CYCLIC SPECTRAL ANALYSIS OF SURFACE ELECTROMYOGRAM TO CHARACTERISE OSCILLATIONS IN THE MOTOR SYSTEM: A SIMULATION STUDY

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Abstract: The present paper introduces a method of analyzing cyclical phenomenon in the surface electromyogram SEMG, like the oscillatory synchronization of motor units. This method, suited for the so-called cyclostationary signals, has proved its efficiency in many applications in mechanics, telecommunications …. This method consists in calculating the spectral correlation density that is function of two variables: the spectral frequency f, and the cyclical frequency α. The spectral correlation density is normalized to give the spectral coherence. Then, we introduce a model of SEMG generation. In the generation of simulated SEMG signals, we create a common oscillatory input of 12 Hz for many motor units. This common input synchronizes some of the impulses of concerned motor units creating, thus, a cyclical phenomenon whose energy increases with increasing number of synchronized motor units. From the spectral coherence, we extract a parameter that quantifies the level of synchronization. The results show an increase in the spectral coherence with respect to percentage of synchronized motor units. But this increase is less important for high contraction levels than for low contraction levels. That would be due to the increasing firing rates (increasing number of non-synchronized impulses with respect to synchronized impulses).

Introduction

Oscillation in neural activity is commonly reported within the central nervous system. Presently, the role of oscillatory synchronization of motor units (MU) in muscle is of considerable interest [1]. It may be related to a common input to many motoneurons, of central and/or peripheral origin [2,3].

Intramuscular EMG is usually used for measuring synchrony between pairs of discharge of single MU. However, surface EMG could present several advantages for studying this synchronization phenomenon: it is non invasive, technically simpler, offers a representative measurement of the activity of the whole muscle, and therefore, may allow to better investigate the global level of inputs common to motoneurons.

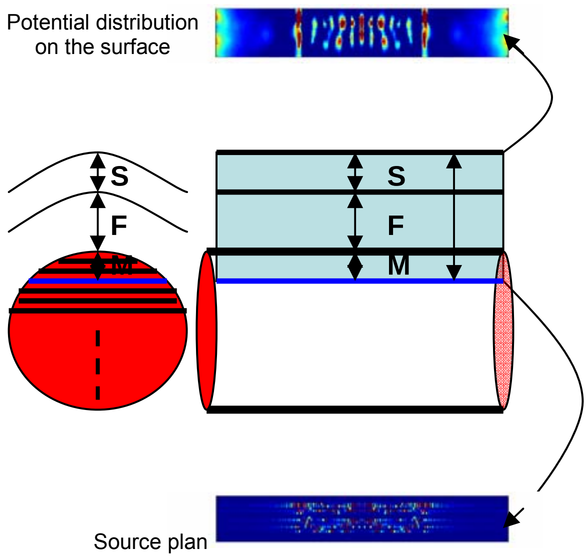

Figure 1: Geometrical representation of the model. Bottom: one of the source plans with some active motor units. Middle: the volume conductor constituted by the muscle layer, the fat layer and the skin layer. Top: the distribution of potential on the skin surface.

The aim of this study is to evaluate, by using surface EMG modeling, cyclic spectral analysis for the quantification of oscillatory synchrony of MUs.

Materials and Methods

The model that we use is mainly constituted by three parts (figure 1):

- *the source plan* which represents the current distribution at a certain depth in the muscle. A certain number of MUs are distributed uniformely in the volume of the muscle. In the volume of each MU, a

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certain number of fibers are distributed also uniformely. All fibers are then grouped into plans parallel to the skin surface. Therefore, one plan contains fibers from different MUs. Some of them could be active but not others.

- *the volume conductor* which is considered as a two-dimensional spatial filter. Its transfer function has been calculated by Farina et al. [4]. It depends on the skin and fat depths and on the depth of the source plan in the muscle. So, each source plan is associated with a volume conductor transfer function.

- *the output plan* which represents the potential distribution on the skin. A source plan is filtered by its associated volume conductor function to give a potential distribution on the skin surface. The output plan is the sum of potentials due to all source plans.

The output plan is then filtered by a two-dimensional filter that represents the electrodes [4]. The filter function depends on the electrode shape and its parameters depend on the electrode dimensions. The recorded SEMG signal is then the difference between two points located on the skin, mid-way between the tendon and the neuromuscular junction (differential configuration). The distance between the two points is 10mm.

In this study, we simulate a mixed type muscle (e.g. biceps brachii) with 350 slow-twitch and 400 fast-twitch MUs. According to real data [5], the ratio of force between a fast-twitch fiber and a slow-twitch fiber is 1.25. The number of active MUs and the mean individual firing rates are function of the activation level. With increasing level, additional MUs are recruited. Slow-twitch MUs are recruited first [6]. Each MU begins to fire at its type specific initial firing rate. Its firing rate converges to a type specific maximal value [7], increasing linearly with activation level [8]. The number of active MUs and their respective mean individual firing rates are computed for each tested contraction level (expressed in percentage of Maximum Voluntary Contraction, MVC). An example of 5 active MUs and their respective action potential trains is shown figure 2.

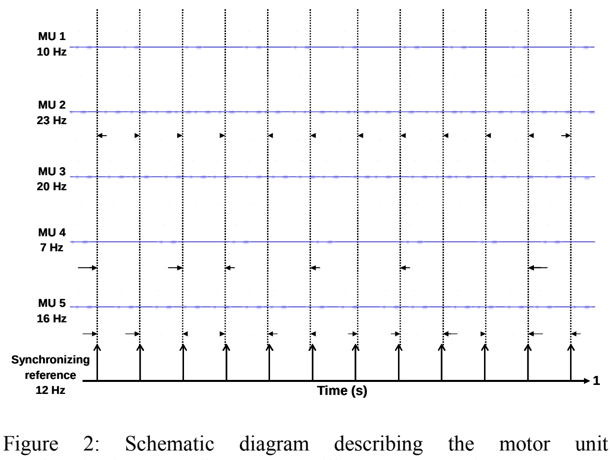

Figure 2: Schematic diagram describing the motor unit synchronization according to an oscillatory common input at 12 Hz. Individual firing rates of 5 motor units are shown. The timing of some action potentials of MU 2, 4 and 5 were adjusted to coincide with impulses of the synchronizing reference.

To simulate an oscillatory common input at 12 Hz, we generate a synchronizing reference signal constituted by a train of impulses of 12 Hz frequency (figure 2). A percentage of active MUs receiving the oscillatory common input (synchronized MUs) is determined. For these MUs, the timing of the nearest action potentials to impulses of the synchronizing reference was adjusted to coincide with them (with a variability of 2 ms). Several percentages of synchronized MUs are tested.

The output EMG signal is then supposed to contain a quasi-cyclic phenomenon, whose energy increases with increasing the percentage of synchronized MUs.

Here, we introduce the notion of cyclostationarity: it is the periodicity of the statistical properties of a signal X(t). X(t) is cyclostationary of the first order if its instantaneous mean is periodic.

$$E\{X(t)\} = m_X(t) = m_X(t+T) \qquad (1)$$

The EMG is a zero-mean random signal. So, we can not talk about cyclostationarity of the first order.

X(t) is cyclostationary of the second order if its autocorrelation function is periodic.

$$E\{X(t)X(t+\tau)\} = R_X(t,\tau) = R_X(t+T,\tau) \qquad (2)$$

The Fourier transform of $R_X(t,\tau)$ ($\tau \leftrightarrow f$) leads to a time-frequency representation (Wigner-Ville) $W(t,f)$ that gives the energy of the frequency f at time t. For a certain frequency $f=f_0$, the time course of the energy is periodic for cyclostationary signal (of 2nd order fig. 3.a) as seen in figure 3.b.

$W_{f=f0}(t)$ being a periodic signal, it can be decomposed in Fourier series ($t \leftrightarrow \alpha$). We obtain the Spectral Correlation Density (SCD) $S_{f=f0}(\alpha)$ (figure 3.c). $S_{f=f0}(\alpha)$ has a non-zero value for α=K/T (T is the cycle time) and is zero elsewhere. If we consider all frequencies we obtain a two-dimensional representation $S(\alpha,f)$ as seen in figure 4.

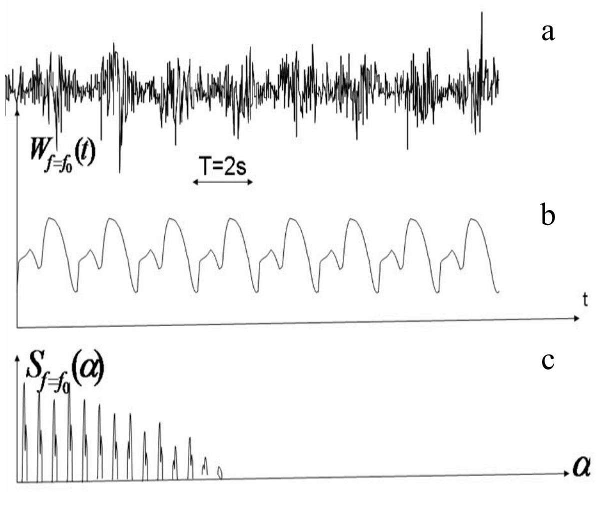

Figure 3: a cyclostationary signal (a), the time course $W_{f=f0}(t)$ of the energy for a frequency $f=f_0$ (b), and the Fourier transform $S_{f=f0}(\alpha)$ of $W_{f=f0}(t)$ (c).

This cyclostationary analysis has proved its efficiency in many applications such as signal processing and communications [9,10,11,12,13], mechanics [14], medicine and biology [15], economics [16], hydrology [17], climatology [18] ….

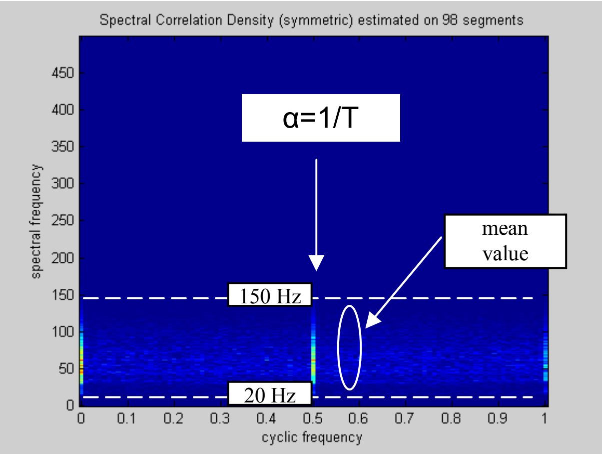

Figure 4: An example of the Spectral Correlation Density of a cyclostationary signal of period T=2s (α=0.5).

We can show that

$$R_X(t,\tau) \leftrightarrow S_X(\alpha,f) = \lim_{T\to\infty} E\{X_T(f+\alpha/2)X_T^*(f-\alpha/2)\} \quad (3)$$

where $X_T(f)$ is the Fourier transform of X(t) in a time window T. The spectral coherence SC is the normalized version of the SCD:

$$SC(\alpha,f) = \frac{SCD(\alpha,f)}{\sqrt{SCD(0,f).SCD(0,f-\alpha)}} \quad (4)$$

with $0 \le SC(\alpha,f) \le 1$.

The spectral coherence is 0 when there is no cyclical component in the signal and SC(α,f)=1 when the frequency f is perfectly periodic of period T=1/α.

The spectrum of the simulated signals is concentrated between 20Hz and 150Hz. To see the evolution of the cyclostationarity with the synchronization level, we compute the mean value of the spectral coherence between f=20Hz and f =150Hz and for α=1/T (figure 4).

Results

Application to simulated signals

We can observe (figure 5) seven curves corresponding to seven activation levels. The results show an increase in the spectral coherence with respect to the synchronization level for all contraction levels.

However, the higher is the contraction level, the less is this increase. But the value of the spectral coherence is significantly different from the zero synchronization value for synchronization levels higher than 20% of active MUs whatever the activation level.

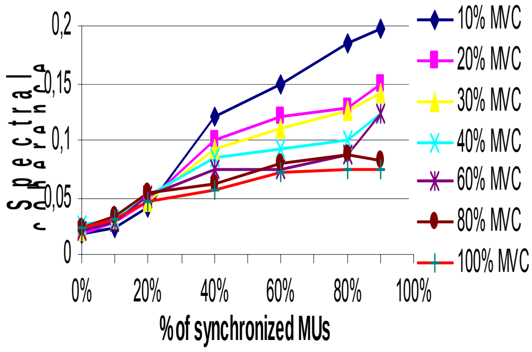

Figure 5: Spectral Coherence (SC) for α=12Hz (averaged value for f between 20Hz and 150Hz) according to synchronized MU percentages and contraction levels. Significant SC for value ≥0.0308 (p≤0.01)

Application to real signals

An example of real surface EMG recording during a physiologic tremor is shown in Figure 6.a. The EMG signal was recorded from the right upper trapezius muscle of a healthy subject while maintaining, during 10s, his right arm positioned in 90° flexion with a 4 kg load in his hand ("postural contraction"). The signal was detected using a differential configuration, amplified, filtered (20-500 Hz), and sampled at 2048 Hz.

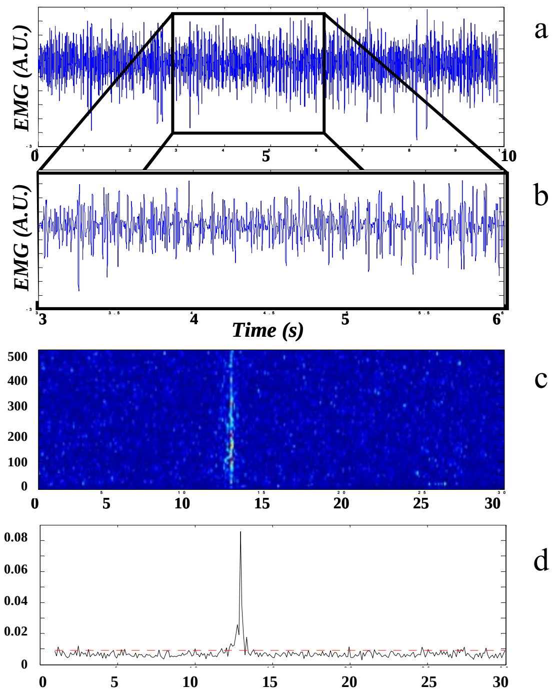

Figure 6: (a) example of surface EMG recording, (b) a zoom of the signal, (c) the spectral coherence showing high values about α=13Hz, (d) mean, over f, of the spectral coherence.

The spectral coherence (figure 6.c) shows a clear region of high values at about α=13Hz. By computing the mean value over f = 20 to 150 Hz, we can see a clear peak around 13Hz (figure 6.d).

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Discussion

On simulated signals, each impulse of a synchronized motor unit produces an action potential detected by the electrodes on the skin surface. Some of the impulses are synchronized and produce a periodic signal of period T=1/12. This is the cyclostationary component. The remainder impulses produce a random signal that is non-cyclostationary. We can show that the higher is the energy ratio of the cyclostationary component, the higher is the spectral coherence. When the percentage of synchronized MUs increases, the energy of cyclostationary component increases and thus, the spectral coherence increases too.

When the contraction level increases, new motor units, with higher firing rates (according to the Henneman principle), are active and the already active motor units increase their individual firing rates. That means that the number of impulses (or action potentials), in one second time, increases, but the synchronized impulses are always 12 per second. So, the increase in impulses number will concern only the non-synchronized ones. The energy of non-cyclostationary component increases and the ratio of the energy of cyclostationary component decreases. Thus, the spectral coherence decreases. That is why we can see (figure 5) that the spectral coherence increases less for high contraction levels than for low contraction levels with respect to synchronization level.

When applied to real signals, related to a physiological cyclic phenomenon (tremor), the spectral coherence permits also to evidence the cyclic characteristic of the surface EMG. More studies are needed to test the limits of this method on real EMG signals, specially in relation to the contraction level.

Conclusions

The Spectral Correlation Density SCD is an appropriate tool for analyzing cyclostationary signals, and detecting hidden periodicity in a random signal. It seems, from this study, that the use of this tool in analyzing cyclic phenomena in surface EMG would be of a good help.

Cyclic spectral analysis may be able to detect oscillatory synchronization of MUs and to evaluate, with a good accuracy, from surface EMG, the level of this oscillatory synchronization, and so oscillatory inputs common to motoneurons.

This method can particularly find some applications in the study of physiologic (in normal population, 6-15 Hz [19]) and pathologic tremors (e.g. parkinsonian or essential tremor, < 10 Hz).

References

[1] BAKER S.N., KILNER J.M., PINCHES E.M., and LEMON R.N. (1999): 'The Role of Synchrony and Oscillations in the Motor Output', *Exp. Brain. Res.*, **128**, pp.109-117

[2] FARMER S.F., BREMNER F.D., HALLIDAY D.M., ROSENBERG J.R., and STEPHENS J.A. (1993): 'The Frequency Content of Common Synaptic Inputs to Motoneurons Studied during Voluntary Isometric Contraction in Man', *J. Physiol.*, **470**, pp.127-155

[3] NORDSTROM M.A., FUGLEVAND A.J., and ENOKA R.M. (1992): 'Estimating the Strength of Common Input to Human Motoneurons from the Cross-Correlogram', *J. Physiol.*, **753**, pp.547-174

[4] FARINA D., and RAINOLDI A. (1999): 'Compensation of the Effect of Sub-Cutaneous Tissue Layers on Surface EMG: a Simulation Study', *Med. Eng. Phys.*, **21**, pp. 487-497

[5] TRAPPE S., GALLAGHER P., HARBER M., CARRITHERS J., FLUCKEY J., and TRAPPE T. (2003): 'Single Muscle Fibre Contractile Properties in Young and Old Men and Women', *J. Physiol.*, **552**, pp.47-58

[6] HENNEMAN I. (1957): 'Relation between Size of Neurons and Their Susceptibility to Discharge', *Science,* **126(3287)**, pp.1345-7.

[7] DELUCA C.J., FOLEY P.J., and ERIM Z. (1996): 'Motor Unit Control Properties in Constant-Force Isometric Contractions', *J. Neurophysiol.*, **76**, pp.1503-1516

[8] MILNER-BROWN H.S., STEIN R.B., and YEMM R. (1973): 'Changes in Firing Rate of Human Motor Units during Linearly Changing Voluntary Contractions', *J. Physiol*., **230**, pp.371-90

[9] DING Z., and LI Y. (1994): 'On Channel Identification based on Second-Order Cyclic Spectra', *IEEE Trans. on Signal Processing*, **42**, pp.1260-1264

[10] GOUDA M., ADAMS E.R., and HILL P.C.J. (1997): 'Estimation and Identification Techniques for DS/SS Signals', 23rd International Conference on Industrial Electronics, Control and Instrumentation, IECON '97, New Orleans, LA, **1**, pp.311-315

[11] CAMPBELL J., GIBBS A., and SMITH B. (1983): 'The Cyclostationary Nature of Crosstalk Interference from Digital Signals in Multipair Cable—Part I: Fundamentals', *IEEE Trans. on Communications,* **31**, pp.629-637

[12] CAMPBELL J., GIBBS A., and SMITH B. (1983): 'The Cyclostationary Nature of Crosstalk Interference from Digital Signals in Multipair Cable—Part II: Applications and Further Results', *IEEE Trans. on Communications,* **31**, pp.638-649

[13] GARDNER W.A. (1987): 'Statistical Spectral Analysis: A Non-Probabilistic Theory', Prentice-Hall, Englewood Cliffs, NJ

[14] CHERMAN P.J. (1991): 'Random Processes in Rotating Machinery', in MIAMIEE, A.G. (Ed): 'Proceedings of Workshop on Nonstationary Stochastic Processes and Their Applications', (World Scientific, New Jersey), pp.211-18

[15] FINELLI C.J., JENKINS J.M. (1991): 'A Cyclostationary Least Mean Squares Algorithm for Discrimination of Ventricular Tachycardia from Sinus Rhythm', International Conference of the IEEE Engineering in Medicine and Biology Society, Baltimore, MD, 1991, pp. 740-741

[16] PAGANO M., and PARZEN E. (1979): 'An Approach to Modeling Seasonally Stationary Time-Series', *J. Econometrics*, **9**, pp.137-153

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[17] KACIMOVA A.R., OBNOSOV Y.V., and YAKIMOV N.D. (1999): 'Groundwater Flow in a Medium with a Parket-Type Conductivity Distribution', *J. Hydrology*, **226**, pp.242-249

[18] HURD H.L., BLOOMFIELD P., LUND R.B. (1992): 'Periodic Correlation in Meteorological Time Series', Fifth International Meeting on Statistical Meteorology, 1992, p. 1-6

[19] RAETHJEN J., PAWLAS F., LINDEMANN M., WENZELBURGER R., and DEUSCHL G. (2000): 'Determinants of Physiologic Tremor in a Large Normal Population', *Clin. Neurophysiol.*, **111**, pp. 1825-1837