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Correlation based analysis of sEMG signals during complex muscle activity. Feasibility study of new methodology

Michał Nowakowski[1], Paulina Trybek[2,3], Łukasz Machura[2,3]

[1]Department of Medical Education, Jagiellonian University Medical College, Kraków, Poland
[2]Department of Computational Physics and Electronics, Institute of Physics, University of Silesia, Katowice, Poland
[3]Silesian Center for Education and Interdisciplinary Research, Chorzów, Poland

Corresponding author: Paulina Trybek, Department of Computational Physics and Electronics, Silesian Center for Education and Interdisciplinary Research
ul. 75 Pułku Piechoty 1A, 41-500 Chorzów, Poland
Phone: +48 32 349 76 05; E-mail: paulina.trybek@smcebi.edu.pl

Abstract: Assessment of complex motor task (CMT) competency is still very prone to bias. Objective assessment is based either on outcomes leaving the process out of the equitation or on checklists with all their limitations. We tested the hypothesis that muscular recruitment patterns assessed with surface Electromyography (sEMG) will be different between novices and skilled trainees. sEMG signals of the muscles that potentially are characterized by the highest level of engagement at complex motor task were submitted to comprehensive correlation analysis. Standard methods of estimating the correlation coefficients were compared with more advanced analysis including cross-wavelet coherence and calculation of mutual information. We conclude that with appropriate analytical tools it is possible to compare sEMG signals during complex motor tasks and that at least on our very small sample it differs between individuals.

Key words: sEMG, laparoscopy, laparoscopic trainer, cross correlation, wavelet coherence.

Introduction

Muscular hyperactivity together with the improper patterns of muscle recruitment are often the cause of decreased accuracy and fluency of performed motor tasks. Complex motor tasks combined with the need of precision, lack of skill and stress resulting from the will to meet strictly set objectives often lead to increase of muscle tension due to over-stimulation of the motor cortex. This may lead to reduction of efficiency of movements and growth of the fatigue. Anything from 30 to 80% of surgeons declares pain of the neck and shoulder girdle as the major discomfort after the surgery [1, 2]. Non-ergonomic construction of laparoscopic instruments and non-physiological, forced position during laparoscopic procedures only aggravate that problem. Several publications that have appeared in recent years are focused on the bio-mechanics of laparoscopic surgical instruments [3–5]. Some researchers have proposed methods of using sEMG for evaluation the physiological muscular fatigue in the context of surgical training in laboratory conditions [6–9]. The effectiveness of the sEMG in the assessment of the level of involvement of the muscular system has some strong evidence in the literature [10–11]. Nevertheless, there are still some interesting and relevant problems to be addressed. This work is focused on an examination of the relationship between the sEMG signals of muscles that potentially are exposed to the increase of muscle tensions during laparoscopic surgical manipulation.

To compare the signals of a muscle activation at the different levels of involvement for the selected individual muscle groups of skilled (surgeon) and novice (student) laparoscopist we used standard box trainer and intracorporeal knot tying exercises.

The standard correlation-based analysis was implemented for identification of strength of linear relation between the sEMG series under consideration. The correlation and cross correlation methods have been widely used in the context of analysis of electrophysiological data, also for sEMG signals [12–15]. Physiological time series due to its typical non-stationary and nonlinear character require an appropriate analytical tools. The standard correlation quantities, measured in time or frequency domain separately are often not sufficient. The wavelet cross-spectrum which is able to identify time-localized common oscillatory behavior of two time series represents an example of more appropriate analytical tool [16]. Current research including neurophysiology [17–18], geophysics [19], cardiovascular system [20] or financial markets [21] are focused on wavelet coherence analysis. Another important feature that can be implemented for measurement of a relation between two variables is a mutual information (MI) function. The MI is the nonlinear analog of standard correlation function. It comes from the information theory and measures entropic relations of two variables. It is known to have a number of application in the context of physiological data [22–23]. For the complete characterization of highly complex relationship between sEMG signals, the standard correlation-based analysis was set with the wavelet coherence and results of the mutual information calculations.

Main goals of this study are twofold: to check feasibility of proposed methodology of complex motor task assessment in terms of sEMG recording and advanced methodology of analysis and checking for presence of measurable differences in the muscle activity of the subjects who represent extremely different level of skills of using laparoscopic instruments.

Materials and method

The experiment was conducted on two individuals — a highly skilled laparoscopic surgeon and a student as a complete beginner. Participants were given the complex motor task on the laparoscopic trainer. They had to tie surgical knots using the intra-corporeal double handed technique. To acquire signifiant amount of data they were recorded for 45 minutes. Electrodes were located over separate groups of muscles: trapezius, deltoid, long palmar muscle and ulnar wrist flexor, abductor muscle of thumb, and flexor brevis on both sides. Additionally the maximum contraction state was measured separately. The interelectrode distance was set to 1cm. Concentric electrodes were used to compensate for the difficulties with the proper placement of electrodes in relation to the direction of muscular fibers and also to compensate for the changes related to the morphology of the shape of the action potential during the movement. The measurements were conducted using the eight-channel sEMG recorder (OT Bioelettrinica, Torino, IT). The system automatically records the mean value of the electromyogram signal over a time interval of 125 ms.

Results

Table 1 summarizes the results of the average values of amplitude of sEMG signals for the corresponding muscles. Channels are assigned to each group of muscles. C_1–C_4 represent the left arm, and C_5–C_8 indicate muscles from the right arm. C_1 and C_5 form a pair of the respective trapezius ridge group of muscles located on the left and right arms. Similarly, channels C_2 and C_6 record signals of the deltoids, C_3 and C_7 represent the forearm muscle group (long palmar muscle and ulnar wrist flexor), and finally C_4 and C_8 are assigned to the group of thenar muscles.

It can be noticed that in the case of advanced laparoscopist (AL) the mean values of amplitude are significantly lower than those of the novice laparoscopist (NL), except for the thenar muscle group of the left hand (C_4) and deltoid of the right hand (C_6). For both analyzed cases the maximum values of amplitude occurs for the thenar muscle group (C_4, C_8).

Table 1. The comparison of the mean values of the signal amplitude measured in μV together with the standard error of the mean of novice and advanced laparoscopist.

Channel nb.	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
Novice	17.374 ± 0.069	13.847 ± 0.089	13.318 ± 0.076	31.551 ± 0.323	14.841 ± 0.066	7.743 ± 0.040	14.515 ± 0.063	40.336 ± 0.191
Advanced	8.191 ± 0.005	8.253 ± 0.007	9.242 ± 0.027	40.413 ± 0.122	8.400 ± 0.006	8.423 ± 0.010	9.940 ± 0.020	35.352 ± 0.139

Correlation coefficients

In it's straightforward meaning the correlation between two time series is a measure of how similar the signals are. There are several approaches and methods of calculating the normalized correlation coefficients. In this work three types of coefficients are compared: the commonly used parametric Pearson coefficient, the nonparametric Spearman's rank correlation coefficient and Kendall's tau coefficient. The details about those quantities can be found in [24]. The calculation was performed between the signals that represent contralateral (left vs right), neighboring (in close proximity over one joint) and ipsilateral distant (thenar and trapezius) muscles for AL and NL separately. The correlations between symmetrical muscles were calculated in order to check if there is any kind of measurable relation between corresponding muscles of the right and left hand during the performed task. Additionally, the results of correlations between neighboring muscles are presented as a correlations matrices. The matrices of the Pearson's correlation coefficient were calculated separately for both AL and NL. For visualization that increase of muscle activity entails an increase in correlation coefficients the correlation matrices for the maximum contraction state were also shown (Fig. 1).

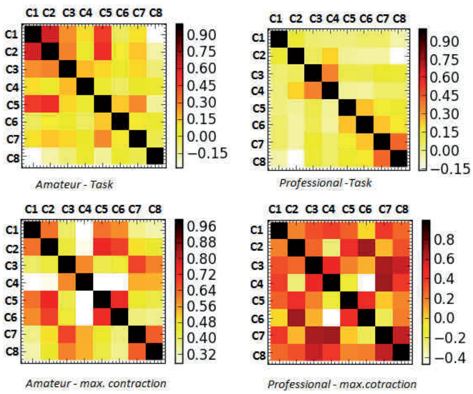

Fig. 1. The matrices of Pearson's correlation coefficients calculated between all muscle group of professional (right) and amateur (left) for the working and maximum contraction state separately.

The analysis of the neighboring muscles of NL during the working state shows that the highest value of correlation coefficient is found between trapezius ridge and deltoids muscle group ($r_{c1,c2} = 0.63$). Relatively high correlation coefficient also occurs between deltoids and forearm muscle group ($r_{c2,c3} = 0.38$). In the case of a right hand, the correlation coefficients are respectively lower and is more difficult to distinguish the most correlated group of muscles.

Different results were obtained for AL. The correlation between the left deltoid and trapezius is significantly lower ($r_{c1,c2} = 0.11$). The negligible correlation occurs between left deltoid and forearm muscle group ($r_{c2,c3} = 0.047$). The highest values of correlation coefficient can be observed between forearm and thenar muscle group ($r_{c3,c4} = 0.37$, $r_{c7,c8} = 0.42$) in case of both, right and left hand.

Table 2 summarizes the results of Pearson, Spearman and Kendall correlation coefficients calculated for the time series of the ipsilateral and contralateral muscles. The results for professional (AL) indicates that there is no evident relationship between symmetrical muscles from the right and left hands. In the case of amateur the results show that the relatively high dependency occurs between right and left trapezius ridge.

Table 2. The Pearson, Spearman and Kendall correlation coefficients calculated between ipsilateral and contralateral muscles for amateur and professional during CMT.

	Amateur (NL)			Professional (AL)		
Symmetrical muscles (left vs right)	Pearson	Spearman	Kendall	Pearson	Spearman	Kendall
c_1–c_5	0.500	0.536	0.383	0.030	0.017	0.015
c_2–c_6	0.033	0.050	0.036	−0.049	−0.004	−0.003
c_3–c_7	0.147	0.217	0.154	0.134	0.178	0.133
c_4–c_8	−0.018	−0.045	−0.030	0.036	0.067	0.047
Ipsilateral (same side)						
c_1–c_4	0.113	0.128	0.089	0.008	0.002	0.002
c_2–c_4	0.033	−0.056	−0.039	0.213	0.151	0.117
c_1–c_3	0.317	0.389	0.268	0.019	0.018	0.015
c_2–c_3	0.375	0.510	0.377	0.047	0.055	0.044
c_5–c_8	−0.173	−0.280	−0.192	0.119	0.169	0.131
c_6–c_8	0.012	0.017	0.012	0.174	0.195	0.149
c_5–c_7	0.292	0.250	0.177	0.166	0.231	0.189
c_6–c_7	0.102	0.118	0.086	0.235	0.311	0.251

Considering the relation between ipsilateral muscles, the biggest differences between amateur and professional can be observed for deltoids and forearm muscle group of the left hand (c_2–c_3). Similar results also occurs for a relation between thenar and forearm muscles (c_1–c_3).

Cross correlations

Correlation quantities described in previous paragraph were not always able to distinguish the best match between any two signals. In the context of time series analysis, the concept of cross-correlation offers promising opportunities. The cross correlation measures the similarity between two signals at different lag positions [25]. This can have a significant impact, due to the fact that the maximum value of cross-correlation coefficient can be shifted with the time lag describing correlations that occur in constant patterns but with time delay. Good example would be sequential muscular activation. Fig. 2 gives an example of cross-correlation calculated between the trapezius ridge and deltoids of the professional and amateur. It has been found that the maximum value of correlation exhibit a shift for the amateur. The time delay for calculated maximum is approximately 8 minutes. In the case of the professional the maximum of cross-correlation function occurs for zero lag.

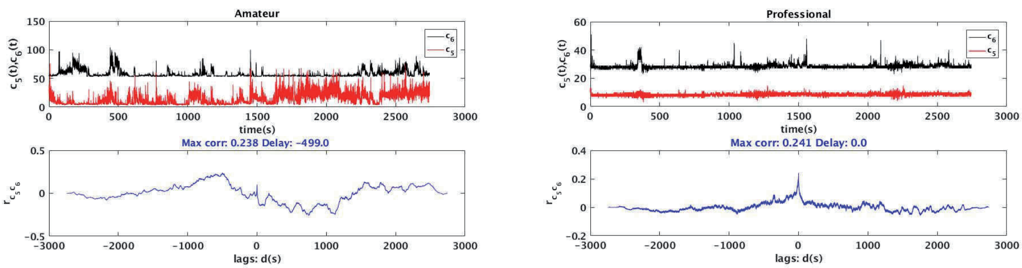

Fig. 2. The comparison of raw signals(upper) and the cross-correlation function (lower) calculated for the right trapezius ridge and deltoids of both professional and amateur. For better visualization raw signals are shifted.

Cross-wavelet spectra

sEMG signals have the highly complex nature which sometimes causes the difficulties in a proper interpretation of the physiological data. To deal with these complexities the cross wavelet coherence analysis was implemented. The wavelet transform can be calculated of time series that contain nonstationary power at different frequency components [26]. The complex theory behind the cross-wavelet and wavelet coherence can be found in the cited studies [27–28]. Here we only mention that this method characterizes the occurrences of spatio-temporal interaction between two time-series. The cross-wavelet analysis is able to identify the local correlations between time series in domains of time, frequency, amplitude, and phase. An example of cross-wavelet spectra calculated for selected muscle group of professional and amateur are shown in Fig. 3. The upper figures illustrates the interaction between left trapezius ridge and forearm muscle group. The lower graphs depict deltoids and forearm group of muscles.

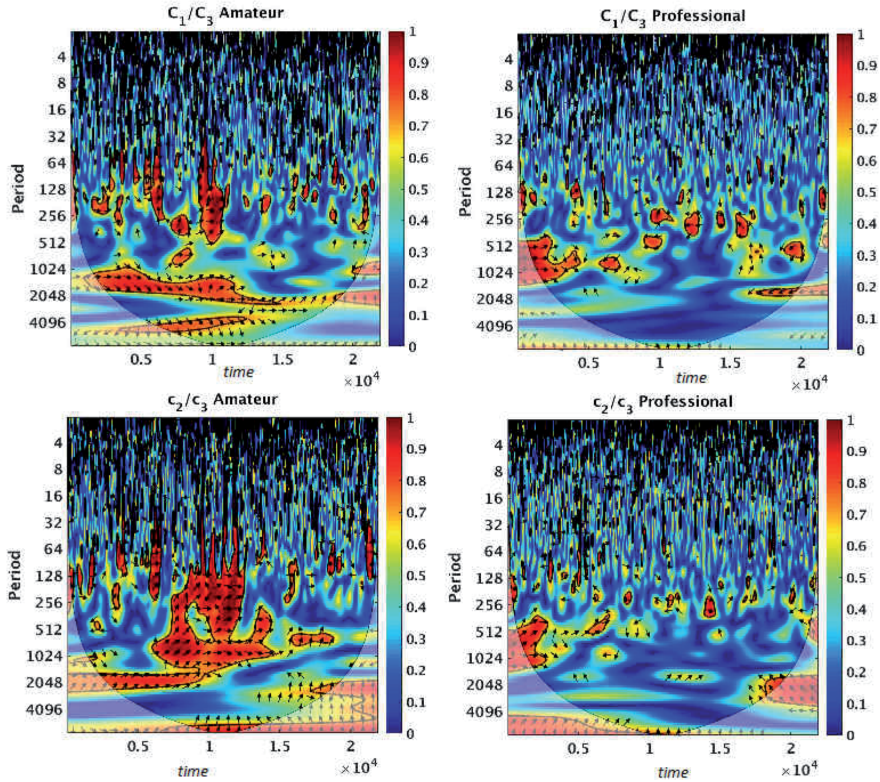

Fig. 3. Wavelet coherence between the series of ipsilateral muscles calculated for professional (right) and amateur (left) separately.

Red areas illustrate high interaction in the frequency domain between analyzed series. Additionally the information about specific scaling factor and the time point of the coherence can be investigated. Comparison of the results is presented in Fig. 3 where the extension of the region with the higher coherence can be observed for both presented cases of amateur. Arrows represent the relative phase, which for all presented cases seem to show dephasing.

Mutual information (MI)

The mutual information is based on Shannon's information theory and is an important measure of statistical dependence [29]. The applicability of this method to the wide range of physiological data is possible due to the fact that MI can be regarded as a nonlinear equivalent of the standard correlation function [30]. In simple words it can be interpreted as the amount of information that one random variable X transfers on another random variable Y (and vice versa). Calculated values of MI are presented in Table 3. For almost all analyzed cases the significant differences between amateur and professional are clearly visible. As can be seen from Fig. 4 where the average values of MI are presented for ipsi and contralateral muscle groups separately. The strongest differences occurs for interaction of the left ipsilateral muscles.

Table 3. The average values of mutual information for ipsi and contralateral groups of muscles calculated for amateur and professional separately.

Channels nb.	c_1-c_5	c_2-c_6	c_3-c_7	c_4-c_8	c_1-c_4	c_2-c_4	c_1-c_3	c_2-c_3	c_5-c_8	c_6-c_8	c_5-c_7	c_6-c_7
Amateur	0.353	0.110	0.205	0.518	0.367	0.403	0.327	0.470	0.335	0.197	0.187	0.111
Professional	0.014	0.017	0.066	0.477	0.029	0.087	0.010	0.024	0.076	0.121	0.055	0.094

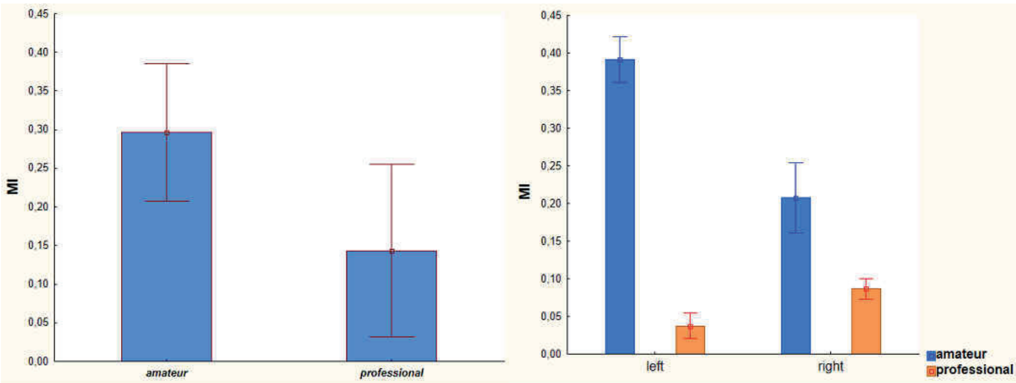

Fig. 4. The average values of mutual information for contralateral (l.h.s) and ipsilateral (r.h.s) group of muscles calculated for amateur and professional separately.

Discussion

Lower amplitudes observed in case of advanced laparoscopist may be of course explained by constitutional factors however lower general muscular tension, easier manipulation, lower force used to achieve same goals could also explain that difference. Also pattern of that difference supports training related difference: left hand thenar muscles of AL were significantly more active than those of NL. As expected AL would utilize all available resources to complete the task and both hands would work without the preference of dominant hand. NL however could rely more on his dominant hand which resulted in observed difference. Analysis of standard correlation coefficients did not prove of any significant relationship between symmetrical muscles except for the case of trapezius ridge of amateur. In the case of relation between ipsilateral muscles the significance of calculated correlations is not so clear. The strongest correlation coefficient was observed within ipsilateral muscles of left hand of novice laparoscopist. That can be easily attributed to relative lack of skill with non-dominant hand in complex motor tasks. The results of this specific muscle group were also confirmed by the cross-wavelet coherence analysis which seems to be more adequate and useful tool for evaluation of interactions between the muscles in comparison with the standard correlation based methods.

Our observation that there is a strong correlation between deltoid muscle and trapezius for NL could be again interpreted as upper body tension frequently observed in novice learners. That phenomenon is absent in case of AL. In this case, there was a distal limb correlation suggesting similar utilization of thenar and forearm muscles which could be a result of equal utilization of short muscles of one's short and long flexors.

For contralateral comparison (left vs right muscle) our observations would confirm the fact that AL would use both hands independently while for NL symmetrical tension of trapezius could be observed.

Time delay of 8 minutes which is rather a random result definitively cannot be interpreted as a value of some physiological meaning in the context of muscle activity at complex motor task. All analyzed results of muscles under consideration did not indicate the advantage of the cross-correlation method in comparison with the standard correlation coefficients. The calculated values of lags positions are too large for possible meaningful interpretation.

Cross-wavelet spectra offer unique opportunity to investigate complex nature of sEMG signal and its spatio-temporal correlations. Dephasing observed depicts a clear decoherence between all the muscles for advanced laparoscopist. This means that proposed cross-wavelet method supports lack of cross-correlations between muscles for all time scales for the professional user suggesting independent application of each muscular group.

The most interesting results came from the mutual information (MI) analysis. Average values clearly indicated lower results for AL. It must be underlined that tasks required both hands to be used hence we can clearly exclude that performing with one hand only influenced the results. In agreement with proposed hypothesis high MI for non-dominant hand of NL was very significantly higher than that of AL while that difference was not so big for dominant hand.

Conclusions

The main concern of this work was to investigate the differences between the sEMG signals obtained from the complete beginner and highly skilled laparoscopist. The differences of mean values of signal amplitude between amateur and professional are clearly visible and confirmed numerically. The correlation based analysis was performed in order to examine the interactions between the signals that characterize the muscle of professional and amateur individually. Cross-spectra gave us definitely more details about character and strength of calculated relations. The values of standard correlation are relatively too low for meaningful interpretation of the obtained results. The biggest differences for the analyzed cases were signalized by the method of mutual information, therefore this method is strongly suggested for the future analysis.

It can be concluded that sEMG and advanced methods of statistical analysis offer possible tool for complex motor tasks training assessment.

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Conflict of interest

None declared.

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