Toward a Brain-controlled Prosthetic Arm through Advanced Machine Learning Methods

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Abstract. The disability associated with limb amputation makes it difficult to perform the simplest everyday activities. Robotic prostheses can be used to address this complication. These prostheses apply machine learning methods to the EMG/ENG signals to understand the amputee's intention. The use of ENG signals compared to EMG signals is very recent, and allows not only the amputee to perform gestures, but also to mitigate the symptoms of the phantom limb and to restore the sense of touch, since the robotic arm can provide tactile feedback to the peripheral nervous system. In this work, a technique to classify ENG signals, recorded from individuals with limb amputation, is described. All the steps that compose the technique are illustrated in detail. In the last part of this article, some innovative deep learning techniques are suggested in order to improve the state-of-the-art.

Keywords: neuroprosthesis, peripheral nervous system, signal decoding techniques, motor command signals, machine learning methods, post-processing.

1 Introduction

More and more people are suffering from motor disabilities that make it difficult to perform trivial activities in everyday life. Among this group of people, some have had an amputation. Problems related to the lack of a limb are both anatomical and psychological [4]. These can be partially solved with the use of robotic prostheses [2]. Ideally, the prosthesis could be directly controlled by the amputee by capturing his/her electromyography (EMG) signals or electroneurogram (ENG) signals and applying machine learning methods to automatically understand the intention on movement based on those signals. State-of-the-art EMG signals are the most widely used, since classification results are accurate, and thanks to the fact that electrodes used to acquire the signal are non-invasive [10].

However, controlling the robotic arm based on the analysis of ENG signals acquired from the peripheral nervous system (PNS) would enhance the user experience, since the robotic arm could provide tactile feedback to the user through the PNS. Even though intrafascicular electrodes are invasive, the availability of tactile feedback allows to mitigate the symptoms of phantom limb syndrome and restores the sense of touch [6]. Moreover, signals extracted from PNS are very selective, receiving signals from a small number of neurons. Hence, they have a good potential to accurately recognize gestures at a fine-grained level.

The use of intrafascicular electrodes presents a challenge. Indeed, they are not fixed, but tend to move within the nerve. This leads, over time, to having different patterns of signals during the execution of the same action, and therefore to confuse the machine learning classifier. It is, therefore, necessary to be able to create a model that can be trained periodically with a small training set, also because the collection of the new training set to update the model is obtrusive and uncomfortable for the user.

This work represents an overview of what we are doing and what we want to do in the future to address this challenging research problem. In Section 2, we describe the steps of the methods that we used. In particular, we present the data collection method, we show how we reduced the signals noise by using Wavelet denoising, and we explain how we detected and sorted the spikes produced by each neuron. Moreover, we illustrate how the features has been extracted, we explain how we classify motor actions, and we present our post-processing method. Finally, in Section 3, we report the issues that are still open and the related solutions that can be developed in future works.

2 Proposed methodology

In this section, we illustrate the main steps involved in the classification of ENG signals controlling the arm movements. Of course, the performance of each step is fundamental for the whole process, and can severely influence the final result of the classification. Figure 1 shows the flow chart which specifies the execution order of the steps in the technique.

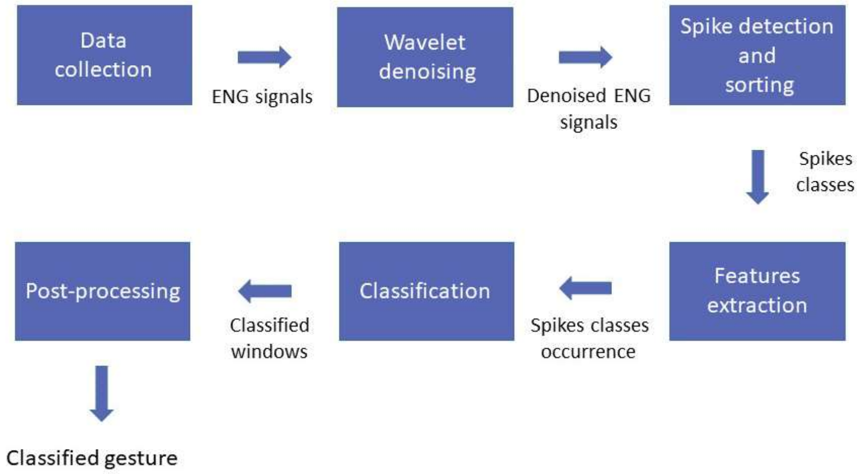

Fig. 1. Flow chart of the main steps used to classify ENG signals.

2.1 Data collection

Here we describe the data collection method used within the Nebias European project[1]. In general, ENG signals can be acquired through the use of different types of electrodes. The one used in the Nebias project is the Transverse Intrafascicular Multichannel Electrode (TIME) [3]. This is inserted transversely into the nerve, in order to communicate selectively with the internal fibres (axons) of the nerve. Its structure allows a multi-site registration and a selective stimulation, thus provides a bidirectional connection between the peripheral nervous system (PNS) and the prosthesis.

After implanting the TIME, in order to acquire a training set for the classifier, the user is asked to imagine performing certain actions, several times, with the missing limb. During the execution of the actions, the neural signals coming from eight sites (channels) and the square wave signal (trigger) were recorded. The latter is produced by a researcher pressing a button during the execution of each action, and allows understanding when an activity begins and when it ends. Figure 2 shows the raw data acquired from the TIME (in blue), as well as the trigger manually set by the researcher. As it can be observed, although many spikes correspond to actions, the signal is very noisy. Moreover, the user's reaction time to the request to execute a command leads to a phase shift between the trigger switch and the action, which results in a small delay between the start of the trigger and the actual start of the activity signal.

[1] http://www.nebias-project.eu/

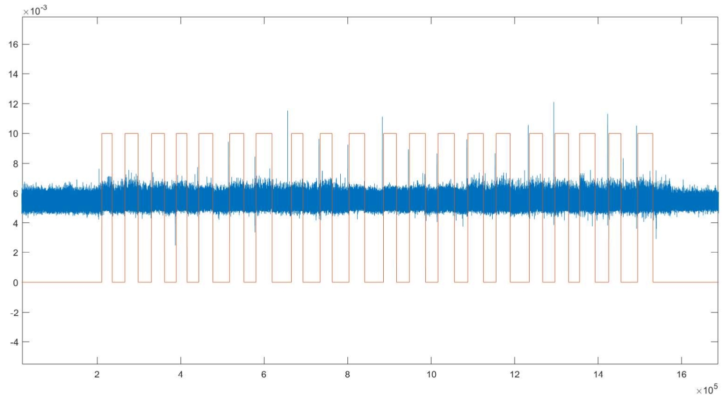

Fig. 2. A sample of the acquired dataset. The ENG signal is represented in blue, while the red lines represent the square wave signal (trigger) which indicates the beginning and the end of an action.

2.2 Wavelet denoising

Real-world ENG signals, being acquired in naturalistic conditions, are affected by a high level of noise. Wavelet denoising (WD) [1] is used to reduce the noise in the raw signal data. WD transforms the noisy signal into noisy wavelet coefficients in an orthogonal time-frequency domain. In this domain, signal features are concentrated in a few large-magnitude wavelet coefficients. Wavelet coefficients, which are small in value, are typically noisy. Hence, we can reduce or remove them without negatively affecting the signal quality. After adjusting the coefficients based on thresholds, we reconstruct the data using the inverse wavelet transform. Figures 3 and 4 show the ENG signal respectively before and after denoising. This phase requires specific expertise, since completely removing the noise can lead to the loss of essential information for the correct classification.

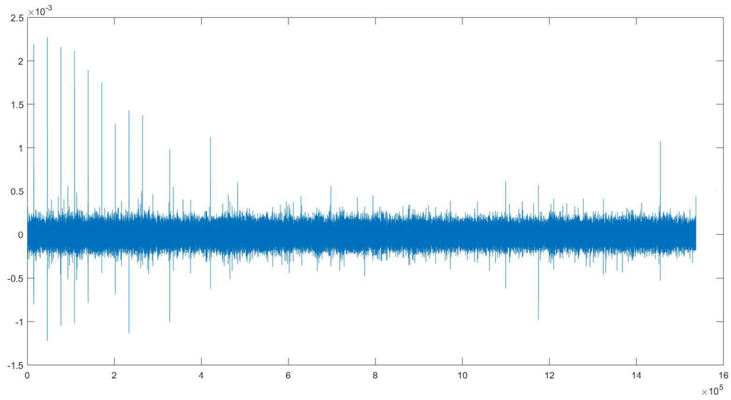

Fig. 3. Raw ENG signal

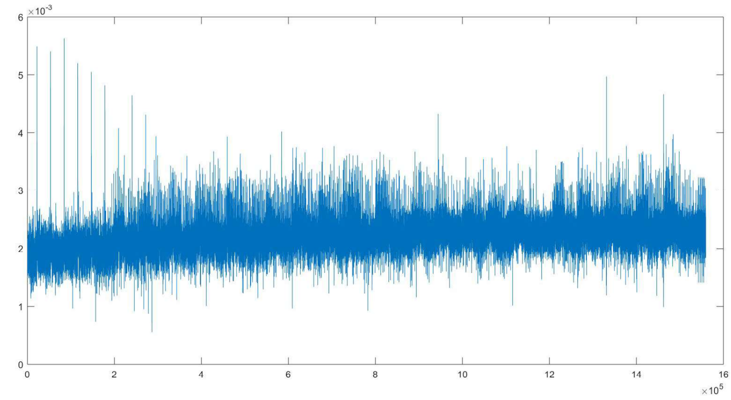

Fig. 4. Partially denoised ENG signal

2.3 Spike detection and sorting

Within the neural signal, each action is characterized by a different set of action potentials. An action potential occurs when a neuron sends information down an axon. The action potential is called a *spike*. Spike sorting [9] creates clusters with spikes having similar shape. Every neuron tends to produce spikes of a particular shape; therefore, each final cluster corresponds to the activity of a supposed neuron.

The spike sorting algorithm is composed of four main steps:

- Filtration: a bandpass filter is applied to continuously recorded data to exclude low-frequency activity so that spikes are more evident.
- Spike Detection: from filtered data, spikes are usually detected using an amplitude threshold.

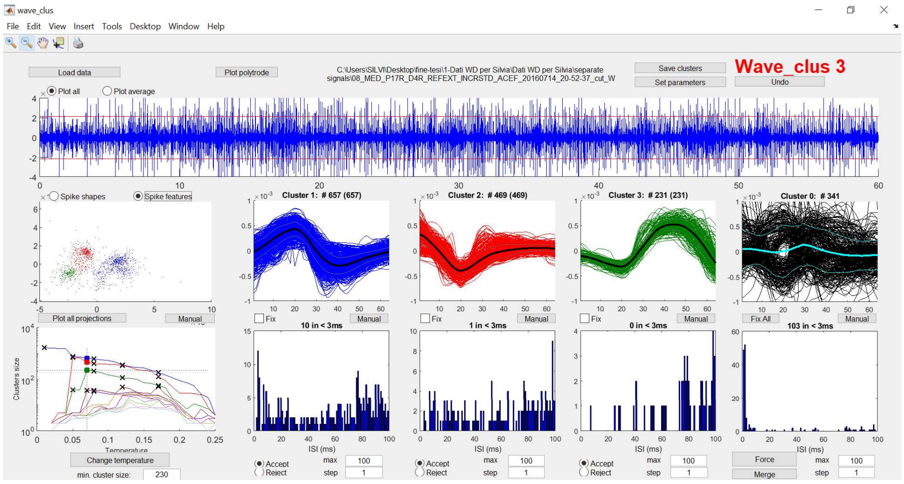

Fig. 5. The wave_clus tool for spike sorting.

– Feature extraction: to perform spike sorting, it is necessary to extract the features of the spike shapes. This step reduces the dimensionality, thus saves computational time and improves clustering results by deleting noise-dominated inputs.
– Clustering: the last step of spike sorting is to group spikes with similar features in clusters, corresponding to different neurons. Usually, with TIME-based data acquisition, spikes are clustered in three classes.

Figure 5 shows the wave_clus tool[2] used to perform the above steps.

2.4 Features extraction

Observing a single sample is not sufficient to understand whether an action is taking place or not. This is because not all samples that compose action have spikes, and some samples that compose inaction may have spikes. Therefore, signal samples have been grouped by a sliding window [8] . The choice of the size of the windows is very important, indeed we want a good spikeness (number of spikes per window) in order to differentiate as much as possible between actions and inactions.

If we use a TIME, which allows multi-site registration (as already mentioned in the Section 2.1), we have to perform feature extraction to reduce the high dimensionality of the windows. From every window, we can extract $n \cdot 3$ features, where n is the number of channels from which the signals were recorded. These features correspond, for each channel, to the number of spikes of each cluster observed in the time window.

[2] https://github.com/csnle/wave_clus

2.5 Classification

Classification, with post-processing, is the focus of this work. Usually, for the classification of motor actions, Support Vector Machines (SVM) are used [7]. SVM is a recognition technique used in many studies for the analysis of biomedical signals. It is a binary classifier and determines the hyperplane that provides maximum class separation. The idea of the method is to divide the feature space, obtained by mapping incoming data into a higher dimensional space using a kernel function, into two parts using linear or non-linear decision boundaries. In the case of multiple classification problems, data is divided into several problems with two classes.

However, acquiring signal data from real patients is difficult. Hence, we target the use of a classifier that allows the use of small training sets. So, in addition to the SVM, we used a Random Tree classifier. Random Tree is a supervised classifier belonging to the ensemble method family. The method is a combination of the Random Forest algorithm and the single tree model algorithm. When building a single decision tree, each node is formed using the best split using all variables. With the Random Forest method, only a random subset of predictors is used. To classify, Random Trees take the feature vector input, classify it using each tree, and assign the class with multiple assignments. Trees are created by resampling the dataset to build each tree (as in the Bagging method), then the algorithm looks for the best split using only a random subset of attributes. This results in decorrelated trees with less error and greater accuracy.

2.6 Postprocessing

After the classification, a post-processing of the results is always performed to understand when the action starts and ends, and to reduce incorrect classifications. Usually, in the literature, a majority voting policy is applied over a sliding temporal window. However, we devised a different post-processing method.

In our method, we analyze the classifier predictions sequentially using two counters: "NA" measures the number of activity predictions, while "NI" measures the number of inactivity predictions. These counters are updated respectively whenever the prediction "A" (activity) and prediction "I" (inactivity) are encountered. Once one of these counters reaches a certain threshold, one of these cases occurs:

- if the threshold is exceeded by "NI" and the previously analyzed sequence was considered an activity, then the currently analyzed sequence is identified as the end of activity;
- if the threshold is exceeded by "NI" and the previously analyzed sequence was not considered an activity, then the currently analyzed sequence is identified as inactivity;
- if the threshold is exceeded by "NA" and the previous analyzed sequence was not considered an activity, the currently analyzed sequence is identified as the start of new activity;

– if the threshold is exceeded by “NA” and the previously analyzed sequence was considered an activity, this means that the previous action is not yet over.

After each case explained above, both counters are set to zero.

3 Future directions

In this paper, we outlined a general framework that we are investigating for addressing this challenging research problem. However, several issues are open, that we will address in future work. In particular, we could reduce the waiting time for the recognition of action by improving the post-processing method. Another direction that we want to investigate consists in the use of different classification techniques. In particular, traditional deep learning methods would seem appropriate for this task. However, it is well-known that in general deep learning classifiers require large training datasets, that currently are not available in this domain. Hence, we will investigate deep learning approaches that do not require large training sets, such as Siamese neural networks [5]. We believe that those networks, which have been used with success for the classification of images, could be successfully applied to these data by devising a novel method for feature extraction. Moreover, we are considering to use active learning algorithms to adapt the model according to the user's feedback.

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