Implementing a Microneurography Setup for Online Denoising of Peripheral Motor Activity: Preliminary Results

Francesco Maria Petrini, Luca Rossini, Federica Giambattistelli, Antonella Benvenuto, Fabrizio Vernieri, Eugenio Guglielmelli, and Paolo Maria Rossini

Abstract—Microneurography has been proposed, since its introduction in the 1960s, as a valuable tool for the study of peripheral neural control of movement, which could drastically improve the current development of neuroprosthetic limbs. The current work on robotic neuroprostheses is predominately performed with amputees surgically implanted with neural electrodes, a procedure whose complexity is currently mastered by very few groups all around the world. The reduced number of reported experiments resolves in poor availability of databases of human peripheral nerve signals, which are needed to fully test the interfacing algorithms, so far limited to animal testing. On the other hand, microneurography is a fully safe and little invasive procedure which can be applied to healthy subjects as well as to amputees and which permits to access peripheral neural motor activity. In order to be implemented as a neuroprosthesis interface, though, the microneurographic data needs to undergo online analysis for motion artifacts removal and white Gaussian noise suppression, features currently missing from the commercial devices. In this paper we report the instrumentation we have been developing to satisfy these requirements. In particular, we currently equipped our setup with an online wavelet denoising filter which substantially reduces white Gaussian noise. Here we present our preliminary results.

I. INTRODUCTION

MICRONEUROGRAPHY (MNG) is the technique, developed by Hagbarth and Valbo, to record percutaneously from human nerve fibers, by mean of a metal microelectrode in the shape of a needle. In a document of 1967 [1], they explain the procedure in detail: the microneurographer stimulates superficially the skin of the subject’s upper or lower limb with a surface probe or a sharp electrode to learn the appropriate path for the needle electrode into the relevant part of the nerve. Successively, he/she inserts two needle electrodes (one of these is used for signal recording and current stimulation whereas the other as reference) through the skin and stimulates by mean of them. Subject’s verbal reports about radiating sensations and contraction of the appropriate single muscle or group of muscles are essential for the correct electrode placement.

In the most recent review about microneurography [2], Gandevia and Hales report experiments and results, the long term effects on subjects, and the required instrumentation. They describe the microneurography as a little invasive and safe procedure: symptoms such as paraesthesia, transient deep aches, hypoaesthesia and muscle weakness, when arisen (10% of all the reported studies), disappear after at most 7 days. However, to avoid any symptom onset, it is recommended that the time spent manipulating the microelectrode is limited to about 1 h and that the same nerve is not restudied within a month.

Moreover, from their paper, three main fields of research emerge. We briefly summarize them in the following.

First, the study of central mechanism involved in pain. The functional properties of unmyelinated C fibers in human skin nerves were studied and their polymodality and receptive field size were illustrated. Second, assessment of autonomic outflow, which is currently studied both for diagnosis and outcome prediction of different chronic diseases. Third, the study of sensations attributed to various cutaneous joint and muscle afferent nerves.

However, there is at least another, potentially breakthrough, application of MNG which was left somehow behind: the analysis of descending motor activity in the peripheral nervous system.

Such a tool could give a huge contribution to the development of robotic neuroprosthesis, whose work is currently predominately performed with amputees surgically implanted with neural electrodes, a procedure whose complexity is mastered by very few groups all around the world [3]. The reduced number of the reported experiments resolves in poor availability of databases of human peripheral nerve signals, which are needed to fully test the interfacing algorithms, so far limited to animal testing [3]. Since microneurography is a fully safe and little invasive procedure, it can give the researchers access to peripheral neural motor activity both from healthy subjects and from amputees.

The current typical microneurographic instrumentation still follows the guidelines described by Gandevia and Hales [2], and can be summarized as a set of analog devices connected as shown in Fig. 1. This setup allows the operator to quickly switch between stimulation and recording sessions, while contemporary listening and viewing the neural signal.
The video signal differs from the audio one because it gets pass-band filtered, full-wave rectified and integrated with a time-constant set. The audio signal, instead, once pass-band filtered, gets reduced of its baseline noise by a threshold discriminator (i.e. a noise slice module). This “two paths” signal conditioning is required by the operator to easily and quickly quantify the nerve activity. More complex signal processing approaches, such as offline wavelet denoising of MNG data [4], can improve the quantification of the nerve activity.

Since Morlet, Grossman and Mayer first talked about wavelet transform [5],[6], its importance rose incredibly in the scientific panorama. In Fig. 2 we report the number of papers per year, published about wavelet transform from 1992 to 2008.

![Fig. 2. Number of papers per year, published about wavelet transform from 1992 to 2008.](image)

In 1994 the wavelet shrinkage, a new method, which used thresholding in the wavelet domain, was demonstrated to be asymptotically near optimal for a wide range of signals affected by additive Gaussian noise [7]. This method was applied to a large number of biomedical applications: Diedrich [4] and Salmanpour [8] filtered raw muscle sympathetic nerve activity (MSNA) offline, Chouakri filtered the electrocardiogram [9], whereas Xia proposed an algorithm for online elaboration of data in industrial applications [10]. Nevertheless, no online human peripheral nerve activity wavelet denoising approach can be found in literature yet.

In this paper we propose an innovative instrumentation set-up which will allow real-time wavelet denoising of MNG signal and we report our preliminary results. Such a system could outdo any standard MNG by compelling the requirements for neuropathesis applications, which are not part of the standard MNG setup. The online monitoring of denoised peripheral nerve activity would allow both clinicians and engineers to realize accurate and reproducible protocols for recording data. In the case of peripheral motor nerve activity, this is of paramount importance because the level of signal is very low: Dhillon et al. [11] report a value in peak to peak equal to about 20 µV.

II. MATERIALS AND METHODS

A. Overview of the system

Our system, shown in Fig. 3, is composed by a high performance single channel amplifier (Model 15LT Bipolar, Quad Amplifier System with shorted inputs noise = 4 µV peak to peak, gain from 5000 to 200000), which is used for the neural signal, and four standard 4-channels amplifiers (Quad AC Amplifier with shorted inputs noise = 4 µV peak to peak, gain from 50 to 50000). All of them have embedded filters (0.01-10000 Hz the first, 0.1-10000 Hz the others).
activity: e.g. in the analysis of the nerve sympathetic activity [12], contemporary and synchronized acquisition of electrocardiogram, pressure, breath frequency and sympathetic skin response (SSR) is mandatory. Superficial and intraneural stimulations are provided by a 2-channels stimulator from GRASS (S88X). The electrodes are the UNP40GAS from FHC. The data acquisition is performed by a 16-bits data acquisition (DAQ) board (National Instruments PCI-6251), installed on a personal computer (PC). The PC controls all the procedures of acquisition, processing, recording, and visual and audio signal representation.

To reduce the signal dispersion and deformation due to multiple analogue devices all connected to the pre-amplified signal [2], the whole signal processing stage of our microneurographic system is digitally executed by a Labview software. The block diagram of Fig. 4 summarizes the implemented system.

![Block diagram of the implemented system.](image)

**Fig. 4. Block diagram of the implemented system.**

**B. Real-time wavelet denoising**

Our approach holds on the theoretical fundamentals of Mallat’s algorithm [13] and Donoho’s method [7]. The algorithm operates on a finite set of N input data, where N is a power of two. These data are passed through two convolution functions, each of which creates an output stream that is half the length of the original one. These convolution functions are filters; one half of the output is produced by a low-pass filter function, the other half is produced by a high-pass one. We used the low and high-pass filters from the family of Symlet 7 mother wavelet that matches with signal from nerves better than others [4], as Fig. 5 shows.

![Shape of an action potential and Symlet 7.](image)

**Fig. 5. Shape of an action potential and Symlet 7.**

The low-pass output contains most of the information content of the original input signal and it is named *approximation*. The high-pass output, named *detail*, contains the detail of the signal and the additive noise [7]. Because of this reason, the denoising technique proposed by Donoho includes a discrimination of the *detail*. We implemented the threshold which Diedrich [4] found to be optimal for wavelet denoising of microneurographic signal:

\[
T = k\sigma \sqrt{2\ln(N)},
\]

where \(\sigma\) is the Gaussian noise standard deviation and \(k=0.8\) is a correcting factor. We estimated, as in [4], the standard deviation of noise from the 5-95 percentile of the first 35 seconds of the acquired signal.

We implemented a method of thresholding called *hard thresholding* by Donoho:

\[
y = \begin{cases} 
  x, & \text{if } |x| > T \\
  0, & \text{if } |x| \leq T.
\end{cases}
\]

Better results were obtained at each reiteration of this operation: Diedrich et al. [4] demonstrated that the best number on reiterations is 5. In our case, two blocks of filter banks were applied to signal windows of 512 samples, in order to guarantee a significant decrease of noise while keeping low the computational load for a real-time application. Finally, the signal is reconstructed by inverse low-pass and high-pass filter orthogonal to those used for the decomposition process. Fig. 6 summarizes what said in this section.

![Scheme of wavelet denoising algorithm](image)

**Fig. 6. Scheme of wavelet denoising algorithm we implemented.** The neural signal is filtered through a low-pass FIR \( (g) \) and a high-pass FIR \( (h) \) from the family of mother wavelet Sym7. The filtered signals are subsequently decimated by a factor of 2 to maintain the same number of data points as the input signal. The result of these processes are the *approximation* \( (a_1) \) and the *detail* \( (d_1) \). The process is repeated with \( a_1 \) as input obtaining \( a_2, d_1, d_2 \) and \( d_2 \) are the result of *detail thresholding*. The synthesis of denoised neural signal is conducted by upsampling by a factor of 2 and convolving with \( g \) and \( h \) the set \( (a_2, d_1, d_2) \). \( g \) and \( h \) are orthogonal with \( g \) and \( h \).
C. Samples recording

Recordings acquired at 48 kHz were later downsampled to 5 kHz which Diedrich et al. [4] discovered to be the best sample rate for nerve signals processed through wavelet denoising. The signal was sampled at 48 kHz to benefit of the pros of oversampling, mainly in the lower phase distortion in the upper part of the band.

The validation tests of wavelet denoising module was conducted on sympathetic nerve activity acquired by the peroneal nerve of a male, 25 years old, healthy subject.

III. PRELIMINARY SYSTEM EVALUATION

The effect of the real-time wavelet denoising on the passband filtered signal has been preliminary evaluated. Relying on research consuetude [9], we compared Signal to Noise Ratio (SNR), before and after wavelet filtering. Furthermore, we separately evaluated the Root Mean Square (RMS) of signal and noise before and after denoising.

We considered sequences of neural signal not showing neural bursts as noise, while sequences which showed neural bursts were treated as signal (Fig. 7). SNR was computed as follows:

$$\text{SNR} = \frac{\text{RMS}_{\text{signal}}}{\text{RMS}_{\text{noise}}},$$

(3)

where $\text{RMS}_{\text{signal}}$ and $\text{RMS}_{\text{noise}}$ represent respectively the Root Mean Square of signal and the Root Mean Square of noise. RMS is calculated as follows:

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} |x(n)|^2},$$

(4)

where $x$ is the sequence of signal sample and $N$ its length.

We did not report any comparison with the traditional frequency filtering, because we aim at removing noise in the band of signal. Traditional frequency filtering does not allow a similar signal conditioning [7].

IV. RESULTS

We show in Table I the RMS of the sequences of signal and noise before and after wavelet filtering. The ratio between the mean of RMS of original and denoised signals results to be equal to 0.9889 indicating that the processing we implemented leaves signal sequences unaltered. On the other hand the ratio between the mean of RMS of original and wavelet filtered noise sequences results to be equal to 0.5407, i.e. the level of noise of neural activity is halved. Finally, we found “SNR after filtering” to “SNR before filtering” ratio to be equal to 1.8289 which is coherent with the previous results.

<table>
<thead>
<tr>
<th></th>
<th>Root Mean Square</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal seq.</td>
<td>0.137</td>
<td>0.225</td>
</tr>
<tr>
<td>WD signal seq.</td>
<td>0.136</td>
<td>0.207</td>
</tr>
<tr>
<td>Noise seq.</td>
<td>0.026</td>
<td>0.026</td>
</tr>
<tr>
<td>WD noise seq.</td>
<td>0.014</td>
<td>0.015</td>
</tr>
</tbody>
</table>

WD states for wavelet denoising and seq. for sequences

In Fig. 8 and 9 this can be seen: Fig. 8 displays a zone of neural burst before and after wavelet denoising and Fig. 9 exhibits the minimization of noise.

![Fig. 7. Examples of sequences of signal and sequences of noise of a portion of the original (undenoised) signal.](image)

![Fig. 8. Detail of a zone of neural burst. The denoised signal (black) overlaps the original one (grey) to show the effect of wavelet shrinkage on nerve activity.](image)
V. CONCLUSIONS

Microneurography has the potential to provide the neuroprosthesis research with a fully safe and powerful tool which could be applied to healthy subjects as well as to amputees. However, a dedicate and accurate system for real-time acquisition and analysis of peripheral nerve motor activity is nowadays missing. The first step, in order to achieve this goal, is to set-up a microneurographic system which supports online suppression of white Gaussian noise while providing audio and video representation of the recorded neural activity. Here we presented our preliminary results in the development of such a tool. Online wavelet denoising was included in the signal elaboration and, thanks to this, we almost doubled the Signal to Noise Ratio while preserving the zones of neural bursts. This makes easier both for clinicians and for any automatic controllers to identify zones of neural bursts in the case of very noisy signals such as peripheral motor nerve activity.

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REFERENCES


