Title: Shoulder electromyography-based indicators to assess manifestation of muscle fatigue during laboratory-simulated manual handling task.

Running head: Fatigue in manual handling

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Word count: 4909 (max 5000)

Abstract

Muscle fatigue is a risk factor for developing shoulder musculoskeletal disorders. The aim of this study was to identify shoulder electromyographic indicators that are most indicative of muscle fatigue during a laboratory simulated manual handling task. Thirty-two participants were equipped with electromyographic electrodes on 10 shoulder muscles and moved boxes for 45-minutes. The modified rate of perceived exertion (mRPE) was assessed every 5-minutes and multivariate linear regressions were performed between myoelectric manifestation of fatigue (MMF) and the mRPE scores. During a manual handling task representative of industry working conditions, *spectral entropy*, *median frequency*, and *mobility* were the electromyographic indicators that explained the largest percentage of the mRPE. Overall, the deltoids, biceps and upper trapezius were the muscles that most often showed significant changes over time in their electromyographic indicators. The combination of these three indicators may improve the accuracy for the assessment of MMF during manual handling.

Keywords: Biomechanics, Entropy, Median frequency, Time-frequency analysis, Shoulder

Practitioner Summary: To date, muscle fatigue has primarily been assessed during tasks done to exhaustion, which are not representative of typical working conditions. During a manual handling task representative of industry working conditions, EMG-derived *spectral entropy*, and *median frequency*, both extracted from time-frequency analysis, and *mobility* extracted from time domain, were the best indicators of the manifestation of muscle fatigue.

Abbreviations

DeltA	Anterior Deltoid
DeltL	Lateral Deltoid
DeltP	Posterior Deltoid
EMG	Electromyography
ISP	Infraspinatus
MMF	Manifestation of muscle fatigue
mRPE	modified Rate of Perceived Exertion
Pec	Pectoralis
SSP	Supraspinatus
Subs	Subscapularis
UpTrap	Upper Trapezius

1 Introduction

Industrial work such as assembling or manual handling involves repetitive movements, elevated arm postures, constrained workplaces, and long periods of sustained muscle activity. These characteristics act in combination to cause muscle fatigue, and have each been identified as risk factors for the development of shoulder musculoskeletal disorders (Côté, 2014; Hanvold et al., 2015; Mathiassen, 2006; Mayer et al., 2012; Nordander et al., 2009; Roquelaure et al., 2009; Svendsen et al., 2004). In western industrialized regions such as the province of Quebec in Canada, the societal costs of shoulder musculoskeletal disorders represented an average of 600 dollars per year per inhabitant, and a total of 4.7 billion dollars per year in 2017 (Busque et al., 2020). Therefore, it is essential to determine effective methods to assess muscle fatigue in common working activities such as manual handling.

Several methods exist to assess the manifestation of muscle fatigue (MMF). Muscle force (Vøllestad, 1997), movement kinematics (Cortes et al., 2014; Côté et al., 2002; Lessi et al., 2017), electromyography (EMG) (Cifrek et al., 2009; Rampichini et al., 2020; Shair et al., 2017), as well as potentials evoked in response to electrical stimulation of the motor neurons or the muscle itself (Bellemare & Bigland-Ritchie, 1987; McKenzie & Gandevia, 1991) are altered under muscle fatigue conditions. Among them, EMG is the most suited to assess MMF to in-field working environment, since the sensors are wearable, lightweight devices, and EMG-based MMF indicators can be measured directly during movement execution without hindering task performance (McDonald et al., 2016; Tse et al., 2016). In addition, EMG is advantageous in that it can measure localized MMF (Korol et al., 2014, 2017) as compared to the measurement of muscle force or movement kinematics measurements which are more global assessments. To date, EMG *activation level* and EMG *median frequency* are the most commonly used indicators of the MMF (Dickerson et al., 2007; Gaudet et al., 2018; Karthick et al., 2014; Korol et al., 2014, 2017; McDonald et al., 2016, 2018; Merletti & Farina, 2006; Pincivero et al., 2003). *Activation level* have been shown to increase (McDonald et al., 2018; Navaneethakrishna & Ramakrishnan, 2015; Patel et al., 2018), while *median frequency* decreases in the presence of muscle fatigue during sustained activities (Karthick et al., 2014; Venugopal et al., 2014). Because of the non-stationarity nature of EMG signals during a dynamic task (Farina, 2006), time-frequency analyses were also introduced to investigate the instantaneous *median frequency* (Farina, 2006; Gaudet et al., 2018; Goubault et al., 2021). More recently, other more complex EMG-based MMF indicators have been introduced to assess MMF during sustained contractions (Karthick et al., 2014; Venugopal et al., 2014). Among them, the *activity* corresponding to the variance of the EMG signal increases in the presence of muscle fatigue (McDonald et al., 2018; Navaneethakrishna & Ramakrishnan, 2015; Patel et al., 2018). The *mobility*, corresponding to the root square of the ratio between the variance of first time derivative and the variance of the EMG signal decreases in the presence of muscle fatigue (Karthick et al., 2014). The *sample entropy* and *spectral entropy*, that detect irregularity in EMG signal, decrease under fatigue conditions (Karthick et al., 2014; Venugopal et al., 2014). Interestingly, during fatiguing tasks, previous studies have shown a close relationship between the modified rate of perceived exertion (mRPE) CR10 (Borg, 1982) and *activation level* as well as *median frequency*, where *median frequency* was found to most strongly correlate with mRPE (Ahmad & Kim, 2018; Cruz-Montecinos et al., 2019; Hummel et al., 2005; Tiggemann et al., 2010; Troiano et al., 2008).

However, to the best of our knowledge, very few studies have assessed the extent to which EMG-based MMF indicators such as *activation level*, *activity*, *mobility*, *sample entropy*, *spectral entropy*, and *median frequency,* explain mRPE variance. This type of assessment would enable which indicator could be used to assess muscle fatigue.

To date, EMG-based MMF indicators have mostly been studied during fatigue-inducing experimental conditions involving high intensity contractions until participants are unable to continue due to physical discomfort or inability to meet task requirements (Gaudet et al., 2018; Karthick et al., 2014, 2016; McDonald et al., 2018; Patel et al., 2018; Yang et al., 2018). For instance, Gaudet et al., (2018) set a protocol where participants had to repeat 50 internal and external concentric contractions of the shoulder at a maximal level. Karthick et al., (2016, 2014) asked participants to repeat a bicep curl task using a 6 kg load until discomfort or failure. McDonald et al., (2018) employed various physically demanding manual tasks, such as weighted push, static drill, and static target matching that required between 50% and 60% of maximal voluntary isometric contraction (MVIC). To our knowledge, Hawley, (2021) used a protocol that better replicates the repetitive lifting task observed in industry. In this study, participants had to lift boxes of 30% of their maximum lifting capacity at a self-selected pace until volitional fatigue or until a maximum time limit of 60 minutes. However, participants lifted boxes without displacement, which is not representative of typical workplace activities which might require pivoting or moving across the floor with the box. Moreover, they assessed the effect of fatigue on movement patterns but not on EMG indicators. Based on observations made in industry (Goubault et al., 2020), manual handling workers maintain an average pace of 5 boxes handled per minute during a standard workday, without reaching a score higher than 4 on the mRPE.

They typically moved boxes of different sizes and masses on multiple pallets with small displacements while holding the loads. Such working tasks, composed of both isometric and dynamic contractions involving the whole body, require moderate muscle activations lower than 30% of their maximum activation (Nussbaum, 2001). Consequently, EMG-based indicators used to detect MMF in high intensity conditions may not be representative of muscle fatigue induced by manual handling in working conditions. Thus, it is essential to explore EMG-based MMF indicators in a context of more moderate muscular repetitive activity that are more representative of working conditions.

The aim of this study was to determine EMG indicators that best predict MMF and to assess how they vary during a laboratory-based manual handling task mimicking realistic working conditions. To this end, EMG was measured in combination with the mRPE (Borg, 1982) during a manual handling task consisting of moving boxes of different masses, representative of a realistic workplace task. We expected that time-frequency indicators such as instantaneous *median frequency* and instantaneous *spectral entropy* would be more predictive of mRPE and therefore more representative of MMF (Cifrek et al., 2009; Farina, 2006; Gaudet et al., 2018; Shair et al., 2017). It was also anticipated that *median frequency* and *spectral entropy* would decrease throughout the manual handling task. Additionally, we expected to detect MMF in the biceps, the anterior deltoid, and the upper trapezius, as they are prime movers during lifting tasks.

2 Materials and methods

2.1 Participants

Thirty-two male participants (32.7 ± 7.1 years; 177.2 ± 7.5 cm; 80.8 ± 12.1 kg) were recruited to this study. To be eligible, participants had to be free of upper-limb and trunk musculoskeletal disorders or any disability as assessed by the Disabilities of the arm, shoulder and hand questionnaire (Hudak et al., 1996) and the Quebec Back Pain Disability Scale (Kopec et al., 1995). The Physical Activity Readiness Questionnaire was administered prior to the experiment (Thomas et al., 1992) to ensure participants' ability to engage in the simulated manual handling task described hereafter. After receiving instructions on the full experimental procedure, participants read and signed a written informed consent. The protocol was approved by the University of Montreal Ethics Committee (16-014-CERES-D).

2.2 Instrumentation

Participants were equipped with wireless EMG electrodes (Trigno EMG Wireless System, Delsys, USA) positioned on the dominant side, since this side is at higher risk of injury than the non-dominant side (Yamamoto et al., 2010). Surface EMG electrodes were positioned on the anterior, lateral, and posterior deltoids, biceps brachii, lateral head of the triceps brachii, upper trapezius, and pectoralis major (Figure 1A). Electrodes' location were determined according to the Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles project (SENIAM) recommendations (Hermens et al., 2000). Hair was removed with a razor and skin was cleaned with alcohol swabs. Additionally, since the rotator cuff muscles are frequently involved in shoulder musculoskeletal disorders among workers (Silverstein et al., 2002), participants were equipped with intramuscular EMG electrodes inserted into the infraspinatus, supraspinatus, and subscapularis muscles using sterile fine needles according to Kadaba et al., (1992) and Perotto, (2011) recommendations (Figure 1A). Electrode placement was validated by a series of 10 submaximal voluntary contractions during which EMG signals were visually inspected in real-time on a display monitor. EMG signals were recorded at a 2000 Hz sampling rate.

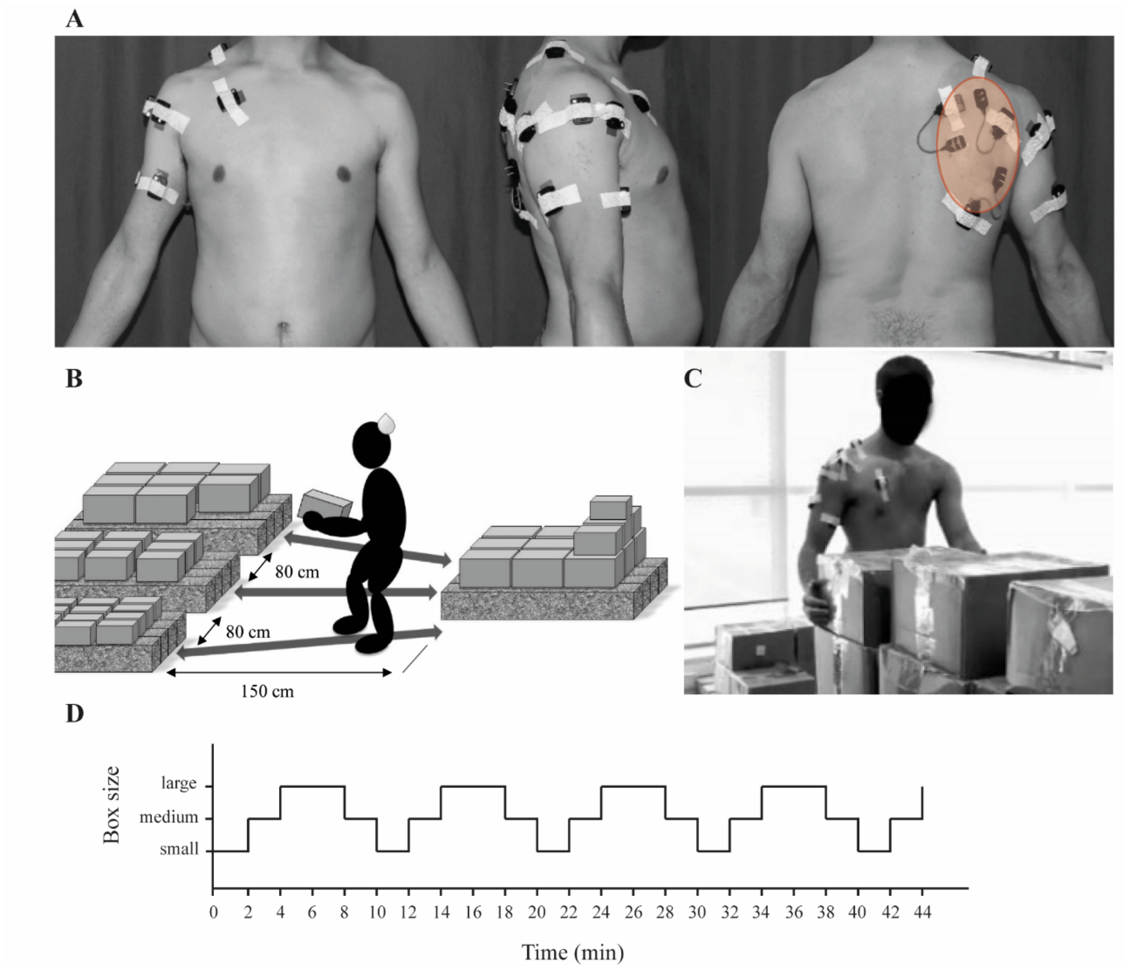

Figure 1: A) Participant equipped with EMG electrodes, intramuscular EMGs located in the red area. B-C) Schematic representation and picture of the experimental setup. Participants moved between the two deposit areas as they transferred the boxes. D) Schematic representation of the boxes handling.

Figure 1 Alt Text: A four-panel figure with A on the top, B on the middle left, C on the middle right, and D on the underside.

Panel A shows the trunk of a male human in the anterior view (left), lateral view (middle), posterior view (right). EMG electrodes are positioned the right side of the person.

Panel B schematizes a pallet on the right with boxes of different sizes lied on it. There are three pallets in a line on the left. The first one has small boxes on it, the second one has medium boxes on it, and the third one has large boxes on it. These three pallets are at 80 cm from each other, and at 150 cm from the right pallet. A workers standing in between the right pallet and the three left pallets is moving a box.

Panel C is a real picture showing a worker reaching a medium box. EMG electrodes are positioned on the right side of his trunk.

Panel D is a schematic graph of the box handling experiment timeline. It shows the time spent moving small boxes, then medium boxes, then large boxes, so on and so forth.

2.3 Experimental prerequisite

2.3.1 Maximum voluntary isometric contractions

Prior to performing the simulated manual handling task, a total of 20 (10 contraction positions x 2 repetitions each) MVICs were performed for the purpose of EMG signal normalization. Contraction positions were selected according to the recommendations of Dal Maso et al., (2016), who identified the combination of isometric contractions most likely to reach a level of 90% of the participants' absolute maximum (

Table ***1*** The mRPE is a measure of perceived effort. However, perception of effort is exacerbated in the presence of physical fatigue (de Morree et al., 2012; Pageaux et al., 2015). Therefore, it has been stated that the increase of the perceived level of effort indicates an increase of fatigue (Pageaux, 2016).

). Each contraction was maintained for 5 seconds followed by at least a 1 minute resting period. Contraction position order was randomized between participants. Verbal encouragement was provided during contractions.

Table 1: Description of the MVIC tests

MVIC	Instructions
MVIC 1	In a seated position, arm flexed at 90º, palm of the hand facing down. Arm flexion with resistance at the elbow.
MVIC 2	In a seated position, arm abducted at 90º, palm of the hand facing down. Arm abduction with resistance at the elbow.
MVIC 3	In a prone position, arm horizontally abducted at 90º, elbow flexed at 90º. Horizontal arm abduction with resistance at the elbow.
MVIC 4	In a seated position, arm at the side, elbow flexed at 30° in supination. Elbow flexion with resistance at the wrist.
MVIC 5	In a seated position, arm at the side, elbow flexed at 30° in supination. Elbow extension with resistance at the wrist.
MVIC 6	In a seated position, arm abducted at 90º, neck side-bent to same side, head rotated toward opposite side, palm of the hand facing down. Arm abduction with resistance at the head and elbow.
MVIC 7	In a seated position, arms flexed at 90º, elbows lightly flexed, palms of the hands together. Pressing hands together with no external resistance.
MVIC 8	In a side-lying position, arm at the side, palm of the hand facing down. Arm abduction with resistance at the wrist.
MVIC 9	In a side-lying position, arm at the side, elbow flexed at 90º. Arm external rotation with resistance at the wrist.
MVIC 10	In a prone position, back hand in contact with upper lumbar spine. Arm internal rotation with resistance at the hand.

The isometric contraction positions used to record MVIC were adapted from Boettcher et al., (2008). The large number of positions used in this study guarantees that all shoulder muscles will contract maximally, ensuring appropriate normalization.

2.3.2 Simulated manual handling task

The manual handling task used in this experiment was designed to simulate actual conditions of pallets loading/unloading performed by workers according to observations made in a grocery chain warehouse (Goubault et al., 2020). Cardboard boxes of different sizes and weights were used (12 small boxes of 6 kg, l×w×h: 10x8x8 cm; 9 medium boxes of 10 kg, 15x12x8 cm; 6 large boxes of 12 kg: 16x14x14 cm). Although the use of fixed weight boxes may increase inter-participants variability as participants may have different strength capacities, this set-up best replicates a real working environment. Boxes were initially arranged in layers on a pallet set according to size (i.e. large boxes at the bottom, medium boxes in the middle, small boxes on the top). Participants were instructed to move the boxes to other pallets according to the size of the box, i.e., participants had to move all the small boxes to a second pallet, before moving the medium boxes on a third pallet, and then moving the large boxes on a fourth pallet (Figure 1B). After moving the boxes to their respective pallets, participants had to then move all boxes back to the original pallet (large boxes first, followed by medium boxes, and then small boxes). We chose a fixed, non-randomized order (small-medium-large, large-medium-small) for all participants based on observation made in industry, where workers would typically handle boxes of the same size in sequential way. This operation was repeated continuously for 45 minutes. Participants were asked to maintain a pace of about 5 boxes handled per minute representing a total of 225 boxes moved during the continuous 45 minute task. This pace is equivalent to unloading 2100 boxes in a 7h workday, which represents 78 pallets of 27 boxes, and is equivalent to processing approximately 11 orders (186 boxes on average per order) (Goubault et al., 2020). The experimenter provided feedback to the participants to ensure that they maintained the requested box transfer pace throughout the experiment. Every 5 minutes, participants were asked to rate their shoulder and overall perceived effort using the mRPE (CR10 Borg scale) (Borg, 1982). The mRPE is a measure of perceived effort. However, perception of effort is exacerbated in the presence of physical fatigue (de Morree et al., 2012; Pageaux et al., 2015). Therefore, it has been stated that the increase of the perceived level of effort indicates an increase of fatigue (Pageaux, 2016).

2.4 Data Processing

Data processing was performed with Matlab R2019a (The MathWorks Inc., Natick, MA, USA). All EMG data were filtered using the following zero-lag, 2nd order Butterworth filters: 10-400 Hz band-pass filter and 59-61 Hz stop-band filter (Gaudet et al., 2018; McDonald et al., 2018). Additionally, intramuscular EMG data were filtered using a 119-121 Hz stop-band filter because of persistent harmonic frequency artefacts. Data were then zero-aligned by subtracting the mean signal value. The 45 minute continuous data were split into sub-trials. A trial was defined as moving a layer of boxes of the same weight. This led to 8 trials on average for each box weight, for each participant. For each trial, EMG indicators were computed only during the times in which the participant was carrying a box, when muscle activity is higher. The following EMG indicators were computed as detailed below: *activation level*, *activity*, *mobility*, *sample entropy*, instantaneous *spectral entropy*, and instantaneous *median frequency*.

Activation levels were obtained from 9 Hz low-pass filtering of the full-wave rectified EMG signals. Maximum voluntary muscle excitation for each muscle was obtained using the average of the maximum 2 second non-consecutive window obtained across all MVIC tests. This value was then used to normalize muscle activations during the box-handling task.

$$Activation\ level = \frac{1}{N}\sum_{x_1}^{x_2} y_0 \qquad (1)$$

where x_1 and x_2 represent the muscle activation segment, N represents the number of elements between x_1 and x_2, and y_0 represents the EMG envelop of the signal.

Activity is the measure of the variance (σ_0) of the signal (Hjorth, 1970; Karthick et al., 2014; Vidaurre et al., 2009). This was calculated for each muscle activation segment of each trial.

Mobility is defined as the root square of the ratio between the variance of the first time derivative of the signal and the variance of the signal (Hjorth, 1970; Karthick et al., 2014; Vidaurre et al., 2009). The first time derivative of the EMG signal was calculated on the entire signal using equation (2):

$$EMG'(t) = \frac{EMG(t+1) - EMG(t)}{dt} \tag{2}$$

The variance of the first time derivative of the EMG signal and the variance of the EMG signal were then calculated on each muscle activation segment, before calculating the root square of the ratio between both.

$$Mobility = \sqrt{\frac{{\sigma_1}_{x1}^{x2}}{{\sigma_0}_{x1}^{x2}}} \tag{3}$$

where ${\sigma_1}_{x1}^{x2}$ represents the variance of the first time derivative of the EMG signal for muscle activation segment between x_1 and x_2, and ${\sigma_0}_{x1}^{x2}$ is the variance of the EMG signal for muscle activation segment between x_1 and x_2.

Sample entropy is the negative natural log of the conditional probability that time series of length *N*, having repeated itself within a tolerance of *r* for *m* data points, will also repeat itself for *m+1* points excluding self-matches (Richman & Moorman, 2000). It is used for assessing the complexity of time-series, and randomness of dynamic systems, describing the rate of information creation (Pincus, 1991; Richman & Moorman, 2000). A higher value is an indication of higher complexity. *Sample entropy* can then be defined mathematically by:

$$SampEn(m, r, N) = -\ln\left(\frac{B_{m+1}^{m}(r)}{B_m(r)}\right) \tag{4}$$

With $B_m(r)$ defined as:

$$B_m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} C_i^m(r) \tag{5}$$

where $B_m(r)$ is the number of matches of length m and $B_{m+1}^m(r)$ as the subset of $B_m(r)$ that also matches for length *m+1*. Here $m = 2$ and $r = 0.2$ times the standard deviation of the signal (Karthick et al., 2014; Zhang et al., 2014).

For instantaneous *spectral entropy* and *median frequency* analysis, the power spectral density of signals was obtained from time-frequency transformation since EMG signals are non-stationary processes (Farina, 2006). Power spectral density corresponded to the square value of the complex magnitude of the Morlet wavelet transformation (wave number: 7, frequency range: 1:400 Hz in 1 Hz steps) to the filtered EMG signals (WavCrossSpec Matlab package (Grinsted et al., 2004)). *Spectral entropy* and *median frequency* were then computed on a time-history basis.

Spectral entropy is defined as Shannon entropy computed over the normalized power spectral density curve (Bachiller et al., 2014; McBride et al., 2014). The following formula was used to calculate instantaneous *spectral entropy*, which measures the irregularity of a signal, at each time instant:

$$SpecEn(t) = -\frac{1}{\log(L)} . \sum_{t=1}^{n} TFR(t). \log\,[TFR(t)] \tag{6}$$

where, L is the number of spectral components in the EMG spectrum, TFR is a power spectral density calculated in the time-frequency resolution, t is a time instant, n is the number of seconds in the trial.

Median frequency is defined as the frequency at which the total spectral power is halved. The following formulae was used to calculate instantaneous *median frequency*:

$$\int_0^{MDF} TFR(t) = \int_{MDF}^{\infty} TFR(t) = \frac{1}{2}\int_1^{\infty} TFR(t) \tag{7}$$

TFR is a power spectral density calculated in the time-frequency resolution, t is a time instant.

2.5 Statistical Analysis

Statistical analyses were carried out with R 3.5.3 software (R Foundation for Statistical Computing, Vienna, Austria) using the 'ez' package and Matlab.

A linear-mixed model analysis with repeated measures on the mRPE (shoulder and overall) scores was performed to assess the effect of *Time* (fixed effect) on the mRPE, with participant as random effect.

For each box size and each EMG-based MMF indicator, multivariate linear regressions were performed between the 10 muscles as predictors and the mRPE scores as responses to determine which indicator(s) best explain variations in the participants' perceived efforts. The indicators used in the regression models corresponded as closely as possible to the time instants where mRPE was collected. To account for the issue of multiple statistical tests, Bonferroni corrections were applied to the *p-values* of multivariate linear regressions, bringing the statistical significance level to $p < 0.0014$ (0.05/36).

A linear-mixed model analysis with repeated measures on the EMG-based MMF indicators was also performed for each muscle separately and on each box size to assess the effect of *time* (fixed effect) throughout the different trials, on each EMG-based MMF indicator, namely the *activation level*, the *activity*, the *mobility*, the *sample entropy*, the *spectral* *entropy*, and the *median frequency*, with participant as random effect. Bonferroni corrections were applied on *p-values* of linear-mixed models bringing the statistical significance level to $p < 2.8e^{-4}$ (0.05/180). Results are presented with boxplots unless otherwise stated.

3 Results

3.1 Modified rate of perceived exertion scores

Statistical analysis showed that *time* had a significant effect on the mRPE shoulder score ($t(247) = 3.70$, $p < 0.001$), and on the mRPE overall score ($t(230) = 19.07$, $p < 0.001$). As represented in Figure 2, both shoulder and overall mRPE scores increased with time. At the end of the 45 minute manual handling task, the average shoulder and overall mRPE scores were 2.79 ± 1.68 (range: 0.5 to 7, only 1 participant reached 7) and 2.98 ± 1.33 (range: 1 to 6, only 1 participant reached 6), respectively.

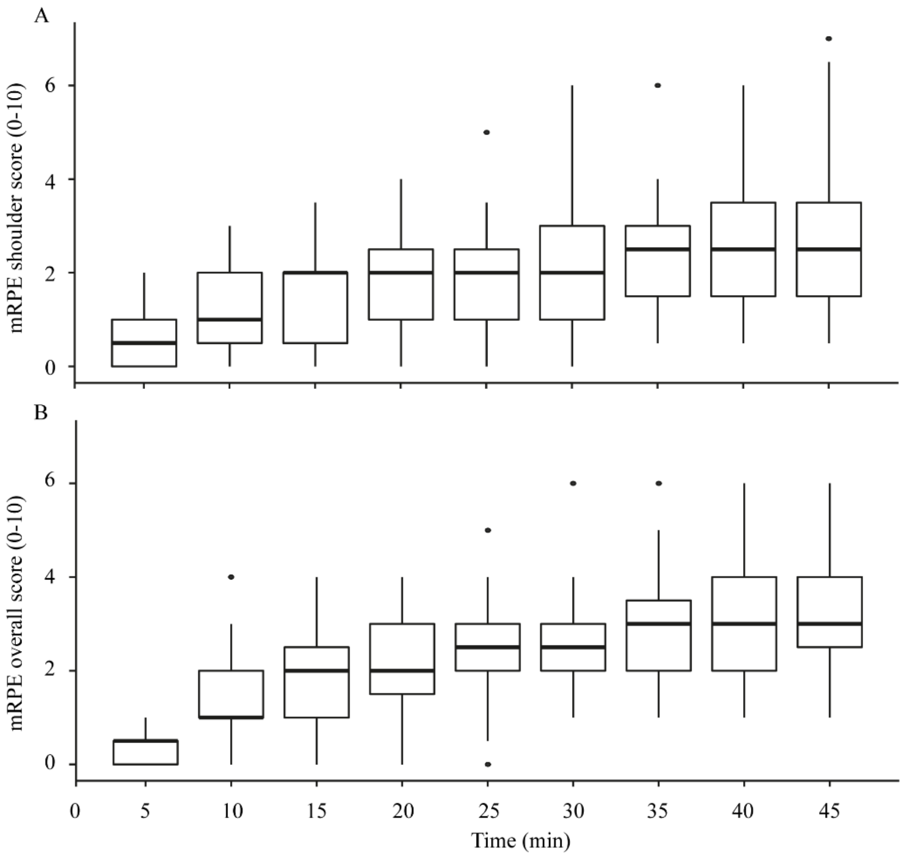

Figure 2: Boxplot representation of the mRPE shoulder score (A), and of the mRPE overall score (B) as a function of time. The bold line represents the median value, while the box represents the 25th to 75th percentile scores and the whiskers represent the 1.5*interquartile range on either side of the 25th and 75th percentile scores.

Figure 2 Alt Text: Two boxplot panels representing the evolution of the mRPE shoulder (top) and overall (underside) scores. Each panel displays a boxplot every 5 minutes from 5 minute of the experiment to 45 minute of the experiment. We observe a progressive increase of mRPE scores in both cases.

3.2 Multivariate linear regressions

Overall, the results of multivariate regressions revealed that only *mobility*, *spectral entropy* and *median frequency* significantly explained the variance of shoulder and overall mRPE scores after Bonferroni corrections in all models (Table 2). One exception was for the *median frequency* where a decreasing trend with the overall mRPE score ($p=0.003$ versus $p=0.0014$ for significance) was observed for small boxes. It was found that *spectral entropy* was the EMG-based MMF indicator that explained the largest part of the variance in mRPE scores in the shoulder and overall across all models (adjusted R^2 range between 18% and 39%) (Table 2). *Mobility* and *median frequency* explained between 11% and 37% of the variance in the shoulder and overall mRPE scores. *Activity* explained between 17% and 21% of variance in shoulder and overall mRPE respectively for the large and medium boxes, and did not significantly explain mRPE variance for the small boxes. Finally, *activation level* and *sample entropy* had no significant relationship with the variance in mRPE scores.

Table 2: Results of multivariate linear regressions performed between the 10 muscles as predictors and shoulder/overall mRPE scores as responses for each EMG-based MMF indicator and each box size.

		mRPE Shoulder score				mRPE Overall score			
		F	Standard error	R^2 adjusted	p-value	F	Standard error	R^2 adjusted	p-value
Large boxes	*Activation level*	2.27	1.18	0.082	0.017	2.37	1.12	0.087	0.013
	Activity	4.09	1.11	0.178	**< 0.001**	3.71	1.08	0.159	**< 0.001**
	Mobility	5.26	1.08	0.230*	**< 0.001**	3.69	1.08	0.158	**< 0.001**
	Sample entropy	1.70	1.20	0.047	0.086	2.41	1.12	0.090	0.011
	Spectral entropy	4.71	1.09	0.206	**< 0.001**	4.05	1.07	0.176*	**< 0.001**
	Median frequency	4.21	1.11	0.184	**< 0.001**	2.81	1.11	0.113	0.003
Medium boxes	*Activation level*	1.70	1.18	0.047	0.086	2.34	1.11	0.086	0.014
	Activity	4.74	1.08	0.207	**< 0.001**	3.95	1.05	0.171	**< 0.001**
	Mobility	6.40	1.03	0.274	**< 0.001**	6.54	0.98	0.279	**<0.001**
	Sample entropy	1.30	1.20	0.020	0.239	1.61	1.13	0.041	0.109
	Spectral entropy	8.16	0.99	0.334*	**< 0.001**	9.98	0.91	0.386*	**< 0.001**
	Median frequency	6.23	1.04	0.268	**< 0.001**	9.50	0.92	0.373	**< 0.001**
Small boxes	*Activation level*	2.53	1.15	0.092	0.008	2.37	1.09	0.083	0.013
	Activity	2.10	1.16	0.068	0.028	2.58	1.08	0.095	0.007
	Mobility	5.48	1.06	0.229	**< 0.001**	5.68	0.99	0.237	**< 0.001**
	Sample entropy	2.11	1.16	0.069	0.027	1.21	1.13	0.014	0.291
	Spectral entropy	8.02	0.99	0.317*	**< 0.001**	8.10	0.94	0.320*	**< 0.001**
	Median frequency	5.45	1.06	0.227	**< 0.001**	7.54	0.95	0.302	**< 0.001**

Bold values indicate significant regression after Bonferroni correction. * indicates the higher R^2 value in each case.

3.3 Evolution of EMG indicators over time

For all box sizes, *time* had a significant effect on most of the EMG-based MMF indicators. Overall, the EMG-based MMF indicators of the anterior, lateral, and posterior deltoids, biceps, and upper trapezius were significantly altered over time during the manual handling task (statistical results are summarized in supplementary materials Table S1). The *mobility*, *spectral entropy* and *median frequency* all demonstrated a similar pattern with respect to the significant effect of *time* (most prominent in the deltoids), whereas there were no significant changes in the rotator cuff muscles, unlike *activation level* and *sample entropy*. Finally, *activity* was found to have little fluctuation across trials and boxes.

More specifically, for small and medium boxes (Figure 3 and Figure 4, respectively), the *spectral entropy* and the *median frequency* of multiple muscles such as the deltoids, upper trapezius, and triceps decreased significantly over the time. The *mobility* also decreased in multiple muscles such as the deltoids and upper trapezius, whereas the *sample entropy* and the *activation level* decreased in the rotator cuff muscles. The *activity* decreased in the anterior deltoid, biceps, upper trapezius and subscapularis. Similar trends were observed when participants lifted the large boxes (Figure 5), however, significant changes were less frequent.

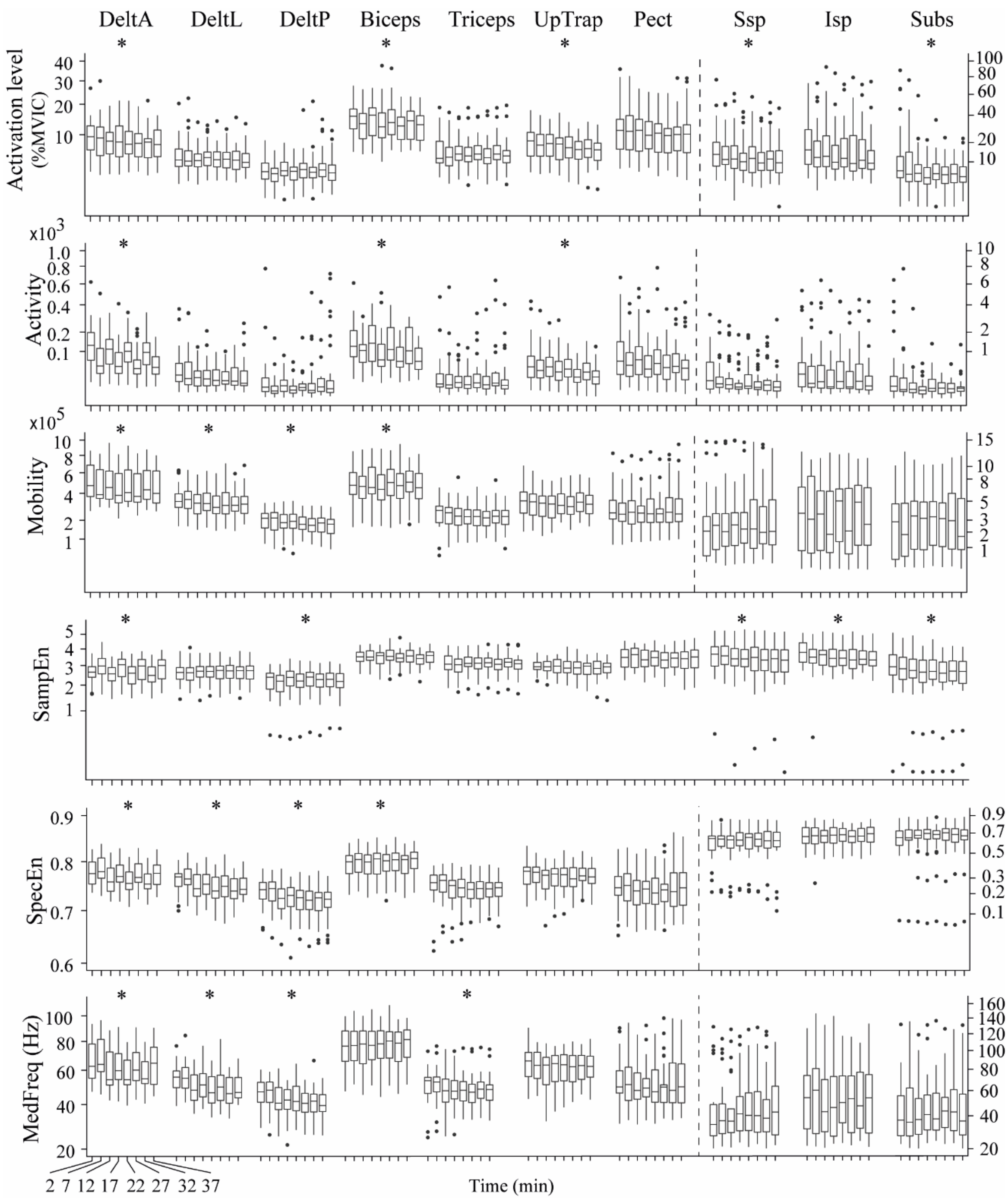

Figure 3: Boxplot representation of the EMG indicators for each muscle during the small box trials. Muscles on the right of dashed lines are rotator cuff muscle and have a different scale, except for *sample entropy* where the same scale was used for all muscles. * indicates a significant *time* effect as determined by the linear-mixed model analysis.

Figure 3 Alt Text: Six boxplot panels in a row for the six EMG indicators assessed. Each panel displays the evolution of the given EMG indicator for the 10 muscles. For each muscle, 8 boxplots are displayed for the 8 trials.

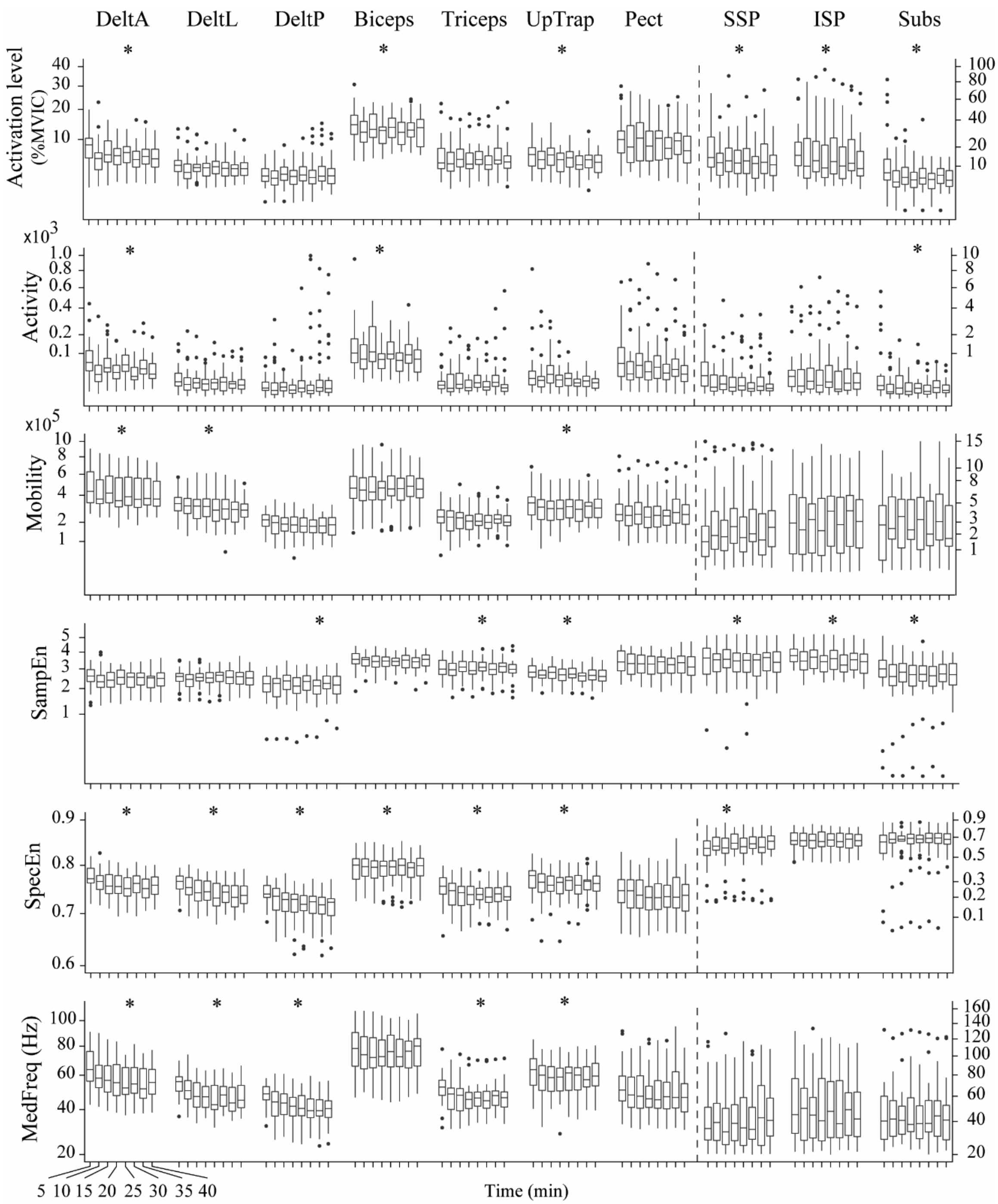

Figure 4: Boxplot representation of the EMG indicators for each muscle during the medium box trials. Muscles on the right of dashed lines are rotator cuff muscle with a special scale positioned on the right except for *sample entropy* where the same scale was used for all muscle. * indicates a significant *Time* effect revealed by the linear-mixed model analysis.

Figure 4 Alt Text: Six boxplot panels in a row for the six EMG indicators assessed. Each panel displays the evolution of the given EMG indicator for the 10 muscles. For each muscle, 8 boxplots are displayed for the 8 trials.

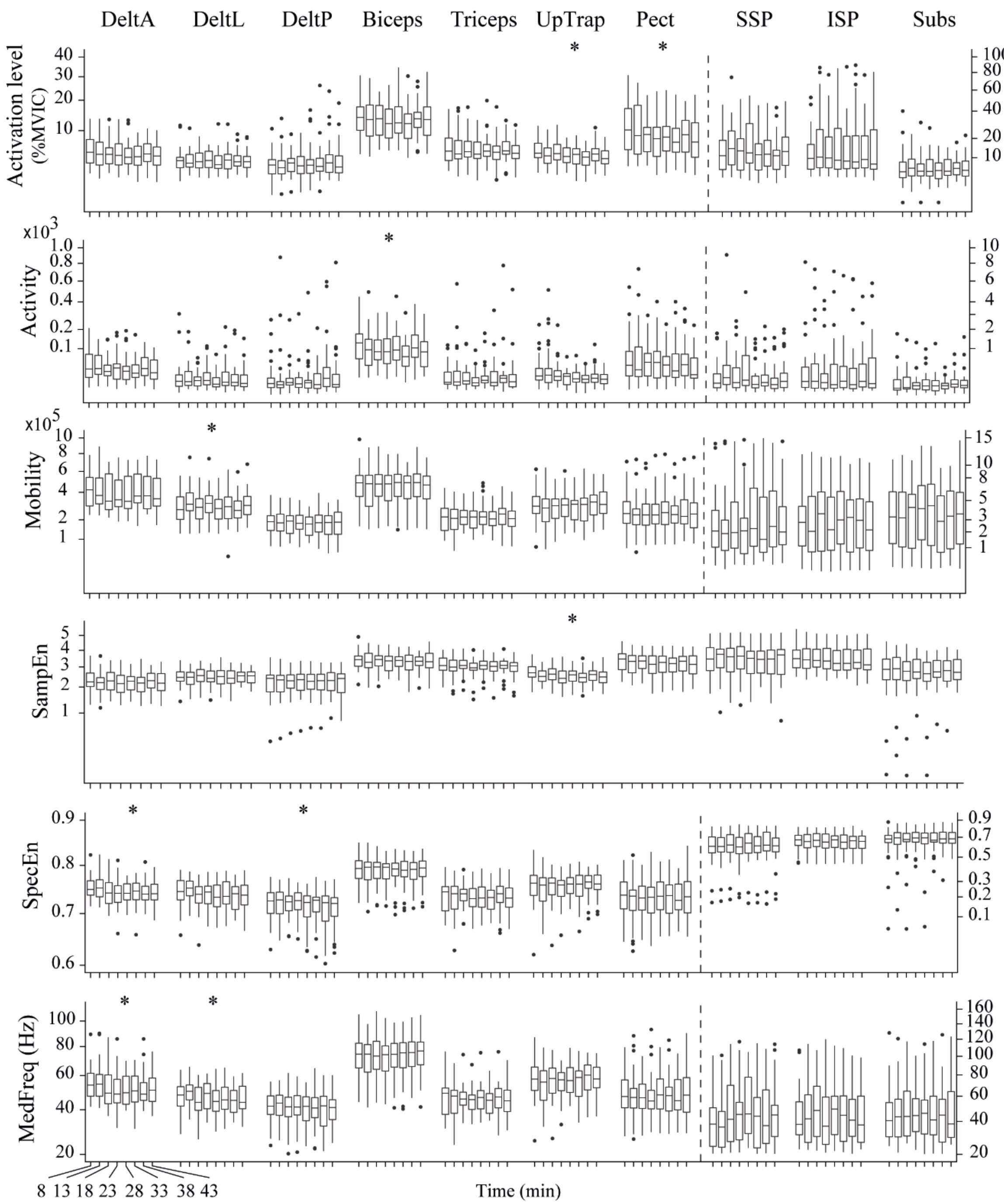

Figure 5: Boxplot representation of EMG indicator for each muscle during large box trials. Muscles on the right of dashed lines are rotator cuff muscle and have a different scale, except for *sample entropy* where the same scale was used for all muscles. * indicates a significant *time* effect as determined by the linear-mixed model analysis.

Figure 5 Alt Text: Six boxplot panels in a row for the six EMG indicators assessed. Each panel displays the evolution of the given EMG indicator for the 10 muscles. For each muscle, 8 boxplots are displayed for the 8 trials.

4 Discussion

The objective of the present study was to determine which shoulder muscle EMG-based indicator(s) were most suitable for assessing MMF during a continuous 45 minute laboratory-based manual handling task designed to mimic actual working conditions. We found a significant increase in the mRPE (shoulder and overall) scores over the course of the task, to reach a score close to what can be expected at work (Jakobsen et al., 2014). In this experimental protocol, *spectral entropy*, *median frequency*, and *mobility* best explained the variance in the mRPE scores, suggesting that these EMG-based indicators are the most suitable for the assessment of MMF, as compared to indicators such as *activation level*, *activity*, and *sample entropy*.

4.1 Validation of the protocol

The infraspinatus was the muscle that had the highest activation level during the task with an average of 16.59 ± 13.92% MVIC. The biceps, the anterior deltoid, and the upper trapezius, which are prime movers during lifting tasks (Bouffard et al., 2019), had mean activation levels of 12.96 ± 4.09% MVIC, 6.26 ± 2.54% MVIC, and 5.45 ± 1.89% MVIC, respectively, indicating that these shoulder muscles were solicited more minimally during the task (Day et al., 2012). Mean shoulder and overall mRPE scores were 2.79 ± 1.68 and 2.98 ± 1.33 respectively at the end of the 45 minute simulated working task, which represents a moderate level of perceived exertion (Jakobsen et al., 2014). These scores were very close to what would be expected in a real working environment, as Jakobsen et al.,

(2014) suggested that mRPE scores between 2 and 4 represent moderate effort and scores above 4 represent a hard effort during working activities. Thus, our laboratory-based experimental protocol succeeded in reproducing a manual handling task whose intensity was similar to that which workers are exposed to on a daily basis. Since a degree of muscle fatigue imparting risk for injury may be reached well before the workers' absolute inability to perform the task (Enoka & Duchateau, 2008), we suggest that the low level of fatigue found in the present study may be clinically significant for overuse injuries.

4.2 Multivariate linear regression

In the present study, *spectral entropy*, *median frequency*, and *mobility* best explained the mRPE scores with adjusted R^2 values in the regression models ranging from 11% to 39%. These relatively low values could be explained by the fact that an individual's perceived effort (mRPE) is a composite of central fatigue, neuromuscular junction fatigue, and muscular fatigue (Merletti & Farina, 2006). EMG signals could be influenced by these three factors in a different proportion, which could explain the range of adjusted R^2 values obtained in that study.

Nevertheless, the multivariate linear regression results were consistent regardless of the weight of the boxes handled and may enable the assessment of EMG-based MMF in real workplace conditions. Regression analyses allowed us to identify that *median frequency* predicted mRPE scores in workplace-like conditions. This result is in agreement with previous findings, which show a high positive correlation between the *median frequency* and mRPE scores during the prone bridging test (Cruz-Montecinos et al., 2019), which further confirms its potential to assess MMF during low load manual handling tasks. Interestingly, *spectral entropy*, also extracted from time-frequency analysis, was the EMG-based MMF indicator that showed the greatest ability to explain the variance of mRPE scores. Therefore, this indicator should also be considered when assessing MMF via EMG. Finally, the *mobility*, which can be considered as the time domain approximation of mean frequency (Vidaurre et al., 2009) was the third EMG-based MMF indicator demonstrating an ability to predict the variance of the mRPE scores. Given that two of the three identified indicators were related to frequency content of the EMG signal, this shows that the indicators related to the frequency content of EMG signals may be more relevant in the explanation of mRPE variance and therefore in the assessment of MMF.

Typically, a negative linear correlation is expected between *median frequency* and the conduction velocity of the active muscle motor units in the presence of muscle fatigue (Cifrek et al., 2009; Farina, 2006; Farina et al., 2004). The reduction of both *spectral entropy* (associated with higher regularity in signal) and *mobility* values, are both sensitive to changes in the frequency content of EMG signals (Karthick et al., 2014). Future studies should focus on the combination of these three indicators to improve muscle fatigue assessment during real working activities. Conversely, *activity*, *activation level*, and *sample entropy* showed inferior ability or did not explain mRPE scores and so according to our findings, would not be of use in predicting MMF during low load manual handling tasks. In future studies, it would be of interest to perform a similar evaluation on more varied low load workplace activities to validate and generalize our findings to workplace tasks.

4.3 Evaluation of Spectral entropy, Median frequency, & Mobility

Overall, *spectral entropy*, *median frequency*, and *mobility* were the indicators that changed significantly throughout the manual handling task in the deltoid muscles, which were the only muscles showing consistent MMF within the different box weights. This result is in agreement with their prime mover function during a manual handling task. Alternatively, these indicators also changed significantly in the upper trapezius, which is involved in lifting boxes (Bouffard et al., 2019). However, this change was only noted in the medium size boxes. The biceps did not show MMF despite their strong involvement in manual handling (Bouffard et al., 2019), suggesting a higher resistance to fatigue than the anterior deltoid and upper trapezius. The *spectral entropy* of the biceps was found to have an increasing trend, which is the opposite of what has been observed in literature (Karthick et al., 2014), and may confirm the absence of muscle fatigue in our study. This observation may be due to a higher percentage of biceps slow twitch fibre motor units in the participants of the present study. Indeed, the mean power frequency of EMG decreased more in individuals with a high percentage of fast twitch, while their opposites demonstrated only a non-significant slight decrease (Komi & Tesch, 1979; Thorstensson & Karlsson, 1976). We suggest that since the biceps is a powerful muscle, it may require higher contraction levels for changes in its biochemical and physiological behaviors to occur (Cifrek et al., 2009), meaning that it could compensate for the increasing muscle fatigue in other muscles over the course of the task. The triceps muscles, acting as an antagonist in the present task, and the supraspinatus showed MMF less frequently when handling the medium boxes compared to the other box sizes. Taken together, these results may suggest that the combination of *spectral entropy*, *median freq*uency, and *mobility* may improve the accuracy in the assessment of MMF.

4.4 Evaluation of Activation level, Activity, & Sample Entropy

Other EMG-based indicators, such as *activation level*, *activity*, and *sample entropy*, had an inferior ability or were not significantly related to the variance in mRPE scores, despite their significant changes over time during the repeated manual handling task. In addition, when a significant effect of *time* was observed, *activation level* and *activity* significantly decreased with time, which is the opposite of what is commonly reported with muscle fatigue (Al-Mulla et al., 2011; Karthick et al., 2014). *Activation level* was also found to have any significant involvement with the mRPE variance. Consequently, although *activation level* has been employed to assess MMF during low load dynamic activities (Korol et al., 2014, 2017), this EMG-based indicator should be interpreted with caution for the assessment of muscle fatigue (Cifrek et al., 2009). Finally, *sample entropy* decreased with time in multiple muscles, which is a trend that has also been observed in literature (Cui et al., 2017; Karthick et al., 2014; Xie et al., 2010). This was the case for the anterior and posterior deltoids for all box sizes, in the rotator cuff muscles for small boxes, and in the triceps and upper trapezius muscles for large boxes. However, *sample entropy* did not explain the mRPE variances in regression models. Therefore, even if the variation of sample entropy is in accordance with previous studies (Cui et al., 2017; Karthick et al., 2014; Xie et al., 2010), and that it affects muscles showing MMF with other EMG-based indicators, such as the deltoid muscles, it may not represent accurate indicators for the assessment of MMF during manual handling tasks.

4.5 Limitations & Conclusion

A limitation is that the MMF reported in this study were extracted from EMG-based indicators, where EMG evaluates the neuromuscular component of fatigue primarily, and was correlated to mRPE, a more holistic representation of fatigue. However, to our knowledge, there is no gold standard measure to evaluate only the neuromuscular component of fatigue during functional manual handling tasks. Additionally, the method used in this study has been used in other studies, and where EMG-based MMF indicators were correlated to mRPE during activities involving a fatigue component (Ahmad & Kim, 2018; Cruz-Montecinos et al., 2019; Hummel et al., 2005; Korol et al., 2014, 2017).

In conclusion, using an experimental protocol replicating industrial manual handling, we found that *spectral entropy*, and *median frequency*, both extracted from time-frequency analysis of EMG signals, and *mobility* extracted from the time domain were the EMG-based MMF indicators with the most promising ability to predict mRPE. In addition, these indicators decreased in value in prime mover muscles, as was expected during a fatigue-inducing task.

5 Acknowledgements

We would like to thank Élodie Monga-Dubreuil for her help in collecting data, the volunteers for their participation in the study, the Institut de recherche Robert-Sauvé en santé et sécurité du travail (IRSST) (Grant number: #2014-0045), and the Canadian Institutes of Health Research (Grant number: #MFE-146666) that provided funding for the study.

6 Author Contributions

EG was responsible for the data analyses and drafted the manuscript. RM was involved in the design of the study, the data collection and provided significant feedback on the analysis of the study. JB was involved in the design of the study and provided critical revision of manuscript for intellectual content. JDM provided critical revision of manuscript for intellectual content. MB and FDM, the lead scientists, helped in all facets of the project. All authors read and approved the final manuscript.

7 Conflict of Interest

The authors have no conflict of interest to report.

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9 Supplementary material

Table 3: Statistical results of linear-mixed models for large boxes

	Activation level	Activity	Mobility	SampEn	SpecEn	MedFreq
DeltA	$t(7) = 19.90$, $p = 2.60^{e-2}$	$t(7) = 18.75$, $p = 9.00^{e-3}$	$t(7) = 19.75$, $p = 6.14^{e-3}$	$t(7) = 17.41$, $p = 1.49^{e-2}$	$t(7) = 35.61$, $p = 8.58^{e-6}$	$t(7) = 32.31$, $p = 3.56^{e-5}$
DeltL	$t(7) = 2.34$, $p = 9.38^{e-1}$	$t(7) = 6.35$, $p = 5.00^{e-1}$	$t(7) = 31.14$, $p = 5.86^{e-5}$	$t(7) = 3.49$, $p = 8.36^{e-1}$	$t(7) = 21.16$, $p = 3.54^{e-3}$	$t(7) = 33.08$, $p = 2.56^{e-5}$
DeltP	$t(7) = 14.63$, $p = 4.11^{e-2}$	$t(7) = 10.27$, $p = 1.74^{e-1}$	$t(7) = 6.80$, $p = 4.50^{e-1}$	$t(7) = 4.61$, $p = 7.08^{e-1}$	$t(7) = 26.39$, $p = 4.29^{e-4}$	$t(7) = 14.62$, $p = 4.11^{e-2}$
Biceps	$t(7) = 15.90$, $p = 2.60e^{-2}$	$t(7) = 37.95$, $p = 3.10^{e-6}$	$t(7) = 25.91$, $p = 5.23^{e-4}$	$t(7) = 9.21$, $p = 2.38^{e-1}$	$t(7) = 7.58$, $p = 3.71^{e-1}$	$t(7) = 10.95$, $p = 1.41^{e-1}$
Triceps	$t(7) = 8.78$, $p = 2.69^{e-1}$	$t(7) = 3.22$, $p = 8.64^{e-1}$	$t(7) = 17.93$, $p = 1.23^{e-2}$	$t(7) = 25.59$, $p = 5.95^{e-4}$	$t(7) = 9.14$, $p = 2.42^{e-1}$	$t(7) = 13.43$, $p = 6.24^{e-2}$
UpTrap	$t(7) = 43.99$,	$t(7) = 22.90$,	$t(7) = 10.99$,	$t(7) = 48.14$,	$t(7) = 4.11$,	$t(7) = 8.41$,

	$p = 2.15^{e-7}$	$p = 1.77^{e-3}$	$p = 1.39^{e-1}$	$p = 3.34^{e-8}$	$p = 7.67^{e-1}$	$p = 2.98^{e-1}$
Pec	$t(7) = 26.47$, $p = 4.15^{e-4}$	$t(7) = 11.62$, $p = 1.14^{e-1}$	$t(7) = 5.90$, $p = 5.52^{e-1}$	$t(7) = 16.79$, $p = 1.88^{e-2}$	$t(7) = 3.11$, $p = 8.75^{e-1}$	$t(7) = 4.67$, $p = 7.01^{e-3}$
SSP	$t(7) = 14.39$, $p = 4.47^{e-2}$	$t(7) = 5.35$, $p = 6.17^{e-1}$	$t(7) = 25.48$, $p = 6.24^{e-4}$	$t(7) = 14.21$, $p = 4.76^{e-2}$	$t(7) = 19.06$, $p = 8.00^{e-3}$	$t(7) = 20.28$, $p = 4.99^{e-3}$
ISP	$t(7) = 17.48$, $p = 1.46^{e-2}$	$t(7) = 8.19$, $p = 3.16^{e-1}$	$t(7) = 11.74$, $p = 1.09^{e-1}$	$t(7) = 21.83$, $p = 2.72^{e-3}$	$t(7) = 14.12$, $p = 4.91^{e-2}$	$t(7) = 9.43$, $p = 2.23^{e-1}$
Subs	$t(7) = 6.77$, $p = 4.53^{e-1}$	$t(7) = 3.67$, $p = 8.17^{e-1}$	$t(7) = 1.44$, $p = 9.84^{e-1}$	$t(7) = 11.62$, $p = 1.14^{e-1}$	$t(7) = 2.33$, $p = 9.39e^{-1}$	$t(7) = 4.17$, $p = 7.59e^{-1}$

Table 4: Statistical results of linear-mixed models for medium boxes

	Activation level	Activity	Mobility	SampEn	SpecEn	MedFreq
DeltA	$t(7) = 46.35$, $p = 7.47^{e-8}$	$t(7) = 43.14$, $p = 3.14^{e-7}$	$t(7) = 67.45$, $p = 4.83^{e-12}$	$t(7) = 10.14$, $p = 1.81^{e-1}$	$t(7) = 94.77$, $p = 1.29^{e-17}$	$t(7) = 101.69$, $p = 4.38^{e-19}$
DeltL	$t(7) = 14.97$, $p = 3.64^{e-2}$	$t(7) = 8.03$, $p = 3.30^{e-1}$	$t(7) = 30.16$, $p = 8.88^{e-5}$	$t(7) = 16.61$, $p = 2.01^{e-2}$	$t(7) = 55.24$, $p = 1.34^{e-9}$	$t(7) = 78.56$, $p = 2.71^{e-14}$
DeltP	$t(7) = 24.35$, $p = 9.91^{e-4}$	$t(7) = 18.72$, $p = 9.10^{e-3}$	$t(7) = 20.59$, $p = 4.42^{e-3}$	$t(7) = 47.33$, $p = 4.81^{e-8}$	$t(7) = 71.52$, $p = 7.28^{e-13}$	$t(7) = 76.99$, $p = 5.65^{e-14}$
Biceps	$t(7) = 39.23$, $p = 1.77^{e-6}$	$t(7) = 43.83$, $p = 2.30^{e-7}$	$t(7) = 24.60$, $p = 8.91^{e-4}$	$t(7) = 14.75$, $p = 3.94^{e-2}$	$t(7) = 30.32$, $p = 8.29^{e-5}$	$t(7) = 19.27$, $p = 7.39^{e-3}$
Triceps	$t(7) = 14.91$, $p = 3.72^{e-2}$	$t(7) = 5.80$, $p = 5.63^{e-1}$	$t(7) = 18.80$, $p = 8.84^{e-3}$	$t(7) = 39.38$, $p = 1.68^{e-6}$	$t(7) = 33.76$, $p = 1.91^{e-5}$	$t(7) = 53.47$, $p =3.00^{e-9}$
UpTrap	$t(7) = 57.56$, $p = 4.63^{e-10}$	$t(7) = 16.43$, $p = 2.14^{e-2}$	$t(7) = 26.76$, $p = 3.67^{e-4}$	$t(7) = 41.01$, $p = 8.06^{e-7}$	$t(7) = 26.58$, $p = 3.96^{e-4}$	$t(7) = 37.21$, $p = 4.29^{e-6}$
Pec	$t(7) = 22.69$,	$t(7) = 8.61$,	$t(7) = 20.68$,	$t(7) = 21.49$,	$t(7) = 17.98$,	$t(7) = 24.17$,

	$p = 1.93^{e-3}$	$p = 2.82^{e-1}$	$p = 4.28^{e-3}$	$p = 3.10^{e-3}$	$p = 1.21^{e-2}$	$p = 1.06^{e-3}$
SSP	$t(7) = 27.43$, $p = 2.79^{e-4}$	$t(7) = 21.54$, $p = 3.04^{e-3}$	$t(7) = 16.58$, $p = 2.03^{e-2}$	$t(7) = 31.08$, $p = 6.02^{e-5}$	$t(7) = 33.17$, $p = 2.46^{e-5}$	$t(7) = 20.76$, $p = 4.15^{e-3}$
ISP	$t(7) = 33.91$, $p = 1.79^{e-5}$	$t(7) = 7.25$, $p = 4.03^{e-1}$	$t(7) = 7.19$, $p = 4.09^{e-1}$	$t(7) = 114.58$, $p = 1.03^{e-21}$	$t(7) = 5.00$, $p = 6.60^{e-1}$	$t(7) = 8.26$, $p = 3.10^{e-1}$
Subs	$t(7) = 40.64$, $p = 9.51^{e-7}$	$t(7) = 28.27$, $p = 1.96^{e4}$	$t(7) = 5.52$, $p = 5.97^{e-1}$	$t(7) = 31.23$, $p = 6.65^{e-5}$	$t(7) = 13.24$, $p = 6.65e^{-2}$	$t(7) = 10.16$, $p = 1.79e^{-1}$

Table 5: Statistical results of linear-mixed models for small boxes

	Activation level	Activity	Mobility	SampEn	SpecEn	MedFreq
DeltA	$t(7) = 32.83$, $p = 2.85^{e-5}$	$t(7) = 86.35$, $p = 6.94^{e-16}$	$t(7) = 75.17$, $p = 1.32^{e-13}$	$t(7) = 86.96$, $p = 5.20^{e-16}$	$t(7) = 123.89$, $p = 1.18^{e-23}$	$t(7) = 110.37$, $p = 7.69^{e-21}$
DeltL	$t(7) = 18.27$, $p = 1.08^{e-2}$	$t(7) = 24.26$, $p = 1.03^{e-3}$	$t(7) = 26.40$, $p = 4.28^{e-4}$	$t(7) = 10.57$, $p = 1.59^{e-1}$	$t(7) = 69.50$, $p = 1.86^{e-12}$	$t(7) = 78.02$, $p = 3.49^{e-14}$
DeltP	$t(7) = 18.50$, $p = 9.90^{e-3}$	$t(7) = 9.51$, $p = 2.18^{e-1}$	$t(7) = 27.15$, $p = 3.13^{e-4}$	$t(7) = 51.99$, $p = 5.86^{e-9}$	$t(7) = 61.10$, $p = 9.10^{e-11}$	$t(7) = 67.43$, $p = 4.88^{e-12}$
Biceps	$t(7) = 30.36$, $p = 8.16^{e-5}$	$t(7) = 58.65$, $p = 2.80^{e-10}$	$t(7) = 52.55$, $p = 4.55^{e-9}$	$t(7) = 23.53$, $p = 1.38^{e-3}$	$t(7) = 26.04$, $p = 4.96^{e-4}$	$t(7) = 5.35$, $p = 6.18^{e-1}$
Triceps	$t(7) = 10.98$, $p = 1.39^{e-1}$	$t(7) = 7.23$, $p = 4.05^{e-1}$	$t(7) = 14.58$, $p = 4.18^{e-2}$	$t(7) = 25.12$, $p = 7.23^{e-4}$	$t(7) = 17.36$, $p = 1.52^{e-2}$	$t(7) = 29.69$, $p = 1.08^{e-4}$
UpTrap	$t(7) = 53.72$, $p = 2.67^{e-9}$	$t(7) = 34.67$, $p = 1.29^{e-5}$	$t(7) = 22.37$, $p = 2.19^{e-3}$	$t(7) = 12.60$, $p = 8.24^{e-2}$	$t(7) = 14.33$, $p = 4.56^{e-2}$	$t(7) = 22.95$, $p = 1.74^{e-3}$
Pec	$t(7) = 23.54$,	$t(7) = 10.74$,	$t(7) = 11.26$,	$t(7) = 17.71$,	$t(7) = 8.40$,	$t(7) = 9.82$,

	$p = 1.37^{e-3}$	$p = 1.51^{e-1}$	$p = 1.28^{e-1}$	$p = 1.33^{e-2}$	$p = 2.98^{e-1}$	$p = 1.99^{e-1}$
SSP	$t(7) = 30.16$, $p = 8.87^{e-5}$	$t(7) = 6.97$, $p = 4.32^{e-1}$	$t(7) = 12.75$, $p = 7.84^{e-2}$	$t(7) = 34.85$, $p = 1.19^{e-5}$	$t(7) = 4.45$, $p = 7.27^{e-1}$	$t(7) = 10.35$, $p = 1.70^{e-1}$
ISP	$t(7) = 13.93$, $p = 5.24^{e-2}$	$t(7) = 6.73$, $p = 4.57^{e-1}$	$t(7) = 5.77$, $p = 5.66^{e-1}$	$t(7) = 26.60$, $p = 3.93^{e-4}$	$t(7) = 2.80$, $p = 9.03^{e-1}$	$t(7) = 7.35$, $p = 3.94^{e-1}$
Subs	$t(7) = 27.42$, $p = 2.80^{e-4}$	$t(7) = 12.21$, $p = 9.37^{e-2}$	$t(7) = 6.57$, $p = 4.75^{e-1}$	$t(7) = 40.39$, $p = 1.06^{e-6}$	$t(7) = 4.85$, $p = 6.78e^{-1}$	$t(7) = 11.09$, $p = 1.35e^{-1}$