organizing maps but none of them provides an automatic detection. Clusot bases on two of these methods [9, 5]. It uses two indicators provided by the trained SOM. The first indicator is, like in the method [9], the euclidean distance between the neurons. The second indicator is the number of hits of a neuron, also called the frequency h [5].

The principle of Clusot is to calculate a surface function basing on the Gaussian probability curve. In a first step, the neurons of the twodimensional SOM with n, m neurons will be mapped on a cartesian system of coordinates

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$z = (x, y)$ with

$$| z | = \sqrt{x^2 + y^2}, \quad 0 \leq x \leq n-1, \quad 0 \leq y \leq m-1, \quad x, y \in \mathbb{R} \quad (1)$$

whereas each neuron n, m will be placed as follows:

$$z = (x_i, y_j), \quad 0 \leq x_i \leq n-1, \quad 0 \leq y_j \leq m-1,$$
$$x_i = i, \quad y_j = j, \quad i, j \in \mathbb{N}_0 \quad (2)$$

In the next step, the euclidean distances between the weight vectors of neighboring neurons will be normalized that way, that the greatest distance d between two neurons will obtain the value $0,99$. For each neuron N_{ij} the corresponding frequency h_{ij} will be assigned and a Gaussian probability curve $\phi_{ij}(z)$

$$\phi_{ij}(z) = \frac{h_{ij}}{\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{|z-(i,j)|}{\sigma_{ij}(z)}\right)^2} \quad (3)$$

will be calculated. For the detection of the cluster a surface function $\Phi(z)$ basing on equation 3 is calculated:

$$\Phi(z) = \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} \frac{h_{ij}}{\sqrt{2\pi}} \cdot e^{-\frac{1}{2}\left(\frac{|z-(i,j)|}{\sigma_{ij}(z)}\right)^2} \quad (4)$$

A crucial point of equation 4 is the computation of $\sigma_{ij}(z)$ which is calculated using the euclidean distance between the neurons. Apart from the outer

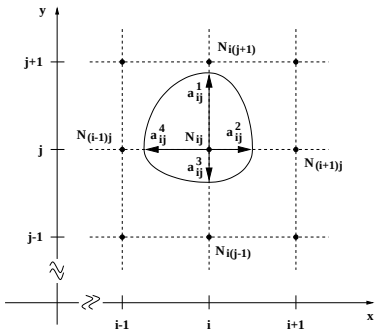

Figure 3: Notation of the ellipsoid radius within the cartesian system of coordinates. The points are representing the artificial neurons.

neurons, each neuron in a twodimensional SOM possesses four neighbours with probably different euclidean distances. Assuming a cartesian subsystem of coordinates with its origin in N_{ij} as shown in figure 3. The values of $\sigma_{ij}(z)$ in the direction of the 4 axis are a_{ij}^1 up to a_{ij}^4 respectively. Remaining values of $\sigma_{ij}(z)$ are calculated basing on the function of an ellipse. For each quadrant of the cartesian subsystem a quarter of an ellipse is calculated whereas neighboring a_{ij} are its radius:

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$$\sigma_{ij}(z) = \quad |\, l \,| \quad = + \sqrt{\frac{1}{\frac{1}{a^2} + \frac{(y-j)^2}{b^2 \cdot (x-i)^2}} \cdot \left(1 + \frac{(y-j)^2}{(x-i)^2}\right)}, \quad x \neq i, \quad y \neq j \quad (5)$$

whereas

$$b = a^1_{ij} = 1 - d_{ij,i(j+1)}, \quad a = a^2_{ij} = 1 - d_{ij,(i-1)j} \quad (6)$$

and $d_{ij,i(j+1)}$ is the normalized distance between the neurons N_{ij} and $N_{i(j+1)}$.

Finally, the local maxima of the surface function $\Phi(z)$ are calculated. Starting from the local maxima, the derivation of $\Phi(z)$ is computed. A cluster border will be defined if the derivation of $\Phi(z)$ exceeds a certain value G fixed by the user. In practical application, values of $0,5 \leq G \leq 2$ are reliable. A more detailed description of Clusot is given in [2].

Result

Applying Clusot to the trained SOM the surface function $\Phi(Z)$ shown in the left illustration of figure 4 was obtained. Using a value of $G = 0.7$ the cluster drawn within the SOM in the right illustration of figure 4 were determined.

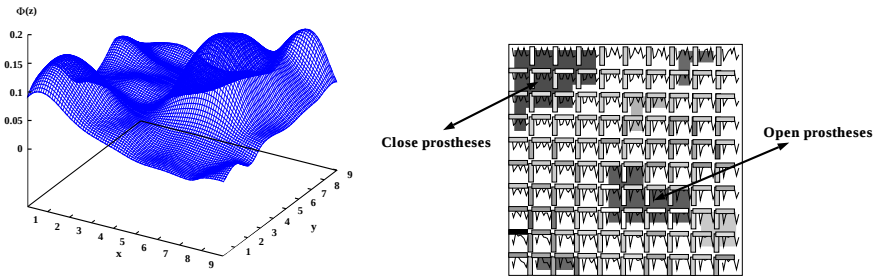

Figure 4: Left illustration: Surface function $\Phi(z)$.
Right illustration: The trained SOM with obtained clusters. Two of the clusters has been chosen to assign an action of the prostheses.

As mentioned above, each cluster represents the signals from an axon respectively from a group of axons (e.g. PD or PY cells). This result has been confirmed by experts working with the STNS of crabs[2]. Every time a nerve signal occurs, it will be classified to its corresponding cluster. Because of this we are able to recognize the signals from certain axons in order to control the movement of the limb prostheses. In our case we control an artificial commercial hand. This hand has two degrees of freedom: open/close and speed/power. The first degree of freedom has been directly coded to the SOM as indicated in figure 4. The second degree of freedom is coded within the frequency of occurance of the signal.

[2]Comparable results have been obtained for nerve signals from the sciatic nerve of a rat which innervates the paw of the rat [2].

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Conclusion

In this paper, we have presented an algorithm for automatic detection of cluster within trained SOMs (Clusot). We have shown the algorithm of Clusot using the example of a nerve controlled prostheses. Clusot is able to detect the cluster within a trained SOM representing specific nerve signals or signals from groups of axons. The use of Clusot allows the application of the SOM for classification tasks in the medical field.

To conclude, we have presented Clusot which realizes an automatic detection of cluster within trained SOM. This algorithm is not only limited to twodimensional SOMs, but it can be used for one-dimensional SOMs as well. Future work will be the extension of Clusot for higher dimensional maps.

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