TEAGER-KAISER ENERGY OPERATOR IMPROVES THE DETECTION AND QUANTIFICATION OF NOCICEPTIVE WITHDRAWAL REFLEXES FROM SURFACE ELECTROMYOGRAPHY

José A. Biurrun Manresa, Carsten D. Mørch, and Ole K. Andersen

Center for Sensory-Motor Interaction, Dept. Of Health, Science and Technology, Aalborg University
Fredrik Bajers Vej 7, DK – 9220, Aalborg Øst, Denmark
phone: + (45) 9940 9838, email: jbiurrun@hst.aau.dk
web: www.aau.dk

ABSTRACT

This paper presents a simple and robust method to improve detection and quantification of nociceptive withdrawal reflexes in surface electromyography, based on pre-processing the signals with the Teager-Kaiser energy operator. Withdrawal responses were recorded from tibialis anterior and soleus muscles in three hundred subjects, and a subset of fifty recordings of each muscle were classified by an expert as either exhibiting a reflex or not. Performance of five detection algorithms was compared against the expert's classification using a receiver operating characteristic analysis. Results showed improvement in the performance of all algorithms when the pre-processing algorithm was applied.

1. INTRODUCTION

The nociceptive withdrawal reflex (NWR) is a typical reaction observed in almost all living species, with the purpose of withdrawing the extremities from potential tissue-damaging agents. It was first described at the beginning of the 20th century by Sherrington, who observed that nociceptive (*i.e.*, painful) electrical stimulation of the limbs in animals caused a flexion of the stimulated limb to withdraw it from the stimulus, associated with an extension of the other limb to preserve balance [1]. This pattern was therefore named 'flexion reflex', although later research showed that an extension reflex could also be elicited [2], thus expanding the concept to the more general term 'withdrawal reflex'. The NWR has been suggested as an electrophysiological measure correlated to pain in humans [3], and it has been proven useful as an assessment tool for chemical and pharmacological modulation of pain processing and nociceptive neurotransmission at spinal level, as well as in the research of chronic pain and other painful disorders (for a review, see [4]).

A NWR can be elicited by natural and artificial stimuli. Examples of natural stimuli are heat and pressure, which activate specific pain receptors in the skin [5]. On the other hand, electrical stimulation is the most widely used artificial method for eliciting the NWR [6]. This kind of stimulus bypasses the skin receptor and generates an action potential directly in the sensory nerve. In both cases, electromyography (EMG) is commonly used to record the reflex response from the muscles [1,2,7].

There are two different recording strategies for EMG: invasive, in which a direct measurement of muscle fibre activity is obtained by intra-muscular needle electrodes, and non-invasive, where integrated potentials are acquired by surface electrodes placed on the skin. For the NWR, surface EMG (sEMG) recording is generally preferred. The most important advantage of sEMG is that it is not necessary to insert needles into the muscle, which could change the sensory inflow to the spinal cord and therefore affect the spinal control. However, sEMG has the disadvantage of possible contamination by noise, *e.g.*, ambient and transducer noise, artefacts and unwanted signals from other muscles in close proximity to the muscle fibres of interest, namely myoelectric cross-talk [8].

Several methods for detection and quantification of the NWR in sEMG recordings have been introduced, *e.g.*, integrated and mean sEMG [9], area under the curve [10], maximal peak to peak values [11], and root mean square [7], among others. Nevertheless, there is no consensus on which one is the best method to define a threshold for the NWR and determine its most significant characteristics. Furthermore, the performance of all these techniques is negatively affected when the sEMG signal is contaminated with noise. Most of the methods developed to overcome this difficulty are complex and computationally intense, and often *a priori* knowledge of the properties of the sEMG signals is required [12]. That is not the case of the algorithm proposed in this paper, which simply consists on a nonlinear operator that tracks the energy of the system that produces a signal instead of the signal's energy itself. It was developed by Teager while working on nonlinear speech modelling, but later applied also in other fields, such as image processing and pattern recognition [13].

In the present study, a fast and simple method to improve the characterization of the NWR is proposed. It consists on pre-processing the sEMG signals with the Teager-Kaiser energy operator (TKEO) prior to the detection and quantification stage. This paper presents the methodology for the recording and analysis of the NWR, the basic theory behind the TKEO and its application on real sEMG data. Results will be presented, demonstrating improvement over traditional detection and quantification techniques.

2. MATERIALS AND METHODS

2.1 Teager-Kaiser energy operator

The TKEO is a simple algorithm that allows estimating the energy required to generate, in a sense, a given signal. This should not be mistaken with the traditional definition of energy from the signal processing field, *i.e.*, the average of the sum of the squares of the magnitude of the signal's samples. It is more related to the 'physical' concept of the energy of a simple oscillation, which is proportional to the square of the amplitude and to the square of the frequency of the oscillation.

The discrete TKEO Ψ is defined in time domain as:

$$\Psi[x_n] = x_n^2 - x_{n+1}x_{n-1} \tag{1}$$

For a given oscillatory signal,

$$x_n = A\cos(\omega_n + \phi) \tag{2}$$

the output of the TKEO is given by (Li *et al.*, 2007)

$$\Psi[x_n] = A^2 \sin^2(\omega_n) \tag{3}$$

This expression is exact when $\omega_n \leq \pi/2$, that is, when the maximum frequency f_m of the signal is one-fourth of the sampling frequency f_s. Also, for small values of ω_n, $\sin(\omega_n) \approx \omega_n$. If $\omega_n \leq \pi/4$, *i.e.*, $f_m / f_s \leq 1/8$, the error of the approximation is below 10%. Thus, we can rewrite (3) as follows:

$$\Psi[x_n] = A^2 \sin^2(\omega_n) \approx A^2\omega_n^{\,2} \tag{4}$$

The above expression gives a good approximation of the energy of an oscillatory signal, based on its instantaneous amplitude and frequency values. The algorithm is very simple and robust (since it involves only two multiplications and a sum, and there are not divisions); it has a very short response time to changes in amplitude and frequency (it depends on three consecutive sampling instants), and the resulting estimation of the energy is independent of the initial phase, ϕ, of the oscillation.

Surface EMG consists of the sum of the electrical activity of the active motor units in a muscle as detected by electrodes placed on the skin. When the muscle contracts, the motor units fire action potentials, which are usually accompanied by an instantaneous increase in both amplitude and frequency contents of the sEMG signal. Therefore, the TKEO becomes a useful tool in order to detect this simultaneous variation and differentiate it from artefacts or cross-talk, which have a different pattern for amplitude-frequency variations.

2.2 Recording and analysis of the NWR

2.2.1 Subjects

Three hundred healthy volunteers (168 men and 108 women, ages ranging from 18 to 80 years) participated in the study. Informed consent was obtained from all subjects, and the Helsinki declaration was respected.

2.2.2 Electrical stimulation

Ten electrodes (copper, diameter 0.8 cm) were non-uniformly mounted on the sole of the foot and a common anode (10 x 14 cm) was placed on the dorsum of the foot. A computer-controlled stimulator delivered a stimulus to one electrode at a time in a randomized order, with a random inter-stimulus interval ranging from 10 to 15 s. Each stimulus consisted of a constant-current pulse train of 5 individual 1 ms pulses delivered at 200 Hz. For each electrode position, the lowest stimulus intensity that evoked pain (*i.e.*, the pain threshold) was assessed, and a stimulation intensity of 1.5 times higher than the pain threshold was selected. Each electrode site was stimulated 4 times.

2.2.3 EMG recordings

The EMG was recorded with surface electrodes from tibialis anterior (TA) and soleus (SOL) muscles. Before attaching the electrodes, the skin was slightly abraded and cleaned with isopropyl alcohol. sEMG signals were amplified (up to 50000 times), filtered (5–500 Hz, 2nd order), sampled (2000 Hz), displayed on the computer screen and stored on a hard drive. sEMG signals were recorded from 200 ms before stimulation to 800 ms after stimulation onset.

2.2.4 Data analysis

Fifty sEMG recordings from each muscle were randomly chosen to be classified by an expert as either exhibiting or not exhibiting a reflex response, in order to have a 'gold standard' against which to compare the performance of the algorithms. All the measurements were calculated on the 60–180 ms post-stimulation interval (where reflex activity may appear), and the 0–120 ms pre-stimulation interval was used as a measurement of background activity. Standard methods for detection and quantification of the NWR were employed, as described in [14]: *Signal-to-Noise Ratio* (SNR, power ratio between the NWR interval and the background activity), *Interval Mean Value* (IMV, mean value of the rectified NWR interval), *Interval Peak Value* (IPV, peak value of the rectified NWR interval), *Mean Z-Score* (MZS, IMV minus background activity mean value and divided by background activity standard deviation) and *Peak Z-Score* (PZS, IPV minus background activity mean value and divided by background activity standard deviation).

2.2.5 Performance assessment

A receiver operating characteristic (ROC) analysis was carried out to determine the performance of each method while detecting the NWR. The methods were compared against the classification of the expert using the area under the ROC curve. The area under the ROC curve corresponds to the

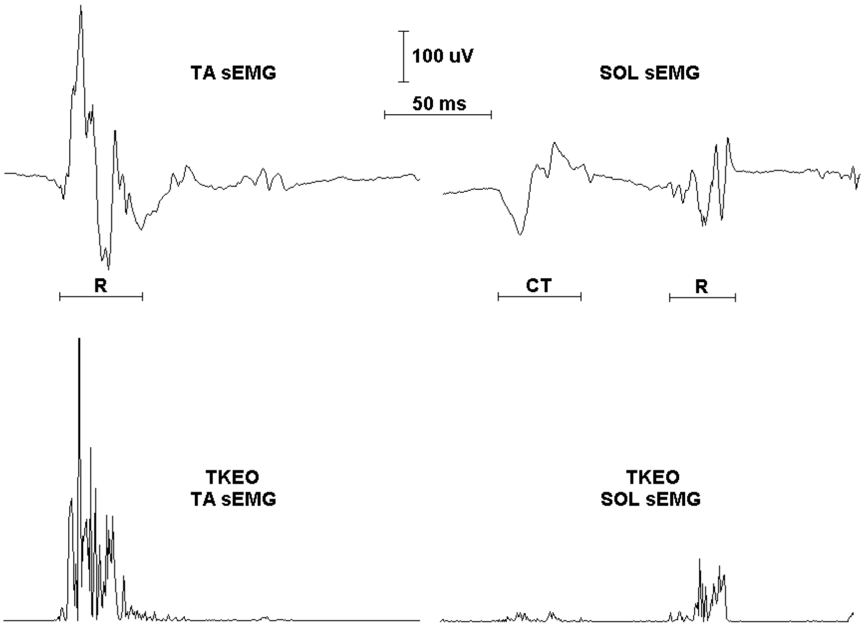

Figure 1: Examples of sEMG signals befor before and after pre-processing (**R**: reflex, **CT**: cross-talk)

probability of correctly identifying which recording is just ‘noise’ and which is ‘signal plus noise’. Thus, an area under the ROC curve close to 1.0 implies good performance of the method, meaning that it is able to discriminate between presence and absence of the NWR in a recording, and an area under the ROC curve close to 0.5 implies that the method is not capable to determine whether there is a reflex in the recording or not.

3. RESULTS

Figure 1 shows the effect of the TKEO on sEMG signals acquired simultaneously. Note the amount of cross-talk in the first part of the SOL signal, and how it is reduced after pre-processing, compared to the reflex size.

A comparison of the areas under the ROC curve for each algorithm is shown in Table 1, with and without TKEO pre-processing. All area under the ROC curve estimates are significant ($p < 0.001$).

Table 1. Receiver operating characteristic analysis.

Method	Tibialis Anterior		Soleus	
	Without TKEO	With TKEO	Without TKEO	With TKEO
SNR	0.94	0.96	0.86	0.98
IMV	0.91	0.96	0.89	0.98
IPV	0.97	0.98	0.95	0.97
MZS	0.92	0.95	0.83	0.95
PZS	0.97	0.98	0.92	0.98

4. DISCUSSION

ROC analysis showed a good performance of all methods in the detection of the NWR, as previously reported in [13]. Methods involving peak values (IPV and PZS) performed best, with areas under the ROC curve greater than 0.92. There is a noticeable difference between performances in TA recordings compared to SOL recordings: NWR detection in TA is in average 5% better than in SOL. This is to be expected because SOL signals are more affected by cross-talk and noise than TA signals, due to the fact that the most common withdrawal pattern is dorsiflexion of the ankle, which mostly involves TA activity [7]. Nevertheless, with TKEO pre-processing this difference disappears (with improvements up to 12% in some cases), and all methods accomplish areas under the ROC curve greater than 0.95, therefore becoming reliable for NWR detection task.

Since there is not an objective pattern to measure the accuracy of quantification for any method, a comparison cannot be established. Previous work using both simulated sEMG models and experimental data showed that the frequency content of the signal recorded alone cannot give any indication on crosstalk, and as a consequence, cross-talk reduction cannot be achieved by temporal high-pass filtering only [15]. Here, it could be argued that if the detection improves after pre-processing the recordings with the TKEO (taking into account *both* amplitude and frequency content), it must be due to a reduction in the effect of noise and cross-talk over the signals, that is, an enhancement in the signal-to-noise ratio (as can be seen on the example in Fig. 1). Thus, if the signal-to-noise ratio improves, then the quantification process should be more accurate, leading to a better characterization of the NWR.

The theory behind the TKEO was originally developed within the field of AM-FM demodulation methods. Over the years, these techniques have evolved in order to find new solutions for the problems within that field, and new algorithms were developed based on the TKEO, such as MESA [16] and PACED [17]. Furthermore, re-evaluation of the Hilbert transform led to the development of techniques like EMD [18] and IHT [19]. All these techniques constitute the current state of the art in AM-FM demodulation [20], and as such, they have grown in complexity throughout the years. On the other hand, the TKEO still preserves its simplicity and robustness that for example makes it suitable for use in online pre-processing of sEMG signals [21].

In conclusion, TKEO pre-processing improves the detection and quantification of the NWR regardless of the methods chosen for these tasks. A more extensive analysis involving a larger number of recordings is planned in order to obtain more accurate statistics.

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