Biomedical Signal Processing and Control 4 (2009) 118–126

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Variance-based signal conditioning technique: Comparison to a wavelet-based technique to improve spike detection in multiunit intrafascicular recordings

Ernest Nlandu Kamavuako [a,*], Ken Yoshida [b], Winnie Jensen [a]

[a] Center for Sensory-Motor Interaction (SMI), Department of Health Science and Technology, Aalborg University, Fredrik Bajers Vej 7 D, DK-9220 Aalborg, Denmark
[b] Biomedical Engineering Department, Indiana Univ-Purdue Univ Indianapolis, Indianapolis, IN, USA

ARTICLE INFO

Article history:
Received 5 September 2008
Received in revised form 26 November 2008
Accepted 27 January 2009
Available online 27 February 2009

Keywords:
Intrafascicular recordings
Signal conditioning
Spike detection
Variance
Wavelet

ABSTRACT

Detection of single unit action potentials (APs) from peripheral nerve recordings is complicated by low signal-to-noise ratio (SNR) due to the activity of nearby muscles, interference from more distant nerve fibers, and thermal noise from the neural interface. In this study, we propose a novel signal conditioning technique for multiunit signals (i.e. a signal comprised of multiple units coming from different nerve fibers), based on the variance to be applied prior to detection of APs. The proposed technique was tested on experimental and simulated intrafascicular recordings; and was compared to a wavelet-based conditioning (also applied before AP detection). The outputs of both conditioning schemes were sent to an AP detection algorithm that used a simple threshold (equal to the standard deviation of the signal). The overall performance of the detection phase was superior when using the wavelet-based conditioned signal especially for SNR $\leq$ 2 dB. However, when using the variance-based conditioned signal, the AP detection phase resulted in lower number of false positives for SNR > 2 dB. The novel variance-based method improves the SNR by attenuating the background noise between APs and can be applied as pre-conditioning processing for AP detection.

1. Introduction

Multiunit, intrafascicular signals from peripheral nerves, recorded using intrafascicular electrodes allow the detection and tracking of single nerve fiber action potentials (APs) (or spikes). Given signal reliability, the information they encode could be used as a means to control an advanced degree of freedom prosthetic limb [1], or as feedback for an advanced closed loop functional electrical stimulation system [2]. However the quality of these signals makes the detection of single unit action potential a challenging task which requires advanced signal processing schemes to be solved. Neural recordings from longitudinal intrafascicular electrodes (LIFEs) appear as spikes with peak-to-peak amplitudes of about 20 μV [3] and the main sources of noise in these recordings arise from (1) the activity of nearby muscles, with several orders of magnitude larger than neural signals [2], (2) interference signals from distant nerve fascicles within the same nerve and (3) thermal noise from the neural interface and recording equipment [4]. In this paper we propose a variance-based signal conditioning technique (VBT) that can be applied to improve the signal quality prior to the detection step for improved performance.

The longitudinal intrafascicular electrode is a recording electrode based on a multichannel ribbon cable. It aims at providing a stable, long-term intraneural interface which relies on the detection and tracking of single unit neural activity from multiunit microneurography like recording. LIFE is designed to be placed parallel to the main axis of the peripheral nerve. The active sites of the electrode are placed along a micro-fabricated flexible polymer structure (typical size of 120 μm $\times$ 20 μm $\times$ 15 mm) that is threaded into the nerve fascicle.

Intrafascicular electrodes have also been developed to provide an alternative and safe neural interface for clinical neuroprosthetic systems [5], and pre-clinical sub-chronic studies have shown promising results [6,7]. For example, Dhillon and Horch [1] have made some recordings with a single channel LIFE implanted in amputee subjects. They have shown that the subject was able to generate and control efferent activity to a single motor unit that projected to a single joint in the missing limb [1,8]. Given stability and a means to reliably track single unit activity from each of the recording sites, control of a multi-degree of freedom prosthetic limb might be possible through direct thought control.

The success of the control task, with LIFE, depends on accurate decoding and interpretation of neural single units in terms of the corresponding motor functions (activation patterns of the nerve fibers). The signal-to-noise ratio (SNR) of intrafascicular recordings is higher than obtained with extraneural devices (e.g. cuff electrodes) but relatively low (<6 dB) [4] compared to most

* Corresponding author. Tel.: +45 9940 2414.
E-mail address: enk@hst.aau.dk (E.N. Kamavuako).

1746-8094/$ – see front matter
doi:10.1016/j.bspc.2009.01.006

biomedical signals, e.g. intramuscular electromyography (iEMG) [9] and electrocardiogram (ECG) [10]. Thus, novel signal conditioning techniques are needed in order to increase the SNR to help and improve performance of later spike detection and classification algorithms. Intensive technical work, including electrode design [11–13] and recording techniques [13,14], has been done in order to improve the SNR of signals recorded with intrafascicular electrodes. For instance, Djilas et al. [15] has presented a recording technique for improving the SNR of LIFE signals, which consists of wrapping a shield (shielding cuff electrode) around the implant site of the recording electrode. Nevertheless the technique was not sufficient to improve the performance of the detection of single unit action potentials.

From the signal processing viewpoint, many approaches have been used in order to accomplish appropriate noise reduction (or conditioning) in electroneurographic signals, including microneurography and intrafascicular signals. A common approach to increase the SNR of these signals is signal averaging [16], where the amplitude of random noise will be diminished and signal component amplitudes will remain. The drawback of this technique is the lost of temporal sensitivity [17]. Another traditional method includes band pass filtering for noise reduction, usually designed based on a priori knowledge of the differences in frequency contents of the signal and noise components. In the case where the spectral characteristics of the signal and noise overlap, wavelet-based conditioning techniques have shown improved performance [18–20]. Common to all wavelet-based techniques (WBTs) is that a threshold is applied in the wavelet domain instead of time domain as originally proposed by Donoho [21]. The main difference between studies lies on the definition of the threshold measure applied on wavelet coefficients for noise reduction [18–20]. Despite the improved performance of the wavelet-based conditioning techniques, the choice of a suitable mother wavelet, with respect to the signal in hand, remains the challenging task.

In the present work, we propose a simple signal conditioning technique, based on the estimation of variance of the multiunit intrafascicular signal. The variance-based technique will be applied on the signal prior to detection of APs. The VBT should attenuate background noise between APs while preserving the shape of the APs and allowing for detection schemes to be applied that take advantage of the undistorted shape of the APs.

The primary aim of this study was to develop and test a variance-based signal conditioning technique for increasing the SNR and later AP detection performance. The secondary aim was to evaluate whether signal conditioning is a necessary step by comparing the performance of the VBT and a previously described wavelet-based de-noising technique [20] to unconditioned signals (control).

2. Methods

2.1. Variance-based technique

The peripheral nerve signals recorded with the LIFE electrode are multiunit in nature, consisting of many trains of action potentials generated by several nerve fibers. In the present work, we assume that the recorded APs are embedded in independent, white, and zero mean additive Gaussian noise. We propose a conditioning technique based on the recordings from a single channel, which is implemented as described in Eq. (1). Application to multichannel is straightforward.

$$y(n) = w(n)x(n) \quad \text{with}\, n = 1, \ldots, N \tag{1}$$

where $x(n)$ is the recorded input signal, $w(n)$ a weighting vector, $y(n)$ the conditioned signal, and N the number of samples.

Mathematically, the task is a classic conditioning problem of finding a suitable weighting vector w, whose elements are equal to 1 for samples corresponding to the time points where the APs occur, and are equal to 0 (in the case of using a hard threshold) or close to 0 (in the case of using a soft threshold). In this study we only apply soft thresholds as given in Eq. (3B), because our preliminary investigation showed similar results when we applied the soft threshold and the hard threshold. The weighting vector w can be estimated by computing the variances of all consecutive portions (or windows overlapped by one sample) of the signal $x(n)$. In other words, this technique utilizes a window (of size Z) that moves down the recorded samples one sample at a time, as described in the following equation:

$$C(n) = \frac{1}{Z-1} \sum_{i=n-(Z/2)}^{n+(Z/2)-1} (x(i) - \mu)^2, \quad n = 1, \ldots, N \tag{2}$$

where μ is the estimated mean of the window, $C(n)$ the set of variance values, $x(n)$ input signal, Z the window size and N the number of samples. Note that $x(i) = 0$ for $i < 0$.

We have chosen to determine the elements of w using the second order statistics (variance) because our pre-investigation did show that the signal-to-noise ratio is improved after computation of the moving variance. Thus, basically this is a moving average filter applied on the square of the original signal, and the effect is that the process of squaring the signal enhances the spikes and the moving average decreases the noise. Fig. 1 shows the result of performing the moving variance computation for signals with different SNR.

The next step is to find a threshold measure (T_1) as a factor α times the S.D. of $C(n)$ as given in Eq. (3A). The weighting vector w is obtained as given in Eq. (3B). The weighting vector is finally multiplied to the raw signal $x(n)$ (see Eq. (1)) to obtain the conditioned output $y(n)$. Alpha (α) will be denoted as the variance threshold.

$$T_1 = \alpha\, \mathrm{std}(C) \tag{3A}$$

$$w(n) = \begin{cases} 1 & \text{if} \quad C(n) \geq T_1 \\ C(n) & \text{elsewhere} \end{cases} \tag{3B}$$

The algorithm can be summarized as followed:

1. Choose a window size, Z
2. Compute the moving variance, C
3. Compute the threshold, T_1
4. Apply threshold as given in formula (3B) and obtain the weighting vector, w
5. Multiply the weighting vector, w and input signal, x to obtain the conditioned output, y.

2.2. Wavelet-based techniques

This section summarizes the wavelet technique used to compare with the VBT, and a complete description of the wavelet technique can be found in [20]. This conditioning technique includes a threshold T_2 for each decomposition level as given in Eq. (4A).

$$T_2 = \beta\sigma\sqrt{2\ln(N)} \tag{4A}$$

$$y = \begin{cases} \mathrm{sign}(x)(|x| - T_2), & \text{if}\, |x| > T_2 \\ 0, & \text{if}\, |x| \leq T_2 \end{cases} \tag{4B}$$

$$y = \begin{cases} x, & \text{if} \quad |x| > T_2 \\ 0, & \text{if}\, |x| \leq T_2 \end{cases} \tag{4C}$$