2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

A Real-Time Algorithm to Estimate Shoulder Muscle Fatigue Based on Surface EMG Signal For Static and Dynamic Upper Limb Tasks

Marianne Boyer[1,2], Laurent Bouyer[2,3], Jean-Sébastien Roy[2,3] and Alexandre Campeau-Lecours[1,2]

Abstract— **Despite prevention efforts, the prevalence of work-related upper extremity musculoskeletal disorders (WRUED) is increasing. A limit in the development of preventive interventions is the lack of devices that can measure and process sEMG signals in order to provide real-time reliable information on muscular fatigue of the upper limb in relation to the physical demands of the work. In this paper, the development and evaluation of a real-time muscle fatigue detection algorithm based on sEMG will be presented. The proposed algorithm uses the median frequency of sEMG power spectrum density (PSD) obtained with the Continuous Wavelet Transform (CWT) as an indicator of the muscle fatigue level. To extend the algorithm's efficiency to dynamic tasks, a muscle contraction detection module is added in order to remove the segments when the muscle is not contracting. To assess the algorithm's performance, eight healthy adults performed simple static and dynamic shoulder tasks using different loads. The results of the proposed time-frequency method (i.e. CWT) were first compared to those of the traditional Short Time Fourier Transform (STFT). It was shown that the CWT performs better than the STFT in both static and dynamic loading conditions. The validity of the algorithm's output as a muscle fatigue indicator was verified by comparing the output's decrease rate with different loads. As expected, the algorithm's fatigue indicator decreased faster over time with heavier loads. It was also shown that the initial muscle fatigue estimation output is independent of the load. Finally, we studied the proposed muscle contraction detection module's efficiency to overcome issues associated with dynamic tasks. We observed a substantial improvement of the smoothness of the fatigue indicator's evolution by using of the muscle contraction detection module.**

I. INTRODUCTION

Work-related upper extremity musculoskeletal disorders (WRUED) are a major problem in modern societies as they affect workers' quality of life and lead to absenteeism, productivity loss and early retirement [1]. Despite prevention efforts, the prevalence of these disorders is increasing [2]. Given the importance of this issue, workplace interventions must be improved. Nevertheless, there is a severe lack of adapted tools to better prevent these injuries.

Working in a fatigue state is known to lead to WRUED. The development of WRUED could thus be potentially prevented by using a real-time feedback system that keeps track of muscle fatigue state and warns users if they are at risk of injury. Studies have shown that the level of muscle activation as well as fatigue can be detected using surface electromyography (sEMG) [3], [4]. While the analysis of muscle activation is based on the time domain, muscle fatigue is rather studied in the frequency domain [5]. Indeed, metrics such as median frequencies (MDF) and mean frequencies (MNF) of the sEMG power spectrum density (PSD) are commonly used as early indicators of neuromuscular changes associated with muscle fatigue [6]. According to [7], these metrics should decrease as the muscle gets tired due to the reduction of muscle fibre conduction velocity. Muscle fatigue has mostly been studied offline, that is, with sEMG signals first recorded, which are then analyzed later on a computer [5]. However, to serve as a preventive measure, the signal processing and the analysis underlying muscle fatigue estimation must be performed in real-time by a device able to provide immediate feedback to the user. Over the past few years, different research groups have developed EMG fatigue detection algorithms adapted for real time monitoring of isometric contractions (i.e. static tasks) [8]–[12]. In the workplace, however, complex dynamic contractions are common. Muscles are contracted only for short periods of time, unlike during isometric contractions. As the sEMG PSD MDF has been shown to be reduced when muscles are not contracting [13], this metric's output could be altered during dynamic tasks. Traditionally, the sEMG time-frequency analysis for fatigue detection has mostly been performed with the use of the Fourier Transform [5]. However, the Fourier Transform brings multiple additional difficulties when used in real time and during dynamic tasks. This comes from the fact that it requires a quasi-stationary signal. Yet, the condition is only met during isometric contractions. Other time-frequency analysis methods have also been considered [5] and the Continuous Wavelet Transform (CWT) has been proposed as an alternative, giving smoother estimates of the PSD frequency drop [13]. Besides, instead of aiming for smoother results, others have thought of ways to get rid of the irrelevant parts of the signal (i.e. when the muscle is at rest). One offline basic approach is for an expert to manually select parts of the signal in which the muscle is contracted to perform the analysis [14]. However, this method cannot be used for real-time feedback applications. To this end, [15] has presented a peak detection method to only consider local maximums which can be applied in real-time. However, this approach is only applicable to cyclic dynamic contractions (e.g. walking) which do not represent adequately usual tasks

*This work was supported by the Canadian MSK Rehab Research Network, by INTER (Engineering of Interactive Rehabilitation Technologies), by the Natural Sciences and Engineering Research Council of Canada and by the Canada First Research Excellence Fund Sentinel North Strategy at Université Laval.

[1] M. Boyer and A. Campeau-Lecours are with the Department of Mechanical Engineering, Université Laval, Canada

[2] M. Boyer, A. Campeau-Lecours, JS. Roy and L. Bouyer are with the Centre for Interdisciplinary Research in Rehabilitation and Social Integration, CIUSSS de la Capitale-Nationale, Canada

[3] JS. Roy and L. Bouyer are with the Department of Rehabilitation, Université Laval, Canada

performed by workers.

The general aim of this project is to develop and validate a real-time biomedical device able to analyze shoulder muscle fatigue in real-time and to provide feedback to the users on their muscle fatigue level in order to prevent musculoskeletal injuries. The objective of this paper is to develop and preliminary validate a muscle fatigue estimation algorithm for simple isometric and dynamic upper limb tasks (i.e. one elevation plane). The proposed algorithm uses the median frequency of sEMG PSD obtained with the CWT as an indicator of the muscle fatigue level. To assess the dynamic contractions issue, the proposed algorithm includes a muscle contraction detection module which automatically determines the segments of the raw sEMG signal that need to be removed prior to analysis/processing.

The specific objectives of the current paper are to create a real-time algorithm that provides an output which 1) is smooth (i.e. robust to transient estimations errors expected during real-time assessment of muscle contractions which would give false fatigue alerts); 2) is a valid indicator of the muscle fatigue; 3) is not affected by other features than the muscle fatigue state (e.g. load magnitude); 4) overcomes issues associated with the periods when muscles are not active during dynamic tasks.

The hypothesis are as follows. 1) For simple tasks during which the load does not change, one should obtain a smooth and non-fluctuating PSD MDF (fatigue indicator) decrease. As proposed in the literature, the CWT method should provide a smoother fatigue indicator decrease than the classic Short Time Fourier Transform (STFT) [13]. 2) It is well known that muscles fatigue faster with heavier loads. The fatigue indicator should thus decrease faster for heavier loads than for lighter ones. 3) As the sEMG sensors are not removed from the participants between tasks, the initial fatigue indicator should remain similar for different loads if given enough rest between tasks. 4) As the sEMG PSD MDF has been shown to be lower when muscles are not contracting [13], the fatigue indicator decrease should be more stable for dynamic tasks with the muscle contraction detection module than without it.

The paper is organized as follows: Section II presents the design of the proposed algorithm with both the CWT and the STFT, which serves as reference for comparison purposes. Section III covers the data acquisition, the experimental and the statistical analysis methods while Section IV presents the fatigue results and discussion. Finally, a conclusion is presented in Section V.

II. Algorithm

As illustrated in Fig. 1, before processing the data, the proposed algorithm first requires a calibration phase during which the user performs three Maximum Voluntary Contractions (MVC) of the targeted muscle. Indeed, each person has different sEMG signal characteristics, which can also slightly differ from day to day. One metric is obtained from the calibration (i.e. maximal signal magnitude). It has been shown that the magnitude of the sEMG signal increases with the level of muscle activation. Therefore, the maximal magnitude is measured during the MVC since it is the highest level of voluntary activation of the muscle. The maximal magnitude of the signal will be used later in the muscle contraction detection phase to determine if the signal is valid or not.

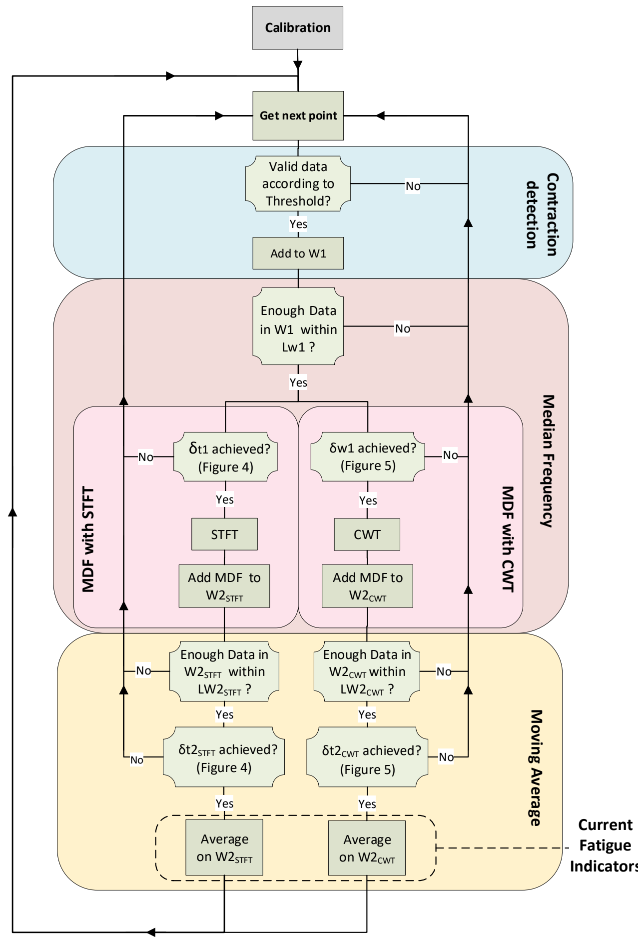


Fig. 1. General algorithm

Once the calibration has been performed, the fatigue detection algorithm begins. The proposed algorithm can be divided in three main phases (i.e. muscle contraction detection, median frequency computation and moving average computation) in which the sEMG samples are processed one by one as presented in Fig. 1. First, in the muscle contraction detection phase, the raw signal is removed when the muscle is not contracting since the MDF of the signal is irrelevant in this case. This phase is especially useful for dynamic contractions. Secondly, in the median frequency computation phase, the MDF of the sEMG PSD is computed. For comparison purposes, the MDF was assessed with two different methods, namely the CWT and the STFT. Finally, in the moving average computation phase, a moving average is performed on the MDF data in order to smooth the median frequency over time. The output of the moving average computation phase is what will be referred as ”fatigue indicator" in this paper. The three algorithm's phases are presented in detail in the following subsections.

The proposed algorithm has been designed to be used in real time, meaning that it does not need the entire data sequence to be effective. In other words, as opposed to offline algorithms, it can provide feedback on events that occurred within the last seconds. Here, the algorithm has been validated offline for comparison purposes. However, to simulate real-time analysis, samples are processed one by one in the algorithm as if it was being acquired in real time.

A. *Muscle contraction detection*

The algorithm first verifies if the raw data signal is valid (i.e. if the muscle is contracted). This phase is especially useful for dynamic tasks since the muscles are not always contracted. To this end, the envelope of the signal (Fig. 2B) is obtained from the raw signal (Fig. 2A) through a rectification followed by a low-pass Butterworth filter (7.5Hz, 2nd order) applied to the last three points of the rectified signal [16]. A proportion (e.g. 10%) of the envelope's maximal magnitude obtained in the calibration phase is then used as a threshold (Fig. 2B). This threshold determines if the muscle is contracted or not, and thus, if the current sEMG sample is valid or not. Invalid samples (i.e. noise) are then removed from the signal (Fig. 2C).

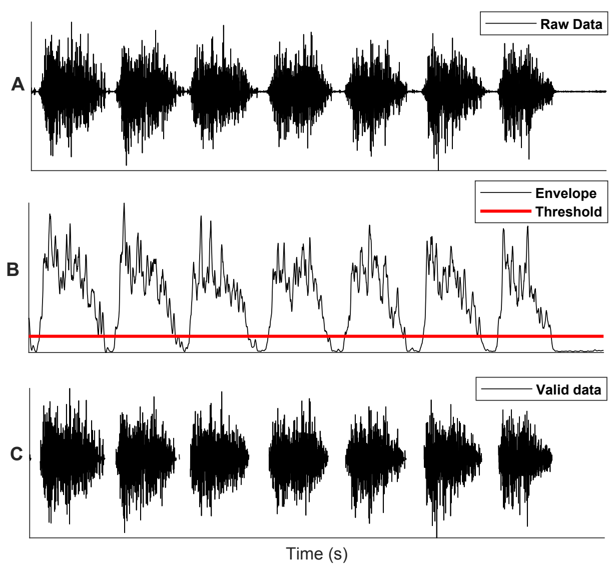


Fig. 2. Example of the contraction detection steps on a dynamic tasks

B. *Median Frequency computation phase*

The aim of this step is to compute either the CWT or STFT on the signal and to extract the MDF from it. In order to perform the STFT/CWT, enough data points must be accumulated for the computation to be valid. This number of points is described as the time window W1 (e.g. the equivalent of 1 second of valid data). Considering only static tasks in which the muscle is always contracted, this step would be straightforward. However, in dynamic tasks, the last W1 samples might not all be valid. Therefore, the algorithm allows to look further back in time in order to accumulate enough valid data to perform the STFT/CWT (i.e. the number of valid samples described by W1). The valid portions of the signal are then concatenated. However, it would not be suitable to join data that occurred too long apart because they would not be relevant to the current fatigue situation. Consequently, the algorithm only allows to join past data if they occurred less than L_{W1} time ago (e.g. 5 seconds). This can lead to different scenarios that are presented in Fig. 3.

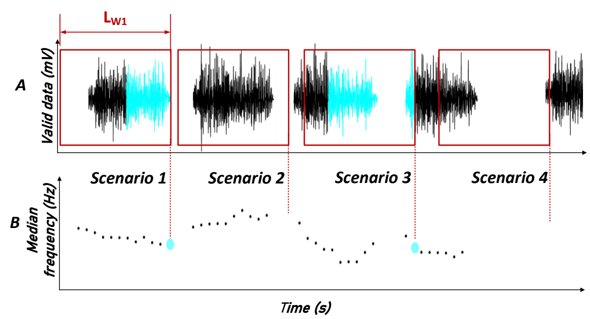


Fig. 3. Possible scenarios of adjusted W1 (cyan) depending on current data validity and L_{W1} (Red) **Scenario 1** : All last W1 EMG data are valid and STFT/CWT is computed with these samples. **Scenario 2** : The current EMG data is not valid : STFT/CWT is not computed. **Scenario 3**: The last W1 samples contains invalid data: Invalid data are removed, the last W1 valid samples are joined together (if those data are contained in L_{W1}) and STFT/CWT is computed with these samples. **Scenario 4** : The last W1 samples contains invalid data and there is not enough valid data in L_{W1} to replace invalid data: STFT/CWT is not computed.

In scenarios for which this applies, either the STFT or the CWT is computed over the last W1 valid samples. In both methods, the signal is transposed into the frequency domain from which the MDF is extracted. In this paper, both the STFT and CWT are computed for comparison purposes but, in the end, only the CWT will be used. The difference between the two methods stands in the way the sEMG signal is transposed into the frequency domain as detailed below.

a) Short-Time Fourier transform: The Fourier Transform is a mathematical transform that determines which frequencies are present in a signal and what are their contribution on that signal. Typically, the entire signal is used. However, in the context of sEMG signal analysis, the objective is to detect the MDF drop over time. Therefore, to observe a decrease in MDF, the Fourier transform must be applied over small consecutive time windows (here defined as W1) (Fig. 4). This method is called the Short-Time Fourier Transform (STFT). To do so, it is desired to use the smallest possible time windows. Nevertheless, the Heisenberg uncertainty principle must be taken into account, meaning that, by reducing the time windows, the resulting frequency precision is decreased [5]. There is thus a tradeoff to be made between time lag and precision to achieve real-time fatigue estimation. In order to minimize this tradeoff, frames of W1 are overlapped with a time increment of (δt1) (Fig. 4). The time increment (δt1) is the best compromise between reducing the time lag and reducing the processing time.

Indeed, although overlapping windows increases precision, it can also substantially increase processing time.

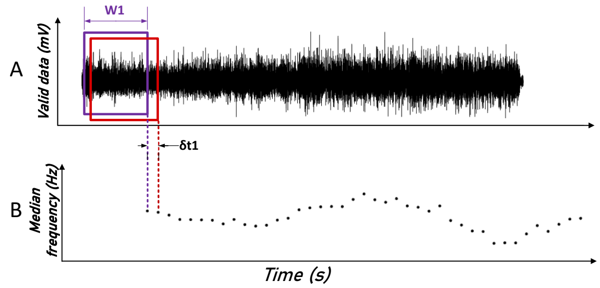


Fig. 4. Example of the Short Time Fourier Transform (STFT) method during a static task

b) Continuous Wavelet Transform: As opposed to the STFT, the CWT gives higher resolution time-frequency representations [13]. As a matter of fact, instead of getting one power spectrum for the entire window W1 as for the STFT (Fig. 4), the CWT gives an estimate of the power spectrum density (PSD) for each point within W1. Therefore, in theory, there is no need to overlap W1 frames. However, since there is a border effect (the precision for the few first and last points of W1 is reduced), a small window overlap of 2xδw1 is used to ignore the first and last δw1 data points as shown in Fig. 5. In this algorithm, the CWT is obtained using the analytic Morse wavelet with frequency range between 20 and 500Hz and 16 voices per octave.

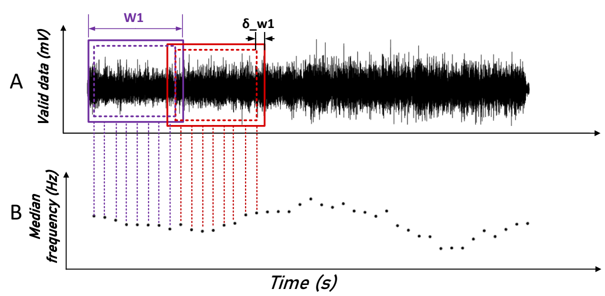
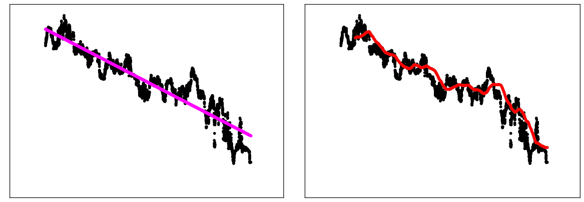


Fig. 5. Example of the Continuous Wavelet Transform (CWT) method during a static task

C. Moving average computation phase

In order to smooth the resulting median frequency estimation, a moving average is performed. The length of this window is defined as W2. Similarly to the process of W1 and L_{W1}, if there is not enough data in the last W2 points at a given time, past data can be joined into W2 up to a maximum time defined as L_{W2}. Applying a moving average to the MDF data, however, increases processing and lag time. Yet, it is necessary since it reduces chances of giving false fatigue alerts that would come from local short term MDF variations. In offline applications, moving averages are not used since the MDF drop is, for instance, obtained through a linear regression that gets ride off the high standard deviation (Fig. 6 (a)) [6]. Nevertheless, in a real-time application, linear regression can hardly be used. In order to remove short term variations of the MDF estimation, it is thus proposed to use a moving average instead. The resulting estimation is then smoothed giving a better visual image of the MDF drop (Fig. 6 (b)).



(a) (b)

Fig. 6. a) Linear Regression (pink) and b) Moving Average (red) on MDF data (black)

The time windows (W2) are overlapped to reduce the lag between events and feedback (Fig. 7). The window increment (δt2) is chosen to be a compromise between reducing the time lag and the processing time.

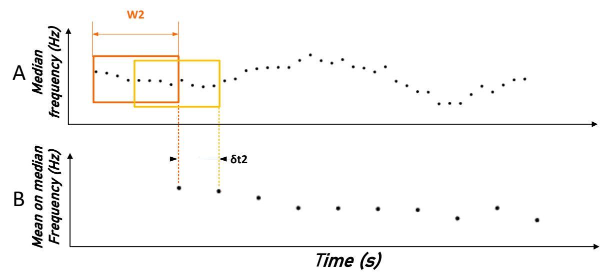


Fig. 7. Example of the Moving average computation phase

III. Methods

A. Data acquisition and values of the algorithm's parameters

sEMG data were recorded using commercial surface EMG sensors (Trigno Wireless EMG system, Delsys, Boston, Massachusetts, USA) placed on the medial deltoid of the dominant arm. The skin was previously cleaned with alcohol to decrease contact impedance. The sEMG signal was sampled at a rate of 1926.926 Hz. It was then passed through a second order Butterworth band-pass filter (20-500Hz) [17] and through an Infinite Impulse Response (IIR) Notch filter with 60Hz corner frequency to get rid of the power line noise.

The threshold used in the muscle contraction detection was set to 10% of the envelope's maximal magnitude obtained in the calibration phase.

Table I presents the values of the algorithm's time dependent parameters used in the experiment. As it can be observed, all parameters except δt2 are defined in terms of time and numbers of samples. These values were selected according to an acquisition frequency of 1926.926 Hz. However, using another frequency would result in modification of either the time value or the number of samples depending on the parameter. Concerning the parameter δt2, the value in time is irrelevant since it represents a number of W1 samples. Thus, it's time value depends on δt1.

TABLE I
VALUES IN TERMS OF TIME AND NUMBER OF SAMPLES OF THE ALGORITHM'S PARAMETERS USED IN THE EXPERIMENT CONSIDERING AN ACQUISITION FREQUENCY OF 1926.926 HZ

Parameter	Value in time (s)	Value in number of samples (pts)
W1	1.1	2120
W2	4	7708
L_{W1}	5	9635
L_{W2}	10	19269
δw1	0.05	96
δt1	0.0052	10
δt2	–	10

B. Experimental Methods

Eight healthy adults with no self-reported musculoskeletal conditions (i.e. pain, movement limitations, recent injuries) took part in a testing session (6 women and 2 men, right-handed, 23-34 years old). The protocol consisted of 7 arm elevation tasks in the frontal plane (humeral abduction [abd]/adduction [add]) for the dominant arm with 25-minute rest between tasks to avoid residual fatigue from previous tasks. The tasks were:

1) Maximum Voluntary Contractions (MVC) in abd
2) Light Static 90° abd
3) Heavy Static 90° abd
4) Light Static 90° abd
5) Heavy Static 90° abd
6) Light Dynamic 0-90° abd
7) Heavy Dynamic 0-90° abd

The MVC is the maximal force one can produce under given static muscle contraction conditions. In order to avoid compensation as much as possible during the MVC evaluations, the subject was seated without backrest, with the dominant arm at 90° of abduction. The experimenter applied a manual dynamometer perpendicular to the distal and dorsal end of the forearm. Three maximum contractions of about 10 seconds were performed, with a gradual rise over one second, a plateau of 7-8 seconds and a gradual release. A one-minute rest was given between contractions. The maximum value (in kg) obtained during the three tests was recorded and used to determine the loads for tasks 2 to 7 according to Table II. For each participant, two levels of loads were considered namely light and heavy, which correspond respectively to values around 15% and 30% of MVC. As the loads available were of finite mass [0.60, 1.30, 1.70, 2.10, 2.27, 3.30, 3.96, and 5.00 kg], the real % of MVC varied slightly across participants. For instance, as shown in Table II, participants with a MVC between 6 and 9 kg used a 1.30 kg for 15% MVC tasks, leading to an actual % of MVC between 14.61 and 21.31%.

TABLE II
LOADS USED DEPENDING ON MAXIMAL MVC (KG)

MVC range (kg)	Light tasks		Heavy tasks	
	Load (kg)	*Actual %MVC*	*Load (kg)*	*Actual %MVC*
[3, 6[	0.60	]10.17, 19.30]	1.30	]22.03, 41.84]
[6, 9[	1.30	]14.61, 21.31]	2.27	]25.51, 37.21]
[9, 12[	1.70	]14.29, 18.68]	3.30	]27.73, 36.26]
[12, 15[	2.10	]14.09, 17.36]	3.96	]26.58, 32.73]
[15, 18[	2.27	]12.68, 15.03]	5.00	]27.93, 33.11]

Each task began with the participant standing straight and looking forward, arms along the body, with the weight in the dominant hand. A mirror was placed in front of participants to provide feedback on their posture during the tasks (to avoid compensation such as shoulder shrugging or trunk lateral flexion). Participants were encouraged by the experimenter to keep an adequate posture without compensating during the task. For static tasks, the participants were asked to lift their dominant arm to 90° of abduction (Fig. 8) and to keep this position until they were unable to maintain it. During dynamic tasks, participants were asked to perform 0° to 90° abductions with their dominant arm with a 0.8Hz rhythm (which was provided by a metronome) until they could not lift the weight anymore without compensations.

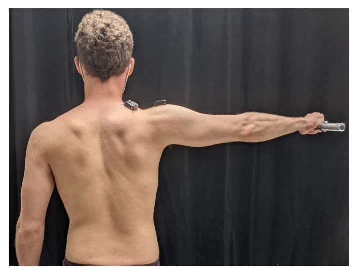


Fig. 8. Static position: 90° in abduction

C. Statistical analysis

1) The fatigue indicators' evolution obtained from the two methods, namely STFT and CWT, were compared in order to determine which of the two exhibits the least fluctuations (is the smoothest). Since there is no theoretical curve representing the expected decrease in frequency, each of them was compared to itself by using multiple linear regressions performed on curve segments of 10sec length every 2sec. For each regression line, the root mean square error (RMSE) between the linear regression and the curve's corresponding points was calculated. An average RMSE is then obtained for each curve, giving an estimate of its fluctuations. A one-way repeated measures ANOVA is then performed on the average RMSE to detect significant changes in smoothness between the two methods in both static and dynamic tasks.
2) To certify that the proposed algorithm is a valid indicator of the muscles fatigue, it must decrease faster for heavier loads than for lighter ones. A one-way repeated measures ANOVA was thus performed one the MDF slopes of all

tasks to observe significant changes between loads. η_p^2 and ω^2 are used as estimates of effect size. 3) In order to confirm that the algorithm's initial output is not altered by the load, the variations of initial frequencies for all static tasks(four) for each participant is compared to the variations between participants via an intra-class correlation (ICC). 4) Finally, the effectiveness of the contraction detection which assesses the problems that comes with the times when muscles are at rest during dynamic tasks, is visually verified by comparing results with and without the contraction detection phase.

IV. Results and Discussion

A. CWT vs FFT (smoothness analysis)

Fig. 9 shows an example of the proposed algorithm fatigue indicators' evolution for participant 1 during the heavy static task. As it can be qualitatively observed, the evolution of the fatigue indicator of the CWT method is smoother than with the STFT (CWT leads to a steady decrease with fewer oscillations). This behaviour is consistent across tasks and participants. Quantitatively, the average RMSE between the fatigue indicator curve and its linear regression approximations is statistically significantly smaller for the CWT method (1.200 +- 0.353) compared to the STFT (1.985 +- 0.877), $t_{16} = -1.302, p < .001, 95\% CI[-1.684, -0.912]$. This difference is observed for both static and dynamic tasks.

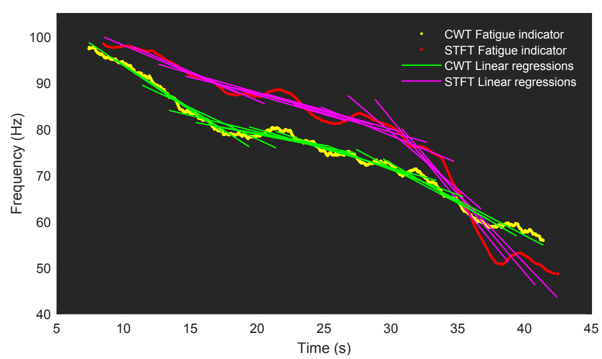


Fig. 9. Evolution of fatigue indicators obtained with the CWT (yellow) and STFT (red) methods along with their linear regressions (CWT : green, STFT : pink) for a static task

B. Slopes (Light vs heavy)

As it can be observed in Fig. 10, slopes showed to be statistically significantly steeper for heavy tasks than for light tasks ($F_{1/7} = 226.845, p < .001, \eta_p^2 = 0.970, \omega^2 = 0.595$). In the same way, slopes were statistically significantly steeper for static tasks than for dynamic ones ($F_{1/7} = 8.968, p = 0.02, \eta_p^2 = 0.562, \omega^2 = 0.242$). Further studies will be required to conclude on the reasons of this result but one hypothesis is that the duty cycle is lower for dynamic tasks since the muscle is not in constant contraction.

C. Initial fatigue indicator (static tasks)

Fig. 11 shows initial (beginning of the task) fatigue indicator values of all four static tasks for each participant. ICC(1) value for initial fatigue indicator is 0.952 with inter and intra subjects variance of 107.7 and 5.4. This means that 95.2% of the variance is attributable to differences between subjects and only the 4.8% remaining is explained by within-subject variations. This indicates that for each participant, initial fatigue indicators were similar for all light and heavy static tasks.

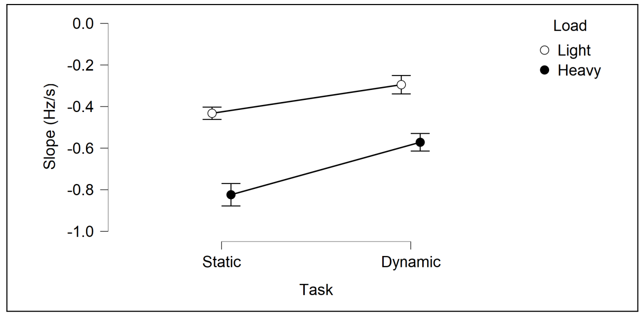


Fig. 10. ANOVA analysis on slopes for static and dynamic tasks performed with light (white) and heavy (black) loads

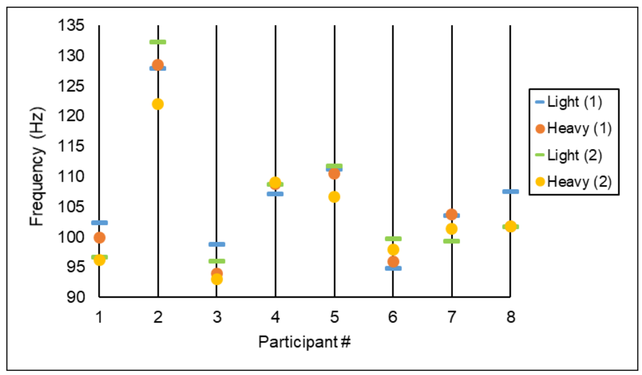


Fig. 11. Initial fatigue indicator values of each participant for the four static tasks (Light (1) : Blue, Heavy (1) : Orange, Light (2) : Green, Heavy (2) : Yellow)

D. Muscle Contraction detection module efficiency

Fig. 12 presents an example of the evolution of the fatigue indicator for a dynamic task with and without the muscle contraction detection module. By observation, it can be qualitatively observed that the evolution of the fatigue indicator is smoother with the muscle contraction detection module than without it.

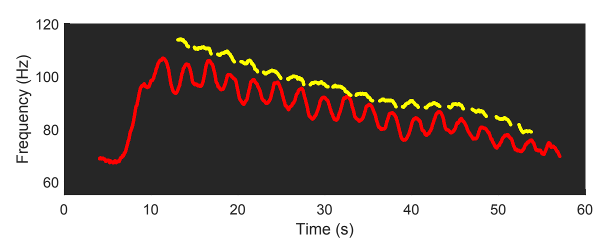


Fig. 12. Example of the evolution of the fatigue indicator for a dynamic task with (yellow) and without (red) the muscle contraction detection module.

E. Limitations

There are few limitations to our study. Muscle fatigue remains subjective to the participants and can also vary depending on the experiment conditions. As the experiment design does not allow the participants to reach complete exhaustion, we cannot discuss the final frequencies and conclude on the state of the fatigue indicator at the end of the tasks. Additionally, in this study, tasks were performed in abduction only. Furthermore, static tasks were only performed at an elevation angle of 90°. Results might differ for movements in other elevation planes and angles. Finally, dynamic tasks were performed at a 0.8Hz which does not allow muscles to rest between contractions. Thus, we cannot conclude on the proposed algorithm's validity for complex tasks such as the ones performed in workplaces (i.e. punctuated by pauses and performed in different elevation planes and angles).

V. CONCLUSION

The objective of this paper was to develop and primarily validate an algorithm capable of estimating muscle fatigue for real time applications including dynamic tasks. We showed that the proposed method provides smoother fatigue indicator evolution than the traditional STFT. Moreover, we demonstrated that our output is a valid indicator of the muscles fatigue as slopes from light and heavy tasks were statistically different. Besides, we verified that our fatigue indicator is not affected by load magnitude. Finally, we investigated our muscles contraction detection module's efficiency to overcome issues associated with the periods when muscles are not contracting during dynamic tasks. We observed a substantial improvement of the smoothness of the fatigue indicator's evolution with the use of the module.

Future work: The long-term objective of this work is to develop a low-cost wearable device using sEMG to provide feedback to workers in order to reduce the risk of musculoskeletal injuries. The next step will be to adapt and validate this algorithm applied to complex movements (i.e. in different elevation planes and angles). Indeed, the shoulder (or glenohumeral joint) is considered as complex joints, meaning that it has several degrees of freedom and, therefore, can move in different planes [18]. Furthermore, the shoulder muscles are used differently depending on the movements performed. Thus, the algorithms may need to consider several muscles simultaneously and adjust their processing methods according to the movements performed. Additionally, for identical loads, the fatigue indicator decreased faster for static than dynamic tasks. Further studies will thus be required to conclude on the reasons of this result.

ACKNOWLEDGMENT

This work was supported by the Canadian MSK Rehab Research Network, by INTER (Engineering of Interactive Rehabilitation Technologies), by the Natural Sciences and Engineering Research Council of Canada and by the Canada First Research Excellence Fund Sentinel North Strategy at Université Laval.

REFERENCES

[1] L. Punnett and D. H. Wegman, "Work-related musculoskeletal disorders: the epidemiologic evidence and the debate," *Journal of electromyography and kinesiology*, vol. 14, no. 1, pp. 13–23, 2004.

[2] B. M. Huisstede, S. M. Bierma-Zeinstra, B. W. Koes, and J. A. Verhaar, "Incidence and prevalence of upper-extremity musculoskeletal disorders. a systematic appraisal of the literature," *BMC musculoskeletal disorders*, vol. 7, no. 1, pp. 1–7, 2006.

[3] P. Palmes, W. T. Ang, F. Widjaja, L. C. Tan, and W. L. Au, "Pattern mining of multichannel semg for tremor classification," *IEEE transactions on biomedical engineering*, vol. 57, no. 12, pp. 2795–2805, 2010.

[4] M. A. Oskoei and H. Hu, "Myoelectric control systems—a survey," *Biomedical signal processing and control*, vol. 2, no. 4, pp. 275–294, 2007.

[5] M. Cifrek, V. Medved, S. Tonković, and S. Ostojić, "Surface emg based muscle fatigue evaluation in biomechanics," *Clinical biomechanics*, vol. 24, no. 4, pp. 327–340, 2009.

[6] S. Thongpanja, A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Mean and median frequency of emg signal to determine muscle force based on time-dependent power spectrum," *Elektronika ir Elektrotechnika*, vol. 19, no. 3, pp. 51–56, 2013.

[7] C. J. De Luca, "Myoelectrical manifestations of localized muscular fatigue in humans.," *Critical reviews in biomedical engineering*, vol. 11, no. 4, pp. 251–279, 1984.

[8] C. Kramer, T. Hagg, and B. Kemp, "Real-time measurement of muscle fatigue related changes in surface emg," *Medical and Biological Engineering and Computing*, vol. 25, no. 6, pp. 627–630, 1987.

[9] T. D'Alessio, M. Knaflitz, G. Balestra, and S. Paggi, "On-line estimation of myoelectric signal spectral parameters and nonstationarities detection," *IEEE transactions on biomedical engineering*, vol. 40, no. 9, pp. 981–985, 1993.

[10] A. Pratt, R. Gander, and B. Brandell, "Real-time digital median frequency estimator for surface myoelectric signals," *IEEE transactions on biomedical engineering*, vol. 38, no. 3, pp. 306–309, 1991.

[11] L. D. Gilmore and C. J. De Luca, "Muscle fatigue monitor (mfm): second generation," *IEEE transactions on biomedical engineering*, no. 1, pp. 75–78, 1985.

[12] R. Seroussi, M. H. Krag, P. Wilder, and M. H. Pope, "The design and use of a microcomputerized real-time muscle fatigue monitor based on the medical frequency shift in the electromyographic signal," *IEEE transactions on biomedical engineering*, vol. 36, no. 2, pp. 284–286, 1989.

[13] S. Karlsson, J. Yu, and M. Akay, "Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study," *IEEE transactions on Biomedical Engineering*, vol. 47, no. 2, pp. 228–238, 2000.

[14] J. R. Fuller, J. Fung, and J. N. Côté, "Time-dependent adaptations to posture and movement characteristics during the development of repetitive reaching induced fatigue," *Experimental brain research*, vol. 211, no. 1, pp. 133–143, 2011.

[15] V. Srhoj-Egekher, M. Cifrek, and V. Medved, "The application of hilbert–huang transform in the analysis of muscle fatigue during cyclic dynamic contractions," *Medical & biological engineering & computing*, vol. 49, no. 6, pp. 659–669, 2011.

[16] W. Rose, "Electromyogram analysis," *Online course material. University of Delaware. Retrieved July*, vol. 5, p. 2016, 2011.

[17] C. J. De Luca, L. D. Gilmore, M. Kuznetsov, and S. H. Roy, "Filtering the surface emg signal: Movement artifact and baseline noise contamination," *Journal of biomechanics*, vol. 43, no. 8, pp. 1573–1579, 2010.

[18] G. Wu, S. Siegler, P. Allard, C. Kirtley, A. Leardini, D. Rosenbaum, M. Whittle, D. D D'Lima, L. Cristofolini, H. Witte, *et al.*, "Isb recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion—part i: ankle, hip, and spine," *Journal of biomechanics*, vol. 35, no. 4, pp. 543–548, 2002.