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Artificial Neural Net Based Signal Processing for Interaction with Peripheral Nervous System

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Abstract **In this paper, two Artificial Neural Net (ANN) based signal processing systems processing signals using interfaces to the peripheral nervous system will be presented. The aim of the paper is to show ANN's capability to meet requirements needed to interact with the biological nervous system.**

First, a system for classification of nerve signals is presented. Recordings of nerve signals done by regeneration type neurosensors interfacing the peripheral nerve system are processed by ANNs in order to identify their origin axons out of a recorded mixture of several axons.

The second system presented is somehow the inverse of the processing system above. In this case, the aim of the signal processing system is to introduce information to the peripheral nervous system by computing appropriate stimulus pattern for functional electrical stimulation. The connection to the peripheral nervous system is done by Cuff-electrodes.

Keywords **ANN-based signal processing, self-organization, man-machine-interface, nerve controlled prostheses, functional electrical stimulation**

I. INTRODUCTION

Inspired by the advance in neurology as well as in sensor technologies and miniaturization combined with the corresponding possibilities, in the middle of the 20th century the idea arose to establish a direct connection between human and machine, a man-machine-interface. A schematic representation of the man-machine-interface, the human paragon and its technical realization is given in figure 1.

One version of these kind of interface is to contact directly the nervous system of human by means of high specialized connectors in order to measure the information flow on the nerves. Another possibility is the stimulation of the nerves in order to introduce information to the nervous system.

Due to the development of new sensor technology establishing a direct connection to nerves, such as regeneration-type neurosensor [1] or Cuff-electrodes [2], man-machine-interfaces became realizable.

Establishing a direct connection towards the nerve will have no use without a adequate signal processing. This paper presents two signal processing systems based on Artificial Neural Nets (ANN) for interfacing the peripheral nervous system. One of them process nerve signals recorded using regeneration-type neurosensors, the other one compute stimulation patterns for functional electric stimulation (FES). Both systems were developed during two different projects granted by the European Community: INTER (Intelligent Neural Interface, BR #8897) and GRIP (Integrated System for the Neuroelectric Control of Grasp in Disabled Persons. RLTR #26322).

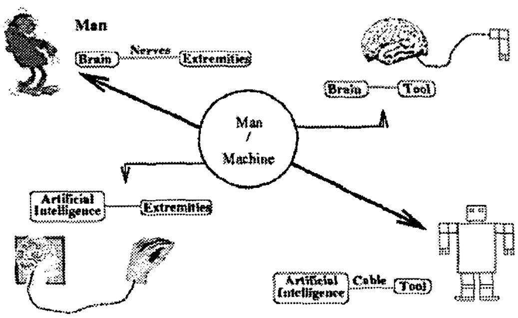

Fig 1: Schematic representation of the man machine-interface

II. ANN BASED CLASSIFICATION OF NERVE SIGNALS

In this section, a system for processing nerve signals recorded from regeneration-type neurosensors is presented. First, the principle for contacting the peripheral nervous system (PNS) is described. Then the signal processing system to identify and to classify nerve signals and thus to extract information form the recording is presented.

A. Recording using Regeneration-Type Neurosensors

Peripheral nerves of vertebrates will regenerate if severed. For this reason, the peripheral nerve can be surgically severed in order to insert the proximal and the distal stump into a guidance channel. The guidance channel encloses the regeneration-type neurosensor. The main functions of the

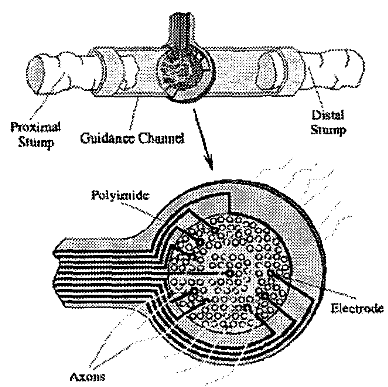

Fig 2: Regeneration-type neurosensor

guidance channel are to provide a stable physical connection between the chip and the stumps of the nerve, and to promote nerve generation and guide axons growth from the proximal nerve stump towards the distal nerve stump.

The sensor is fabricated of polyimide perforated by multiple 'via holes'. The axons regenerate through the via holes from the proximal stump towards the distal stump of the nerve. Nerve signals can be recorded by electrodes, which are enclosing some of the via holes. A circuitry amplifies and preprocesses the nerve signals. The amplified signals are transferred to the units which are controlling the prostheses as shown in figure 2. For more details about the chip, please refer to [1].

Due to the recording method, several problems arise. Here, only the most important ones regarding the signal processing system are mentioned. First of all, not only one axon will regenerated through an electrode, but several of them (approx. 10-15 axons). Also, there will be cross talk between the electrodes introducing redundant information within the recordings on different electrodes. Finally, in the case of *In Vivo* recordings in animals, the action corresponding to nerve activity is a priori not known.

B. Modus Operandi

A global overview of our proposal for the signal processing is shown figure 3. For separating the different nerve signals from the recorded mixture of different axons grown through an electrode, we are proposing to use INCA, presented by Jutten and Hérault [3]. The algorithm allows to separate different signals from several independent sources (in our case a source is an axon) without any knowledge about the sources. It is a so called blind separation of sources.

Since the recordings will be obtained by *In Vivo* tests with animals, there will be no defined target pattern corresponding clearly to the recorded nerve signal [4]. Thus the classification of the nerve signals must be done by unsupervised learning algorithms. We are going to apply Kohonen's self-organizing map (SOM) [5,6].

Once the SOM is trained, it is important to identify the clusters within the SOM since every cluster represents specific nerve signals originating from a certain axon. Since the detection of the cluster requires an experienced user whereas the tool should also be usable for user without large experience in ANNs, Clusot has been developed [8]. Clusot detects automatically Cluster within trained SOM.

A more detailed description of the proposal is given in [4,7].

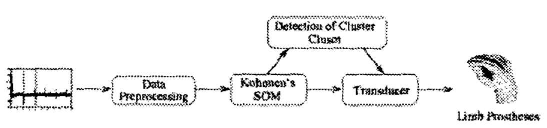

Fig 3: Modus Operandi

C. Results

The signal processing system has been tested with a data set, which has been recorded by the Institut für Biomedizinische Technik (IBMT). IBMT has chosen the stomatogastric nervous system (STNS) of the crab *Cancer pagurus* which contains about 30 nerve cell bodies [4]. The duration of the recordings are 24 respectively 40 seconds. The data set were recorded using a sample frequency of 5 kHz.

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 [4,7].

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 [9] which returns a value of -0.0024 for the trained map [7].

After obtaining a well ordered map, what is an important condition for the application of Clusot, the cluster within the trained SOM have been identified

Applying Clusot to the trained SOM, the cluster shown in figure 4 have been obtained. Each cluster represents the signals from an axon respectively from a group of axons (e.g. the PD or PY cells of the stomatogastric nervous system). This result has been confirmed by experts working with the STNS of crabs. Every time a nerve signal occurs, it will be classified to its corresponding cluster.

Applying this system not only to the above mentioned data set but also to recordings from the sciatic nerve of a rat, it has been shown, that the system is able to work in real time on a Sun SPARCstation 10. It is able to classify a nerve signal from the moment of occurrence up to the classification done by the SOM within less than 0.8 msec. Thus, using this ANN based signal procesing system, nerve signals from PNS can be classified and interpreted nerve signals in real time, what is a substantial need for an applicable man-machine-interface. The signal processing system has also been successfully applied to recordings from the sciatic nerve of a rat [7] as well as to recordings from the central nervous system [10].

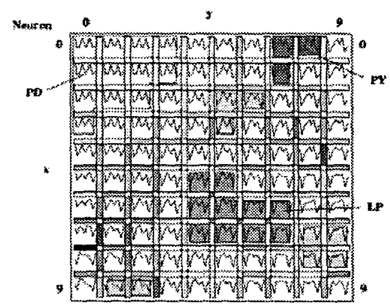

Fig 4: Cluster within the trained SOM obtained by Clusot representing the recognized nerve signals. PD, PY and LP cells are marked.

III ANN BASED FUNCTIONAL ELECTRICAL STIMULATION

In order realize a system to introduce information to the PNS, somehow the inverse of the nerve signal processing described above must be established. One possibility to introduce stimuli to the PNS is functional electrical stimulation (FES). In this section, after a short introduction to a FES system using a Cuff-electrode, an ANN-based processing system for computing appropriate stimuli for FES is presented.

A Cuff-Electrodes for Functional Electrical Stimulation

Designing a system of functional electrical stimulation (FES) it is necessary to use an interface to the PNS that can transmit various neuroelectric stimulation patterns which are similar to the corresponding axonal stimuli in biological systems. One possibility is to use Cuff-electrodes. The Cuff-electrode realizes the man-machine-interface towards the PNS transmitting the stimuli computed by an signal processing system situated outside of the body as shown in figure 5. The stimuli pattern will then be send via a radio link to the Cuff-electrode resp. a subcutaneous amplifier connected with the Cuff-electrode.

The Cuff-electrode which has been used wihtin the GRIP-project was developed by the Fraunhofer Institut für Biomedizinische Technik (IBMT), St.Ingbert (Germany). This 3-polar electrode for the connection with the nerve is manufactured of flexible polyimide. It encloses axon bundles of the PNS. Thus, the stimuli can be transferred to the PNS. For more details about the Cuff-electrode please refer to [2].

An important point using Cuff-electrodes is their relative position. Depending how the Cuff-electrode is situated relative to the nerve and how the polarity of the Cuff-electrode is chosen, differentiated stimulation can be introduced to the PNS. A detailed description about this problem is given in [11].

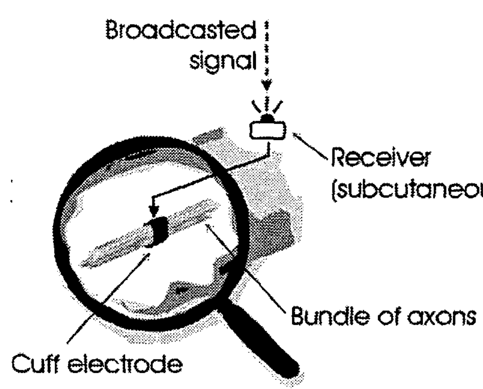

Fig 5: Implementation scheme for the subcutaneous receiver unit and the cuff electrode.

B Modus Operandi

In contrast to the interpretation of nerve signals for the stimulation of the PNS it is absolutely necessary to know the corresponding reaction due to a certain stimuli. Thus, in a first step, e.g. the reaction of a concerned extremity innervated by the stimulated PNS must be recorded.

Once several experiments about the reaction of the concerned extremity regarding different stimulation patterns are recorded, an ANN can be trained. The task of the trained ANN is to compute an appropriate stimuli for a desired reaction of the concerned extremity.

Since desired action and related stimuli is known, supervised learning can be applied. Since the system should be applicable for closed loop control the focus was on ANN architectures like Multi-Layer-Perceptron (MLP), CascadeCorrelation and FlexNet. Several algorithms for supervised learning like Backpropagation, Quickprop, CascadeCorrelation, Cascade-2 learning algorithm, Flex learning algorithm and Resilient Propagation has been investigated for accomplishing this task [12]. The ANN architecture that performed best with high generalization ability and high stability were FlexNet using the Flex learning algorithm [13]. Thus, FlexNet has been selected for computing the appropriate stimuli for a certain task.

C Results

In order to validate the approach, an animal model has been chosen. In this case, a pig was designated for *In Vivo* experiments since it has similiar anatomic conditions compared with humans (especially for the nerve sizes). The experimental set up is shown in figure 6.

In the animal model, an arbitrary angle trajectory which can be defined by an user has been chosen as target position of the pig's limb. In order to control the limb's position, the angle of the rotation axis is measured. Thus, the given trajectory describes an angle dependent on time. Nevertheless, the actual angle position is given to the processing system, which is in fact the ANN, and thus close the loop for the control of the pig's limb.

The data consists of several trials over 27 seconds using exactly the same stimulation patterns in order to record the corresponding reaction of the limb. In-between the trials well

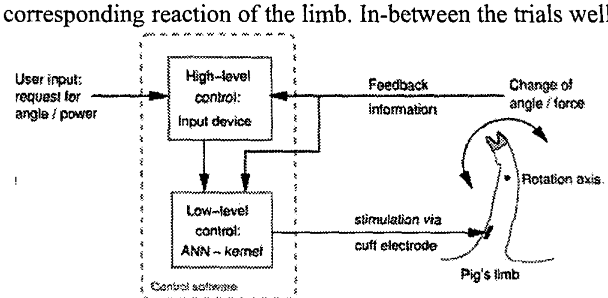

Fig 6: Scheme for experimental set up for closed loop control of a pig's limb

defined rest periods has been carried out in order to reduce fatigue effects.

After recruiting the data, FlexNet was trained for computing appropriate stimuli for the PNS for an arbitrary trajectory. After a training time from less than 10 min the training of FlexNet was completed performing less than 1200 training epochs. The resulting FlexNet had 16 hidden neurons and showed a training error of less then 5 percent averaged absolute error. The net structure was 2-2-2-2-2-8-1 with a total number of 155 weights.

The resulting trajectory during an animal experiment is shown in figure 7. Nevertheless the real angle do not perfectly hit the target trajectory, the resulting trajectory do not exceed the limit of 5 percent averaged absolute error. This is a promising result since it has to be taken into account, that this signal processing system not only computes an corresponding stimuli but also have to adjust the position of an unstable nonlinear system. Nevertheless, investigations to ameliorate the system are currently undertaken.

IV Conclusion

In this paper, two signal processing systems able to interact with the PNS have been presented. One system is able to classify nerve signals recorded by regeneration-type neurosensors in real time. The other one is able to compute appropriate stimuli for functional electrical stimulation of the PNS in order to achieve a predefined task.

Both signal processing systems are based on Artificial Neural Nets (ANNs). In both cases, the ANNs show the capability to perform the signal processing tasks in a non-linear way as often required in biological system. To conclude, regarding the presented systems, ANNs are capable to interact with the biological nervous system for signal processing purposes.

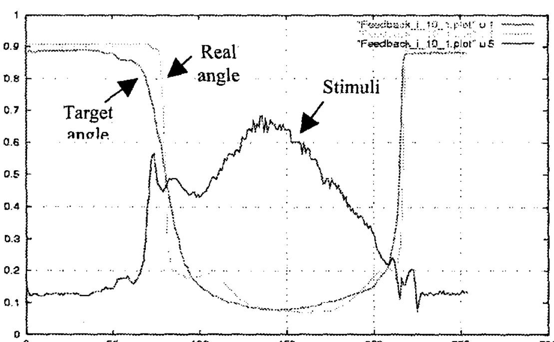

Fig 7: Result for stimulation experiment in a pig.

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