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Biceps and Triceps Electrical Activity Analysis based on using Low-Cost Sensor: Case Study

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Abstract— **Upper limb's Surface Electromyography (sEMG) has been widely investigated and used for controlling of rehabilitation and prosthetic robots. However, accurate acquiring and processing of the sEMG signals requires an expensive commercial EMG system. In addition, proper analysis of the processed sEMG signal is also required to obtain beneficial information. Therefore, this research investigates the efficiency of using a low-cost EMG sensor, specifically MyoWare Muscle Sensor from advancer technology, in collecting an accurate sEMG signal. The electrical activity of biceps and triceps muscles were collected using Myoware Muscle sensor to investigate how accurate the aforementioned sensor in fulfilling two objectives. Firstly, interpreting the subject's intention in terms of flexing and extending the upper limb at elbow joint. Secondly, assessing the localized muscle fatigue that accompanies biceps and triceps during contraction. The collected sEMG signals were processed, filtered, segmented and specific features were extracted in time and frequency domains. Six features, namely, MAV, RMS, SAV, SD, ZC, and SSC, were extracted from the segmented sEMG in time domain to predict the user's intention of flexing and extending the elbow joint. In addition, frequency-domain features, specifically the mean frequency MNF and the median frequency MDF, were also extracted to evaluate the sensor's efficiency in assessing the localized muscle fatigue. In terms of predicting the user's intention, results showed that only particular features, specifically SAV and SD, were able to efficiently interpret the flexion and the extension of the elbow joint. However, MNF and MDF have both accurately assessed the localized muscle fatigue over the time. Consequently, special attention should be taken when dealing with low-cost EMG sensor.**

I. INTRODUCTION

World health organization (WHO) has reported that up to 20% of stroke survivors requires an intensive rehabilitation program. The rehabilitation process can be implemented by either professional therapist or special designed rehabilitation robots [1]. The high cost of providing a therapist for each stroke patient pushed the researchers to improve the performance of the rehabilitation robots [2]. Analyzing the surface Electromyography (sEMG) signal is one of the controlling techniques that is widely used for rehabilitation robots [3]. sEMG extracted from limbs' muscles was frequently investigated by many researchers to predict the user's intention in terms of limb movements [4]. Additionally, biceps and triceps were identified as the main muscles that are responsible for flexing and extending the elbow joint respectively [2] [5].
The analysis of the sEMG involves extracting specific features that are useful for interpreting the limb movement and muscle fatigue. The sEMG features are categorized according to the analyzing domain, hence there are two types of features that are Time-Domain features and Frequency-Domain features [6] [5]. Time-Domain (TD) features includes Mean Absolute Value (MAV), Root Mean Square (RMS), Waveform Length (WL), Log Detector (LD), Skewness (SKEW), kurtosis (KURT), Standard Deviation (SD), Summation of the Absolute (SAV), etc. [5]. Frequency Domain (FD) features includes Mean Frequency (MNF), Median Frequency (MDF), Wavelet Decomposition (WDC), etc. [7]. Time-domain features, however, require less computing time and hence are preferred for real time applications [8] [5] [9].

Time-domain features such as RMS, MAV, SD and SAV have been reported to have high value when the muscle is contracted. In contrast, low values of the aforementioned TD features were recorded when the muscle is relaxed [10] [3]. On the other hand, Frequency Domain features such as MNF and MDF have been widely used to assess the localized muscle fatigue, where the value of both features decreases as the fatigue progresses [1] [11] [12] [13] [14]. It should be noted that "muscle fatigue" and "pain" are also alternatives terms to the localized muscle fatigue [14] [11].

The electrical activity of the Biceps and triceps were repeatedly investigated using both commercial expensive EMG system and low-cost EMG configuration. MyoWare Muscle EMG Sensor produced by the Advancer technologies is a low cost EMG sensor that is popularly used by the researchers [15]. However, most of the recent studies lack for proper acquisitioning and proper analyzing for the acquired signal.

MyoWare muscle sensor has been used in several researches to collect the sEMG and further analyzing was then applied on the collected signals. [16] have used four MyoWare muscle sensors that were placed on the upper limb muscles. The sEMG was extracted from biceps, triceps, wrist flexor carpi radialis, and wrist extensor carpi radialis muscles to predict the potential movements of the upper extremity including flexion and extension of upper limb. K-NN classifier and three specific features that are (RMS), (WL), and (MAV) were used for detecting the user's intention. The obtained mean classification error was identifying as 5.9% according to the authors. However, Arduino Mega was used to digitize the acquired signal which may weigh down the sampling frequency [15]. Furthermore, the study involved using the ready enveloped EMG signal, not the raw EMG, that is provided by the MyoWare sensor and ultimately a proper analyzing for the raw EMG signal is still required.

[17] have used Double MyoWare muscle sensors to collect the sEMG signals from biceps and triceps for the purpose of interpreting the basic hand movements. Multiple features such

as root mean square, Skewness and kurtosis were extracted and then an Artificial Neural Network was used to classify the acquired sEMG signal. According to the authors, the proposed methodology was able to interpret basic hand gestures including hand closing, hand opening, hand clipping and clipping to resting. In this study, Arduino Mega was used as data acquisition card to digitize the acquired signal and import it to the Matlab for further analyzing. In addition, the authors used the enveloped signal, not the raw EMG, provided by the MyoWare sensor [18]. Proper analyzing for the acquired signals and feature extraction was not included in this study though. Nonetheless, the value of the sampling frequency of the acquired signal was not identified in the aforementioned study.

The validity of using the MyoWare muscle sensor on acquiring the sEMG was also evaluated by [15], where a single sensor was placed on the rectus femoris to report the muscle activity. Arduino Mega was also used to digitize the acquired signal. The study compared between the MyoWare sensor configuration and a commercial expensive EMG system. The results showed a similar behavior between the two configurations according to the authors. However, neither time-domain nor frequency-domain features were extracted and compared from both systems.

As mentioned earlier, the MyoWare muscle sensor accompanied with an Arduino was used to acquire and digitize the sEMG signal. The obtained results, however, are not hundred percent reliable as the Arduino has its own memory limitations. Furthermore, the sampling frequency was not accurately specified which may produce wrong information due to Nyquist rate [15].

Extracting the optimum EMG features based on using MyoWare muscle sensor and analyzing them properly require further investigation. In other words, MyoWare muscle sensor that is intended to be used for controlling potential robots requires further experiments and analyses to prove its efficiency. Therefore, this research tests the efficiency of using MyoWare muscle sensor to collect the sEMG signal from the Biceps and Triceps muscles. A proper analyzing is then applied on the acquired signal to fulfil two objectives: firstly, extracting specific time-domain features for detecting the user's intention in terms of flexing and extending the upper extremity at elbow joint. Secondly extracting specific frequency-domain features for assessing the localized muscle fatigue of the contracted biceps and triceps.

The rest of the paper is arranged as follows: next section explains the general configuration of the research and the materials were used. Section 3 discusses the results and identifies the most suitable features for controlling purposes and fatigue assessment. Finally, section 4 concludes the results .

II. Materials and Methods

Evaluating the ability of the MyoWare muscle sensor in acquiring an accurate sEMG signal from the biceps and triceps is the main purpose of this research. Data were collected from five healthy subjects with mean age of 33 ± 3.5 years. The two targeted muscles, biceps and triceps, were firstly shaved and cleaned before the application of the electrodes [15]. European Recommendations for Surface Electromyography (SENIAM) [19], and the guidelines of the International Society of Electrophysiology and Kinesiology (ISEK) [20] were followed for better acquiring of the EMG signal. Subjects were asked to perform two protocols to collect the sEMG through the MyoWare muscle sensor as following:

Protocol one: subjects were asked to fully extend their upper limb (forearm is straight, contracted triceps while relaxed biceps), and the raw EMG was collected for 10 seconds from both muscles (triceps and biceps). Then, the subjects were asked to flex their upper limb at angle of approximately 150° (contracted biceps while relaxed triceps), and also the raw EMG was collected for 10 seconds from both muscles (triceps and biceps) as shown in Figure 1. In conclusion, we had four types of raw EMG data (relaxed triceps' EMG data, contracted triceps' EMG data, relaxed biceps' EMG data and contracted biceps' EMG data). This protocol was dedicated to predicting the user's intention in terms of flexing and extending the upper extremities at elbow joint.

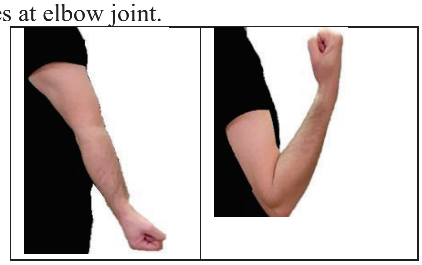

Fig.1 protocol of Collecting the raw EMG data from the Biceps and Triceps During Extension and Flexion

Protocol Two: subjects were asked to fully extend their elbow joint while holding a weight of 2 Kgs. The raw EMG was continually collected from the contracted triceps until the subjects reported a sort of discomfort as shown in Figure (2A). Same steps were followed to record the raw EMG data from the biceps. Where the subjects were asked to flex their elbow joint against a force and the raw EMG data from the contracted biceps was also continually recorded until the subject reported a sort of discomfort [12] as shown in Figure (2B). In conclusion, we had two types of raw EMG data (contracted triceps' EMG data and contracted biceps' EMG data with applied force) This protocol was dedicated to assessing the localized muscle fatigue using the potential sensor.

Such protocol was followed as it was previously proved that the fatigue becomes onset once the subject cannot keep the activity. Therefore, the subjects were encouraged to perform this protocol until they had a sort of discomfort feeling, which was considered the fatigue was being progressed throughout the session.

The mentioned two Protocols were approved by the ethics committee of the Universiti Putra Malaysia (UPM) with reference number (JKEUPM-2021-263). The experiment setup and configuration is shown in Figure 3, MyoWare muscle sensor (AT-04-001) from advancer technology was placed on the biceps and triceps muscles to acquire the surface EMG signal [15]. Following subsections explain the configuration in detail

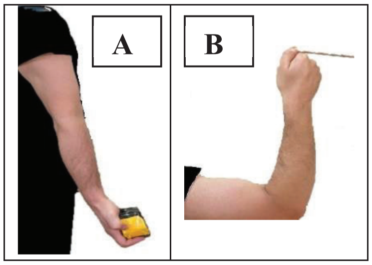

Fig. 2: Protocol of collecting the raw EMG: (A) triceps, (B) biceps

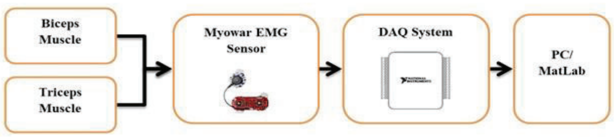

Fig. 3: Experiment setup and configuration

A. Data Collection

MyoWare Muscle sensor, that converts muscles' electrical activity to an analog output signal, was placed on the biceps and the triceps. This sensor is characterized by having three bio potential pins which are responsible for detecting the muscle's electric activity. Each pin is connected to a disposable electrode for better acquiring of the sEMG signal. Covidien disposable electrode (H124SG) was used for this purpose which has shown an efficient acquiring for the signal [17].

Two electrodes were placed on the middle of the muscle and the last electrode was used as reference electrode and placed on non-adjacent muscular tissue. The small size of the MyoWare Muscle sensor makes it suitable to be placed on the muscle, in addition a tie was applied on the sensor to assure fixed attachment between the sensor and the muscle as shown in Figure 4 [6].

Data Acquisition device (USB6001) provided by National Instrument was used to convert the produced analog sEMG signal into a digital signal which was then sent to a PC for further processing. DAQ device (USB6001) has a resolution of 14-bits and sampling rate of 20,000 samples/second. However, the acquired analogue signal was sampled at frequency of 2000 Hz as explained in next subsection.

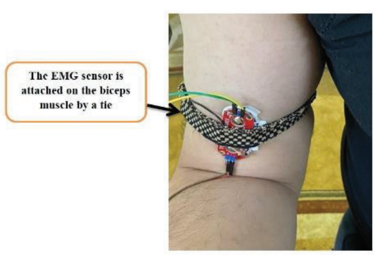

Fig. 4: shows how the tie was used to assure the fixed contact between the EMG sensor and the biceps muscle

B. Signal Processing and Filtration

Analog input recorder, which is an application that is provided by Matlab (2018), was used to record the acquired sEMG signal. The frequency of the recorded sEMG signal lies within a range of 400-500Hz, therefore sampling the recorded signal at frequency of 2000Hz was considered sufficient to avoid aliasing based on the Nyquist rate. It should be noticed that increasing the sampling frequency could provide more information about the recorded signal, however high sampling frequency requires high computation time and compromises the real time processing.

sEMG signal is usually accompanied with many noises due to cross talk, motion artifacts and ambient noise [5]. Therefore, preprocessing and filtration is required prior features extraction. Matlab 2018 was used to process and filter the recorded EMG signal. Firstly, the DC offset of the recorded signal was eliminated [10]. Secondly, Butterworth band pass filter was applied on the produced signal to pass only EMG frequencies components that lay within a range of (4-500Hz). Butterworth filter was chosen as it provides maximum flat response between the cutoff frequencies [10]. Finally, band stop filter was applied on the recorded signal to eliminate power line's frequency component which is 50Hz (or 60Hz in other countries) [15].

C. Segmentation Process

Processed and filtered EMG signal should be continuously measured for the purpose of real-time motion pattern classification. Hence, the raw EMG signal was firstly segmented prior the application of feature extraction.

The raw EMG signal was segmented to windows of 250ms, and overlapped of 125ms between segments for extracting the time-domain features [16]. Provided that the acquired sEMG was sampled at 2000Hz, this segment's length provides 500 samples per each segment which is considered sufficient for real time processing. However, increasing the segment time would increase the computation time and decrease the real time response [5]. Segmentation process for extracting the frequency domain features, however, requires longer segment length [12]. Therefore, a segment length of 3 seconds was used [6]. Segment length of 3 seconds provides 6000 samples per segment which ultimately provides more reliable results.

D. Feature Extraction

Feature extraction is the mathematical operation that transforms the raw EMG signal into more meaningful information which is called Envelop. Thus, Feature extraction plays a significant role in pattern classification [5] [10].

Six time-domain features were chosen to be extracted from the processed, filtered, and segmented sEMG signal. The six features are Mean Absolute Value (MAV), Root Mean Square (RMS), Standard Deviation (SD), Summation of the absolute Value (SAV), Zero Crossing (ZC) and Slop Sign Change (SSC). The aforementioned features were chosen due its ability in distinguishing and differentiating elbow joint flexion and extension [5] [17]. Following are mathematical expressions of the six features [10][17]

Mean Absolute value (MAV) is represented as following:

$$MAV_i = \frac{1}{n}\sum_{k=1}^{n}|EMG_k| \quad (1)$$

Root Mean Square (RMS) is represented as following:

$$RMS_i = \sqrt{\frac{1}{n}\sum_{k=1}^{n} EMG_k^2} \quad (2)$$

Standard Deviation (SD) is represented as following:

$$SD_i = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_k - X_m)} \quad (3)$$

Summation of the Absolute Value (SAV) is represented as following

$$SAV_i = \sum_{k=1}^{n}|EMG_k| \quad (4)$$

Where (i) represents the segments number, (n) represents the length of the segment, (k) represents the value of the current bin, and (X_m) represents the mean value of the whole segment.

Zero Crossing (ZC) refers to the number of times that the raw EMG signal crosses the zero baseline or another identified baseline, and eventually reflects the frequency components of the signal, ZC is represented as following

$$ZC_i = \sum_{k=1}^{n-1}\delta_{ZC(k)} \quad (5)$$

$$\delta_{zc(i)} = \begin{cases} 1 & if\ (EMG_k > 0\ and\ EMG_{k+1} < 0) \\ & or\ ((EMG_k < 0\ and\ EMG_{k+1} > 0) \\ & and\ (|EMG_k - EMG_{k+1}| > threshold) \\ 0 & Otherwise \end{cases}$$

Slope Sign Change (SSC) shows the number of times that the waveform's slope changes its sign. SSC is represented as following:

$$SSC_i = \sum_{k=1}^{n-1}\delta_{SSC(k)} \quad (6)$$

$$\delta_{zc(i)} = \begin{cases} 1 & if\ (EMG_k > EMG_{k-1}\ and\ EMG_k > EMG_{k+1}) \\ & or\ (EMG_k < EMG_{k-1}\ and\ EMG_k < EMG_{k+1} \\ & and\ (|EMG_k - EMG_{k+1}| > threshold) \\ & and\ (|EMG_k - EMG_{k-1}| > threshold) \\ 0 & Otherwise \end{cases}$$

As shown in equations (5) and (6), the threshold must be identified prior the application of ZC and SSC which can be represented as following:

$$threshold_i = \mu_i + \mathrm{G}.\sigma_i \quad (7)$$

μ_i represents the mean value of the identified segment
σ_i represents the standard deviation value of the identified segment, G has been calculated by and hence was set to 3

Mean frequency (MNF) and median frequency (MDF) are the frequency-domain features that were chosen to assess the localized muscle fatigue. MNF and MDF have been identified in several studies and shown an accurate assessment for the localized muscle fatigue [11][12] [14]. The instantaneous mean frequency and median frequency were calculated from previously segmented signal using time-frequency analysis which is popularly known as short time Fourier transform (STFT) [14]. Furthermore, linear regression analysis was used to show the slope coefficients of the obtained results in addition to the intercepts values [11]. Following are mathematical expressions of the MNF and MDF [14]:
Mean Frequency (MNF) is represented as following:

$$MNF_i = \sum_{k=1}^{n} f_k P_k \ / \ \sum_{k=1}^{n} P_k \quad (8)$$

Median frequency is defined as the frequency that divides the power spectrum into two regions with equal amplitude [14]. Median Frequency (MDF) is represented as following:

$$\sum_{k=1}^{MDF_i} P_k = \sum_{MDF_i}^{n} P_k = \frac{1}{2}\sum_{k=1}^{n} P_k \quad (9)$$

Where (i) represents the segments number
(n) represents the length of the segment
(f_k) represents the frequency value at bin (k)
(P_k) represents the power spectrum value at bin (k)

Consequently, this study has considered the parameters that could substantially affect the accuracy of the acquired sEMG signal.

III. RESULTS AND DISCUSSION

As mentioned earlier, the purpose of this study is to evaluate the efficiency of the MyoWare muscle sensor in acquiring an accurate sEMG signal from the biceps and triceps. The acquired sEMG signals were then analyzed in time and frequency domains.

Firstly, analyzing the acquired signal in time domain was dedicated for detecting user's intention in terms of flexing and extending the upper limb at elbow joint. MAV, RMS, SD, SAV, ZC and SSC are the time-domain features that were extracted from the acquired signal from both muscles (triceps and biceps) during the first protocol.

As shown in table (1), It was found that the average magnitude of the MAV, RMS, SD and SAV for five seconds are higher for the triceps during the extension, while they are smaller during flexion. The situation is completely opposite for the biceps, where the magnitude of the MAV, RMS, SD and SAV are higher during the flexion and smaller during extension. Moreover, SD and SAV showed a distinct difference between flexion and extension for both biceps and triceps. It also should be noticed that the SAV showed larger differences in terms of its magnitude for both triceps and biceps during extension and flexion.

Table 1: shows the differences between EMG features for triceps and biceps during extension and flexion

Triceps	Extension	Flexion
MAV	0.0087	0.0024
RMS	0.0129	0.0036
SD	0.0131	0.0033
SAV	52.1455	14.2220
ZC	43.8533	44.6000
SSC	81.87	139

Biceps	Extension	Flexion
MAV	0.0034	0.0058
RMS	0.0044	0.0078
SD	0.0050	0.0093
SAV	20.2863	35.0413
ZC	29.3261	24.2000
SSC	113.2391	98

The other two features (ZC and SSC) follow different behavior during extension and flexion. Both features are higher for the biceps during extension and smaller during flexion. Whereas the ZC and SSC are higher for the triceps during flexion and smaller during extension (table 1). Furthermore, SSC showed more accurate behavior when it is compared to the ZC. Where the value of the SSC magnitude varies dramatically when the state changes from flexion to extension and vice versa. It can be concluded that the MAV, RMS, SD and SAV are higher when the muscle is active. ZC and SSC, however, exhibit small values when the muscle is active and vice-versa.

Based on the obtained results, MAV, RMS, SD, SAV and SSC are the features that have efficiently interpreted the flexion and the extension of the upper limb at elbow joint. ZC, however, showed different and intersected values during flexion and extension of the upper extremities. Furthermore, SD, SAV and SSC are the features that have shown better performance when they compared to the rest of the features. Thus, it's also recommended to combine these three features extracted from double sensors for better detection of user's intention [21]. However, if using double EMG sensors is not feasible, the authors suggest using single EMG sensor placed on the triceps which has shown better explanation of the flexion and extension of the upper limb at elbow joint.

Secondly, the acquired signal was also analyzed in frequency domain to evaluate the efficiency of the MyoWare muscle sensor in assessing the localized muscle fatigue. MNF and MDF are the frequency-domain features that were extracted from the acquired signal from both muscles (triceps and biceps) during the second protocol.

As shown in figure (5), Results showed that MNF and MDF exhibited negative slope. Moreover, the existence of force accelerates the progress of localized muscle fatigue, which agrees with literature [11][14][12]. In conclusion, MyoWare muscle sensor showed good performance in assessing the localized muscle fatigue based on the calculated MNF and MDF.

Tables (2&3) summarize the obtained results of the aforementioned features in terms of interpreting the flexion and extension of elbow joint and muscle fatigue assessment.

Table 2: Summarizes the efficiency of the time-domain features in interpreting the flexion and extension of the elbow joint using Myoware Muscle Sensor.

Time-Domain Features	MAV	RMS	SAV	SD	ZC	SSC
Did the feature exhibit distinct behaviors between contracted and relaxed investigated muscle?	Yes	Yes	Yes	Yes	No	Yes

Table 3: Summarizes the efficiency of the frequency-domain features in detecting the progressing of localized muscle fatigue Using Myoware Muscle Sensor.

Frequency-Domain Features	MNF	MDF
Did the feature efficiently assess the progressing of localized muscle fatigue?	Yes	Yes

Using low-cost non-invasive EMG sensor requires special attention for ensuring accurate acquiring, processing, and analyzing of the EMG signal. For instance, sensor's main two electrodes had to be placed in a line with the muscle, where one of the electrodes was placed on the muscle's belly and the second one was lined up along the length of the muscle. It was found that wrong attachment of the electrodes substantially affects the strength of the acquired signal. In addition, it is recommended to place the reference electrode on boney or non-adjacent tissue, otherwise the strength of the acquired signal is compromised.

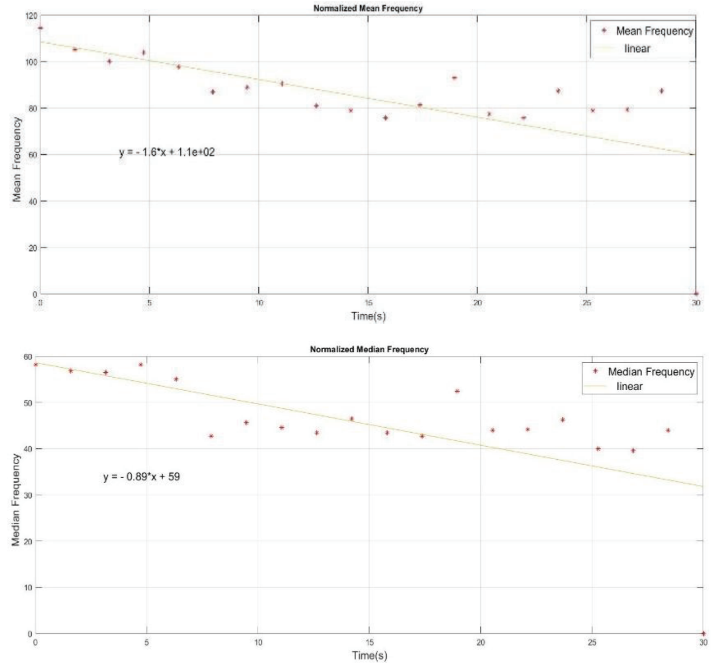

Fig. 5: shows how MNF and MDF behave throughout protocol two

Although Covidien electrode has a gelled adhesive side that assures a good conduction between the sensor and the muscle [17], a tie was required to assure the fixed attachment on the muscle. Loose attachment of the sensor could cause a sudden movement and ultimately effect on the acquired signal.

IV. Conclusion

sEMG signals of the biceps and triceps were acquired using MyoWare Muscle sensor from advancer technologies. The acquired signal was processed, filtered, and segmented, then time-domain features (MAV, RMS, SAV, SD, ZC, and SSC) and frequency-domain features (MNF and MDF) were extracted. These features were extracted to check how accurate the MyoWare sensor in interpreting elbow joint movement and fatigue assessment.

The study showed that the MAV, RMS, SD, and SAV follow the same behavior, where their magnitude is high during the activation of the muscle. ZC and SSC, however, showed different behavior, where their magnitude is small during the activation of the muscle. Furthermore, SAV, SD and SSC are the most accurate features that can be used to explain the flexion and the extension of the upper limb at elbow joint.

In addition, localized muscle fatigue was also assessed by calculating the MNF and MDF. Both features, the MNF and MDF, showed good performance in assessing the fatigue.

To conclude, MyoWare muscle sensor can efficiently be used to assess the localized muscle fatigue. However, detecting the user's intention in terms of flexing and extending the elbow joint requires special attention to choose the optimum feature.

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