Surface EMG based muscle fatigue evaluation in biomechanics

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\textbf{Abstract}

In the last three decades it has become quite common to evaluate local muscle fatigue by means of surface electromyographic (sEMG) signal processing. A large number of studies have been performed yielding signal-based quantitative criteria of fatigue in primarily static but also in dynamic tasks. The non-invasive nature of this approach has been particularly appealing in areas like ergonomics and occupational biomechanics, to name just the most prominent ones. However, a correct appreciation of the findings concerned can only be obtained by judging both the scientific value and practical utility of methods while appreciating the corresponding advantages and limitations. The aim of this paper is to serve as a state of the art summary of this issue. The paper gives an overview of classical and modern signal processing methods and techniques from the standpoint of applicability to sEMG signals in fatigue-inducing situations relevant to the broad field of biomechanics. Time domain, frequency domain, time–frequency and time-scale representations, and other methods such as fractal analysis and recurrence quantification analysis are described succinctly and are illustrated with their biomechanical applications, research or clinical alike. Examples from the authors’ own work are incorporated where appropriate. The future of this methodology is projected by estimating those methods that have the greatest chance to be routinely used as reliable muscle fatigue measures.

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1. Introduction

Muscle fatigue represents a complex phenomenon encompassing various causes, mechanisms and forms of manifestation. It develops as a result of a chain of metabolic, structural and energetic changes in muscles due to insufficient oxygen and nutritive substances supply through blood circulation, as well as a result of changes in the efficiency of the nervous system. In general, one may refer to Merletti et al. (2004) who stated that the potential sites of neuromuscular fatigue can be grouped under three headings: (1) central fatigue, (2) fatigue of the neuromuscular junction and (3) muscle fatigue.

The usual term “muscle fatigue” (which we shall use in this paper), meaning in fact “local muscle fatigue” (introduced by Chaffin, 1973) is therefore, sometimes substituted by, or equivalent with, “neuromuscular” fatigue.

 Probably, the simplest way to determine the onset of muscle fatigue is to measure time during which an individual is able to perform certain work, such as keeping a defined level of static (isometric) contraction, ergometrically imposed loading, etc. This is known as “mechanical manifestation of muscle fatigue” and may be defined as a “failure to maintain the required or expected force” (Edwards, 1981), “state of temporary lowered capacity to perform work of a certain intensity, caused by this work itself” (Heimer, 1987), or “any exercise-induced reduction in the maximal capacity to generate force or power output” (Vollestad, 1997). Although simple to determine, results obtained in this manner depend also on psychological factors like motivation, associated with task conditions (Enoka, 1995; Enoka and Duchateau, 2008). Besides, such a method does not give an insight into muscle fatigue as a continuous process of biochemical and physiological changes during performance of the defined work, but detects it only after it has occurred. Finally, this method cannot be used to determine fatigue of a particular muscle when more agonists are contracting participating in physical effort and/or movement.

Muscle fatigue may also be estimated by determining lactate concentration in a muscle based on blood samples taken at predefined time intervals during performing certain work. Due to the mere manner of taking samples, and the way in which lactate concentration is being determined, it is not possible to monitor the state of fatigue in real-time. Also, this kind of measurement, used routinely in sports medicine, gives an estimation of global fatigue of the organism, i.e. of the total active body musculature.

Continuous monitoring of local muscle fatigue during performance of certain work is possible by measuring myoelectric activity of particular muscles by the method of surface electromyography (sEMG). Biochemical and physiological changes in
muscles during fatiguing contractions are, namely, reflected also in properties of myoelectric signals recorded on the surface of the skin above the muscle(s) concerned (De Luca, 1984).

In spite of the limitations of the application of sEMG method to muscles positioned directly below the skin, and the problems of cross talk of myoelectric signals from neighbouring muscles (Farina et al., 2002c), the method, due to its advantages, is used even more often to determine local muscle fatigue. Its principal advantages, hence, in this respect are (1) non-invasiveness, (2) applicability in situ, (3) real-time fatigue monitoring during the performance of defined work, (4) ability to monitor fatigue of a particular muscle and (5) correlation with biochemical and physiological changes in muscles during fatiguing.

This paper aims to present a state of art in the area of local muscle fatigue evaluation in biomechanics by using sEMG information. Mathematics for the extraction of amplitude and spectral variables from the sEMG signal is described concisely, and sorted according to particular methods. Selected examples from the literature are presented in order to support the application of a particular signal processing method. Finally, some trends for the future in this field are projected.

2. A look at the history of sEMG signal processing methods in muscle fatigue evaluation

Almost a century ago Piper, a professor of physiology at the Royal Friedrich-Wilhelms-University in Berlin, noticed a certain “slowing” of surface myoelectric signals during static contraction (Piper, 1912). In addition to this phenomenon Cobb and Forbes (1923) also noted an increase in the signal amplitude as one of the manifestations of fatigue during the static contraction. Unfortunately, due to imperfect instrumentation, these have remained only laboratory efforts of a kind.

The development of electronics in the second half of the 20th century has brought the possibility to reliably measure and record myoelectric signals, while digital computers made applications of digital signal processing methods possible and quite “handy”.

Systematic research on the influence of fatigue on the properties of myoelectric signals has begun around 1950s. One of the first papers addressing this issue reported an increase in the signal amplitude during the fatiguing process (Knowlton et al., 1951). Frequency analysis of myoelectric signals with the aim to monitor muscle fatigue was provided for the first time by Kogi and Hakanmada (1962), who observed the shift toward lower frequencies of surface myoelectric signal power spectrum. A number of authors reported on a similar observation in various muscles in the human body, with different explanations for the phenomenon (De Luca, 1984; Basmajian and De Luca, 1985).

Lindström et al. (1970) developed a mathematical model directly relating power spectrum of surface myoelectric signal to muscle fibre conduction velocity. Kwatinetz et al. (1970) applied digital signal processing (PDP-6 computer) to explore properties of power spectrum density of a surface myoelectric signal recorded during fatiguing task. They introduced the mean frequency of the spectrum (MNF, or MPF as denoted by the authors) to determine differences before and during fatigue. Besides MNF, the second most popular spectral descriptor is the median frequency (MDF), the frequency value dividing the spectrum in two equal halves, (Stulen and De Luca, 1981; Medved, 2001, pp. 197).

The development of digital computers and their general availability enabled the implementation of various digital signal processing methods to sEMG signal. In the earliest investigations, the method most often used for estimating the spectrum of the sEMG signal was the Fourier transform, partially due to the computationally effective fast Fourier transform (FFT) algorithm (Coo-ley and Tukey, 1965; applied in Medved, 1987). Another parameter that has been used to measure frequency shift is the number of zero crossings of the raw EMG per time unit (Hägg, 1981). This parameter has been shown to have properties similar like MNF and MDF. Some investigators have, more recently, used spike properties (Gabriel, 2000) as an alternative indicator of the sEMG spectral changes.

Along with the popular FFT method, parametric (autoregressive) identification methods have also been used to estimate the spectrum of the EMG signal (Paiss and Inbar, 1987; Merletti et al., 1995; Merletti and Lo Conte, 1995).

The applicability of surface electromyography for detection and evaluation of local muscle fatigue has resulted in the development of specialized equipment for real-time muscle fatigue monitoring, based on the power spectrum shift (Stulen and De Luca, 1982; Gilmore and DeLuca, 1985; Merletti et al., 1985; Basano and Ottolino, 1986; Inbar et al., 1986; Kramer et al., 1987; Seroussi et al., 1989; Pratt et al., 1991; D’Alessio et al., 1993).

Although fatigue is most often the consequence of practicing movement and exercise (sports training, kinesiological rehabilitation, ergonomics), the majority of studies in the past were carried out to quantify muscle fatigue resulting from isometric, i.e. constant length (static) muscle contractions. The principal causes for this situation were problems which arose during the measurement of myoelectric signal in dynamic contractions, as well as the problem of their mathematical analysis.

Intensive studies of fatigue in dynamic conditions were performed only during the last decade or so, using various time–frequency signal processing methods in order to investigate changes in the frequency content of the sEMG data that relate to the progression of fatigue. Bonato et al. (1996) suggested Choi–Williams distribution as the most suitable method to be applied to the non-stationary sEMG signal. Karlsson et al. (2000) compared the short-time Fourier transform, the Wigner–Ville distribution, the Choi–Williams distribution, and the continuous wavelet transform in order to analyze myoelectric signals during dynamic contractions by estimating time-dependent spectral moments. The results have shown that the estimates provided by the continuous wavelet transform have better accuracy than those obtained by using other methods.

Regardless of the method of analysis the relative movement of the electrodes with respect to the measured muscle during the sEMG measurement in dynamic conditions makes such estimates questionable and may lead to incorrect conclusions (Farina et al., 2001).

A number of topics describing procedures designed to study sEMG signals recorded during dynamic contractions were presented in the November–December 2001 issue of the IEEE Engineering in Medicine and Biology Magazine (IEEE EMB, 2001).

Recently, non-linear methods such as recurrence quantification analysis (RQA) have been introduced for the study of sEMG signals, mainly in fatigue assessment (Felici et al., 2001; Clancy et al., 2004). Methods for analyzing fatigue at the single motor unit level relying on non-invasive multichannel recordings and joint use of spatial filtering and spatial sampling are currently under study (Merletti et al., 2003; Farina et al., 2004).

The European initiative called Surface Electromyography for Non-invasive Assessment of Muscles (SENIAM), started in 1996. The main goal was to attain consensus on key items (sensors, sensor placement, signal processing, and modelling) to enable exchange of data and results obtained with sEMG (Hermens et al., 1999).

The book “Electromyography – Physiology, Engineering, and Non-invasive Applications” has appeared a couple of years ago
3. Insight into physiological phenomena underlying changes in sEMG signal with fatigue

As already mentioned the properties of the sEMG signal are related to the biochemical and physiological changes in skeletal muscle during fatiguing contractions.

One consequence of the muscle contraction is the increase in the concentration of lactic acid, a metabolic product. Besides the type and size of the dominant muscle fibres, the net lactate concentration depends also on the force level and on the type of contraction (static or dynamic), since blood flow that determines the rate of metabolic removal is, during sustained contraction of about 20% of maximum voluntary contraction (MVC) and more, usually restricted (Humphreys and Lind, 1963). During dynamic contractions blood flow is increased due to the pumping effect of the contracting muscle.

At a certain level of contraction, blood flow is stopped by intramuscular pressure and the muscle becomes ischemic. Myoelectric manifestations of muscle fatigue are affected by this event (Merletti et al., 1984).

Increased concentration of the lactates is responsible for fatigue by changes in intracellular pH. As a result, muscle fibre conduction velocity (CV) decreases, directly changing the shape of the motor unit action potential (MUAP) waveform (Fig. 1 – the case of a sustained contraction), and, finally, the properties of the surface EMG as an interference signal of all generated MUAPs (so-called “interference pattern” according to Basmajian and De Luca, 1985). Brody et al. (1991) show (in vitro) that the decrease of pH in fact determines the decrease of muscle fibre CV, and as a consequence, the decrease of median frequency (MDF).

Therefore, the lowering of muscle fibre conduction velocity (CV) is one of the causes of signal power spectrum shift toward lower frequencies, and also of the increase in sEMG signal amplitude because of a spatial low-pass filtering effect of tissue as a volume conductor (De Luca, 1984).

Viitasalo and Komi (1977) analyzed surface myoelectric signal of the rectus femoris muscle in static contractions. They reported a series of changes in the signal as a result of fatigue: increase of the mean absolute value of a signal, increase of the amplitude and duration of an averaged action potential of motor unit, frequency shift in power spectrum toward the lower frequencies. An increase in amplitude of averaged motor unit action potential measured on the skin surface above the muscle has shown contradictory to results of intramuscular measurements showing decrease of amplitude due to fatigue. The mentioned contradiction was explained by De Luca (1979). He developed mathematical model of myoelectric signal, based on knowledge of contraction mechanisms. The results of simultaneous measurement of myoelectric signals within muscles and on the surface showed that fatigue increased the RMS of the surface myoelectric signal, while simultaneously decreased the RMS of the signal measured within muscle (Stulen and De Luca, 1978). This was explained as a result of frequency shift of the power spectrum toward lower frequencies. The tissue acts as a low-pass filter, allowing more energy to reach surface electrodes (Basmajian and De Luca, 1985).

It is observed that power spectrum changes are often greater than those predictable by the changes of CV, suggesting that myoelectric manifestations of muscle fatigue cannot solely be attributed to CV decrements, and other factors must be considered (Merletti et al., 1990; Dimitrova and Dimitrov, 2003).

Besides the decrease of fibre conduction velocity, two more phenomena are hypothesized as the cause of the observed signal changes (1) remaining activity of the slow motor units, while the fast ones fatigue quickly and are switched off and (2) time synchronization in the activity of particular motor units.

The influence of muscle fatigue on the properties of the sEMG signal during isometric voluntary and electrically elicited contractions is clearly shown in Fig. 2 (Merletti and Lo Conte, 1997). In this example a subject maintained target torque level for 60 s before a mechanical manifestation of muscle fatigue occurred (healthy tibialis anterior muscle). Increase of the RMS value and decrease of CV and power spectrum mean frequency are evident from the beginning of the contraction. This is even more evident during electrically elicited contractions (vastus medialis stimulated for 30 s at...

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**Fig. 1.** Factors which affect the shape of the motor unit action potential during a sustained contraction. Shaded boxes indicate factors that are modified as function of time during a sustained constant-force isometric contraction above 30% MVC. Temperature is less relevant than the other highlighted factors. Other indicated factors are relevant only during weaker contractions or non-isometric contractions (De Luca, 1992).
30 pulses/s), and it appears to be a combination of scaling (stretching in time and in amplitude) and a change of shape of the M-wave.

4. Signal processing methods suitable for muscle fatigue evaluation in biomechanical applications

A succinct description of signal processing methods suitable for application in sEMG-based muscle fatigue evaluation follows. Typical application in the domain of biomechanics is referred to where appropriate. The intention is not to enlist all relevant papers but instead to provide a brief overview.

4.1. Time domain methods

4.1.1. Estimates of sEMG amplitude

Modulation of the amplitude due to muscular effort and/or fatigue represents the dominant change of sEMG signal in the time domain. First continuous EMG amplitude estimators consisted of full-wave rectifier followed by a resistor–capacitor low-pass filter (Inman et al., 1952).

In modern digital systems two indicators of sEMG amplitude are used: mean absolute value (MAV), also called average rectified value (ARV), and root-mean-square (RMS) value. They are defined by following equations:

\[
\text{MAV} = \frac{1}{N} \sum_{i=1}^{N} |x_i| \tag{1}
\]

\[
\text{RMS} = \left( \frac{1}{N} \sum_{i=1}^{N} x_i^2 \right)^{1/2} \tag{2}
\]

In both equations \(x_i\) is the \(i\)th sample of a signal and \(N\) is the number of samples in the epoch.

According to Clancy et al. (2002) the amplitude of the single channel sEMG signal can be estimated using cascade of five sequential processing stages: (1) noise rejection/filtering, (2) whitening, (3) amplitude demodulation, (4) smoothing and (5) relinearization (Fig. 3).

The role of noise reject filter is to limit the effect of unwanted signals added to sEMG during measurement (for example motion artefacts, power line interference, and electronic noise). Whitening
process makes the samples statistically uncorrelated and reduces the variance of amplitude estimation (Bonato et al., 1998). The demodulator (the Detect block on Fig. 3) rectifies whitened sEMG and then raises the result to power 1 for MAV or 2 for RMS processing. In the smoothing stage, several demodulated samples are time-averaged to form one amplitude estimate using sliding window. The length of the window can be optimally selected (Clancy, 1999). Other smoothing methods are also possible, for example, Kalman filter (Evans et al., 1984).

Surface EMG signal amplitude, itself, is rarely used as an indicator of muscle fatigue. It is used in combination with other indicators, often in combination with spectral analysis (Joint Analysis of EMG Spectrum and Amplitude, JASA).

In Sekulic et al. (2006) an application of simple rectification and smoothing of sEMG signals is presented. The aim of the paper was to establish the characteristic values of the particular electromyographic indicators in the simulation of hiking in the laser-standard class in dinghy sailing. Top Croatian athletes participated in the experiment. Simple averaging of the smoothed signals provided a valuable means to quantify muscle load which, presumably – as this was only a simulation of real sports activity – was exerted during this highly demanding physical activity.

4.1.2. Zero-crossing rate (ZCR) of the signal

The zero-crossing rate or zero-crossing frequency $f_z$ of the signal $s(t)$ is defined as half the number of zero crossings of $s(t)$ per second (Hägg, 1981; Inbar et al., 1986). If both the signal $s(t)$ and its first derivative $s'(t)$ have a Gaussian amplitude the distribution of the expected zero-crossing rate $Z$ can be calculated as (Rice, 1945):

$$Z = 2 \frac{\int_{0}^{f_s/2} f^2 S(f) \, df}{\int_{0}^{f_s/2} S(f) \, df}$$

where $S(f)$ is the PSD of the signal and $f_s$ is the sampling frequency.

Zero-crossing rate showed properties close to MDF and MNF (Hägg, 1991), but since the zero-crossing rate is highly dependant on signal-to-noise ratio (SNR) of the analyzed surface EMG, and also very sensitive to deviations of the amplitude distribution from Gaussian one, its use for analysis of sEMG has been abandoned.

4.1.3. Spike analysis

Spike analysis is most certainly not a newly emerging method in the area of sEMG signal analysis (Viitasalo and Komi, 1977). A peak is any pair of upward or downward deflections within a spike that do not together constitute a discrete spike, except in the case of a spike with a single peak. In this case, the deflections of the spike and the peak are the same. Any deflections that do not constitute discrete spikes as previously defined and are found before, between, or after identified spikes, are assumed to be a background noise and not a sEMG signal. Spike analysis can be used to provide similar information as spectral analysis, and does not require stationarity.

Nevertheless, contradictory results on the reliability of sEMG spike parameters are not in favour of their use. Since this method is not frequently used for sEMG signal analysis it will not be presented here. Interested readers are advised to consult (Gabriel, 2000).

4.2. Frequency domain methods

In a frequency domain, the dominant change in sEMG signal during sustained contractions is a compression of the signal spectrum toward lower frequencies. Measures of this compression can be obtained by using various methods of signal frequency analysis.

4.2.1. Fourier-based spectral estimators

We will assume that the sEMG signal is a zero mean wide sense stationary (WSS) process. This stands at least for isometric
constant-force contractions, e.g. for time intervals short enough to exclude fatigue.

In practical sense this means that autocorrelation sequence $r_{mm}(k)$ can be estimated from the single realization of a stochastic process or, in our case, from the samples of a recorded finite length sEMG signal:

$$r_{mm}(k) = \frac{1}{L} \sum_{l=0}^{L-k-1} m(k+l)m(l), \quad 0 \leq k < L$$  \hspace{1cm} (4)

where $m(k)$ is a single process realization, and $L$ is the number of recorded signal samples. The estimator (4) is a biased estimator of the autocorrelation sequence.

Furthermore, the estimate of the power spectral density (PSD) of such a process is provided as:

$$\hat{S}_{mm}(e^{j\omega}) = \sum_{k=-\infty}^{\infty} r_{mm}(k)e^{-jk\omega}$$  \hspace{1cm} (5)

where $e^{-jk\omega}$ is the $k$th sinusoidal harmonic and $r_{mm}(k)$ is the estimation of an autocorrelation function.

The estimation equivalent to the one defined by relation (5) is called periodogram:

$$\hat{S}_{mm}(e^{j\omega}) = \frac{1}{L} |M(e^{j\omega})|^2$$  \hspace{1cm} (6)

where $|M(e^{j\omega})|^2$ represents energy spectral density of the finite energy signal obtained by windowing one realization of the stochastic process. The periodogram is an asymptotically unbiased estimator of the power spectrum, e.g. if signal is infinite, $L \rightarrow \infty$, the expected value of the periodogram is equal to the true spectrum. Nevertheless, the periodogram is not consistent in the mean square sense since its variance tends to the square of the spectrum value as $L \rightarrow \infty$.

There are different methods for the reduction of estimation variance. Bartlett method (Oppenheim and Shafer, 1989) averages multiple periodograms from non-overlapping segments of the original signal sequence. Welch method (Welch, 1967) is similar to the Bartlett’s, but uses data windows and allows the segments to overlap. The averaging methods reduce the variance of the periodogram but increase the bias and decrease the frequency resolution. An alternative method based on wavelet shrinkage has been proposed (Moulin, 1994; Gao, 1997).

This frequency domain method for muscle fatigue evaluation has been used in many areas of human activities. Roy et al. (1990) showed that frequency analysis of myoelectric signals recorded from muscle erector spinae can be used to select individuals with lower back pain problem among the population of professional rowers. A similar diagnostic method has been previously verified for subjects who are not professionals in sport (Roy et al., 1989).

4.2.2. Parametric based spectral estimators

From digital systems analysis it is known that the system may be defined by its transfer function. Under the assumption that surface EMG is a stochastic process, and that the system is physically realizable, the stochastic process under study can be presented as the output of a causal linear time invariant filter with white noise as input having a rational transfer function and a finite number of poles:

$$H(e^{j\omega}) = \frac{\sum_{k=0}^{p} b_k e^{jk\omega}}{\sum_{k=0}^{q} a_k e^{jk\omega}}$$  \hspace{1cm} (7)

where $b_k, k = 0, 1, 2, \ldots, q$ are the zeros, and $a_k, k = 0, 1, 2, \ldots, p$ are the poles.

In such an approach, instead of spectral estimators one looks for a finite number of parameters which are sufficient to describe the stochastic process of interest. Eq. (7) is the general transfer function that defines a so-called autoregressive moving average (ARMA) model. If $a_0 = 0; i = 1, 2, \ldots, p$ and $a_0 = 1$ the model is called moving average (MA), and if $b_0 = 0; i = 1, 2, \ldots, q$ and $b_0 = 1$ the model is called autoregressive (AR) model. A mere list of these three models provokes a question – how to choose an appropriate model as well as the order of a model? Ideally, the model type should be the ARMA since it is the most general one and the order should be larger or equal to the real order. From the practical point of view, AR parameters are much easier to compute than MA parameters. Also, ARMA and MA models can be presented by an infinite AR model, which in practice is truncated at a specific order. These are the reasons why the AR model is the most widely used for EMG investigation. As for the order, the number of parameters has to be chosen appropriately, since the unnecessary parameters are never estimated as zero.

The random variables, e.g. the estimates of the parameters, are associated with certain variance. A smaller order of the model leads to a smaller variance. On the other hand, if the order of the model is small it will lead to poor AR approximation of the true spectrum. A number of criteria have been proposed to estimate the appropriate order of a model; among them one may mention Akaike’s final prediction error (FPE), Akaike’s information criterion (AIC, Akaike, 1974); Parzen’s autoregressive transfer function criterion (CAT, Parzen, 1974), and Rissanen’s minimum description length criterion (MDL, Rissanen, 1978, 1983).

Paiss and Inbar (1987) used autoregressive analysis of sEMG signals during fatiguing maximum voluntary contraction of m. biceps brachii. The estimation model chosen in this case was the AR model of the order 10. The model showed a significant decrease of parameter $a_1$ and a small increase of parameter $a_2$, while parameter $a_3$ remained unchanged. These trends were unchanged for the order of AR model ranging from $p = 3$ to $p = 30$. The authors concluded that parameter $a_1$ can be used for muscle fatigue monitoring (Fig. 4).

Merletti and Lo Conte (1995) introduced the detection techniques, reviewed and compared the methods of spectral estimation based on FFT and autoregressive (AR) models. They discussed their applications and limitations in extracting information from the surface myoelectric signal in particular regard to muscle fatigue during sustained voluntary or electrically elicited contractions. Their results showed that model orders of 4–6 were satisfactory for voluntary sEMG signals, while orders of 8–11 were preferable for the analysis of M-waves measured during electrical stimulation.

4.3. Joint analysis of EMG spectrum and amplitude (JASA)

It is known that EMG spectrum and EMG amplitude are influenced by both force and fatigue. Simultaneous consideration of amplitude and spectrum of a surface EMG can provide information on whether EMG changes are fatigue-induced or force-related. The method is especially useful in situations like those encountered in occupational studies, where intervals of fatigue and recovery interchange (Hagg et al., 2000; Wang et al., 2003; Jonkers et al., 2004).

Briefly, four different cases can be distinguished: (1) If the EMG amplitude increases and EMG spectrum shifts to the right, muscle force increase is the probable cause, (2) If the EMG amplitude decreases and EMG spectrum shifts to the left, muscle force decrease is the probable cause, (3) If the EMG amplitude increases and EMG spectrum shifts to the left, this is considered to be result of muscle fatigue, (4) If the EMG amplitude decreases and the EMG spectrum shifts to the right, this is considered to be recovery from previous muscle fatigue. Even though dependencies of spectral variables on force are neither fully explained nor clear (Farina et al., 2002b), it is possible to reach rather precise conclusions based on
this simple and easy to implement four-case algorithm (Luttmann et al., 2000).

4.4. Time–frequency and time-scale methods

During sustained isometric contractions the signals may be assumed to be stationary during short-time intervals (0.5–2 s). Under this assumption spectral analysis based on the Fourier Transform can be applied. However, for dynamic contractions the assumption does not hold and other methods must be used. Besides, in these conditions one measures the EMG of a muscle that moves underneath the electrodes. This fact complicates the signal considerably, adding confounding factors. Quadratic time–frequency representations do not require stationarity and are being investigated. Some of them introduce unacceptable artefacts due to cross-terms (Hlawatsch and Boudreaux-Bartels, 1992; Jones and Parks, 1992). The Choi–Williams transform seems particularly promising because of the small amplitude of the cross-terms. Examples of possible approaches have been provided (IEEE EMB, 2001). In general, the results obtained during dynamic contractions should be treated with caution because of the limited information available regarding the effect of the relative muscle-electrode movement (Farina et al., 2001; MacIsaac et al., 2001).

4.4.1. General time–frequency representations (Cohen class)

General time–frequency representation or Cohen’s class of distributions is defined as

\[ C_s(t, f) = \int \int e^{j2\pi(s-f)t} f^*(s, \tau) x(s+\tau/2)x^*(\tau/2) sdsd\tau \]

where \( f^*(s, \tau) \) is the kernel of the distribution, \( x \) is the signal, \( x^* \) is its complex conjugate, \( t \) is the time, \( f \) is the frequency and \( \tau \) is the running time (Cohen, 1995).

The word “distribution” should be used when referring to specific members of Cohen’s class, and the word “representation” should be used when referring to all members in order to emphasize the fact that they are not distributions in probabilistic sense.

We present only a subgroup of time-shift and frequency shift invariant \( t-f \) distributions that are most often used for sEMG signal analysis, like spectrogram, Wigner distribution (WD) and reduced interference distribution (RID).

4.4.2. Short-time Fourier transform and spectrogram

Variations of the sEMG signal spectrum as a function of time cannot be analyzed by simply applying Fourier transform, since information about time would be lost. Also, generally speaking, sEMG signals do not conform to the stationarity requirement of the Fourier transform. One way to satisfy this requirement is to apply Fourier transform only to signal segments that are short enough to fulfill this requirement. This approach also provides an insight into variations of the spectrum as a function of time and leads to the short-term Fourier transform (STFT), defined by

\[ \text{STFT}_x(t, f) = \int x(u)h^*(u - t)e^{-j2\pi fu} du, \]

where \( x(t) \) is the signal, \( t \) is time, \( f \) is frequency, and \( h(t) \) is normalized window.

The definition can be interpreted in different ways but we choose two of them:

1. Decomposing the signal \( x \) on a basis of finite length waves (of frequency \( f \) and central instant \( t \)) obtained by windowing the waves of Fourier basis;
2. Decomposing the windowed signal on infinite length waves of a Fourier basis.

Under the assumption of the finite energy signal and normalized window, Parseval’s theorem can be extended to the STFT:

\[ E_s = \int \int |\text{STFT}_x(t, f)|^2 dt df \]

where the spectrum is defined as

\[ S_{\text{STFT}_x}(t, f) = |\text{STFT}_x(t, f)|^2, \]

and represents the distribution of the signal energy in the \( t-f \) plane.

Even though the spectrogram has proven to be very useful, it has several limitations like the stationarity requirement or the uncertainty principle – long time windows will provide high-frequency resolution, but poor time resolution. On the other hand, short-time windows will provide low frequency resolution, but high time resolution.

Cifrek and his collaborators (Cifrek, 1997; Cifrek et al., 1998, 2000) developed a method of surface myoelectric signal measurement and analysis aimed at evaluating muscle fatigue in healthy subjects during cyclic dynamic contractions of upper leg musculature in a simple cyclic flexion–extension movement of the lower leg, recorded during exercise on a training device. The signal processing part of the method is schematically presented in Fig. 5. As an indicator of muscle fatigue a change in the power spectrum median frequency (MF), calculated from the spectrogram, was used. The authors also discussed the influence of analysis parameters (Cifrek et al., 1999) on the results. For example, Fig. 6 shows the influence of the analysis parameters \( R \) (step) and \( L \) (window length) on the fatigue index \( k \) (slope of the regression line).

4.4.3. Wigner distribution (WD)

Wigner distribution, also called Wigner–Ville distribution, overcomes some limitations of the spectrogram and provides a high resolution representation in time and in frequency for non-stationary signals. Yet, due to severe cross-terms, or interference terms, between the components in different time–frequency regions, it can be rather difficult to interpret.

The Wigner distribution is defined as:

\[ \text{WD}_x(t, f) = \int x(t + \frac{\tau}{2})x^*(t - \frac{\tau}{2})e^{-j2\pi f\tau} d\tau. \]

where \( x(t) \) is signal.
4.4.4. Time-varying autoregressive approach (TVAR)

When a spectrogram is used for analysis of the sEMG signal, the signal is portioned into short enough segments to ensure stationarity. Each analyzed segment for which spectrogram is calculated provides information about the spectrum of the segment. A similar approach can be applied to autoregressive modelling. It is then called time-varying autoregressive approach.

Korosec (1999) proposed that the technique in which the time-varying coefficients of the linear model are assumed to be a linear combination of the basis functions is advantageous in some applications, because it produces a smooth, continuous spectrum providing a better view to the slowly changing frequency content of a wide-band non-stationary signal. Clancy et al. (2005) compared various conventional methods to estimate the mean and median power spectral frequencies, and amplitude of the surface electromyogram during 30–90 min, of cyclic, force-varying, constant-posture contractions. Subjects produced hand-grip contractions (of the flexor digitorum superficialis and extensor carpi radialis) in a repeated intermittent pattern until exhaustion. The authors concluded that estimates based on the short-time Fourier transform...
were similar to those based on time-varying autoregressive methods.

4.4.5. Choi–Williams distribution (exponential distribution)

An attempt to improve WD is the Choi–Williams distribution (CWD), also called Exponential distribution (ED). It is a member of Cohen’s class of distributions, where kernel is defined to be:

\[ f(\xi, \tau) = e^{-|\xi|^2/2\sigma^2} \cdot e^{-|\tau|^2/2\sigma^2}. \]  

(13)

By varying the parameter \( \sigma \), a trade-off between interference suppression and high auto-term \( t-f \) resolution is varied. The larger the parameter \( \sigma \) gets, the better the resolution, but the cross-terms increase. For very large values of the parameter \( \sigma \), CWD kernel approaches the WD kernel.

Knaflițz and Bonato (1999) discuss the assessment of the electrical manifestations of muscle fatigue during cyclic dynamic contractions. They introduce instantaneous spectral parameters suited to tracking spectral changes due to muscle fatigue, discuss the issues of quasi-stationarity and quasi-cyclostationarity, and present different strategies of signal analysis to be utilized with cyclic dynamic contractions. The time–frequency representation was obtained by means of the Choi–Williams transform. Preliminary results are presented, obtained by analyzing data collected from paraspinal muscles during repetitive lifting movements, from the first dorsal interosseus during abduction–adduction movements of the index finger, and from knee flexors and extensors during isokinetic exercise. The authors concluded that these techniques allowed for evidencing the electrical manifestations of muscle fatigue in different paradigms of cyclic dynamic contractions.

4.4.6. Wavelets

Following the definition of the STFT transform, as presented earlier in this paper, it is easier to understand how a shorter time window \( h(t) \) causes better time resolution along with poorer frequency resolution if a simple example is presented. Let us use Dirac delta function as window function in order to select a part of a signal. When applied to such a windowed signal, STFT will result in a pseudo-frequency corresponding to scale \( s \), the average period of exercise (Akay, 1998).

\[ \text{CWT}_{a}(t, \tau) = \int x(t) \psi_{a}^{*}(t) dt. \]  

(15)

where \( a \in \mathbb{R}^{+} \) represents the scale parameter, \( t \) is a time, and \( \tau \in \mathbb{R} \) represents the translation parameter (time shifting). The basis function \( \psi_{a}^{*}(t) \) is obtained by scaling the mother wavelet \( \psi(t) \) at time \( t \) and scale \( a \):

\[ \psi_{a}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t-\tau}{a} \right). \]  

(16)

In order to ensure inverse transform, \( \psi(t) \) has to satisfy the condition

\[ \int_{-\infty}^{+\infty} \psi(t) dt = 0. \]  

(17)

Information about frequency is not lost. There is a general relation between scale and frequency:

\[ f_s = \frac{f_0}{a^{1/2}}, \]  

(18)

where \( a \) is the scale parameter, \( f_s \) is a sampling frequency, \( f_0 \) is the pseudo-frequency corresponding to scale \( a \). The idea is to associate

![Fig. 6](image_url)  

Fig. 6. Influence of analysis parameters \( R \) (step) and \( L \) (window length) on fatigue index \( k \) (slope of the regression line). \( T_{av} \) is the average period of exercise (Cifrek et al., 1999).

![Fig. 7](image_url)  

Fig. 7. Tiling of the time–frequency plane by the STFT. The rectangles centred at \((t_0, f_0)\) represent regions of the time–frequency plane where the functions \( h(t) \cdot \exp(-j2\pi ft) \) are concentrated. These rectangles therefore also indicate the time and frequency resolution of the STFT (Akay, 1998).
a purely periodic signal of frequency $f_0$ with a given wavelet, where $f_0$ is the frequency maximizing the FFT of the wavelet modulus. Unlike STFT, tiling of time–frequency plane by CWT is not the same for all values of time and frequency as illustrated schematically in Fig. 8.

Similar to the spectrogram, which represents the distribution of the signal energy in the $t$–$f$ plane, energy distribution along time and scale called scalogram is defined as:

$$\text{SCAL}_{\omega}(a, \tau) = |\text{CWT}_{\omega}(a, \tau)|^2.$$  \hspace{1cm} (19)

Continuous wavelet transform can be sampled. There are two variables available for sampling: scale $a$ and time-shift $\tau$. The sampling has to be fine enough to ensure reconstruction of a signal from the sampled transformation. The most common approach is sampling on a dyadic grid in the time-scale plane, also known as a Wavelet series expansion (WSE), where $a = 2^i$ and $\tau = k2^i$. The time remains continuous. Very similar to WSE is the Discrete wavelet transform (DWT). The difference between the two is that the DWT is applied to discrete-time signals, e.g. time is no longer continuous.

Karlsson et al. (2000) introduced the non-stationary signal analysis methods to analyze the myoelectric (ME) signals during dynamic contractions by estimating the time-dependent spectral moments. The time–frequency analysis methods including the short-time Fourier transform, the Wigner–Ville distribution, the Choi–Williams distribution, and the continuous wavelet transform were compared in order to estimate accuracy and precision on synthesized and real ME signals. They found that the estimates provided by the continuous wavelet transform had better accuracy and precision than those obtained with remaining time–frequency analysis methods on simulated data sets. In addition, ME signals by four subjects (vastus lateralis and rectus femoris muscles) during three different tests (maximum static voluntary contraction, ramp contraction, and repeated isokinetic contractions) were also examined.

Karlsson et al. (2001) summarized the application of the continuous wavelet transform to the analysis of the surface myoelectric signal. They used wavelets to study movements at different angular velocities, and found the continuous wavelet transform to be very reliable for the analysis of non-stationary biological signals, not requiring any smoothing function as do methods based on Wigner–Ville distribution. However, using time–frequency methods involves two main tradeoffs: i.e. potential increase in performance for a given application versus computational complexity and storage requirements. They also confirmed findings of earlier studies showing MNF’s independence of angular velocity.

### 4.5. Spectral shape indicators

During fatigue contractions the PSD of an analyzed sEMG signal shifts toward lower frequencies. The shift, in a simplified version, can be described as a compression of the spectrum. If so, one parameter would be enough to represent the compression. Among possible choices, the most common parameters are mean and median frequency (as stated in the Introduction).

Mean frequency (MNF) is defined as:

$$f_{\text{mean}} = \frac{\int_0^{f_s/2} P(f) df}{\int_0^{f_s/2} P(f) df}$$  \hspace{1cm} (20)

where $f_s$ is the sampling frequency, and $P(f)$ is the PSD of the signal.

Median frequency (MDF) is defined as:

$$f_{\text{med}} = \frac{\int_0^{f_s/2} P(f) df}{\frac{1}{2} \int_0^{f_s/2} P(f) df}$$  \hspace{1cm} (21)

where $f_{\text{med}}$ is the median frequency, $f_s$ is the sampling frequency, and $P(f)$ is the PSD of the signal.

The mean and the median frequency, as defined in above equations, give no information on time dependence of the frequency content. In order to overcome this, instantaneous mean frequency (IMNF)

$$\text{IMNF}(t) = \frac{\int_0^t \omega P(t, \omega) d\omega}{\int_0^t P(t, \omega) d\omega},$$  \hspace{1cm} (22)

and instantaneous median frequency (IMDF)

$$\int_0^{\text{IMDF}(t)} P(t, \omega) d\omega = \int_0^\infty P(t, \omega) d\omega - \int_0^{\text{IMDF}(t)} P(t, \omega) d\omega,$$  \hspace{1cm} (23)

are defined, where $P(t, \omega)$ denotes time dependent power spectrum density of the signal (time–frequency spectrum, Knafliitz and Bonato, 1999).

### 4.6. Other mathematical methods

#### 4.6.1. Frequency-band method

Alternatively, muscle fatigue can be tracked by monitoring changes within different frequency ranges, like low frequency band (Dolan et al., 1995; Maisetti et al., 2002), mid-frequency range (Lowery et al., 2000), and a ratio between high and low frequency bands (Moxham et al., 1982; Allison and Fujiwara, 2002).

Among the methods that have shown a rather good repeatability are the one investigated by Allison and Fujiwara (2002) and Yassierli and Nussbaum (2008): the sEMG signal is portioned into segments, and for each segment the PSD is calculated. From such PSD the sum of the power within low frequency band (10–45 Hz) is calculated as a percentage of the total power. Even though simple, this method should be carefully used since PSD shape depends on the experimental protocol and investigated muscle, thus challenging selection of the adequate frequency band.

#### 4.6.2. Logarithmic power–frequency representation

The sEMG signal is portioned into segments, and for each segment the PSD is calculated and transformed into the logarithmic function. After the normalization with total power, peak frequency (PF), slope of lower frequency (SLF) and slope of higher frequency (SHF) are calculated. More details on how the parameters are defined can be found in Yassierli and Nussbaum (2008).

#### 4.6.3. Fractal analysis

Among the possible choices for fractal analysis, the most recently used methods rely on computing parameters which represent lower and higher frequency behaviour of an analyzed sEMG.
signal. Dispersion analysis and detrended–fluctuation analysis are such methods (Yassierli and Nussbaum, 2008).

4.6.4. Recurrence quantification analysis (RQA)

Recurrence quantification analysis is a non-linear method. The sEMG signal is mapped onto bidimensional space, and the set of variables is calculated in order to evaluate recurring patterns and non-stationarities in the analyzed signal. Among them, the most commonly used variables are the percentage of recurrence structures (%REC) and the percentage of determinism (%DET) indicating how far the time series of the surface EMG samples is from a purely random dynamic system and indicating the “level” of determinism, respectively. Experimental studies have shown RQA to be suitable for muscle fatigue assessment, providing results that highly correlate with those of traditional spectral techniques (Filligoi and Felici, 1999; Felici et al., 2001).

Similar conclusions were drawn from one combined theoretical and experimental study where the effect of motor unit short-term synchronization and conduction velocity (CV) on EMG spectral variables and two previously mentioned RQA-generated variables: %REC and %DET were studied (Farina et al., 2002a). The comparison of simulation with experiments was carried out for high-force level isometric fatiguing contractions of the biceps brachii. The simulation approach allowed the change of synchronization degree and mean CV for a number of motor units. Simulations and experimental results have both shown that spectral variables, %REC and %DET were influenced by CV and degree of synchronization (Fig. 9). Spectral variables were highly correlated with %DET, while variations of %DET and %REC in response to changes in muscle properties were significantly larger than the variations of spectral variables. The latter property gives the RQA method an advantage over classical spectral analysis.

4.6.5. Hilbert–Huang transform

Hilbert–Huang transform (HHT) is a new time–frequency representation method of signal analysis which was initially proposed in the study of fluid mechanics (Huang et al., 1998a). The method has also found applications in biomedical engineering (Huang et al., 1998b; Echeverria et al., 2001).

Hilbert–Huang transform comprises the empirical mode decomposition (EMD) and Hilbert transform. The aim of EMD is to decompose a signal into a set of “intrinsic mode functions” (IMFs), where the characteristics of each IMF are such that they may be Hilbert transformed. Then, through the Hilbert transform, the instantaneous frequency with meaningful feature of each IMF at any point in time may be calculated. The decomposition is based

Fig. 9. From top to bottom: raw simulated signals, power spectra with mean (MNF) and median spectral frequency (MDF) values, and recurrence maps and their percentage of determinism (%DET) and recurrence (%REC). The electromyographic signals are generated with 5 m/s conduction velocity (CV) and 0% MU synchronization level (a) and 3 m/s CV and 25% MU synchronization level (b). The signals in the top row as well as the power spectra in the middle row are in arbitrary units. The recurrence quantification analysis parameters are \( D = 15 \), \( R = 60 \), \( i = 3 \), and \( L = 20 \), providing a plot of 982 \times 982 pixels (Farina et al., 2002a).
5. Conclusion and further prospects

Surface EMG represents a fairly non-invasive source of information on the state of skeletal muscle fatigue. This review paper shows that an interdisciplinary bioengineering approach has been quite successful in providing quantitative sEMG-based information about the fatigue state of skeletal musculature, as evidenced by numerous methods and their practical biomechanical applications. Currently, the merging of improved measurement techniques (including multichannel approaches targeted at a single muscle; one pair of electrodes per muscle in a convenient differential setup is normally understood) with sophisticated mathematical methods and digital signal processing techniques provides a solid basis for validation, refinement and standardization of suitable methods to be applied in biomechanical situations.

We feel confident that in realms of biomechanical research the presented methods will be further developed, exercised, improved and standardized. In clinical diagnostic applications – both in sport and in medical rehabilitation contexts – standardization of modern methods embodied in a novel type of a “muscle fatigue monitor” device is yet to be realized. It may appear in a form of a compact device of portable design and makeup, offering a menu of several correlated fatigue indices, (including, possibly, some non-EMG based as well); a usual common goal of engineers working in the biomedical field.

Conflict of interest

The authors hereby declare to have no conflict of interest.

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