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Sliding window averaging in normal and pathological motor unit action potential trains

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HIGHLIGHTS

- A new sliding window algorithm for averaging trains of MUAPs has been tested.
- It performed better than relevant averaging algorithms with normal, myopathic and neurogenic signals.
- The algorithm can be of service for the quantitative analysis of MUAP waveforms.

ABSTRACT

Objective: To evaluate the performance of a recently proposed motor unit action potential (MUAP) averaging method based on a sliding window, and compare it with relevant published methods in normal and pathological muscles.
Methods: Three versions of the method (with different window lengths) were compared to three relevant published methods in terms of signal analysis-based merit figures and MUAP waveform parameters used in the clinical practice. 218 MUAP trains recorded from normal, myopathic, subacute neurogenic and chronic neurogenic muscles were analysed. Percentage scores of the cases in which the methods obtained the best performance or a performance not significantly worse than the best were computed.
Results: For signal processing figures of merit, the three versions of the new method performed better (with scores of 100, 86.6 and 66.7%) than the other three methods (66.7, 25 and 0%, respectively). In terms of MUAP waveform parameters, the new method also performed better (100, 95.8 and 91.7%) than the other methods (83.3, 37.5 and 25%).
Conclusions: For the types of normal and pathological muscle studied, the sliding window approach extracted more accurate and reliable MUAP curves than other existing methods.
Significance: The new method can be of service in quantitative EMG.

1. Introduction

The analysis of motor unit action potential (MUAP) is one of the fundamental tests in routine clinical neurophysiology. Electromyography (EMG) signals are recorded intramuscularly with conventional concentric needle electrodes. These signals usually contain several MUAP trains. Manual, semi or completely automatic techniques (Nandedkar and Barkhaus, 2002; Merletti and Parker, 2004) are used for decompose EMG signals into different MUAP trains. From each MUAP train a representative waveform is formed (Malanda et al., 2015) and characterized with clinically useful

Abbreviations: BPM, best performing method; EA, ensemble averaging; EMG, electromyography; FCA, five-closest averaging; GSMW, gold standard MUAP waveforms; MA, median averaging; MUAP, motor unit action potential; MWP, MUAP waveform parameters; NBP, normalized baseline power; NDEP, normalized differential error power; NEP, normalized error power; SD, standard deviation; SPMF, signal processing merit figures; SWSA, sliding window selective averaging.

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parameters (Stålberg et al., 1986; Zalewska and Hausmanowa-Petrusewicz, 1995; Nandedkar and Barkhaus, 2002; Kimura, 2002). For diagnostic evaluation, getting a reliable and representative MUAP waveform is thus an essential goal of quantitative EMG.

Noise and artifacts from different sources can distort MUAP waveforms. Averaging methods have been designed for obtaining representative waveforms from MUAP trains. Conventional averaging methods based on the mean of samples are noticeably sensitive to noise and artifacts, particularly, to the interference of potentials from different motor units (Malanda et al., 2016). Furthermore, such methods sometimes perform excessive smoothing of the resulting curves, which can lose morphological details of potentially useful physiological implication. Finally, these methods give rise to amplitude bias when alignment errors are present (Malanda et al., 2015; Sörmo and Lagunas, 2005). Methods based on the median are more robust, but tend to produce ragged waveforms (Malanda et al., 2015).

Robust methods of averaging are especially relevant in automatic extraction of MUAP trains by means of multi-MUP systems (Stålberg et al., 1995; Nandedkar and Barkhaus, 1995), which are designed to reduce the time of MUAP extraction (and consequently patient discomfort), being able to obtain several MUAP trains (generally up to six, in commercial systems) from each point of needle insertion. Patients are asked to perform moderate voluntary muscular contractions, so that several motor units are activated. The presence of different MUAP trains in the recordings leads to frequent superimpositions of potentials, whose waveforms are consequently distorted to some extent, making further demands on the averaging method used to disentangle and extract a representative waveform.

The building of a waveform that serves as a model or template for a set of curves in a repetitive signal is a recursive problem in the field of biomedical signal analysis. Several methods have been put forward for obtaining such templates from biomedical repetitive signals of different kind: EMG (i.e, MUAP analysis) (Stålberg and Antoni, 1983; Nandedkar and Sanders, 1989; Stålberg and Sonoo, 1994; Nandedkar and Barkhaus, 1995), evoked potentials (Hoke et al., 1984; Mühler and von Specht, 1999; Sörmo and Lagunas, 2005; Leonowicz et al., 2005; Rahne et al., 2008) and electrocardiography (Leski, 2002). A comprehensive review of these methods together with a comparative evaluation of a selection of them was recently published (Malanda et al., 2015).

In 2016, the current authors presented a new method for obtaining a representative waveform from a train of MUAPs. Briefly, a window slides along the time axis selecting and averaging the most similar sections of the potential train within its scope. From the obtained pieces of potentials, an assembled potential is generated, that satisfactory represents the waveforms of the MUAP train. This approach was referred to as *Sliding-window selective averaging* (SWSA).

The SWSA approach was compared with a selection of the nine methods evaluated in the previously-conducted comparative study (Malanda et al., 2015) and was found to improve on the performance of the older methods in terms of the criteria of comparison (various signal analysis-based merit figures and MUAP waveform parameters used in the clinical practice). Regarding MUAP waveform parameters, the new algorithm outperformed the other methods evaluated.

The current study extends our previous work to evaluate performance with MUAP recordings from pathological muscles. In the following section, a description of the materials used in the study is given. Next, we briefly describe the SWSA method and the other methods evaluated. Then comes an explanation of the gold standard and the figures of merit used in comparisons. After providing a report of the comparative evaluation results and further discussion of these results, our final conclusions are given.

2. Methods

2.1. Subjects and signals

For this study we made use of the material used in a previous work (Rodríguez-Carreño et al., 2010), with the expressed approval of the Public University of Navarre's Ethical Committee. Specifically, we used 313 EMG signals, between 5 and 6 seconds long, acquired during slight voluntary contractions: 68 signals were from normal muscles, 105 from myopathic muscles, 27 from chronic neurogenic muscles and 72 from subacute neurogenic muscles. The types of muscles and particular neurological diseases related to these signals can be consulted in the previous reference. Details about the recording equipment and acquisition set-up can also be found in that reference.

MUAP trains were extracted from EMG signals using an automatic decomposition procedure (Florestal et al., 2006). The potentials in the MUAP trains consisted of 50 ms-long EMG signal epochs. For all the extracted MUAP trains the potentials were segmented from the EMG signals in such a way that their maximal negative peaks appeared at 40% of the length of the epoch.

Next, the potentials of each MUAP train extracted by the decomposition algorithm were aligned in the time axis by maximum correlation (Campos et al., 2000) and in the amplitude axis by Euclidean distance minimization (Navallas et al., 2006). MUAP trains with an excessively noisy visual appearance or that yielded average waveforms with unrealistic MUAP shapes to the eyes of an expert electromyographer (LG), were considered unacceptable and discarded for subsequent analysis. MUAPs with satellite potentials were also excluded. All the selected MUAP waveforms were well-defined above BL activity and had a rise-time lower than 1 ms (most of them lower than 0.5 ms). Finally, MUAP trains with less than 80 potentials were discarded, as this was set as the minimum MUAP train size for the comparative analysis. A total of 218 MUAP trains were accepted for the study: 37 from normal muscles, 69 from myopathic muscles, 64 from subacute neuropathic muscles and 48 from chronic neurogenic muscles.

2.2. The Sliding-window selective averaging method

The SWSA algorithm starts with the potentials in the MUAP train already aligned in time and amplitude (Fig. 1A). Then a window slides along the MUAP time span delimiting intervals of the set of potentials (Fig. 1A and B). For each time interval, the so-called *median section* is calculated as the median of the samples of all the potentials in the train. The standard deviations of the amplitude samples of the different potentials in the train are also obtained and the minimum value across the time samples in the interval is extracted. Then, the algorithm evaluates potentials with a small Euclidean distance to the *median section*. Potentials with Euclidean distances that are lower than the previously-estimated minimum standard deviation multiplied by a constant parameter (η), are selected and averaged. In this way, the algorithm obtains representative sections for the time intervals under consideration (Fig. 1C). In the final stage, the representative sections obtained as the window slid along the MUAP time span are assembled (Fig. 1D) and averaged to form the final representative waveform. A complete description of the SWSA algorithm can be found in the original article in which it is presented and evaluated (Malanda et al., 2016).

To evaluate the SWSA algorithm, the parameter η is set to 1.0, while three different values of the window length are considered: L_w = 50, 150 and 250 samples (i.e., 2.5, 7.5 and 12.5 ms, respectively). These parameter values were chosen, on the basis of results in the original study (Malanda et al., 2016), in which L_w was tested