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Artificial neural networks and machine learning for man-machine-interfaces - processing of nervous signals

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Abstract. Recently, Man-Machine-Interfaces contacting the nervous system in order to extract information resp. to introduce information gain more and more in importance. In order to establish systems like neural prostheses or Brain-Computer-Interfaces, powerful (real time) algorithms for processing nerve signals or their field potentials are required. Another important point is the introduction of information into nervous systems by means like functional neuroelectrical stimulation (FNS). This paper gives a short introduction and reviews different approaches towards the development of Man-Machine-Interfaces using artificial neural networks respectively machine learning algorithms for signal processing.

1 Introduction

In 1868, although the biophysical basics of the nervous system were unknown at that time, Helmholtz already depicted the nervous system as the system transmitting information in a biological subject while comparing it with wires of the telegraph system [1]. It took more than 60 years until technical development made it possible to prove this assumption by observing single neuron activity in detail, which led to the discovery of action potentials by later Nobel price laureate Adrian in cooperation with Bronk [2]. Already five years earlier, in 1924, Berger discovered the electroencephalogram (EEG, published 1929) which allows to observe neuronal activity of the brain [3]. In contrast to Adrian & Bronk who used concentric needle electrodes to observe motor units, Berger employed surface electrodes placed on the scalp to measure neuronal activity. Thus, Berger measures sum potentials from diverse regions of the brain whereas Adrian & Bronk observe dedicated signals of single nerve fiber units.

Inspired by the advancement in knowledge of the neuronal system, the development of new recording methods as well as the possibility of miniaturising electronic devices, the idea to connect the nervous system with technical devices via an interface, the so called Man-Machine-Interface (MMI) arose in the middle of the 20^{th} century. Figure 1 shows a scheme of a MMI in principle. Examples are prostheses driven by signals from the peripheral nervous system (PNS) as well as brain computer Interfaces (BCI) for locked-in patients based on signals from the central nervous system (CNS). Vice-versa, the introduction

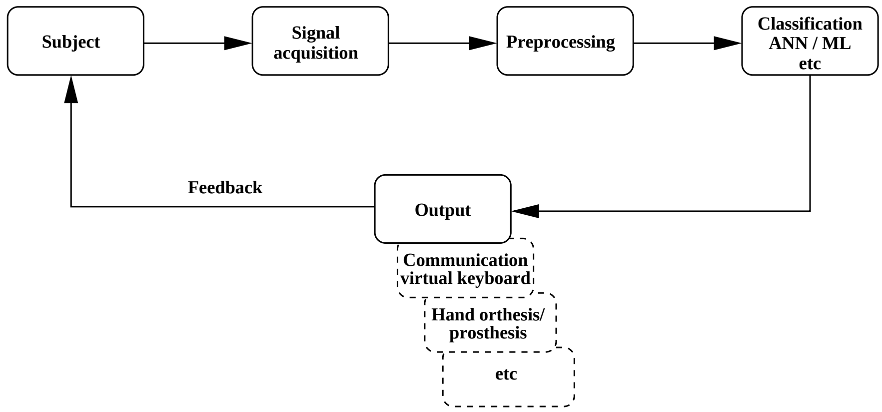

Fig. 1: Scheme of a MMI in principle. Nervous signals are acquired from a subject. Recorded signals are preprocessed in order to ameliorate the classification and thus the correct interpretation of the measured signals. Due to the interpretation, various applications can be driven by means of nervous signals. Finally, some output devices may give feedback, closing the loop back to the subject.

of information into the nervous system in order to control paralysed extremities via functional neuroelectrical stimulation (FNS) of nerves has been realised. Not yet mentioned, but quite important to some MMI and especially for the understanding of information coding within nervous tissues, is the detection and identification of neuronal spikes (spike sorting). Depending on the diversity of applications and thus the use of different technologies a wide range of approaches towards MMI have been developed. In this paper we focus on approaches applying artificial neural nets (ANN) and/or machine learning (ML) to MMI and spike sorting.

After giving a short overview of techniques to connect nervous tissue using invasive as well as non-invasive methods, the paper focusses more or less extensive on three topics within MMI: spike sorting, FNS and BCI based on ANN/ML processing methods. At the end, a short conclusion will be drawn.

2 Connecting nervous tissue

A broad range of technical devices to realise connection with nervous tissue have been developed throughout the last decades. Their main distinctive feature is whether they are invasive or non-invasive. In a second step, they may be classified regarding the area they are used in, e.g. PNS or CNS. In the following, a very short overview about often used devices to contact nervous tissues regarding the classification system mentioned above is given.

2.1 Non-invasive methods

The probably most well-known device to contact the nervous system is the surface electrode since it is used commonly for EEG. Also, it is applied for recording of muscle activity in the case of electrocardiogram (ECG). Surface electrodes are provided in a broad range of different sizes and forms. Mainly, they consist of a flat round surface made of silver/silver chloride. Using electrographic gel, electrodes can be fixed on the skin. Surface electrodes are often used for BCI. In this case, electrode caps can be used. Further non-invasive methods for BCI are magneto-encephalography (MEG) [4] and functional magnetic resonance imaging (fMRI).

Other non-invasive devices are planar microelectrode arrays (MEA) [5, 6]. On these planar MEA nervous tissue can be cultivated in order to investigate the application of drugs or information processing [7, 8]. Thus, they are not usable for MMI, but since they are important regarding the investigation of nervous information processing, at least they should be mentioned.

2.2 Invasive methods

Most commonly used as invasive method are needle electrodes in all possible variations. The simplest needle electrode is just a pointed conductive material connected to an amplifier which is introduced into nervous tissue. For the most part of needle design, the electrodes are made of iridium, platinum, steel or tungsten with diameters from 13 μm up to 80 μm [9]. Starting for this simple configuration, multielectrodes have been developed. A multielectrode is (more or less) simply the composition of several single electrodes into a bunch, whereas all electrodes contact the nervous tissue. Mainly used are stereotrodes where 2 electrodes are mounted like a twisted pair cable and tetrodes where 4 electrodes are used. In order to stabilise this construction, different techniques have been applied. A quite tricky one has been developed by Uwe Thomas Recording [10, 11]. They grow quartz around 4 platinum/tungsten electrodes and sharpen the quartz cylinder. Thanks to its stability, this design has found widespread use.

Since we live in a century dominated by semiconductors, the idea to use semiconductor for electrodes came up quickly. Due to its crystalline architecture very pointed needles can be etched. Additionally, several electrodes can be placed on a needle using common techniques from semiconductor production [12]. Most known representatives of this approach are the so called Michigan [9] and Stanford probes [13]. Both used initially 30 μm thick silicon plate to etch structure by photolithography. Currently, in some projects these kind of electrodes are designated for use in CNS to establish BCI [14]. A further development of this technique led to 3-dimensional electrode arrays designated to be implanted in the cortex [15, 9]. In fact, the arrays consist of a semiconductor plate into which a number of needle electrodes, sometimes with different lengths, have been etched. This architecture is dedicated to be implanted into the cortex to investigate larger regions at the same time and in different depth. Well known are single microelectrodes penetrating deep into the brain capable of measuring action potentials of few neurons, and multiple electrode array systems penetrating only 1–2 mm into the brain. A compact review of invasive techniques is available [16]. Lately, invasive methods are being used increasingly for BCI. Of these, the most well-known are electrocorticography (ECoG), whereby a grid of typically 64 electrodes is placed subdurally onto the cortex [17, 18].

A special form for PNS are regenerative multielectrodes [19]. These electrodes take advantage of the property that 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 which encloses the chip.

The sensor itself 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 widespread electrode for PNS used not only for recording but often for functional neuroelectrical stimulation of nerve fibers are cuff electrodes [20]. These electrodes are made of flexible materials which are able to enwrap a nerve fibre. Electrodes are placed at the inner side of the roll in order to record nervous signals or to stimulate the nerve fibre. In order to provide optimal selectivity regarding the area within the stimulated nerve fibers, cuff electrodes can be equipped with point electrodes [21].

3 Spike sorting

An important issue in the processing of nerve signals is the detection of the original source of action potential occurring in a recorded time stream of signals from (multi-)electrodes, the so called spike sorting. Current multielectrode arrays allow recording from as many as one hundred neurons [22]. The ability to identify the origin of an action potential is important to interpret information processing as well as the direction of information flow. With increasing number of electrodes, the level of automation becomes an important factor in addition to the accuracy of spike sorting which affects the accuracy of all subsequent systems. In order to achieve the goal of automation as well as to meet the challenge of adaptability to individual circumstances, ANN have often been applied to this problem. A selection of these approaches will be described below. An overview on spike sorting can be found in [23].

Already in 1988, Hopfield nets [24] have been applied to spike sorting [25]. In this work, Hopfield nets have been compared with template matching, a common tool for spike sorting. According to [25], template matching is superior to Hopfield nets.

Of course, feedforward-nets have been often used to classify action potentials from nerves [26, 27, 28]. A comparison with template matching has been done in [29]. In this case, a fully connected feedforward-net with 24 input neurons, 8 neurons in the hidden layer and 3 output neurons was used. This approach shows better classification results than template matching, especially in the case of a high signal-to-noise ratio.

Nevertheless, all approaches described above lack the important ability to learn automatically. Thus, in recent years ANNs used for spike sorting concentrate more and more on unsupervised learning algorithms. In 1994 ART2 [30] was applied to spike sorting [31]. Due to the obviously high variance within the action potentials used for the training of the net, 8 prototypes were identified whereas only two different nerve signals were presented within the data base. Thus, ART2 tends to overclustering. Kohonen's self-organising map (SOM) [32] was found to to avoid this problem, but at a first glance only in a complex hybrid system including 4 ANNs [33, 34]. A complete system, from recording via multielectrodes up to the control of a limb prosthesis including a complete automatic spike sorting system for signals from PNS, has been presented in [35]. The spike sorting system consists of a signal processing flow called ISC which uses 3 different processing steps: Independent Component Analysis (ICA), SOM and Clusot [36]. This architecture has been successfully transferred to signals from the CNS and even ameliorated by replacing SOM by a modified version of Growing Grid [37], taking into account refractory periods of action potentials [38].

4 Functional neuroelectrical stimulation

Even though ANN are quite popular for neuromuscular stimulation, surprisingly they are not often used for direct FNS of nerve fibers. In [39] different architectures of ANN have been investigated in order to stimulate nerves controlling the knee. Mainly different architectures of feedforward nets including time-delay structures have been applied to the problem of closed-loop control. According to the author, a feedforward net with time-delay structure obtains better control results than classical control techniques from control engineering.

Another example of direct FNS of nerves is given in [40]. In this paper a closed loop strategy for the control of hand grasp movements for paralysed patients which is based on an ANN is presented. To this end, an ANN controller applies FNS to a peripheral nerve with the aim to initiate axonal stimulation patterns similar to those generated by the central nervous system. Training and testing of the control strategy were based on data gained in vivo from a pig's limb while applying FNS. The heart of the controller consists of a FlexNet [41]. Starting with input and output neuron layers this algorithm incrementally builds a multi layer perceptron architecture during the training phase. Using Rprop learning for the weight adaption, FlexNet determines the best suited position in existing or new layers for competing groups of candidate neurons in the current network. Despite muscle fatigue and other nonlinear disturbances the control strategy results in high control quality.

5 Brain computer interfaces

The aim of brain computer interface research is to establish a new augmentative communication system that translates human intentions—reflected by suitable brain signals—into a control signal for an output device such as a computer application or a neuro-prosthesis [42]. This section introduces BCI terms and techniques and current state of the art in rehabilitation.

Recent years have witnessed growing research interest in BCIs. Firstly, this is due to the fact that man machine interfaces have the potential to alleviate many neurological and neuromuscular diseases. Stroke and spinal cord injury rehabilitation by neural prosthetics is also possible. Secondly, the task of extracting and interpreting useful information from the brain or nervous system remains a difficult and interesting challenge for researchers.

Non-invasive input methods for BCIs are usually the brain's neuronal activity recorded at the scalp by electroencephalography (EEG), magneto-encephalography (MEG) and functional magnetic resonance imaging (fMRI) [43]. An MEG-BCI using SVM was presented in 2005 with 10 healthy subjects (offline) and 4 healthy subjects spelling a name online [44].

Lately, invasive methods are being used increasingly. Signal acquisition is by electrocorticography (ECoG), whereby a grid of typically 64 electrodes is placed subdurally onto the cortex, single microelectrodes penetrating deep into the brain capable of measuring action potentials of single neurons [45], and multiple electrode array (MEA) systems penetrating only 1–2 mm into the brain. Invasive methods offer higher spatial resolution and the promise of finer-grained control.

Classification of the brain signal requires high accuracy and speed. High accuracy is required to prevent mishaps when controlling an artificial hand, for example. Patients' frustration levels are bound to rise if unintended communication output is given. Fast classification is of the essence for online feedback (patient must be able to relate feedback to current brain state). Also, training time should be short to avoid user frustration. BCI systems currently in use at patients' homes still rely on simple, linear methods such as discriminant analysis (DA) or similar methods due to consistent and interpretable results.

Researchers are working towards increasing the information transfer rate by increasing accuracy, speed, or number of classes of the classifier. This can involve specialised preprocessing such as generating complex features (ICA, common spatial patterns [46]) or feature selection methods (such as stochastic, genetic algorithms or recursive feature elimination [47]). Specialised classification algorithms are nonlinear methods such as SVM, ANN, LVQ and decision trees. An overview is given in [48].

Slow cortical potentials and DA were used for classification to enable the first ALS patient to communicate a message with a BCI spelling device [49]. A three-class speller for communication using DA was tested with three healthy subjects who reached an average of 2 letters/min [50]. A BCI was successfully combined with functional electrical stimulation (FES) of forearm muscles to allow a paraplegic patient to regain use of his hand [51]. Wheelchair control, which would enhance mobility of ALS patients, is a problem which could be solved in the coming 3 years.

Many research groups have successfully completed studies with invasive techniques for control and movement prediction in monkeys. Linear methods and ANN were used to predict hand trajectories with MEA implants in 2 primates [52]. Monkeys have used neural control to move a cursor onto a target [53]. Amongst other methods, SOM was used to generate control signals [54]. In humans, first communication successes using ECoG grids were achieved with subjects who obtained an ECoG implant to monitor epileptic activity [17, 18].

6 Conclusion

In this paper, an overview regarding MMI focusing three topics has been given: spike sorting, functional neuroelectrical stimulation and brain computer interfaces. Even though in all these areas linear methods have been successfully applied, ANN and ML have been investigated as well in order to ameliorate the approaches. For example, BCI combined with FNS/FES of leg muscles for gait rehabilitation could become a future application, but is still far from reach due to the fine-grained control needed which may be provided by ANN/ML. In most cases, ANN and/or ML have been shown to be superior compared with classical methods. Thus, we predict that, in due course of time, ANN/ML will become essential to MMI-applications.

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