Intelligent Neural Interface - Signalprocessing of Nerve Signals using Artificial Neural Nets

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Abstract

In this paper we shortly review the aim of the INTER[1]-project (*I*ntelligent *N*eural In*TER*face) and present our proposal for the modus operandi to process real nerve signals. In the second part we present a Self-Organizing Map (SOM) that classify nerve signals from the gastric nerve of a crab. Thereafter we present the interpretation of the obtained clusters by an integration based signal interpreter and the control of a limb prostheses using the data set.

Introduction

The aim of the INTER project (*I*ntelligent *N*eural In*TER*face) is to investigate fundamental issues related to the design and fabrication of a new generation of microsystems applicable as neural prostheses. A global overview for a peripheral nervous system (PNS) remoted limb prostheses is given in [3] and is shown in figure 1.

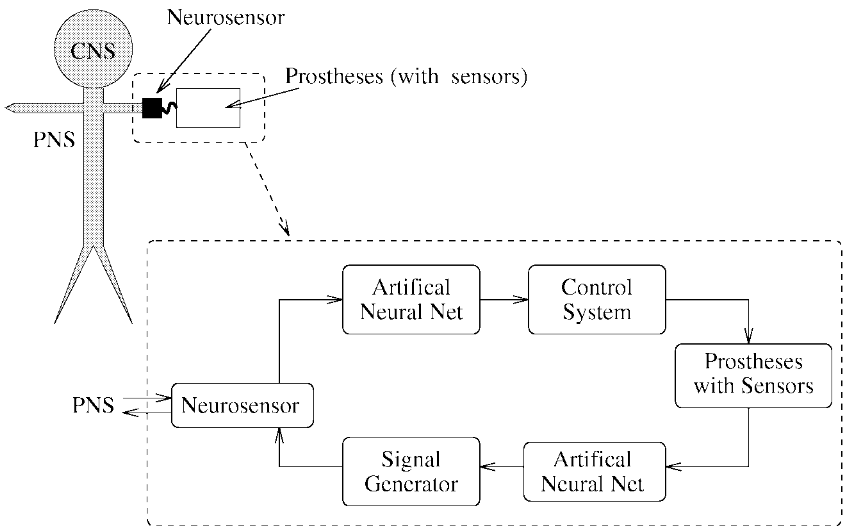

Fig. 1: Scheme Configuration of a bio-neural controlled prostheses

Nerve signals will be recorded and amplified by a neurosensor. The neurosensor is a regeneration-type sensor. The principle of the neurosensor is explained below. The signal will first be processed by an artificial neural net (ANN), which eliminates crosstalk and leads to pure axon signals.

Then, a second 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.

[1]The INTER project is supported by the European Community under ESPRIT BR project #8897.

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 peripheral nervous system (PNS). This means, the prostheses will be completely controlled from the PNS like a natural limb.

The neurosensor

The principle of the implementation and the neurosensor which will be used in the INTER-project is shown in figure 2 [3].

Peripheral nerves of vertebrates will regenerate if severed. For this reason, the surgically severed axons regenerate through the via holes of the perforated chip from the proximal stump towards the distal stump of the nerve. Nerve signals can be recorded by electrodes, which are enclosing some of

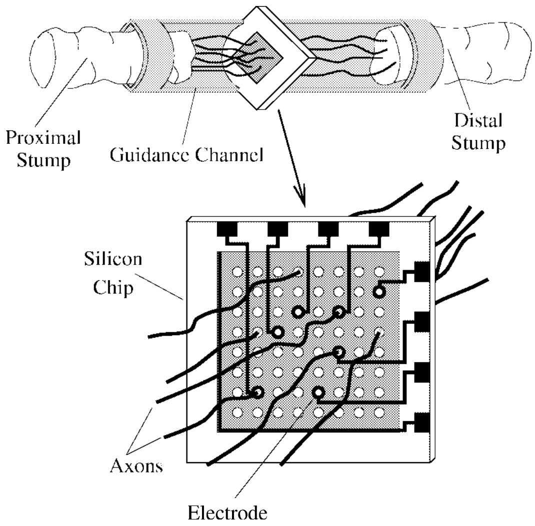

Fig. 2: Implementation scheme for the regeneration-type neurosensor

the via holes. The amplified signals are transferred to the units which are controlling the prostheses as shown in figure 1.

Modus Operandi

A global overview of our proposal for the signal processing is shown in figure 3. In order to avoid recording effects like crosstalk the preprocessed data (in this case preprocessed means amplified and filtered) will be separated concerning to their sources using Independent Components Analysis (INCA), presented by Jutten and Hérault [5].

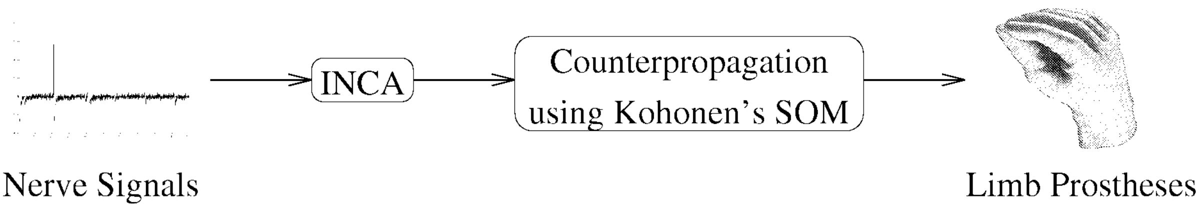

Fig. 3: Proposal for signal processing

The classification of the nerve signals must be done by unsupervised learning algorithms because we have to verify our approach using the results of In Vivo tests. For this reason we are going to apply Kohonen's self-organizing map (SOM) [6]. A more detailed description of the proposal is given in [1].

Data set

In order to prove the use of Kohonen's SOM [6] within the proposal we have used a data set which has been given at our disposal by our INTER partner IBMT, St. Ingbert. They made single electrode recordings from the gastric nerve of a crab like they are described in [4]. 21 motor neurons has been identified until now, among them 2 PD, 1 LP and 8 PY cells. The durations of the recordings are 40 seconds. The data sets were recorded using a sample frequency of 5 kHz.

Data preprocessing

In a first step of the data preprocessing we are using a low pass filter in order to reject the drift effects which are introduced by the recording unit.

In the upper illustration of figure 4 the typical waveform of a nerve signal after the rejection of the drift is shown. The shape of the recorded nerve signal can be divided into three parts: one positive peak followed by one negative peak and again one positive peak. This (+|-|+)-sequence appears every time a spike occurs. In addition to the occurance of a (+|-|+)-sequence a time criterion must be fulfilled: the (+|-|+)-sequence must be finished within 6 msec. If both criteria are fulfilled, we assume that this (+|-|+)-sequence was due to a true nerve signal. In order to reject the noise, only signals exceeding a threshold of 1.5 and consisting of a (+|-|+)-sequence are considered as a nerve signal.

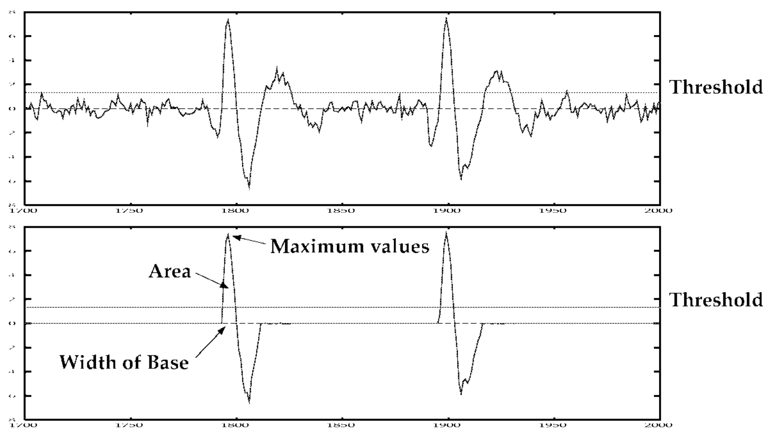

Fig. 4: Upper illustration: Typical waveform of a recorded nerve signal.
Lower illustration: The signal after filtering and spike detection. To characterize the waveform, the area, the width of the base and the maximum respectively minimum values are detected.

A critical point of this method is the threshold. Because we want to detect as many nerve signals as possible, we have chosen a threshold of 1.5, which is in fact very close to the noise. Using this method to judge the recorded data, all nerve signals within the noise are rejected. To avoid this problem, we are currently working on another method, which will judge the signal by a fuzzy rule [2].

Since the third peak is not physiological and is due to the filtering during the recording as well as the next generation of amplifiers and filters are expected to avoid the third peak within the (+|-|+)-sequence, we have cut it. The result of the nerve signal detection is shown in the lower illustration of figure 4. Compared with the upper illustration, only the sequences of the recorded data which are judged as a nerve signal are available. The waveform of these signals are characterized using the area, the width of base and the maximum respectively minimum value of the peaks. Using this characterization we have computed for each spike a vector containing six components (area, width of base and maximum (minimum) value of each peak).

Classification with Kohonen's SOM

For the classification of the data set we have used a two dimensional SOM with 10 neurons in both dimension. The training data set consists of 2667 vectors with six components. The computation of the training vectors has been described above.

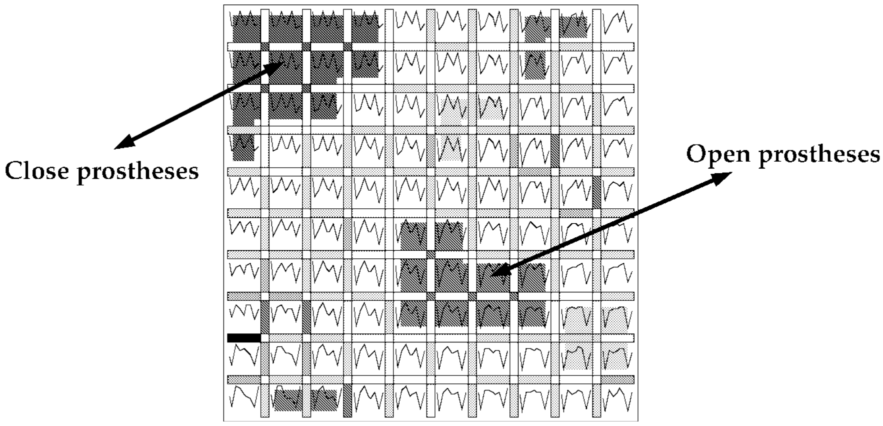

Fig. 5: The trained SOM with obtained clusters. Two of the clusters has been chosen to be assigned for an action of the prostheses.

Each square of the trained SOM shown in figure 5 represents a neuron. The greyscaled rectangles are corresponding to the euclidean distances between the neurons. The curves within the squares are the codebook vectors.

The SOM also contains the clusters we have obtained after training. Each cluster represents the signals from an axon respectively from a group of axons (e.g. PD or PY cells). This means, every time a nerve signals 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 hand which is shown in figure 6. This hand has two

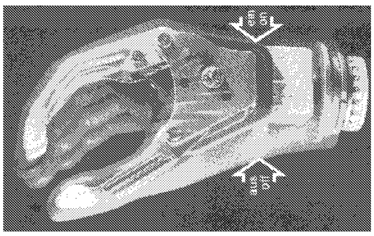

Fig. 6: The used prostheses. The hand has two degrees of freedom: open/close and speed/power.

degrees of freedom: 1) open/close and 2) speed/power (if the hand runs against an obstacle it changes automaticly from speed into the power mode). The first degree of freedom has been directly coded to the SOM as indicated in figure 5. The second degree of freedom is coded within the frequency of occurance of the signal.

Control unit of the prostheses

The interpretation of the frequency has been done by an integration based signal interpreter. The principle of the system is shown in figure 7. Assuming the occurance of an spike train which has been classified by the SOM. The spike train will be integrated and will assign an action to the prostheses while the integrated signal exceed a minimum value. This avoids that a hazardous or spontaneous single nerve signals leads to an action of the prostheses. The higher the frequency of the spike train the higher the integration value. In order to stop an action as fast as possible the

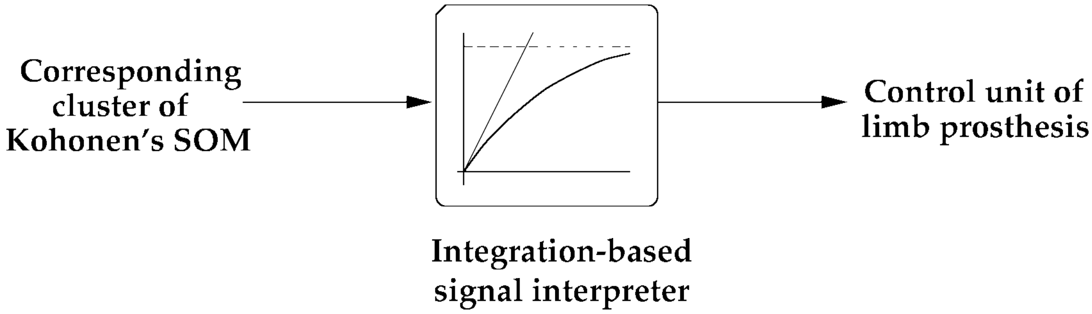

Fig. 7: The principle of the control unit. The output for the control unit is integration based, but not linear.

integration value will be decreased much faster than increased. For this reason the function of the control system is nonlinear.

Since the integration value is directly coupled with the speed of the movement respectively the power, the second degree of freedom can be controlled through the frequency of the occurance of the nerve signals. In fact, the processing system consisting of the SOM and the integration based signal interpreter realizes a pulse-frequency decoder.

Conclusion and future work

After presenting the aim of the INTER-project, we have shown a nerve signal processing unit which is able to control a limb prostheses. The nerve signal unit consists of a Kohonen's self-organizing map (SOM) and an integration based signal interpreter. The SOM classifies the nerve signals corresponding to its meaning. The integration based signal interpreter controls the movement of the limb prostheses based on the frequency of occurance of the nerve signals. The two parts of the processing unit realize a pulse-frequency decoding of nerve signals. Since this version of the integration based signal interpreter is still a very simple model, we have to validate this approach using a more complex biological inspired function in the future.

Acknowledge

The INTER project is supported by the European Community under *ESPRIT BR project #8897*. The INTER consortium consist of 6 partners:

- *Scuola Superiore S. Anna*, Pisa, Italy
- *Hahn-Schickard-Gesellschaft, Institut für Mikro- und Informationstechnik*, Villingen-Schwenningen, Germany
- *Centro Nacional de Microelectronica*, Barcelona, Spain
- *Centre Hospitalier Universitaire Vaudois*, Lausanne, Switzerland
- *Fraunhofer Institut, Biomedizinische Technik*, St. Ingbert, Germany
- *Universität Tübingen, Institut für Physikalische und Theoretische Chemie* and *Lehrstuhl für Technische Informatik*, Tübingen, Germany

Coordinator of the project is *Scuola Superiore S.Anna* at Pisa. The *Lehrstuhl für Technische Informatik* is junior partner of the *Institut für Physikalische und Theoretische Chemie*.

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