Wavelet Transform in EMG Analysis

Andrej Šoštarič, Dean Korošec, Damjan Zazula
Faculty of Electrical Engineering and Computer Science
Smetanova 17, 2000 Maribor, Slovenia
andrej.sostaric@uni-mb.si, dean.korosec@uni-mb.si, zazula@uni-mb.si

Abstract *This paper presents the phenomena of electromyography and the nature of electromyographic signals. The meaning of decomposition (separation) of this kind of signal is pointed out and we present a new idea for the decomposition approach, based on the wavelet transform. Definition and basic properties of the transform are addressed and used in the experimental part of the paper.*

Keywords electromyography, electromyogram, decomposition, wavelet transform

1 EMG Signals

An electromyogram (EMG) is the signal obtained by measurement of the electrical activity in a muscle (Fig. 1). Muscles consist of muscle fibers which are activated by motoneurons. Impulse coming from the spinal cord through a single motoneuron triggers a recruitment of several muscle fibers. These fibers form a group called motor unit (MU). Shape of the electrical response to the stimulation of a motor unit is called motor unit action potential (MUAP) and contains a weighted sum of electrical responses of each muscle fiber (depending on the spatial distribution of fibers belonging to the MU). Physiochemical process responsible for the activation of a single MU electrical response is called Na-K pump and produces travelling of the stimulation impulse along and inside the muscle fiber in both directions starting from the stimulation point.

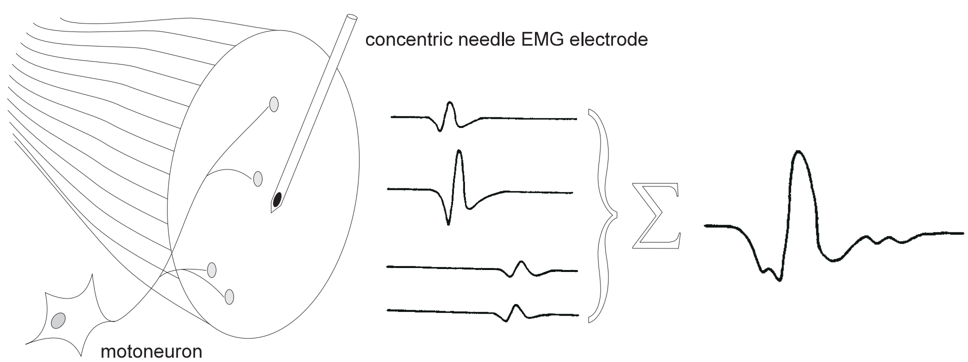

Figure 1: MUAP waveform

Complete EMG signal is made of trains of MUAPs which result from repetitive discharges of MUs. Firing pattern of an active motoneuron can be described as a train of δ functions. The distance between consecutive pulses is called interspike or interpulse interval (IPI) and is a random variable. Retrieval of parameters of this variables is one of two main goals of the decomposition process. But perhaps the most important result of decomposition is a complete database of characteristic MUAP waveshapes whose parameters have been proven to be of major importance for the clinical diagnosis of neuropathies and myopathies, whereas the innervation statistics are mainly used for investigations of the neuromuscular control loop.

When observing the muscle electrical activity different techniques can be applied [2]. For the purpose of decomposition, nowadays only *needle electromyography* is used, which is invasive in comparison to *surface electromyography* which is not. There is a number of differences between signal detected by needle electrodes and surface myoelectric signals (SMES): (a) The detection volume of surface electrodes is much larger than of the needle electrodes. SMES are therefore consisting of the activity of several tens of MUs, while needle electrodes detect the activity of only a few motor units. (b) Due to the larger distance of muscles from the surface probes and the filtering effect of the tissue, the SMES power spectrum is limited to 500 Hz, while the spectrum of the needle EMG signal extends to 5 and even 10 kHz. (c) SMES are considered a more general overview of muscle activity, but its interpretation in the time domain is much more complicated and no diagnostic application would be possible without computers.

Some other clinically significant analysis techniques beside the decomposition are also: (a) *muscle fiber conduction-velocity estimation*, (b) *muscle fatigue evaluation*, and (c) *noninvasive fiber typing*, but they are not of such importance for us at this point.

But the most complete picture of muscle activity of course yields the decomposition which was done manually in the early age of electromyography. This is extremely time consuming and can be achieved with complete success only for low contraction forces, because at stronger contractions the MUAPs are so numerous that the EMG becomes a noise-like interference pattern and visual inspection only is no longer possible. It has been shown that the accuracy of decomposition must be very high [3] in order to properly study a motor unit behavior. Another known fact are also slow changes in MUAPs waveforms and amplitudes due to relative position variation of the recording electrode and muscle fibers during a contraction.

So the decomposition problem is not an easy one at all, although very obvious and simple to understand. While there are many decomposition methods mentioned in the literature, we are going to describe our approach which is based on wavelet transform.

2 Wavelet transform

The wavelet transforms, particularly those of orthonormal wavelets with finite support, have emerged recently as a new mathematical tool for multiresolution decomposition of different types of continuous-time signals. In this section we present the wavelet transform as a signal analysis tool with capability of variable time-frequency localization.

In multiresolutional analysis, we often use the term *local spectrum* [6], where the signal is decomposed into a sum of complex exponentials, weighted by a function that plays a role of a localization window. This procedure is well suited for the identification of periodic structures in the signal, but it is not appropriate for the signals which contain short (mostly high frequency) disturbances which are delocalized, and their energy is distributed over a region determined by the width of the window [5, 6, 7].

At time-frequency analysis we look for techniques that stress the time aspect at high frequencies and the frequency aspect at low frequencies [7]. These requirements are satisfied by a technique of analysis and synthesis - by wavelet transform, which is founded on basis functions formed by dilation and translation of a prototype function $\psi(t)$. These basis functions are short-duration, high-frequency and long-duration, low-frequency functions. They are much better suited for representing short bursts of high-frequency signals or long-duration, slow varying signals. Having in mind that EMG signals do have such behavior, wavelet transform should be an ideal tool for their analysis.

The wavelet family is defined by scale and shift parameters, a and b, respectively, as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right). \tag{1}$$

The wavelet transform of function $f(t)$ is the inner product

$$W(a,b) = \int_{-\infty}^{\infty} \psi_{a,b}(t) f^*(t) dt = \langle \psi_{a,b}, f \rangle, \tag{2}$$

where $a \in \mathcal{R}^+$, $b \in \mathcal{R}$. A typical wavelet and its dilations are shown in Fig. 2. Functions that are admissible prototype wavelets fulfil next two conditions [4]: they have finite energy: $\int |\psi(t)|^2 dt < +\infty$ and they contain no DC bias: $\int \psi(t) dt = 0$.

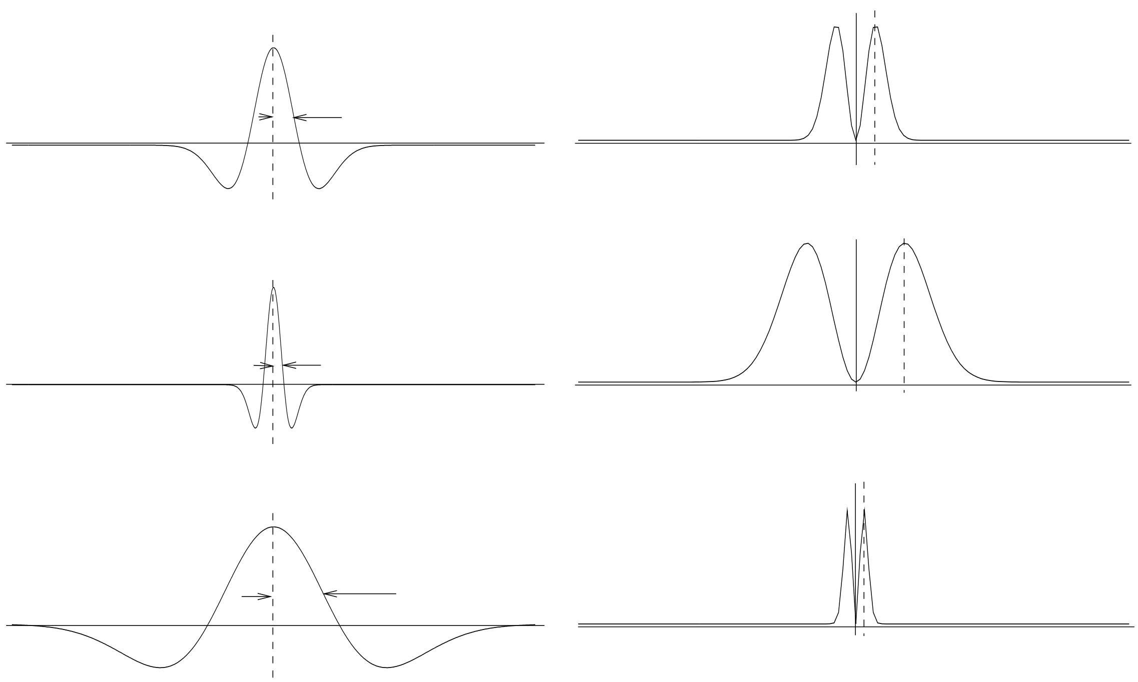

Figure 2: Typical wavelet family in the time and frequency domain.

By discretizing dilation and translation prarameters ($a = a_0^m$ *and* $b = nb_0a_0^m$), so that

$$\psi_{m,n}(t) = a_0^{-m/2}\psi(a_0^{-m}t - nb_0),$$

we can express any $f(t) \in L^2(\mathcal{R})$ ($L^2(\mathcal{R})$ denotes the vector space of measurable, square-integrable one-dimensional functions $f(x)$) as the superposition

$$f(t) = \sum_m \sum_n d_{m,n}\psi_{m,n}(t). \tag{3}$$

Now we can imagine wavelet coefficients $d_{m,n}$ as being generated by the wavelet filter bank, which has a form of convolution of $f(t)$ with $\psi_m(-t)$ at the certain scale n. In this case we are speaking about subband filtering [4]. If we set $a_0 = 2$ and $b_0 = 1$, which is usual procedure, sampling lattice bacome octave or dyadic grid.

3 Experiments with a needle EMG

Finally, we applied wavelet transformation on a real EMG signal. As we've pointed out, EMG signal is composed of multiple MUAPs. First, we were interested in global time-frequency (time-scale) presentation. We were observing and analyzing the frequency content of active and inactive parts of the EMG signal. Second, more important, was the idea of detecting different MUAPs inside the real signal. For that purpose we used the signal which has already been analyzed by Gerber's algorithm for interactive and automatic MUAP detection [9]. It is based upon signal segmentation and detection of specific MUAP shapes and firing instants. Their results claim that the analyzed EMG signal contains 7 different MUAPs. Signals in Fig. **??** present just parts of the whole signal and are 384 samples long. Horizontal axis denotes time in ms, while vertical axis denotes logarithmic frequency scale which is divided into 8 octaves (8 voices each). MUAP types and firing positions are denoted by Roman numerals.

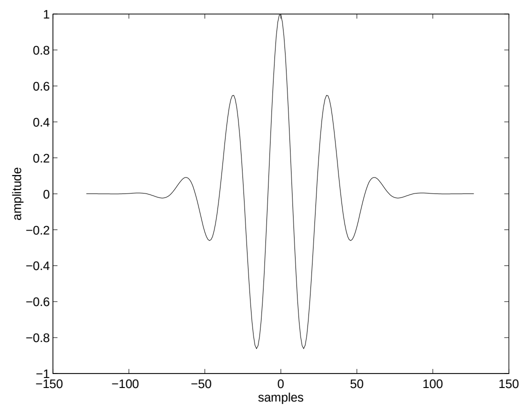

Figure 3: Mother wavelet used in the wavelet analysis experiments

The wavelet transforms presented were obtained using the mother wavelet function of a modulated Gaussian type (Fig. 3):

$$\psi(t, \omega_0) = e^{(-t^2/2)} e^{i\omega_0 t}. \tag{4}$$

Figures with the transforms confirm the starting conjectures:

- Inactive periods significantly differ from the active ones, both in frequency contents and the amplitude (compare the wavelet transform in Fig. **??**a, the part of inactivity up to 25 ms to the remaining active interval from 25 ms to 38 ms).

- MUAPs exhibit higher amplitudes in the corresponding frequency intervals (see darker areas in all the figures). At the same time, their fiducial points (set-ups and ends) may be roughly located by an appropriate amplitude threshold in the right frequency interval. For example, the MUAP denoted by VI appear in three different situations: one completely alone (Fig. **??**a) and then combined with some other MUAPs (Figures **??**b and **??**c). Its frequency content lies between 5 and 10 Hz approximately, covering the whole duration of the MUAP with higher amplitudes in this band.

4 Conclusions

The experimental results in Section 3 show that the wavelet-based approach may act as a compact basic processing modul. In the future, more tests are to be done with different wavelets in order to find an optimum separability of the MUAPs and to establish the necessary conditions and the thresholds for that. Apparently, the problem of the MUAPs overlapping as in the time as in the frequency domain will, however, still not be solved in this way.

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