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New Joint Analysis of Electromyography Spectrum and Amplitude based methods towards real-time muscular fatigue evaluation during a simulated surgical procedure: a pilot analysis on the statistical significance

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Abstract

The Joint Analysis of Spectral and Amplitude (JASA) method offers a valuable tool for the indication of four muscle conditions in occupational field studies. It has both advantages of an easy computation and an ergonomic display of the results. However, several limitations are pointed out such as the lack of information on the change of the muscle condition all along the completion of task. This paper proposes two evolutions of the JASA method to quantify muscular fatigue in real time for comfort analysis. The *evolutionary* method focuses on increased time windows; and the *sequential* method analyses the muscle conditions on constant sliding time lapses. A pilot study is conducted for a minimally-invasive laparoscopic procedure. The outcome results obtained with the original, the *evolutionary* and the *sequential* methods are compared. Both new methods provide a complementary analysis of the muscular fatigue over a task and the statistical significance of the condition.

Keywords: muscular fatigue, surface electromyography, musculoskeletal disorders, JASA method, statistical significance, surgical procedure

Word count: 4080

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2 **1. Introduction**

3 Muscular fatigue provides information on work-related musculoskeletal disorders
4 (WRMSD) development risks [1]. It can be quantified using the JASA (Joint Analysis
5 of Spectrum and Amplitude) method [2]. This method uses surface electromyography
6 (sEMG) signals acquired from electrodes placed on specific positions along the muscle.
7 Derived from the raw EMG signals, the most often used measures are the Median
8 Frequency (MDF) to characterize EMG power spectral distribution and the Root Mean
9 Square (RMS) or the Electrical Activity (EA) as the integrative measure of the EMG
10 amplitude. As pointed out by Hägg [1], these latter can equally be used. The rate
11 of change in amplitude or in power spectral distribution is quantified by the slope of
12 the regression line of the amplitude vs time and spectral distribution vs time plots
13 respectively. The principal relationships between the EMG amplitude and spectrum,
14 on the one hand, and the muscle condition, on the other hand, are then plotted in an
15 intuitive four-quadrant diagram, as shown in Figure 1. It allows the identification of
16 four kinds of muscle conditions: recovery (R), force increase (FI), force decrease (FD)
17 and fatigue (F) [3].

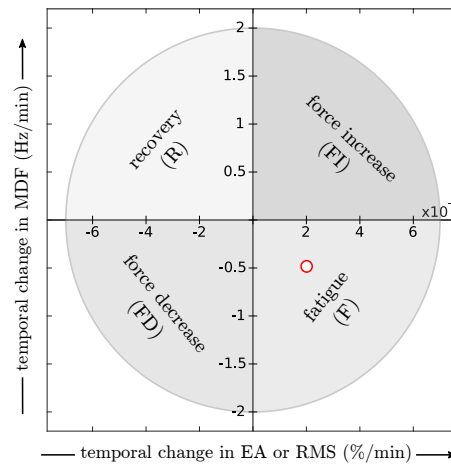


Figure 1: JASA diagram as defined by Luttmann *et al.* [1]. In this example, the slope of the regression line of the RMS vs time plot is 2 %/min and the slope of the regression line of MDF vs time plot is -0.5 Hz/min. This corresponds to a Fatigue condition of the muscle.

18 This method has the advantage of a fast computation and uses parameters (MDF,

RMS) which previous implementations have been successfully demonstrated for muscle condition determination [4] [5] [6]. However, limitations of the JASA method to fully describe fatigue occurrence during dynamic contractions have recently been pointed out [7] [8].

Some investigations suggested to substitute these parameters with more elaborate algorithms, based on time-frequency distribution or non-linear parameters computation [9] [10]. For instance Potes [11] proposed an evolution of the JASA method based on instantaneous indices to take into account the non-linearity of sEMG parameters variations as a function of time. Conforto *et al.* [12] defined a bi-dimensional vector based on the JASA diagram whose magnitude and phase describe the muscle condition evolution during the task. However, these methods do not take into account the initial muscle condition and have yet to be tested for dynamic contractions.

Real time tracking of muscle fatigue has also been investigated in recent studies and results are showing great promise in comfort analysis [4] [13] or in the assessment of the impact of a workspace or an instrument [14]. They can be used to detect an overload of the muscles and warn the operator to prevent further development of musculoskeletal conditions.

The aim of this paper is to propose and evaluate two JASA-based methods allowing real time feedback on the muscle condition evolution during an occupational task. It is organised as follows. The first part presents the chosen occupational task and details the experimental setup. Results of the data analysis using the two JASA-based methods are presented in a second part. The third part focuses on the discussions about the JASA methods and the results significance. The last part concludes on the new methods contribution to the muscles condition investigation.

2. Experimental setup

2.1. Description of the task

A male right-handed surgeon was recruited for this preliminary study. With more than twenty years of practice in laparoscopic surgery, he was considered an expert in this field. He was asked to operate on a physical pelvitrainer.

48 The considered occupational task was the vesicourethral anastomosis, a minimally-
49 invasive laparoscopic procedure that consists in suturing the urethra with the bladder
50 after a radical prostatectomy. With a conventional instrument, high dexterity is required
51 to transmit the adapted trajectories to the suturing semi-circular needle. This kind of
52 procedure usually induces neck, back and upper limbs articulations pains [15]. Ac-
53 cording to 95% of surgeons [16], this is mainly due to the working set-up which is not
54 adapted. Indeed, the table height, the laparoscopic instruments length and difficult ac-
55 cess to the surgical site requires the surgeons to adopt static deleterious postures (strong
56 abduction and elevation of shoulders or awkward wrist positions) to guide the tool in
57 the operating site [17]. These postures, combined with sustained short and precise
58 movements, lead to muscle exhaustion and contribute to increase the risk of WRMSD
59 development. The upper trapeziuses (right: RUT and left: LUT) are particularly at risk
60 as they present quasi-static contractions all along the procedure. They were the focus
61 of the present study.

62 2.2. *Simulated medical set up*

63 The implemented environment simulated representative equipment under the real-
64 istic workplace conditions of an operating room. The pelvitainer modeled the anatomy
65 of the intracorporeal cavity after the resection of the prostatic gland. Identical replace-
66 able phantoms were used in order to offer a good reproducibility of the trials. The
67 pelvitainer was installed on a table whose height was adjusted by the expert as per
68 recommended requirements [16]. The surgeon could visualise the operating site on
69 a screen, using a camera positioned into the pelvitainer. The instruments were stan-
70 dard needle holders (Tonglu Kanger Medical Instrument Co., Hangzhou Tonglu, CN)
71 constituted of a long non-articulated shaft, a one-mobile jaw tool and a V-type axial
72 handle.

73 2.3. *Myoelectrical signal measurement*

74 SX230 sEMG sensors based on dry-electrode technology (Biometrics Ltd, New-
75 port, UK) were used to record myoelectrical signals. The sensors were connected to a
76 DataLOG MWX8 datalogger which transmitted data via a Bluetooth communication

to a laptop with a dedicated interface. The sEMG signals were recorded at a sampling rate of 1 kHz.

The sEMG measurement procedure followed the SENIAM (Surface EMG for Non-Invasive Assessment of Muscles) guidelines [18]. The participant's skin was prepared to get a good skin-electrode contact, and the sensors were aligned along the muscle fibres.

2.4. Maximal strength assessment of the upper limb

All measurements were carried out in accordance with ethical rules and written informed consent was obtained from the participant. The participant was positioned in an upright seated posture with a belt applied around the upper-arm in an initial horizontal extension position, as depicted in Figure 2. The end resistance ring of the belt was hooked up to a LSB300 load cell (FUTEK Advanced Sensor Technology, Inc., Irvine, CA, USA) attached on the ground. It measured the maximal force that the surgeon could produce while involving the trapeziuses. The force was acquired with a NI 6211 data acquisition device (National Instruments, Austin, TX, USA) and a custom-built LabVIEW program. The muscle activity was also recorded at the same time while participant was extending the arm up.

Three successive contractions were recorded at the beginning of the session with a one-minute break in between the exercise. The operator incited the participant to overtake his previous maximum and to reach the real maximal contraction [7]. Then, we extracted the maximal voluntary contraction (MVC) from the data. MVC is defined as the value of the sEMG signal recorded during the maximal peak of force. It is conventionally used to normalise the recorded data in order to compare different sessions, muscles and/or surgeons [19].

3. Analysis methods

3.1. Data processing

Data analysis was performed using CAPTIV software environment (TEA, Vandoeuvre lès Nancy, FR) and MATLAB (The MathWorks Inc., Natick, MA, USA). As

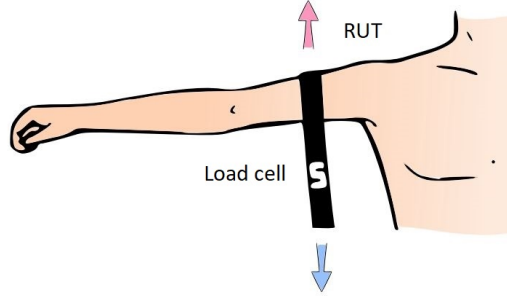


Figure 2: Maximal voluntary contraction measurement.

105 muscular fatigue and pain are closely related during sustained contractions [20], the
 106 analysis was stopped when the surgeon complained of the onset of discomfort at the
 107 shoulder site.

108 3.1.1. Normalised Root Mean Square

The normalised RMS value of the EMG signal, noted $\overline{N_{RMS}}$ is computed as:

$$\overline{N_{RMS}} = \frac{V_{RMS}}{E_{rate@MVC}} \quad (1)$$

109 where V_{RMS} is the RMS value of the EMG amplitude and $E_{rate@MVC}$ is the normalised
 110 exposure of the muscle to an amount of action potentials on a chosen time range
 111 $t = [a; b]$ corresponding to the MVC. These parameters are defined as:

$$V_{RMS} = \sqrt{\frac{1}{N+1} \sum_{i=-N/2}^{N/2} x_i^2} \quad (2)$$

112 with N , the number of samples and x_i , the i^{th} sample of the sEMG signal.

$$E = \int_a^b V_{RMS}(t) dt \quad (3)$$

and,

$$E_{rate} = \frac{E}{t} \quad (4)$$

113 E_{rate} is directly associated to the muscular activity regardless of the interval duration.

We used a time range t of ten seconds in our analysis as per recommendation [1]. 114

3.1.2. Median Frequency computation 115

The MDF is the frequency at which 50% of the total power within the epoch is 116
reached. It is computed as follows [7]: 117

$$\int_0^{MDF} PS(f) df = \int_{MDF}^{5000} PS(f) df \quad (5)$$

where $PS(f)$ is the power spectrum of EMG signal, calculated over a five-second win- 118
dow. $PS(f)$ is defined as the square of absolute value of the Fourier transform of the 119
EMG signal divided by the number of points in the time interval. 120

3.2. JASA diagram with evaluation of the results significance 121

$\overline{N_{RMS}}$ and MDF are plotted as a function of time. For a set of data, and on a 122
considered analysis time lapse, the values of the slope of the regression line, $\Delta_{\overline{N_{RMS}}}$ and 123
 Δ_{MDF} , are extracted from these graphs and finally reported on the JASA diagram axes. 124

In regression building procedures, when there is a lot of variability in the dependent 125
variable, the R-Squared (R^2) coefficient of determination can be low as in the current 126
study. However, there are enough data points to get metrics on the p-value. It indicates 127
if the relationship described by the regression line is significant. To summarise, the 128
coefficients estimate the trends while R^2 represents the dispersion around the regression 129
line. So, even when R^2 is low, low p-values still indicate a real relationship between 130
the significant predictors and the response variable. Our analysis is thus focused on 131
the p-values of the slope of the regression line which are more relevant to quantify the 132
significance of the results. 133

The p-values are calculated from a linear binomial regression model, using the 134
statistic toolbox of MATLAB for each $\overline{N_{RMS}} = f(t)$ and $MDF = f(t)$ graphs slopes. 135
One of our improvement lays in displaying the statistical significance of $\Delta_{\overline{N_{RMS}}}$ and 136
 Δ_{MDF} next to the JASA points directly in the diagram. The following marks are used 137
to indicate the significance of the slopes: * if $p < 0.1$; ** if $p < 0.05$ and *** if $p < 0.01$. 138
The indicated p-values correspond to the worst of the two p-values calculated on both 139
JASA diagram axes. 140

141 3.3. *Evolutionary JASA method*

142 A first modification of the JASA method is proposed in order to visualise the evo-
143 lution of the muscle condition during the task. Named *evolutionary* JASA method, it
144 consists in implementing the JASA analysis on increased time lapses, the largest one
145 corresponding to the entire duration of the task. The principle is illustrated in Figure 3,
146 for the $\overline{N_{RMS}}$ vs *Time* plot.

147 In this study, the successive time windows ranged from 30 s to 780 s, corresponding
148 to a number of points between 30000 and 780000. The chosen time interval between
149 two successive analyses has no impact on the result. It only changes the diagram res-
150 olution by adding or removing points. It was arbitrarily set to 30 s, to get a sufficient
151 number of points for the analysis. All the successive results were reported on the same
152 JASA diagram in order to follow the muscle condition tendency along the duration of
153 the task.

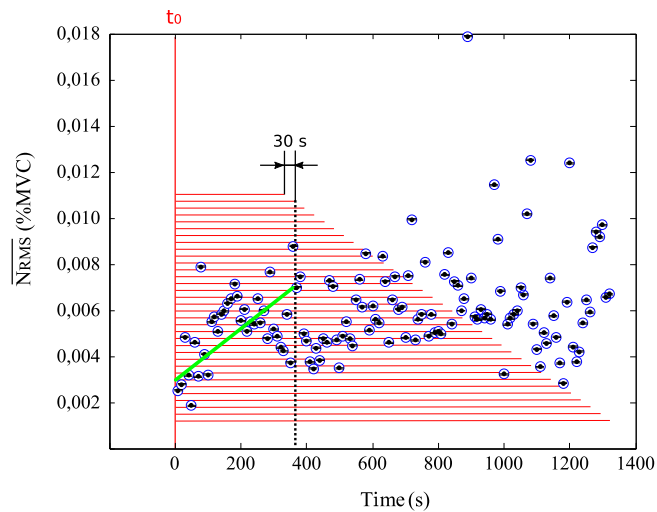


Figure 3: Illustration of successive analysis durations for the *evolutionary* JASA method application. The time intervals were arbitrarily set to 30 seconds. As an example, the green line represents the linear regression computed for a group of data in range [0-330] s.

154 3.4. *Sequential JASA method*

155 A second proposition, called the *sequential* JASA method, consists in computing
156 the JASA diagram for a constant-time sliding window. The time duration was set to 5

min (N=300000 points), and the sliding interval to 30 s in order to have a good temporal resolution of the JASA diagram. The principle is illustrated in Figure 4, for the \overline{NRMS} vs *Time* plot.

A preliminary analysis was carried out in order to determine the optimal length of the analysis sliding window, called *sequence*. We lead successive *sequential JASA* analyses for that purpose and reported the percentage of statistically significant JASA points as a function of the sequence duration (Figure 5), for a suturing task of 13 min. Poor results were obtained with sequence durations lower than 7 min and greater than 11 min for both muscles. The number of statistically significant points was found to be maximum for a 9-min sequence duration for both muscles with best performance obtained for the dominant arm (45% of significant points for the RUT). Therefore, a 9-min sequence duration was chosen for the *sequential* analysis.

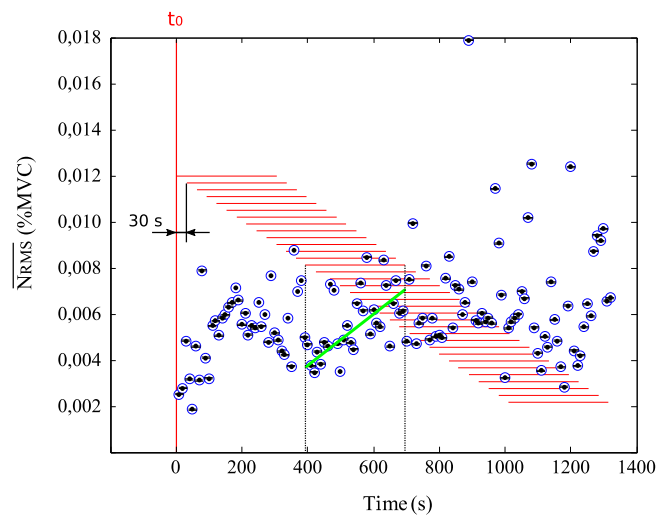


Figure 4: Illustration of the sliding analysis for the *sequential JASA* method application. The time intervals and sequence duration were arbitrarily set to respectively 30 s and 5 min. As an example, the green line represents the linear regression computed for a group of data in range [420-720] s.

4. Results

No discomfort was reported for the left shoulder during the completion of the task, but the surgeon indicated an onset of discomfort at the right shoulder after 13 min-

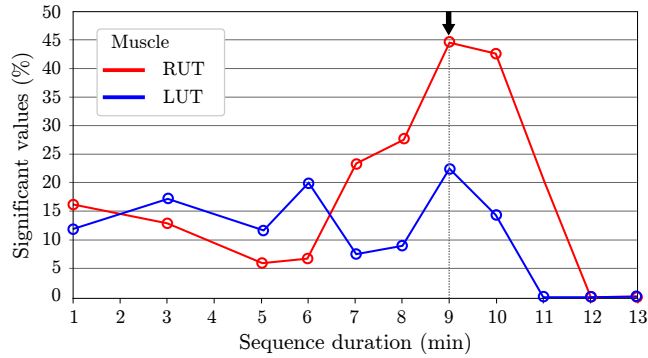


Figure 5: Determination of the optimal sequence duration. Significant worst p-values percentage are associated with each sequence duration analysis for a suturing task.

172 utes. Hence, only data collected during this time lapse was analysed, on the same data
 173 set, with the original JASA methods and two new proposed methods. The results are
 174 presented and compared in this section.

175 4.1. Results with the original JASA method

176 The diagram, presented in Figure 6, corresponds to the implementation of the orig-
 177 inal JASA method for both RUT and LUT. The outcome for the muscles conditions are
 178 respectively fatigue and force decrease.

179 *Evaluation of the results significance.* Although $\Delta_{\overline{N}_{RMS}}$ values are relatively low, they
 180 are considered reliable with regards to the associated uncertainties. The p-values as-
 181 sociated to Δ_{MDF} are lower than the ones to $\Delta_{\overline{N}_{RMS}}$, especially for the RUT. However,
 182 none of the points reported on the original JASA diagram can be considered significant
 183 as listed in Table 1. The only information that can be significantly validated is a muscle
 184 condition located in the inferior part of the diagram, indicating a worsening of muscle
 185 contraction capabilities.

186 4.2. Results with the evolutionary JASA method

187 The *evolutionary* JASA diagram is presented in Figure 7. The first point is com-
 188 puted over a duration of five minutes. This choice has been made as the uncertainties
 189 on the slopes computed on shorter duration analysis are important (superior to 50% of
 190 the slope value).

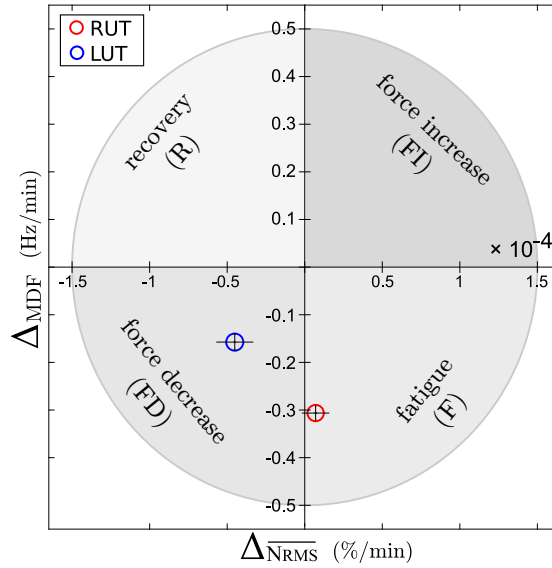


Figure 6: The original JASA diagram for RUT and LUT muscle during a 13-min task and associated uncertainties.

Table 1: p-values associated with JASA analysis.

	p-value parameter		
	Δ_{NRMS}	Δ_{MDF}	JASA point
RUT	0.853	0.001	> 0.1
LUT	0.380	0.133	> 0.1

Qualitative assessment of the muscle condition. The evolutionary JASA diagram of the RUT condition, Figure 7, shows a gradual evolution from force decrease to fatigue after 12 minutes. The fatigue occurs briefly before the surgeon complains of shoulder pain. The estimation of the LUT muscle condition corresponds successively to a recovery and a force decrease without attaining the fatigue quadrant.

Evaluation of the results significance. The p-values associated with the vertical (Δ_{MDF}) and horizontal axes (Δ_{NRMS}) for each point are reported as a function of time in Figure 8. The significance estimation of the muscle condition is indicated in the bottom line. Highlighted in light green on the graph, the muscle condition can only be considered significant when for each axis both p-values are less or equal to 0.1.

201 For the RUT, none of the muscle conditions can be considered significant. How-
 202 ever, when considering the Δ_{MDF} axis only, the last six points are clearly associated
 203 with a force decrease or a fatigue occurrence (p -value < 0.1). The low p -values on
 204 the Δ_{NRMS} axis for the first five points states that the muscle does not initially present a
 205 fatigue condition.

206 The same analysis was carried out for the LUT and the results are presented in
 207 Figure 9. The recovery condition observed at the beginning of the exercise, highlighted
 208 in light green, is significant. Thereby, the muscle initially presented an optimal muscle
 209 condition. The loss of the muscle capabilities after 11 minutes is due to the studied
 210 task, but the significance relative to the Δ_{NRMS} axis (p -value > 0.1) does not allow to
 211 confirm if the muscle presents a force decrease or a fatigue condition.

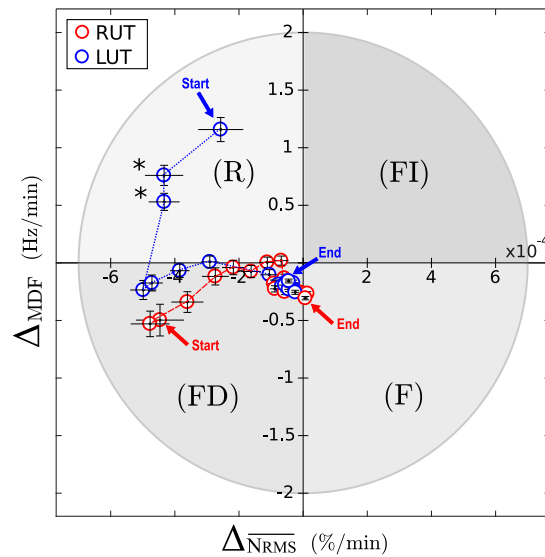


Figure 7: The *evolutionary* JASA diagram for RUT and LUT muscle during a 13-min task. The first and the last points are indicated by an arrow. Marking: star (*): p -value < 0.1 .

212 4.3. Results with the sequential JASA method

213 *Qualitative assessment of the muscle condition.* Figure 10 presents the evolution of the
 214 muscle conditions throughout the *sequential* JASA method, during a 13-min suturing
 215 task. For the RUT, the *sequential* JASA analysis shows a transition from force decrease
 216 to fatigue. For the LUT, the points are globally situated in the fatigue quadrant.

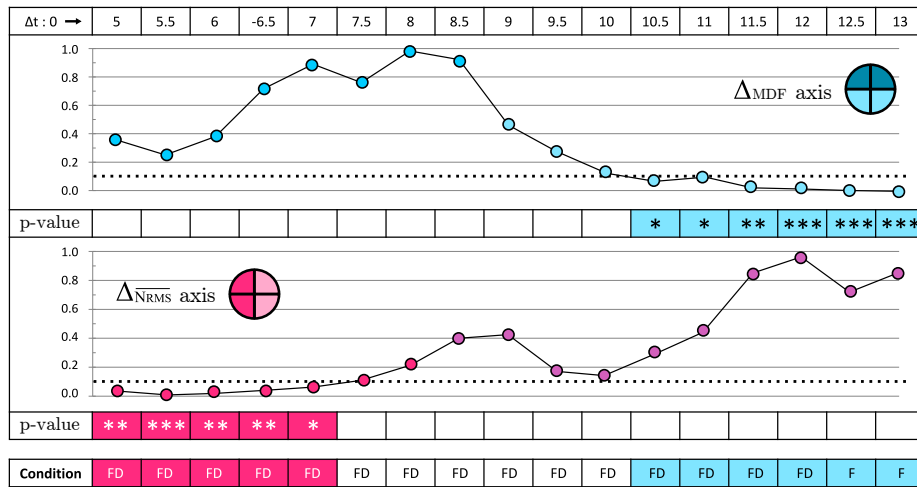


Figure 8: P-values associated with the *evolutionary* RUT muscle condition analysis as a function of time for successive increased intervals. Legend: dark blue: significant increase of Δ_{MDF} , light blue: significant decrease of Δ_{MDF} , dark pink: significant decrease of Δ_{NRMS} , light pink: significant increase of Δ_{NRMS} , light green: significant p-value for both parameters, * if $p < 0.1$; ** if $p < 0.05$; no star: p-value > 0.1 .

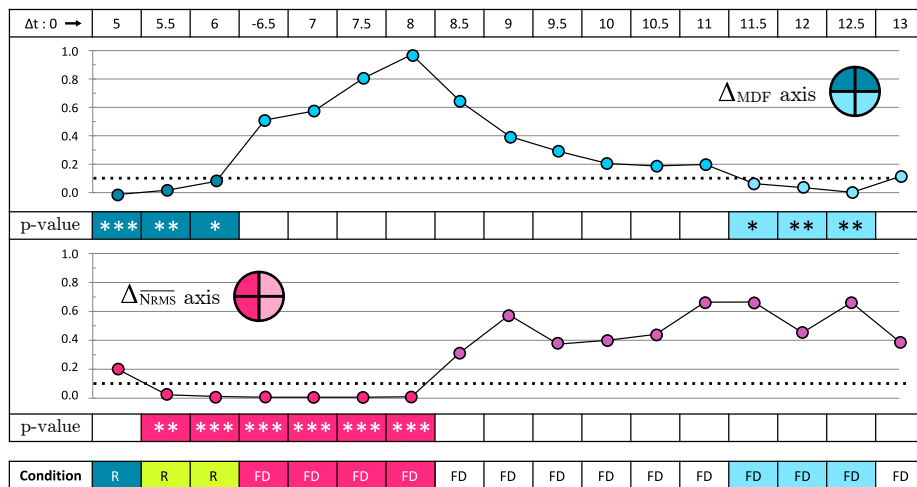


Figure 9: P-values associated with the *evolutionary* LUT muscle condition analysis as a function of time for successive increased intervals. Legend details: cf. Figure 8.

Evaluation of the statistical significance of the results. Figures 11 and 12 present the p-values corresponding to the *sequential* JASA analyses for RUT and LUT. The fatigue occurrence is significant for both analyses.

For 9-min sequences successively analysed through the *sequential* JASA method

221 for the RUT, a transition from force decrease to fatigue is reported (Figure 10). High-
 222 lighted in light green in Figure 11, the fatigue observed for the last four points is sig-
 223 nificant (p -values ≤ 0.1 for both axes). This result completes the *evolutionary* analysis
 224 which is not able to significantly identify fatigue or force decrease for the last minutes
 225 of the task.

226 For the LUT, a transition from force decrease to fatigue is reported in Figure 10,
 227 but the muscular condition significance is only proven for two points (p -value ≤ 0.1).
 228 However, the p -values computed on the Δ_{MDF} axis validates a decrease of muscle ca-
 229 pabilities (Figure 12), with a p -value ≤ 0.01 .

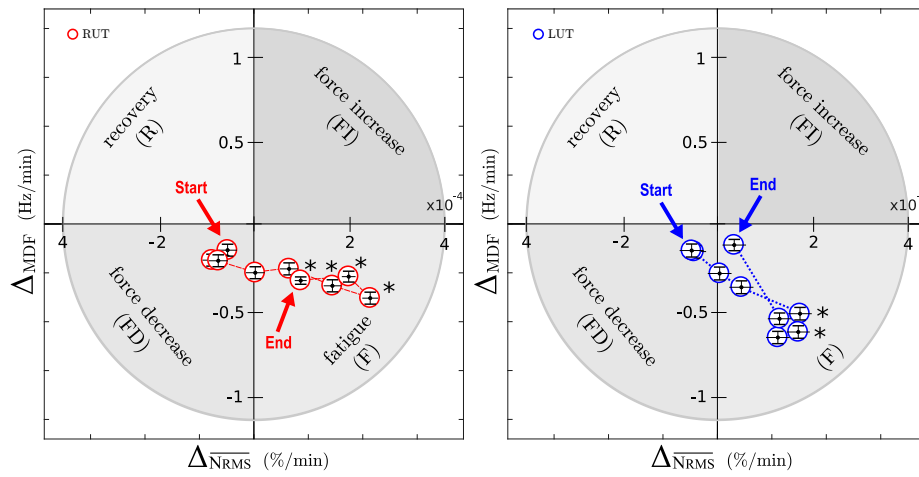


Figure 10: 9-min *sequential* JASA diagram for RUT (left) and LUT (right) muscles during a 13-min suturing task. The star (*) indicates a p -value < 0.1 .

230 5. Discussion

231 All the JASA diagrams are globally consistent with what the surgeon felt during
 232 the test. Indeed, referring to the relationship between muscle pain and fatigue [20], a
 233 fatigue condition is spotted on the shoulder for which the surgeon reported an onset of
 234 muscle soreness.

235 However, with the original JASA method only, the relevance of the results cannot
 236 be significantly proven. Conversely, with the proposed JASA methods, the analysis
 237 on the p -values of the Δ_{MDF} and Δ_{NRMS} parameters tells when the current muscular

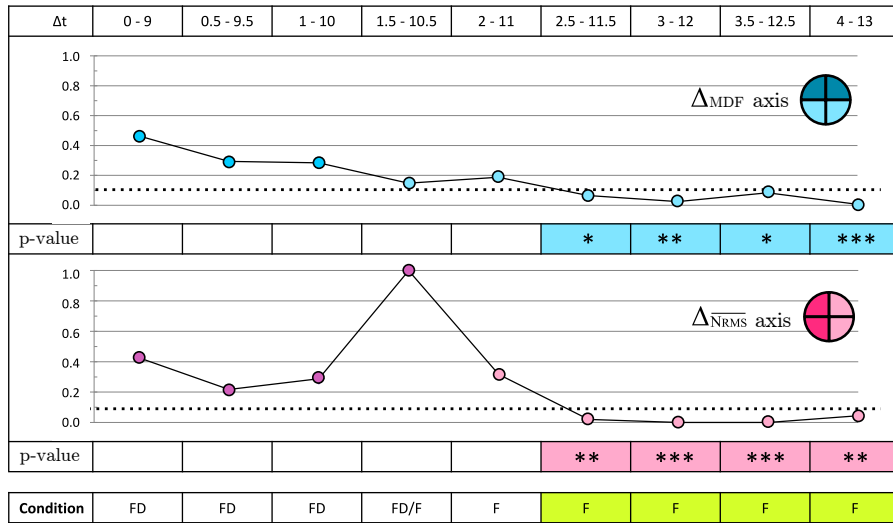


Figure 11: P-values associated with *sequential* RUT muscle condition analysis as a function of time for 9-min intervals. Legend details: cf. Figure 8.

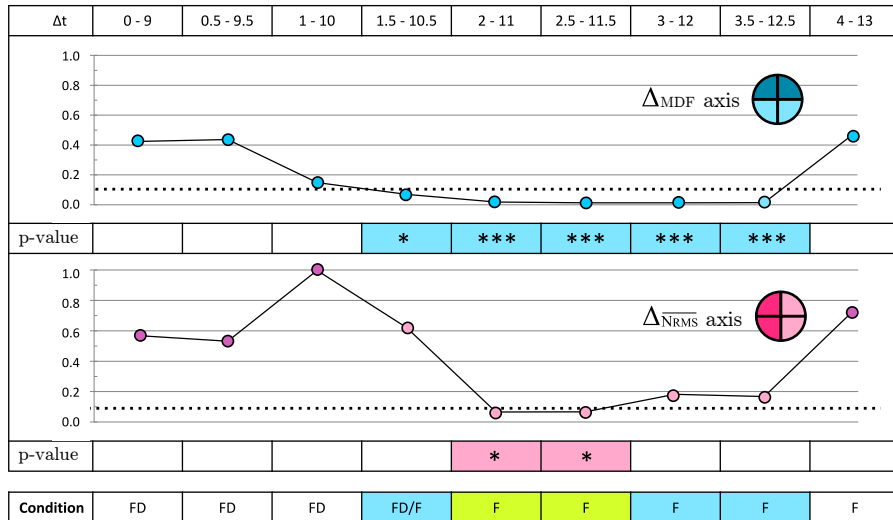


Figure 12: P-values associated with LUT *sequential* muscle condition analysis as a function of time for 9-min intervals. Legend details: cf. Figure 8.

condition is statistically significant. When $p \leq 0.1$ for Δ_{MDF} , it indicates whether the 238
 JASA point is significantly located in the upper or the lower hemisphere. When $p \leq$ 239
 0.1 for Δ_{NRMS} , it indicates whether the JASA point is significantly located in the left or 240
 the right hemisphere. When eventually both parameters exhibit a $p \leq 0.1$, the muscle 241

242 condition on the JASA diagram is significant.

243 By using conjointly the *sequential* and *evolutionary* JASA methods there are two
244 complementary details brought by the analyses. The first one gives a cumulative anal-
245 ysis over the entire occupational task whilst the second one allows to determine the
246 current muscle condition. These results, obtained in real-time, could be used to take
247 action to prevent prolonged fatigue condition by proposing recovery exercises, adapted
248 muscular stretching or micro-breaks.

249 As opposed to the original and to the *evolutionary* JASA methods, the *sequential*
250 JASA method requires to carry out an initial analysis of the practice. The real-time data
251 processing can only be implemented once the optimal sequence duration is determined.
252 The choice of the shifting interval between each analysis has only an impact on the
253 temporal resolution of the final JASA diagram and can therefore be arbitrarily chosen.

254 The choice of the sequence duration has an influence on the statistical significance
255 of the results. This may be problematic as the optimal duration is probably task or
256 subject-specific. A initial analysis is hence required to fit all the experimental condi-
257 tions for a given task. This has to be validated by complementary trials. Besides, an
258 interesting result lays in getting the highest significance of the conditions correspond-
259 ing to the dominant arm muscles, which are, by definition, the most loaded.

260 Last, Table 2 summarises the parameters which have to be clearly defined before
261 applying the chosen JASA variant method on a set of sEMG data. Further work will
262 focus on verifying if the temporal window chosen by Hägg *et al.* presents a task-
263 dependency and hence, should be fine tuned regarding to the set of data.

264 **6. Conclusion**

265 The present study focuses on the determination of the muscle condition during a
266 laparoscopic task by analyzing the EMG amplitude as well as the frequency spectrum.
267 Although the original JASA method is convenient for the display of the results, some
268 limits have been pointed out. Indeed, as this method gives only a global insight of
269 the muscle condition over the exercise duration, it does not allow to apprehend the
270 successive physiological mechanisms that occur in the muscle during the achievement

Table 2: Input and output parameters for the proposed JASA methods evolutions

	Original [1]	Evolutionary	Sequential
Analysis Duration	entire task	entire task of increased duration	successive sequences
Time interval	$t_0 \rightarrow t_f$	$t_0 \rightarrow t_{f_i}$ $\forall t_{f_i} \in [t_{min}; t_{max}]$	$t_{0_i} \rightarrow t_{f_i}$ with $t_{f_i} - t_{0_i} = C$ $\forall t_{0_i} \in [0; t_{max} - C]$ $\forall t_{f_i} \in [C; t_{max}]$
Muscular condition	global	successive global	sequential
Horizontal axis parameter	$\Delta_{N_{RMS}}$	$\Delta_{N_{RMS}}$	$\Delta_{N_{RMS}}$
Vertical axis parameter	Δ_{MDF} or Δ_{EA}	Δ_{MDF} or Δ_{EA}	Δ_{MDF} or Δ_{EA}
Computation on N_{RMS}	average over 10 s	average over 10 s	average over 10 s
Computation on frequency	median over 5 s	median over 5 s	median over 5 s
Shift interval	×	arbitrary	arbitrary
Minimal duration	×	$t_{min} = \text{arbitrary}$	$t_{min} = \text{optim. sequence duration}$
Optimal sequence duration	×	×	p-value analysis

of the task.

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Two evolutions of the method have thus been proposed. The first one, called the *evolutionary* JASA method, analyses increased task durations whilst the second one, called the *sequential* JASA method, focuses on constant sliding time sequences.

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The three methods have been successively applied and compared for a simulated vesicourethral anastomosis performed by an expert surgeon. All of them are consistent and show a reduction of the upper trapezius capabilities over the task. For the studied task, none of the muscle conditions are considered significant with the original JASA method. The *evolutionary* and *sequential* JASA methods show a better results significance, particularly for the dominant arm and for the chosen parameters.

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Besides, in this context, we observed that the time duration of the analyses windows has an impact on the statistical significance of the results. For a practical implementation of the proposed methods, it is therefore important to define a relevant sequence duration in order to maximise the strength of the outcomes. Moreover, the sequence duration is very likely task-dependent or subject-dependent and its definition requires preliminary statistical intra and inter-subjects analyses. There is a trade-off between

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287 the accuracy of the analysis and the statistical significance of the results.

288 The real-time tracking of the muscular condition offers a valuable tool to apprehend
289 the impact of a new workspace or instrument on the surgeon comfort. By bringing
290 an information on the way the muscles are loaded all along the procedure, one can
291 determine if a working configuration lead to less fatigue occurrence. The possible
292 application of these new methods techniques in patients with neuromuscular disorders
293 is the development of a recovery strategy during the practice (with specific stretching or
294 micro-breaks [21] [22]) before the presence of a fatigue condition and the development
295 of WRMSD.

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306 **Bibliography**

307 **References**

308 [1] G. M. Hägg, A. Luttmann, M. Jäger, Methodologies for evaluating electromyo-
309 graphic field data in ergonomics, *Journal of Electromyography and Kinesiology*
310 10 (5) (2000) 301–312.

311 [2] A. Luttmann, M. Jäger, J. Sökeland, W. Laurig, Electromyographical study on
312 surgeons in urology. ii. determination of muscular fatigue, *Ergonomics* 39 (2)
313 (1996) 298–313.

- [3] M. Cifrek, V. Medved, S. Tonković, S. Ostojić, Surface EMG based muscle fatigue evaluation in biomechanics, *Clinical Biomechanics* 24 (4) (2009) 327–340. 314
315
- [4] S. W. Chen, J. W. Liaw, H. L. Chan, Y. J. Chang, C. H. Ku, A real-time fatigue monitoring and analysis system for lower extremity muscles with cycling movement, *Sensors (Switzerland)* 14 (7) (2014) 12410–12424. 316
317
318
- [5] S. P. Arjunan, D. K. Kumar, G. Naik, Computation and evaluation of features of surface electromyogram to identify the force of muscle contraction and muscle fatigue., *BioMed research international* 2014 (2014) 197960. 319
320
321
- [6] L. Kahl, U. G. Hofmann, Comparison of algorithms to quantify muscle fatigue in upper limb muscles based on sEMG signals, *Medical Engineering and Physics* 38 (11) (2016) 1260–1269. 322
323
324
- [7] M. González-Izal, a. Malanda, I. Navarro-Amézqueta, E. M. Gorostiaga, F. Mallor, J. Ibañez, M. Izquierdo, EMG spectral indices and muscle power fatigue during dynamic contractions, *Journal of Electromyography and Kinesiology* 20 (2) (2010) 233–240. 325
326
327
328
- [8] M. González-Izal, A. Malanda, E. Gorostiaga, M. Izquierdo, Electromyographic models to assess muscle fatigue, *Journal of Electromyography and Kinesiology* 22 (4) (2012) 501–512. 329
330
331
- [9] S. Karlsson, J. Yu, M. Akay, Time-frequency analysis of myoelectric signals during dynamic contractions: A comparative study, *IEEE Transactions on Biomedical Engineering* 47 (2) (2000) 228–238. 332
333
334
- [10] P. A. Karthick, S. Ramakrishnan, Surface electromyography based muscle fatigue progression analysis using modified B distribution time–frequency features, *Biomedical Signal Processing and Control* 26 (2016) 42–51. 335
336
337
- [11] C. M. Potes, Assessment of human muscle fatigue from surface emg signals recorded during isometric voluntary contractions, in: *IFMBE Proceedings*, Vol. 24, Springer, 2009, pp. 267–270. 338
339
340

- 341 [12] S. Conforto, a. M. Castronovo, C. De Marchis, M. Schmid, M. Bertollo,
342 C. Robazza, S. Comani, T. D'Alessio, The fatigue vector: A new bi-dimensional
343 parameter for muscular fatigue analysis, in: IFMBE Proceedings, Vol. 41,
344 Springer, Cham, 2014, pp. 149–152.
- 345 [13] V. J. Davila, T. K. Weidner, M. Morrow, B. Low-Ndes, A. M. Abdelrahman,
346 M. S. Hallbeck, S. R. Money, Real-Time Ergonomic Issues in Vascular Surgeons:
347 How We Are Hurting Ourselves While Operating, *Journal of Vascular Surgery* 67
348 (2018) e242.
- 349 [14] J. A. Sánchez-Margallo, F. M. Sánchez-Margallo, Initial experience using a
350 robotic-driven laparoscopic needle holder with ergonomic handle: assessment of
351 surgeons' task performance and ergonomics, *Int J CARS* 12 (2017) 2069–2077.
- 352 [15] A. Park, G. Lee, F. J. Seagull, N. Meenaghan, D. Dexter, Patients Benefit While
353 Surgeons Suffer: An Impending Epidemic, *Journal of the American College of*
354 *Surgeons* 210 (3) (2010) 306–313.
- 355 [16] U. Matern, P. Waller, C. Giebmeier, K. D. Rückauer, E. H. Farthmann, Er-
356 gonomics: Requirements for Adjusting the Height of Laparoscopic Operating
357 Tables, *Jsls* 5 (1) (2001) 7–12.
- 358 [17] S. D. Choi, A Review of the Ergonomic Issues in the Laparoscopic Operating
359 Room, *Journal of Healthcare Engineering* 3 (4) (2012) 587–603.
- 360 [18] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, G. Rau, Development of
361 recommendations for SEMG sensors and sensor placement procedures, *Jour-*
362 *nal of Electromyography and Kinesiology* 10 (5) (2000) 361–374. [arXiv:](https://arxiv.org/abs/1005.00027)
363 [S1050-6411\(00\)00027-4](https://arxiv.org/abs/1005.00027).
- 364 [19] N. Hubert, Analyse ergonomique de la charge de travail physique du chirurgien
365 en coelochirurgie standard et assistée par robot. Une évaluation subjective, mus-
366 culaire et posturale, Ph.D. thesis, Université Henri Poincaré, Nancy 1 (Oct. 2010).
- 367 [20] F. L. Mastaglia, The relationship between muscle pain and fatigue, *Neuromuscu-*
368 *lar Disorders* 22 (2012) S178–S180.

- [21] A. M. Abdelrahman, B. R. Lowndes, J. Bingener, A. E. Park, M. S. Hallbeck, 369
Intraoperative Microbreaks Exercises Impact Surgical Trainees' Musculoskeletal 370
Discomfort and Workload, *Journal of the American College of Surgeons* 225 (4) 371
(2017) S120–S121. 372
- [22] M. S. Hallbeck, B. R. Lowndes, J. Bingener, a. M. Abdelrahman, D. Yu, a. Bart- 373
ley, a. E. Park, The impact of intraoperative microbreaks with exercises on sur- 374
geons: A multi-center cohort study, *Applied Ergonomics* 60 (Supplement C) 375
(2017) 334–341. 376