NEURAL NETWORKS: A DIAGNOSTIC TOOL FOR GASTRIC ELECTRICAL UNCOUPLING?

Catherine Gooi and Martin Mintchev

Abstract: *Neural Networks have been successfully employed in different biomedical settings. They have been useful for feature extractions from images and biomedical data in a variety of diagnostic applications. In this paper, they are applied as a diagnostic tool for classifying different levels of gastric electrical uncoupling in controlled acute experiments on dogs. Data was collected from 16 dogs using six bipolar electrodes inserted into the serosa of the antral wall. Each dog underwent three recordings under different conditions: (1) basal state, (2) mild surgically-induced uncoupling, and (3) severe surgically-induced uncoupling. For each condition half-hour recordings were made. The neural network was implemented according to the Learning Vector Quantization model. This is a supervised learning model of the Kohonen Self-Organizing Maps. Majority of the recordings collected from the dogs were used for network training. Remaining recordings served as a testing tool to examine the validity of the training procedure. Approximately 90% of the dogs from the neural network training set were classified properly. However, only 31% of the dogs not included in the training process were accurately diagnosed. The poor neural-network based diagnosis of recordings that did not participate in the training process might have been caused by inappropriate representation of input data. Previous research has suggested characterizing signals according to certain features of the recorded data. This method, if employed, would reduce the noise and possibly improve the diagnostic abilities of the neural network..*

Keywords: *Neural Networks, Gastric Electrical Activity, Gastric Electrical Uncoupling*

1. Introduction

Neural networks are useful tools in medical settings. They have been applied successfully in classifying various forms of Parkinson syndrome [1], in diagnostic electromyography [2], and in studying breast cancer disease [3]. These applications are usually implemented using Kohonen self-organizing neural networks [1-3]. Kohonen maps build clusters based on the similarities among input data. In the present study this technique will be applied in diagnosing gastric electrical uncoupling.

1.1. Medical Condition

Gastric motor function is an important part of the digestive process, and entails the storing, mixing and grinding of food, as well as its movement towards the intestines. This process requires the coordination of gastric smooth muscle contractions. Similarly to cardiac contractions, stomach contractions are preceded by electrical activity. These electrical events determine the frequency, velocity and direction of the contractions [4]. Accordingly, abnormal gastric function can occur when electrical signals are not synchronized, i.e. the electrical signals are uncoupled. To detect uncoupling, internal recordings of gastric electrical activities are made [5]. From these recordings it is important to be able to categorize the severity of uncoupling. This paper proposes the use of neural networks for such categorization.

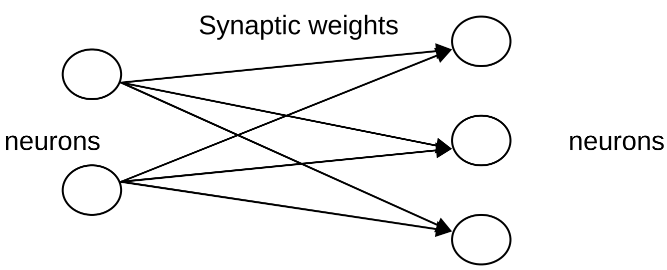


Figure 1: Simple Neural Network Architecture

1.2. What Is a Neural Network?

Neural networks consist of interconnected simple computing cells, referred to as "neurons" [6]. The strengths of the interconnections between these neurons are called synaptic weights (Figure 1).

Through modification of the synaptic weights, called learning or training, the neural network is able to store information.

1.3. Neural Network Training

In the first part of the training process the synaptic weights are initialized to small random values. Next, a training set of data is introduced to the network. There are two types of learning: (1) supervised learning, and (2) unsupervised learning. In supervised learning, a set of inputs along with target outputs is provided to the network. The network passes the inputs through the layers of neurons and modifies the synaptic weights according to a learning algorithm, which adjusts the outputs closer to those of the desired target outputs. In the case of unsupervised learning, no target outputs are provided. An example of unsupervised learning is the Kohonen map's competitive learning [7-8]. Kohonen maps cluster input data according to their similarities.

1.4. Kohonen Maps

Kohonen self-organizing maps are a type of neural network. They consist of two layers of neurons, the input neurons and the output neurons. Each input neuron is connected to every output neuron [6]. An example of Kohonen map architecture is shown in Figure 2.

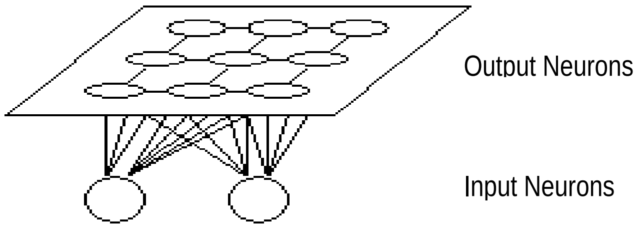


Figure 2: Kohonen Map

Kohonen maps learn in a competitive manner. First, the synaptic connections between the input and the output neurons are initialized, and each output neuron is characterized by a synaptic weight vector. Next, an input pattern (vector) is randomly selected. The Euclidean distance between the input vector and each synaptic weight vector is computed, and then the output neuron with the shortest Euclidean distance is declared the winning neuron. The synaptic weights of the winning neuron are adjusted, increasing the similarity between its synaptic weight vector and the input vector. Similarly, the weight vectors of the neurons in the proximity of the winning neuron are adjusted, increasing their similarity, but to a lesser degree than that for the winning neuron [8]. The algorithm for weight adjustment is:

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \eta(t)\big(x_i(t) - \omega_{ij}(t)\big) \qquad (1)$$

where $\omega_{ij}(t)$ is the synaptic weight value from input neuron *i* to output neuron *j*; $x_i(t)$ is the input to neuron *i* at time *t*; and $\eta(t)$ $(0 < \eta(t) < 1)$ is the learning rate coefficient.

Due to its ability to group similar data, competitive networks are particularly useful for diagnosis, allowing similarly characterized inputs to be clustered together. This learning method, however, does not allow the user to control the categories into which the input will be classified. Learning vector quantization (LVQ) networks, on the other hand, allow the user to classify the input vectors into predetermined categories.

1.5. Learning Vector Quantization (LVQ).

LVQ is a supervised learning technique employed in combination with Kohonen maps [8]. As illustrated in Figure 3, an LVQ network consists of an input layer, a competitive layer and a linear layer [9].

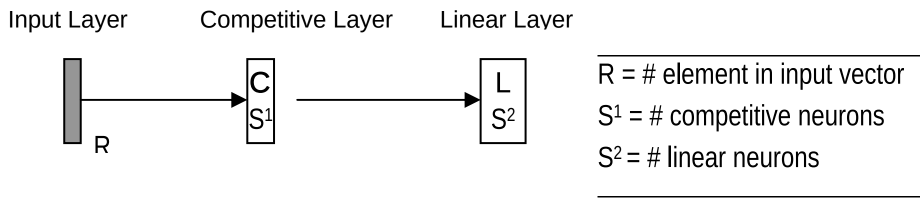


Figure 3: LVQ Network Architecture

The competitive layer classifies the inputs as described above, while the linear layer classifies the outputs from the competitive layer into target values. In other words, the outputs of the competitive layer are subclasses of the target layer. If the output of the input vector matches the target value, the weight vectors of the winning neuron, n_w, are modified with the following algorithm,

$$n_w(t+1) = n_w(t) + \eta(t)[x(t) - n_w(t)], \qquad (2)$$

otherwise they are modified using:

$$n_w(t+1) = n_w(t) - \eta(t)[x(t) - n_w(t)], \qquad (3)$$

Equation (2) moves the competitive neurons closer to vectors that belong in its same class, and Equation (3) moves the competitive neurons farther from vectors that do not belong in its same class. In Equations (2) and (3), $n_w(t)$ represents the winning neuron's present synaptic weight vector, i.e. at time t, $n_w(t+1)$ represents the winning neuron's modified synaptic weight vector, i.e. at time $t+1$, $\eta(t)$ $(0 < \eta(t) < 1)$ represents the learning rate coefficient, and $x_i(t)$ is the input to neuron i at time t.

2. Aim

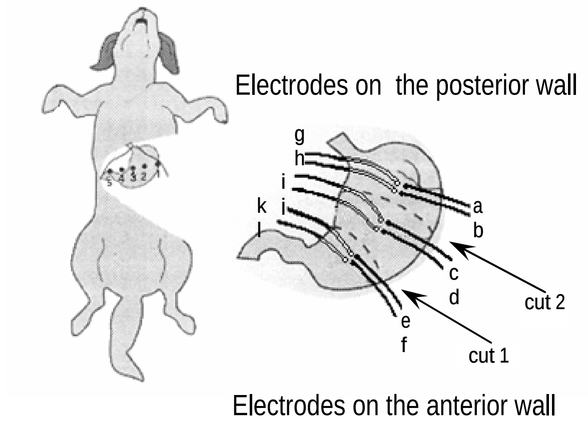
The aim of this paper is to apply Learning Vector Quantization neural networks in recognizing gastric electrical uncoupling from internal recordings of canine gastric electrical activity.

3. Experimental Design

3.1. Data Acquisition

In order to understand and recognize varying degrees of uncoupling, 16 anesthetized dogs underwent surgically induced gastric uncoupling [9]. Data were obtained from each dog in the three different states, basal, mild uncoupling and severe uncoupling. Six pairs of electrodes were placed on the gastric antral wall, three along the anterior and three along the posterior. These six pairs of electrodes provided 6 channels from which half-hour recordings of gastric electrical activity (GEA) were made for each state. During the first session the dogs were in the basal state, in the second session the stomach was divided by a single circumferential cut of the entire gastric muscle between the distal and the middle electrode sets, dividing the organ into two electrically active regions each oscillating at different electrical frequency, thus producing mild uncoupling. Finally, a second circumferential cut surgically divided the stomach between the middle and the proximal electrode sets, dividing the organ into three electrically active regions, simulating severe uncoupling (Figure 4).

Gastric electrical activity (GEA) signals were filtered in a frequency band of 0.02 - 0.2 Hz and digitized with a 10 Hz sampling frequency. In total, 18 000 samples were collected for each channel per session.



Internal Canine GEA	
Channel	Electrode Combination
1	a-b
2	c-d
3	e-f
4	g-h
5	i-j
6	k-l

Figure 4: Data acquisition setup. The locations of the circumferential cuts are also denoted.

3.2. Neural Network Modelling

The aim of the neural network is to categorize the condition of the dogs into one of the 3 states:

1. Basal;
2. Mild Uncoupling: One circumferential cut;
3. Severe Uncoupling: Two circumferential cuts.

In view of the fact that the categories were predetermined, an LVQ network was chosen for the implementation. The network was created, trained and simulated using the Neural Network Toolbox from MatLab 6.0 (MathWorks, Natick, MA).

Since the neurons from the competitive layer form subclasses for the linear layer's target neurons, the number of neurons in the competitive layer should always be larger than the number of target neurons [9]. In addition, the number of neurons in the competitive layer should be smaller than the number of training examples, otherwise each training example would have a separate winning neuron in the competitive layer and the competitive layer would serve no purpose in the classification process. Given these limitations the number of neurons in the competitive layer was chosen to be six, two neurons belonging to each target class.

Next step in the implementation process was the training of the network. In order to train the network, data were to be selected and represented in a vector form acceptable to the input neurons.

3.3. Data Selection and Representation

To determine which data samples should be used, the data from dogs 1 through 16 were displayed using locally designed gastrointestinal signal acquisition and analysis software, GAS v. 3.0. Visual inspection indicated that channel 2 was not functioning for dog 1, thus it was not used for training the neural network. In addition, data from dog 2 and 3 were collected utilizing filters with smaller bandwidths. This was inconsistent with the data acquisition parameters utilized for the other records, so these two recordings were also disregarded when training the neural network. It was also noted that sometimes signals were not adequately registered within the first few seconds of recording, thus data for training and validation were extracted from the middle of the recording time. 5000 data samples from each channel were utilized. Each training session was, therefore, characterized by an input vector of 30 000 elements, 5000 from each of the six channels.

3.4. Training and Simulating

The LVQ network was trained by repeatedly feeding the network with data from dogs 4 through 13, and their corresponding target outputs. Each time the data was fed through the synaptic weights were modified according to the learning algorithm described earlier. The first output neuron was designated for the basal state, the second for mild uncoupling, and the third for severe uncoupling.

Data from dogs 4 through 16 were used for simulation and verification. The vectors for each case were input and the output was recorded and compared with the desired outputs. Outputs from dogs 4 to 13 provided verification of the network ability to diagnose for cases it had seen before during the learning process and outputs from dogs 14 to 16 were used to demonstrate the network ability to generalize.

4. Results

4.1. Neural Network Training and Verification

Training was performed with thirty training vectors from Dog 4 to Dog 13 (three from each dog), and subsequently, seven simulations were executed with data from Dog 4 to Dog 16. The average result is shown in Table 1.

	Percentage of correct diagnosis
Dog 4 – Dog 13	89.5%
Dog 14 – Dog 16	31.0%

Table 1: Verification results

The performance of the network for diagnosing dogs within the training set was fairly high, at 89.5%. However, its generalization ability was poor and had an accuracy of only 31%.

5. Conclusion

The network diagnosed well for the training data, but was unable to provide accurate diagnosis for new cases. Performance of a neural network is directly related to the quality of its input data. Therefore, it is necessary for these data to contain sufficient information [10]. It is important to represent the input data in an appropriate fashion, eliminating noise where possible, and capturing characterizing features. Similar study [2] suggested that segments of the signal could be characterized by seven parameters, duration, spike duration, amplitude, area, spike area, phase and turns. This study involved diagnosing neuromuscular disorders based on the electromyography (EMG) recordings of muscle electrical activity. The study resulted in an accurate diagnosis in the order of 80%. As a proposal for further study, a similar approach might be applied for characterizing gastric electrical signals.

Acknowledgement

This study was sponsored in part by the Natural Sciences and Engineering Research Council of Canada

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FOURIER NEURAL NETWORKS: AN APPROACH WITH SINUSOIDAL ACTIVATION FUNCTIONS[1]

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Abstract: *This paper presents some ideas about a new neural network architecture that can be compared to a Fourier analysis when dealing periodic signals. Such architecture is based on sinusoidal activation functions with an axo-axonic architecture [1]. A biological axo-axonic connection between two neurons is defined as the weight in a connection in given by the output of another third neuron. This idea can be implemented in the so called Enhanced Neural Networks [2] in which two Multilayer Perceptrons are used; the first one will output the weights that the second MLP uses to computed the desired output. This kind of neural network has universal approximation properties [3] even with lineal activation functions.*

Enhanced Neural Networks

The only free parameters in the learning algorithm are the weights of one *MLP* since the weights of the other *MLP* are outputs computed by a neural network. This way the backpropagation algorithm must be modified in order to propagate the *Mean Squared Error* through both *MLPs*.

When all activation functions in an axo-axonic architecture are lineal ones ($f(x)=ax+b$) the output of the neural network is a polynomial expression in which the degree n of the polynomial depends on the number m of hidden layers [2] ($n=m+2$). This lineal architecture behaves like *Taylor* series approximation but with a global schema instead of the local approximation obtained by Taylor series. All boolean functions $f(x_1,\dots,x_n)$ can be interpolated with a axo-axonic architecture with lineal activation functions with n hidden layers, where n is the number of variables involve in the boolean functions. Any pattern set can be approximated with a polynomial expression, degree $n+2$, using an axo-axonic architecture with n hidden layers. The number of hidden neurons does not affects the polynomial degree but can be increased/decreased in order to obtained a lower *MSE*.

This lineal approach increases *MLP* capabilities but only polynomial approximations can be made. If non lineal activation functions are implemented in an axo-axonic network then different approximation schema can be obtained. That is, a net with sinusoidal functions outputs *Fourier* expressions, a net with *ridge* functions outputs ridge approximation, and so on. The main advantage of using a net is the a global approximation is achieved instead of a local approximation such as in the Fourier analysis.

[1] Supported by INTAS 2000-626, INTAS YSF 03-55-1969, INTAS INNO 182, and TIC 2003-09319-c03-03.