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Analysis of a Low-cost Sensor Towards an EMG-based Robotic Exoskeleton Controller

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Abstract — This paper describes the evaluation of the MyoWare Electromyographic (EMG) sensor performance during a typical end-use application to help determine if it could be used for an EMG-based controller of an upper-limb robotic exoskeleton. Tests were conducted to study the signal-to-noise ratio (SNR) and a series of experiments were performed to determine the sensor's capability of capturing key EMG signal features while a subject performed bicep curls. LabVIEW was used for data collection and processing, and Matlab was used for statistical analysis. The results revealed that the SNR was between 10dB and 33dB for the average peak root mean square (RMS) EMG, and between 1dB and 27dB for the average voluntary contraction (AVC) EMG which – except for one case – were all above the acceptable level in the field. The validation of the sensor performance showed a correlation consistent with literature between the force exerted and the RMS EMG signal under both dynamic and static loading. These initial results indicate that the MyoWare EMG sensor could be used in a more advanced robotic exoskeleton EMG-based controller beyond its current popular use as an EMG-level threshold-based ON/OFF switch.

Keywords- electromyography, EMG, muscle, myosignals, upper limb, robotic exoskeleton.

I. Introduction

With the expected surge in the global aging population and the inevitable motor impairment in the elderly, it is anticipated that the already overloaded medical workforce will not be able to keep up with the onset of anticipated rehabilitation demands [1]. To address this issue, the field of Robotic Exoskeletons is growing rapidly, though most of the existing systems are at the research level or are too cost-prohibitive to be widely available. It is pertinent for the technology to be accessible now to educate future researchers and developers in the field. Consequently, Beyond Robotics GmbH released the EduExo Robotic Exoskeleton kit in October of 2017. The kit contains all the major subsystems relevant to a Robotic Exoskeleton including an Electromyography (EMG) sensor – the MyoWare EMG sensor (AT-04-001) from Advancer Technologies. This sensor reads a wearer's EMG signals which are indicative of muscle activation levels [2]. The controller implemented with this kit activates the exoskeleton elbow joint motor when the measured EMG signal surpasses a set threshold value. In this paper the present authors investigate the performance of the sensor in an application to determine the possibility of using it in a future-build robotic exoskeleton controller to, for example, provide proportional control of the motors to assist the user in achieving the desired motion. A brief background is provided on EMG controllers to justify why studying the sensor's SNR and its degree of linearity are important for the intended application. Factors which influence the fidelity of the signal will also be discussed, followed by a description of the sensor specifications. The experimental setup and procedure will then be presented, the results will be shown and discussed, after which conclusions will be drawn.

II. Background

There are numerous factors that can influence the quality and amplitude of EMG measurements. On the apparatus side, De Luca [3] states that the "main issue of concern that influences the fidelity of the [EMG] signal is the signal to noise ratio." Additionally, the design of the electrodes, the distance between them, and the placement and the orientation of them along the muscle affect signal fidelity. Furthermore, the quality of the contact between the electrodes and the skin, the wire length to the amplifier, the characteristics between the electrodes [4], the amplifier unit, and the signal processing methods are also important. There are many factors which can influence the EMG signal on the subject side as well, such as the conditions of the muscles. For example, EMG measurements can look very different depending on whether or not a muscle has been warmed up or fatigued. Other factors that could affect the EMG levels are age, sex, quality of the skin, body mass index (BMI) level (which is indicative of the thickness of the fat layer over the muscle), and quality and health of the muscle. EMG readings can also vary from day to day [5] even if the subject is performing the same tests as on the previous day. It is also to be noted that the subject's psychophysiological factors, such as emotions, play a factor in the produced levels of the EMG signal [6].

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Numerous existing Robotic Exoskeleton Systems [7,8,9] use these EMG signals as the primary command signal to robot controllers. The EMG signal is typically captured using electrodes on the body that are connected to commercial amplifiers, such as those from Biopack Systems [10]. These controllers incorporate muscle models (myoprocessors) which rely on a correlation between the EMG signal amplitude and dynamic or static exerted force. This information can enable either position control or torque control of the joints with the goal of providing seamless assist-as-needed support to the user. An example of an EMG high-level position controller is shown in Fig. 1 where an EMG sensor is used to determine the desired position of a joint. It is, therefore, critical to identify the correlation between the EMG signal under different loads. Perry [7] points out that a great advantage of EMG controllers is that, due to the "electromechanical delay in the human neuromusculoskeletal physiology, the system can predict the operator's intention". The EMG signal changes in magnitude 20-80ms before the actual contraction of the muscle [11]. As a result, the controller can provide smooth motion coordination between the user and the exoskeleton [7] before the muscles have even begun to move.

An EMG controller "needs to provide the correct amount of support to the user with correct timing" [12]. Control systems rely on sensor feedback updates – sometimes hundreds of times per second in motor control applications. When discussing applications that depend on EMG signals, De Luca [2] emphasizes that the EMG signal should be detected and recorded with maximum fidelity as it is an indicator of the initiation of muscle activation and it has a relationship to the force produced by the muscle. If the signal is noisy and not properly filtered, the resulting exoskeleton motion could be unstable and unsafe. High EMG signal SNR is thus crucial.

The question at hand is: Is the MyoWare EMG sensor able to collect EMG data that is high-fidelity and relatable to the amount of effort exerted by the user so that it could be used in a future-build Robotic Exoskeleton EMG controller for more sophisticated control strategies than just ON/OFF?

III. EMG Sensor and System Description

Table I summarizes the MyoWare EMG sensor characteristics that will be studied in this paper, along with what they indicate, their relevance, how they will be characterized, and the location from where they are calculated as shown on a sample EMG signal (Fig. 2).

The MyoWare EMG sensor, shown in Fig. 3, measures electrical signals which are detected on the skin just before and during muscle contraction. These signals are usually on the order of μVolts to low mVolts [5] and need to be amplified so that they can be digitized, recorded, analyzed and utilized. The MyoWare EMG sensor is an all-in-one device which amplifies, rectifies and filters the raw EMG signal, and provides the RMS EMG envelope as an output with an amplitude between 0 and the supply voltage (2.9-5.7V). Some of the advantages of the sensor are that it is inexpensive, the raw signal is also available, and the electrode connectors, which are placed 3 cm apart, are embedded on the sensor board to minimize noise.

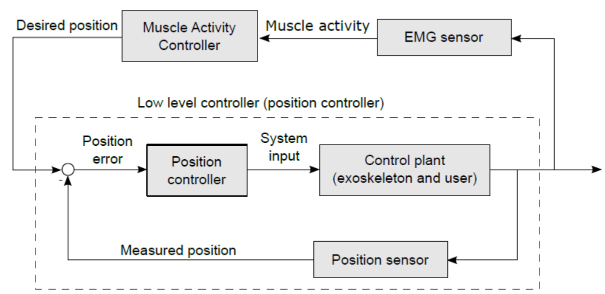

Fig. 1 High-level EMG-Controller implemented on top of the Low-level Position Controller (used with permission from [12])

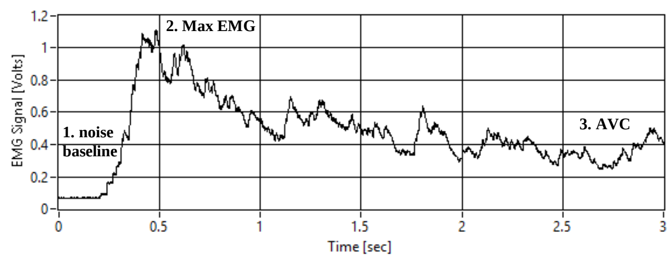

Fig. 2 Sample EMG Signal while subject curled a 5 lbs weight

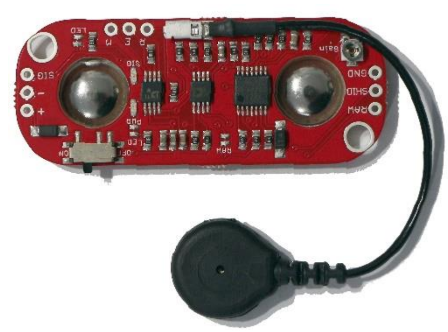

Fig. 3 The MyoWare EMG Muscle Sensor (shown at full scale)

TABLE I
SENSOR BEHAVIOUR CHARACTERISTICS PERTINENT TO EMG CONTROLLERS

Characteristic to be measured	Indicator	Relevance to Robotic Exoskeleton EMG Controllers	Characterization	Location in Fig. 2
SNR	Fidelity of the signal	High-fidelity data is crucial for timely and appropriate motor commands	Compare the EMG signal amplitude between rest and Max EMG signal, and rest and static loading EMG signal	1 vs 2 (dyn. loading) and 1 vs 3 (static loading)
Linearity Max RMS EMG (dynamic loading)	Indication of the intended exerted force	The EMG signal is used as control input to the EMG controller to prepare the assist-as-need routine before the muscles have even moved	Compare the Max EMG signals from 200 tests performed with different weights	2
Linearity AVC RMS EMG (static loading)	Indication of the sustained force	The EMG signal is used as control input to the EMG controller to command required torque or position command to the low-level controller	Compare the Average EMG signals during static loading from 200 tests performed with different weights	3

IV. TESTING METHODOLOGY

The evaluation process consisted of initial tests to verify the sensor's SNR after which a series of extensive tests were performed by a subject to validate the linearity between exerted force and the EMG signal.

A. *SNR Tests*

To measure the baseline noise level of the sensor and verify the SNR of the MyoWare EMG sensor, the EMG signal from the sensor was collected while the two parallel electrodes were connected to the reference potential and when the electrodes were connected to the subject's arm and the bicep muscle was relaxed. The data was captured using the National Instruments USB-6361 Analog/Digital Converter (A/DC) and a LabVIEW program which sampled the data for 500ms at a sampling frequency of 2000Hz.

B. *Linearity Tests*

A series of tests were then carried out to observe the performance of the sensor and to determine the degree of linearity during a typical end-goal application scenario, such as those performed during upper-limb robotic exoskeleton assisted rehabilitation sessions.

The tests were performed on a healthy female with no history of bicep pathology, neuromuscular conditions or cardiac disorder. As the SNR is determined almost "exclusively by the electrodes, and more specifically, the properties of the electrode-electrolyte-skin contact" [6, 13], great effort was taken to ensure optimum contact. In particular, the subject's skin at the contact site was exfoliated, cleaned and dried. Next, tape was applied and swiftly pulled from the skin to remove any remnant dry skin at the site. Two 3M RedDot bi-polar surface Ag/AgCl monitoring electrodes with soft cloth tape and solid gel were placed parallel on the subject's dominant (left) belly of the bicep branchii in accordance with the sensor manufacturer's instructions. Furthermore, as suggested by De Luca [3], the subject flexed her bicep to find the optimum placement of the electrodes to minimize cross-talk noise from neighbouring muscles and increase SNR. A third electrode was placed as far as possible from the bicep branchii, which in this case was limited by an 8 cm length of wire which connected the reference electrode snap to the sensor board. During the tests, the subject sat on a chair and watched the LabVIEW User Interface shown in Fig. 4. Each test lasted 3 seconds.

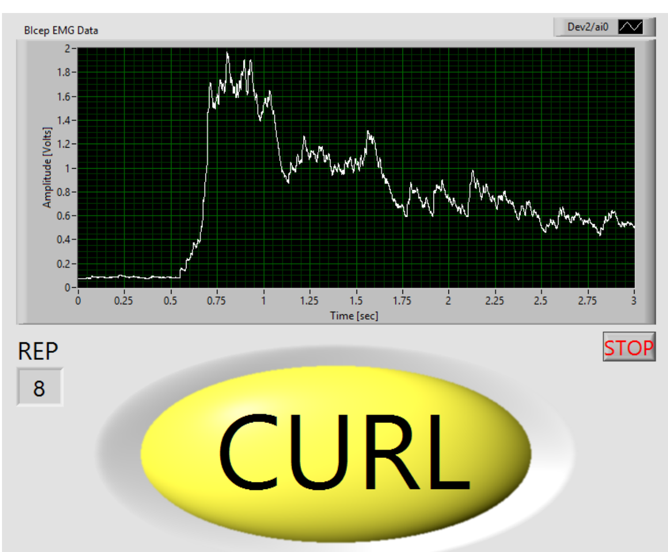

Fig. 4 LabVIEW User Interface for Curling Tests.

At the beginning of the test, the subject had her arm down holding the weight at full extension (0°) with the bicep muscle relaxed. When the 'CURL' indicator on the LabVIEW User Interface turned yellow, the subject lifted the current weight to full elbow flexion (90°). The subject then maintained a static hold at 90° for the remainder of the 3 seconds. Then there was a 3 second rest period after which the next repetition started. This procedure was carried out 40 times for a specific weight. When completed, the subject was given a 5-minute rest period. The set of 40 repetitions were performed consecutively with 5 different weights: 0lbs, 3lbs, 5lbs, 10lbs, and 15lbs. A total of 200 tests were, therefore, performed by the subject. Note that the maximum weight was limited to the 15lbs dumbbell since the amplifier sometimes saturated during tests with heavier weights and the subject could also not perform 40 tests in a row using the larger weights. The data was collected using the National Instruments USB-6361 A/DC and a LabVIEW program with a sampling rate of 2000 Hz which was consistent or faster than tests in the literature [6, 10]. The experimental setup diagram in Fig. 5 shows the computer running the LabVIEW program, the Arduino Uno microprocessor which was used in this case to power the EMG sensor, the EMG sensor placed on the bicep, and the EMG sensor's connection to the NI A/DC which digitized the data that was then collected by the LabVIEW program running on the computer.

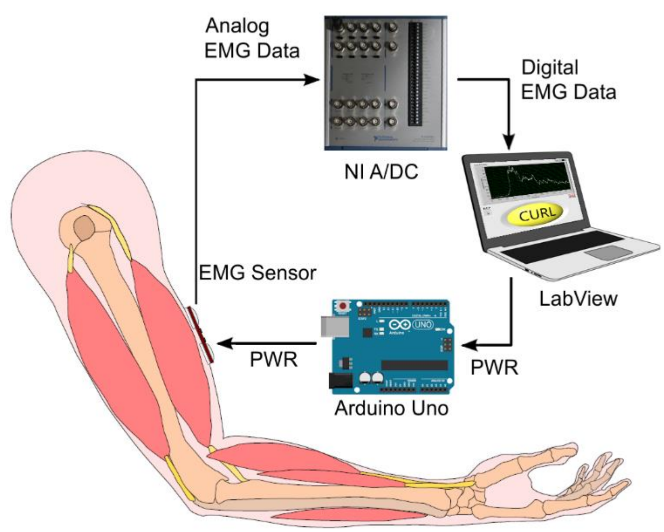

Fig.5 Experimental Setup Diagram for the Curl Tests (modified and used with permission from [12])

V. Results and Discussion

LabVIEW was used to process the EMG data and Matlab was used to perform statistical analysis and plot the results.

A. SNR Tests

The measured (amplified and processed) baseline noise $Vrms_{noise}$ was 65mV (for both when the electrodes were connected to the reference electrode and when the muscle was relaxed). The SNR was then calculated as follows [14,15]:

$$SNR = 20 \log_{10}(Vrms_{signal}/Vrms_{noise})$$

Table II shows the calculated average maximum RMS EMG (dynamic loading) values for the groups of tests performed with each weight, while Table III shows the Average Voluntary Contraction (AVC) RMS EMG (static loading) values for the groups of tests performed with each weight. As can be seen in these tables, as the amount of effort increased, the EMG signal amplitude also increased – resulting in a greater SNR. Delysis Inc [16], an industry leader in wearable sensors, states that SNR values above 1.2 are acceptable. Except for the SNR of the AVC averages at 0lbs, the SNR for the MyoWare EMG sensor is very good.

One important value to note in the noise baseline of the EMG signal when the muscle is relaxed. Florimond [5] has pointed out that it is generally accepted that the surface EMG of a muscle at rest should be below 5μV, while De Luca [2] indicated that it should be less than 2μV. The voltages measured during the tests carried out in this paper are amplified. Thus, to determine the relaxed muscle (noise) voltage, it was necessary to divide the measured EMG voltage at the skin by the amplification factor of 9,306.3 [17] resulting in 65mV/9,306.3=7μV which is consistent with the literature. This value is satisfactory.

TABLE II
SNR: Average Max RMS EMG (Dynamic Loading)

Weight (lbs)	Avg Max RMS EMG at this weight [mV]	SNR	SNR (dB)
0	0.2150	3.26	10
3	0.5599	8.48	19
5	0.8816	13.36	23
10	1.5280	23.15	27
15	2.7970	42.38	33

TABLE III
SNR: AVC RMS EMG (Static Loading)

Weight (lbs)	AVC RMS EMG at this weight [mV]	SNR	SNR (dB)
0	0.0748	1.13	1
3	0.1693	2.57	8
5	0.3299	5.00	14
10	0.6328	9.59	20
15	1.4142	21.43	27

B. Linearity Tests for Dynamic Loading

Fig. 6 plots the maximum RMS EMG signal for all 200 tests (40 tests at each of the 5 weights). As can be seen in the figure, the Max RMS EMG signal became progressively larger as the exerted force increased. Fig. 7 plots the average maximum RMS EMG signal as a function of the weights lifted along with the corresponding 95% confidence intervals. A straight line and a second-order polynomial were fit to the data, with R^2 values of 0.9728 and 0.9949 (shown), respectively.

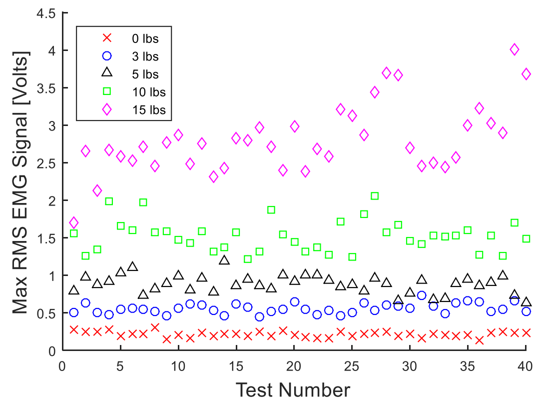

Fig. 6 Maximum RMS EMG Signal for Tests with Different Weights (Dynamic Loading)

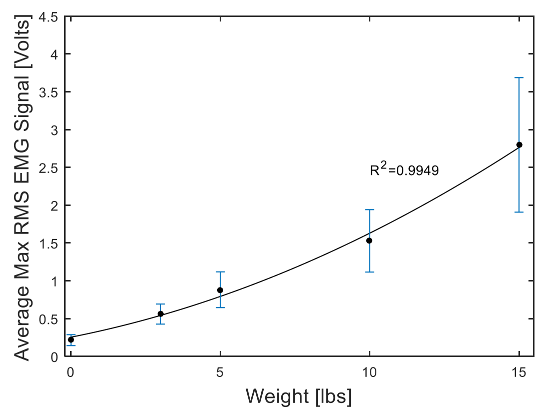

Fig. 7 Average Max. RMS EMGS for Different Weights with 95% Confidence Interval (Dynamic Loading)

C. Linearity Tests for Static Loading

Fig. 8 plots the Average Voluntary Contraction RMS EMG (Static Loading) signal for the last 500 ms of each of the 200 tests (40 tests for each of the 5 weights). Similar to the Max RMS EMG signal, the AVC RMS EMG signal also became progressively larger as the exerted muscle force increased, but with roughly half of the amplitude. Fig. 9 plots the average AVC RMS EMG signal as a function of the weights lifted along with the corresponding 95% confidence intervals. A straight line and a second-order polynomial (shown) were fit for the static loading as was done with the dynamic loading plots. R^2 values of 0.9311 and 0.9921, were calculated for the straight line and the second-order polynomial fits, respectively. Like with the dynamic loading, a correlation between the exerted force and the measured AVC RMS EMG signal was observed and are both consistent with the curves attained in literature [18, 19] for 61 subjects and 10 subjects respectively. Since the results show a characterizable relationship, the sensor would likely be suitable for a future-build robotic exoskeleton EMG-based controller.

A correlation was also observed between the variability of the EMG signal and the applied force for both types of loading – up to 50% for the 15lbs dynamic loading tests. Similar observations were presented in [20]. Some possible solutions to minimize variability could be to apply sensor-side or controller-side processing or limit the number of repetitions in each test and the payload to 5lbs or less - where the spread is significantly smaller.

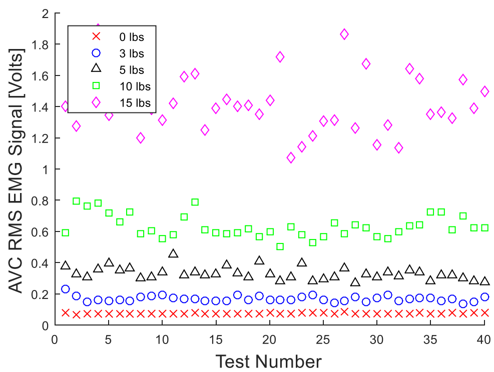

Fig. 8 Average AVC RMS EMGS for Different Weights with 95% Confidence Interval (Static Loading)

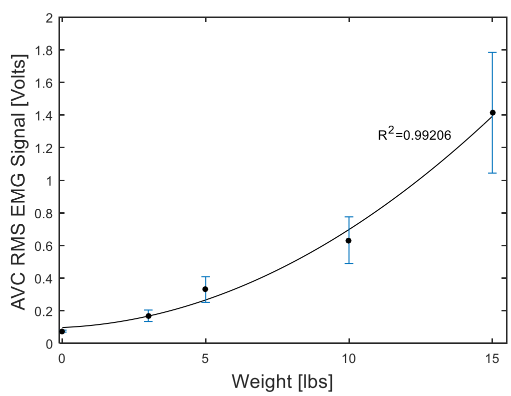

Fig. 9 Average AVC RMS EMGS for Different Weights with 95% Confidence Interval (Static Loading)

VI. CONCLUSION

Experimental tests were performed on a subject using the MyoWare EMG sensor to evaluate its use for future robotic exoskeleton applications. Verification test showed acceptable SNR values. The degree of linearity of the sensor was studied while it was utilized in a typical end-use application and the results showed expected correlation between the exerted force and both the dynamic and static load EMG signals. Although these results look promising and suggest that the sensor would be a good candidate for a proportional robotic exoskeleton EMG controller, further investigation would be beneficial to verify the linearity of the sensor itself without the human in the loop. It would also be interesting to perform the same tests on more subjects, and with other EMG sensors. Additionally, it would be beneficial to examine the sensor's raw EMG signal and explore its performance in the frequency domain.

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