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APPLICATION OF SPECTROGRAM IN ANALYSING ELECTROMYOGRAPHY (EMG) SIGNALS OF MANUAL LIFTING

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ABSTRACT
The fast Fourier transforms (FFT) is commonly applied in transformation of electromyography (EMG) signals from the time domain to the frequency domain. However, this technique has a limitation to provide the time-frequency information for EMG signals. This paper presents the analysis of EMG signal for contraction of muscle activity by using spectrogram. Spectrogram is one of the time-frequency representations (TFR) that represents the three-dimensional of the signal with respect to time and frequency in magnitude presentations. The contraction of muscle activity was based on manual lifting of a 5 kg load performed by the right biceps brachii at lifting height of 75 cm and 140 cm. Ten healthy volunteers in fresh condition participated as subjects to acquire raw data of EMG signals. The raw data of EMG signals were then analysed using MATLAB 2011 to obtain the TFR. Based on the TFR, this study obtained the instantaneous RMS Voltage ($V_{rms}(t)$) to visualize the trend of the EMG signals performance in window size of 1024. Results of this study evince that the lifting height of 140 cm obtained higher V_{rms} than 75 cm. It concluded that the application of spectrogram is able to counter the limitation of FFT in providing the time-frequency information for EMG signals.

Keywords: electromyography signal, lifting height, time-frequency representation, spectrogram, instantaneous RMS voltage (V_{rms}).

INTRODUCTION
Clinical diagnosis and biomedical applications became the main reason why the researchers interested in EMG signals analysis (Reaz *et al*., 2006). The field of management and rehabilitations of motor disability is identified as one of the important applications areas (Reaz *et al.*, 2006). It has been deployed in many industrial applications (Phinyomark *et al*., 2012). The EMG is known as biomedical signal that consists of electrical current that generated during contraction and relaxation phase of muscles (Gokgoz and Subasi, 2015), (Ruchika and Dhingra, 2013), (Reaz *et al.*, 2006). It was originally developed for investigating muscular disorders. Additionally, the EMG signals are used for studying the functional state of the muscle during various motions (Rekhi *et al*., 2009).

EMG signals are complicated and non-stationary signal with highly complex time and frequency characteristics which is controlled by nervous signal because it is directly involved in muscle activity (Ruchika and Dhingra, 2013), (Canal, 2010). During the measurement and recording process of EMG, the signals acquire noise, and thus distorts the signal while travelling through different tissues (Reaz *et al.*, 2006). Moreover, if a study used surface EMG (sEMG) equipment, the EMG electrodes are attached to the skin of human. Thus there are potentials of noise interference and generate interaction of different signals (Reaz *et al.*, 2006). In this case, feature extraction and function classification are the keys in processing and analysing the EMG signals (Rekhi *et al*., 2009). The EMG signals represent the contraction of muscles corresponding to activities performed by human. One of the activities that can produce EMG signals is manual lifting. In manual lifting, skeletal muscles perform a crucial function to execute the task. Human should lift a suitable load mass and lifting height to avoid the muscles to experience fatigue and injury (Halim *et al*., 2014).

A previous research works been conducted to study the EMG signals processing (Bekka and Chikouche, 2003), (Reaz *et al.*, 2006), (Gokgoz and Subasi, 2015). The study applied the fast Fourier transform (FFT) to analyse the EMG signals. It is a mathematical technique that is used to convert the data from time domain to frequency domain (Sulaiman *et al.*, 2013), (Abdullah *et al*., 2012), (Abidin *et al.*, 2013). However, application of FFT in analysing the EMG signals has a limitation to process non-stationary signals due to spectral characteristics change in time (Abidin *et al.*, 2013). The FFT is one of the most widely used tools in signal processing (Ling and Xiaofeng, 2006). The purpose of performing FFT is to extract its frequency characteristics as the first step in analysis data of EMG signals.

As an alternative to FFT, the EMG signals are also can be processed using wavelet technique (Reaz *et al*., 2006), Shi *et al.*, 2009). This technique offers high time resolution for high frequency component and high frequency resolution for low frequency component such as transient (Zawawi *et al.*, 2013), (Abdullah and Sha'amer, 2010), (Andreotti *et al.*, 2009). This technique provides poor frequency resolution for high frequency component and poor time resolution for low frequency components (Andreotti *et al.*, 2009). However, most of wavelets have multi resolution analysis and required neural network programming technique which can increase computer

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memory and computational overhead due to the large number of features (Ahmad *et al*., 2014).

In continuous wavelet transformation, the calculation of wavelet coefficient is complicated and time consuming because the parameters of measurement and transformation change continuously (Canal, 2010). Besides that, wavelet transformation is unable to produce an accurate result when the EMG signals are interfered by noise (Reaz *et al*., 2006).

The objective of this study is to investigate the performance of EMG signals that acquired from the contraction of the right biceps brachii muscle while performing a manual lifting of a 5 kg load at lifting height of 75 cm and 140 cm.

The EMG signals analysis is performed using spectrogram. This paper contains of two parts which are window size selection and EMG signal analysis. The time-frequency distribution (TFD) is employed to analyse the pattern and characteristic of EMG signals components.

EXPERIMENTAL SETUP

Subjects selection

Ten volunteers, five male and five female in healthy conditions participated in the experimental work. The number of subject was calculated using G power analysis software to determine sufficient EMG raw signals for the analysis. The subjects between the age range of 22 to 25 years was selected because this age range is commonly available in the industries (Setiawan and Woyanti, 2010). All subjects are right handed. The demographics of the subjects is shown in Table-1.

Table-1. Demographics of the subjects.

Criteria	Minimum	Mean	Maximum
Age (year)	22	23.5	25
Body mass (kg)	50	62.5	75
Body height (cm)	156	163	170

Data collection and electrode placement

The surface EMG (TeleMyo 2400T G2, Noraxon, USA) as shown in Figure-1 and MyoResearch XP Master Software (Noraxon, USA), illustrated in Figure-2. Both are utilized to measure and store the EMG raw signals. The skin of the right biceps brachii was shaved as shown in Figure-3. It was cleaned by the BD alcohol swabs of 70 % isorophyl alcohol, and rubbed with the Signa Gel. Then, the skin was attached with Ag/AgCL, 10 mm diameter EMG electrodes.

Figure-1. The surface EMG (TeleMyo 2400T G2, Noraxon, USA).

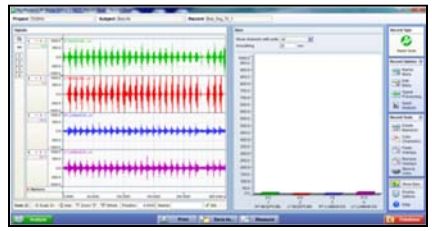

Figure-2. MyoResearch XP master software (Noraxon, USA).

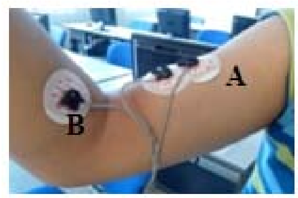

Figure-3. Surface EMG electrode's placement at the right biceps brachii.

This study referred the Non-Invasive Assessment of Muscle (SENIAM) guideline to ensure all the surface EMG protocols are compiled (Halim, *et al.*, 2014). Surface EMG electrodes are attached in the right biceps brachii muscle as input (A) and reference electrode location (B). The experimental procedures have been approved by the Research Ethics Committee of the Universiti Teknikal Malaysia Melaka.

MATLAB 2011 (MathWorkInc, USA) is used to analyse of the EMG signals. The sampling frequency (fs) 1500 Hz and a low pass filter with the range of 0-500 Hz were used to filter the EMG raw signals. Once the raw signal been acquired, the first process is transforming them from time domain to frequency domain through FFT technique.

A new algorithm for the mathematical calculation is written in the program to produce FFT (for Power Spectrum), spectrogram and instantaneous RMS voltage, $V_{rms(t)}$. The Hanning window size 1024 is used to compare the EMG signals. This window size produces the best results for the EMG signals to be analysed.

Each subject is tested and their EMG signals were analysed using the spectrogram and expressed in V_{rms}. Based on the pattern of the signals, this study can identify the performances of the muscles involved in manual lifting.

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Manual lifting experiment

The subjects have to lift a 5 kg load with a neutral body twist (0º) - symmetric lifting. The lifting height was set to 75 cm and 140 cm. In each lifting height, the subject must repeat the load lifting in five times. Each lifting produced EMG signals of contracted muscle, and each EMG signal was divided into four phases as illustrated in the Figure-4 and Figure-5. The details for the phases are described as follows:

Phase 1: Subject holds the load (located on the floor).

Phase 2: Subject lifts the load and put it on the shelf.

Phase 3: Subject arranges the load properly on the shelf.

Phase 4: Subject release the load

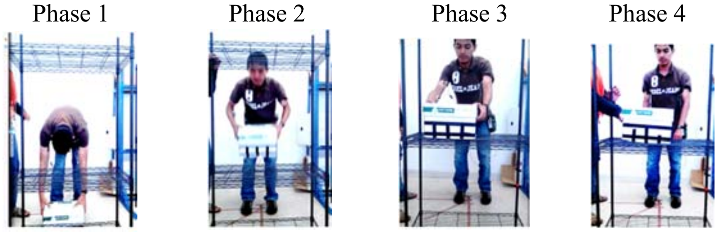

Figure-4. Four phases of lifting for 75cm lifting height

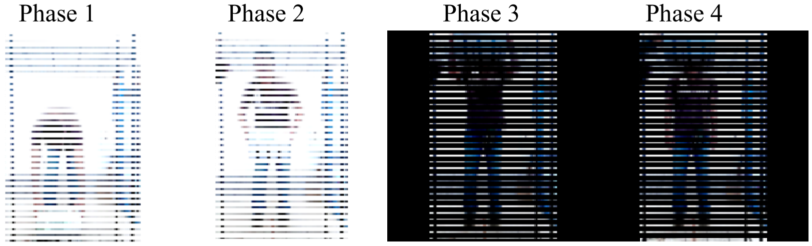

Figure-5. Four phases of lifting for 140cm lifting height.

EMG SIGNALS ANALYSIS TECHNIQUES

Spectrogram

Spectrogram is one of the TFR that represents the three-dimensional of the signal with respect to time and frequency in magnitude. The FFT has a limitation in processing non-stationary signals due to spectral characteristic changes in time and frequency. It is the result of calculating the frequency spectrum of window frames of compound signal (Abidin *et al.*, 2013), (Abdullah *et al.*, 2010). Spectrogram provides high frequency resolution and can be calculated using Equation (1) below:

$$S_x(t,f) = \left| \int_{-\infty}^{\infty} h(\tau) w(\tau - t) e^{-j2\pi f\tau} d\tau \right|^2 \quad (1)$$

where $h(\tau)$ is the input and $w(t)$ is the observation window. In this paper, the Hanning window was used as it has a lower peak side slope.

Parameter: Instantaneous root mean square (RMS) voltage

The parameter used to analyse the pattern of signal from spectrogram is instantaneous RMS voltage, $V_{rms}(t)$. $V_{rms}(t)$ can be calculated using Equation (2) below (Abdullah *et al.*, 2010), (Abdullah and Sha'amer, 2010):

$$V_{rms}(t) = \sqrt{\int_0^{fmax} S_x(t,f)dt} \quad (2)$$

where $S_x(t,f)$ is the time-frequency distribution and f_{max} is the maximum frequency of interest.

RESULTS AND DISCUSSIONS

Results validation

The validation is a very important process to acquire accurate results. Firstly, the validation process is conducted by manually calculating the V_{rms} of EMG signals. Then, the EMG signals are uploaded into MATLAB 2011 to test the accuracy of the created computer program. Figure-6 and Figure-7 show the validation of the result analysis process of EMG signal for this task. The inputs are stated for each phase with 0.5V for phase 1, 3V for phase 2, 2V for phase 3 and 1V for phase 4 as shown in Figure-6. Figure-7 shows the $V_{rms}(t)$

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values to prove that the program used in the analysis of EMG signal is correct with 0.25V, 4.5, 2v and 0.5 for Phase 1, Phase 2, Phase 3 and Phase 4.

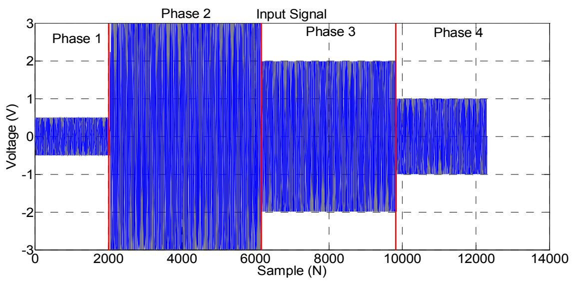

Figure-6. Input signal stated.

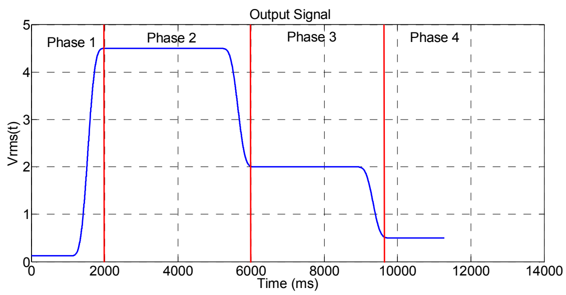

Figure-7. Output signal after through $V_{rms}(t)$ formula.

Window size selection

Two sizes of windows are compared to distinguish the best window size to select for EMG signal analysis either window 1024 or 2048. The best window size is verified by observing which figures will give clearer information. Spectrogram is used to analyse the information and then estimated by $V_{rms}(t)$.

Figure-8 represents spectrogram technique that would be used in the analysis for each contraction of the muscle. The highest amplitude is represented by the red colour while the blue colour for lowest amplitude.

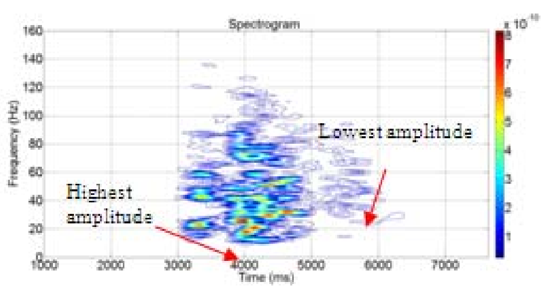

Figure-8. Spectrogram of the EMG signals.

Figure-9 shows the instantaneous RMS Voltage ($V_{rms}(t)$) for window size 1024. It shows a clear pattern of EMG signals while the subjects performing the manual lifting task. It would able to detect the muscle activity based on time interval in the experiment. The tasks are separated into four phases as in the methodology.

Based in Figure-10, it represents the instantaneous RMS Voltage $V_{rms}(t)$ for window size 2048. By using this window, the observation shows that $V_{rms}(t)$ performed quite general for each phase and it is difficult to analyse detail about the flow of muscle activity while doing manual lifting task.

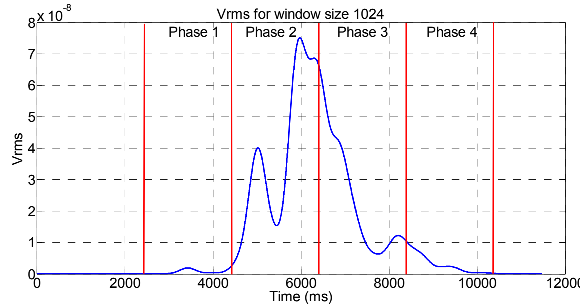

Figure-9. Instantaneous RMS voltage (V_{rms}) for window size 1024.

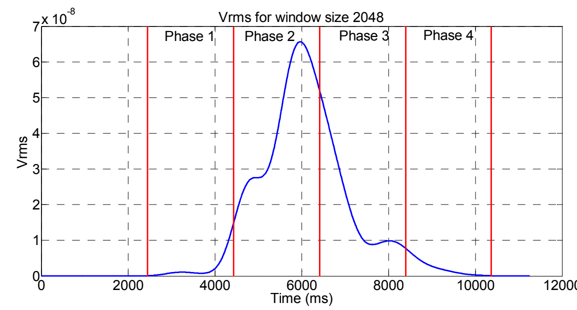

Figure-10. Instantaneous RMS voltage (V_{rms}) for window size 2048.

A previous study found that the most frequency power is in the range 20-500 Hz (Konrad, 2005). It is mean that the minimum is 20 Hz. The FFT for both window size shows that window size 1024 would able to display 20 Hz but 2048 is vice versa. It is important to know the minimum frequency in the analysis process.

Thus, from the overall observation for both window sizes, it is shown that window size 1024 is suitable to be used to analyse EMG signal compared to 2048.

EMG signals analysis for lifting height of 75cm

Figure-12 indicates the pattern of EMG raw signals acquired from all subjects. These signals were obtained when the subject lifted a 5 kg load with lifting height of 75 cm. The subjects repeated 34 times of lifting test. The pattern of EMG raw signals shows that all subjects were able to lift the load without experiencing any decline of muscular performance.

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The EMG raw signals were then transformed from the time domain to the frequency domain using FFT. In the frequency domain, this study extracted the EMG signals to obtain instantaneous energy which represents the energy used by the subjects to lift the load, as shown in Figure-13. The highest energy is 75µ and the lowest energy is at the end of lifting test which is 18.5µ. At this time, the subjects tend to experience muscle fatigue.

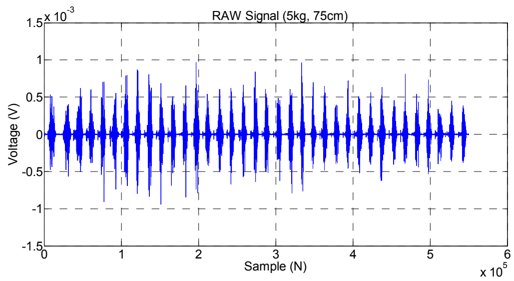

Figure-11. EMG raw signal for lifting height of 75 cm.

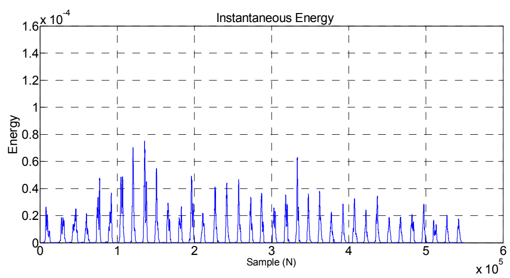

Figure-12. Instantaneous energy for lifting height of 75 cm.

EMG signals analysis for lifting height of 140cm

Figure-13 displays the pattern of EMG raw signals acquired from all subjects. These signals were obtained when the subject lifted a 5 kg load with lifting height of 140 cm. In this setting, the subjects were able to repeat 23 times of lifting test before experiencing muscle fatigue. The instantaneous energy shown in Figure-14 highlighted that the highest energy is 150µ and lowest energy is 70µ, recorded at the end of lifting test.

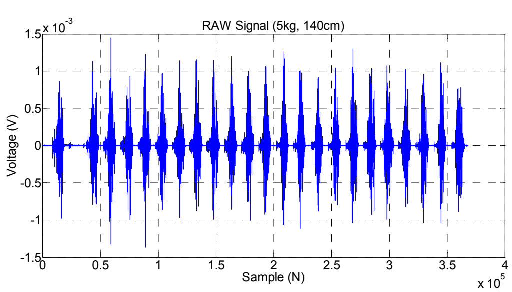

Figure-13. EMG raw signals for lifting height of 140 cm.

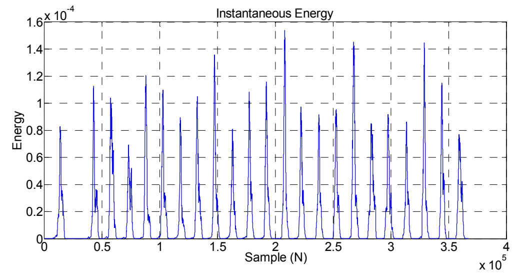

Figure-14. Instantaneous energy from FFT for 140 cm lifting height.

Comparison of instantaneous RMS voltage between 75 cm and 140 cm lifting heights

Figure-15 to Figure-18 shows the difference of average instantaneous RMS Voltage (V_{rms}) of Phase 1 to Phase 4 for 75 cm and 140 cm lifting heights.

The results of this study pointed that the V_{rms} for a lifting height of 140 cm is higher than the lifting height of 75 cm (Figure-15). Average V_{rms} for a lifting height of 140 cm is decreased from 15.97µV to 4.97µV when the number of lifting is increased. Besides that, average V_{rms} for a lifting height of 75 cm also decreases from 15.43µV to 3.62µV. The lifting height of 140 cm is slightly higher performance compared to 75 cm. It is decreasing from 15.97µV to 4.97µV, meanwhile at 75 cm lifting height; it decreases from 15.43µV to 3.62µV.

Figure-16 represents comparison of average instantaneous RMS Voltage V_{rms} between 75 cm and 140 cm of lifting heights for Phase 2. The values of average V_{rms} show a significant difference between the two lifting heights. This is because phase 2 involves the maximum voltage to lift the load and put it on the shelf. It directly decreases for 140 cm from the maximum 112.33µV to the minimum at the end of contraction which is 63.19µV. Meanwhile, it shows the lower maximum voltage which is 75.9µV and minimum 16.13µV at 75 cm.

Figure-17 shows a slightly difference in average V_{rms} of 75 cm and 140 cm of lifting heights for Phase 3. This is due to the subjects did not contribute much effort compared to Phase 2. The average V_{rms} for 140 cm of the lifting height is declined from 79.18µV to 28.73µV. It is decreasing from 47.69µV to 20.32µV at 75 cm of lifting height.

Refer to Figure-18; it presents the performance of average V_{rms} for Phase 4. At 140 cm lifting height, the highest average V_{rms} is at the first lifting which is 39.27µV and the lowest is 14.55µV at the end of the contractions. At 75 cm lifting height, 29.88µV is recorded the highest average V_{rms} and it is decreased proportionally to 5.36µV.

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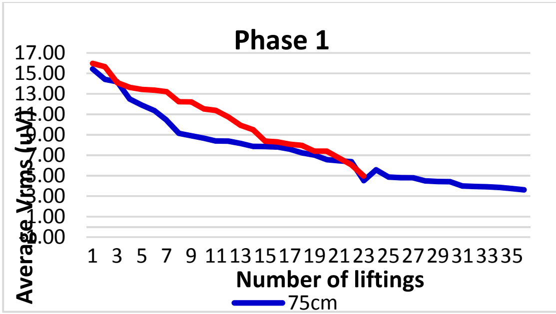

Figure-15. Comparison of RMS Voltage (V_{rms}) between 75 cm and 140 cm of lifting heights for Phase 1.

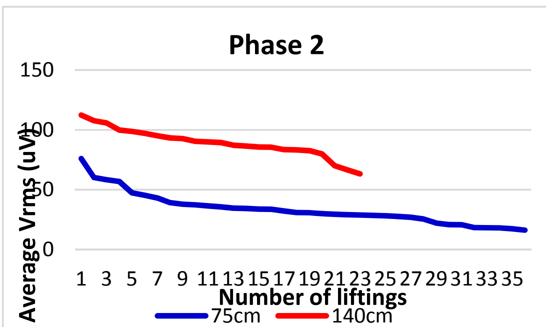

Figure-16. Comparison of RMS Voltage (V_{rms}) between 75 cm and 140 cm of lifting heights for Phase 2.

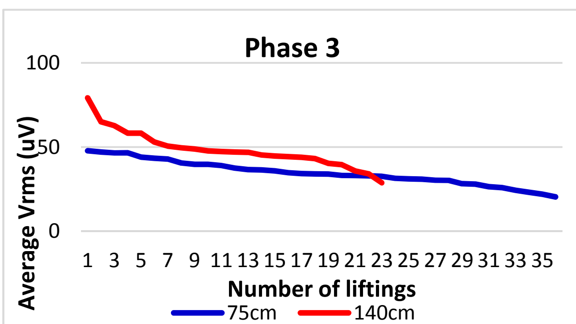

Figure-17. Comparison of RMS Voltage (V_{rms}) between 75 cm and 140 cm of lifting heights for Phase 3.

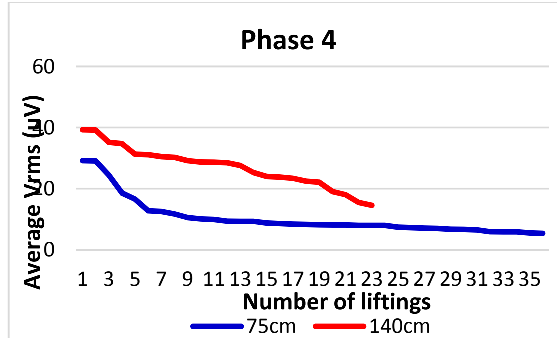

Figure-18. Comparison of RMS Voltage (V_{rms}) between 75 cm and 140 cm of lifting heights for Phase 4.

Based on the analysis of all phases, it shows that average V_{rms} is decreased with increasing the number of lifting. Phase 2 produced the highest average V_{rms} for both 75 cm and 140 cm because of the maximum effort used in order to travel the load onto the shelf.

CONCLUSIONS

Based on the analysis of EMG signals, this study concluded that the application of spectrogram is able to counter the limitation of FFT in determining the time-frequency representation (TFR).

Additionally, the windows size 1024 has produced optimum results to visualize clear and suffice information on contraction of muscle activity.

Furthermore, the average instantaneous RMS voltage (V_{rms}) increased when the lifting height is increased. However, the $V_{rms}(t)$ declined when the number of lifting increased.

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