ORIGINAL ARTICLE

A simple surface electromyogram signal simulator for testing of measurement equipment

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Electromyography is a biomedical technique that examines muscle function by analyzing electrical signals generated during muscle contractions. Signal recording of the electromyogram is done using a device called an electromyograph. This device reveals the electrical potentials created by the muscle cells in both surface and interior method. This signal can be used in various fields such as medical and rehabilitation studies. To develop and validate bioelectric signal measurement systems, there will be an accurate validation method. If the system is being developed, its validation in several stages will increase the cost of this test, but the costs can be significantly reduced with the help of a software simulator. In this paper, we investigate and simulate a simple EMG Simulator in LabVIEW Software.

Key Words: *Electromyograph; Muscle simulator; LabVIEW; MATLAB; Bioelectric signals*

INTRODUCTION

The structure of each muscle consists of several motor units known as the smallest practical unit of muscle contraction. Each motor unit contains of a neural fiber (Motor neurons trunk, dendrites, axon, and numerous branches), as presented in Figure 1, all muscle fibers that have been inflicted on the nerve [1].

The muscle tissue is inactive when resting, but following the muscle contraction, an action potential is developed which increases the number of muscle fibers involved in the production of this potential. After the complete contraction of the muscle, these potentials of action appear in a group and with different domains. This bioelectric potential is the voltage caused by cell electrochemical activity, which can be transformed into an electrical voltage by a transducer [1] (Figure 2). Electrical activity of each cell can be considered as one of the most important biological parameters of cell survival. In other words, the human body can be viewed as an electricity generator, transmitting neural signals between the brain and organs by this electricity.

One of the types of bioelectric potentials is the Electromyogram signal (EMG). During the contractions of the muscle, this bioelectric signal generated by motor units, which represents the physiological and anatomical characteristics of the muscles [1-4].

This technology can be attributed to the application of engineering science to increase the convenience of people with various disabilities specially motion disabilities [5], which provide a broad field for research and development of alternative methods and tools associated with mobility and alternative communication [6]. Electromyography can be used to monitor daily activities [7-9] and in addition to displaying the levels and patterns associated with muscles activity, are also helpful in identifying the active or passive motions and the time or intensity of muscle activation [10,11].

One of the most important applications of this signal is the control of rehabilitation equipment (such as prostheses) [12], detection of patient's movement in order to monitor the patient and emergency response [13,14], the creation of detection systems [15,16], and also provide intelligent assistance to the elderly and patients with Alzheimer's and Parkinson's disease [17,18].

The recording of this signal is done with two methods, surface EMG and intramuscular EMG. Due to non-invasive, non-anesthetic, easy to use and painless, surface EMG is more widely considered in conventional clinical applications [19]. This method is performed using silver/silver chloride electrodes on the skin (Body index points for surface electromyography are shown in Figure 3). These electrodes are electrically stable and have an appropriate SNR [20,21]. Multiple types of research have shown that this

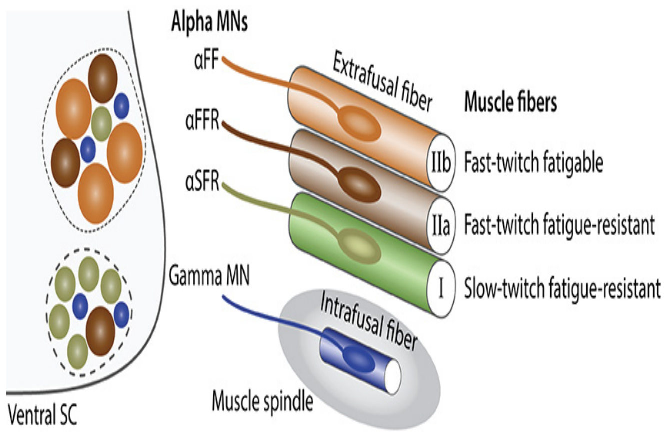

Figure 1) *Motor unit structure [2]*

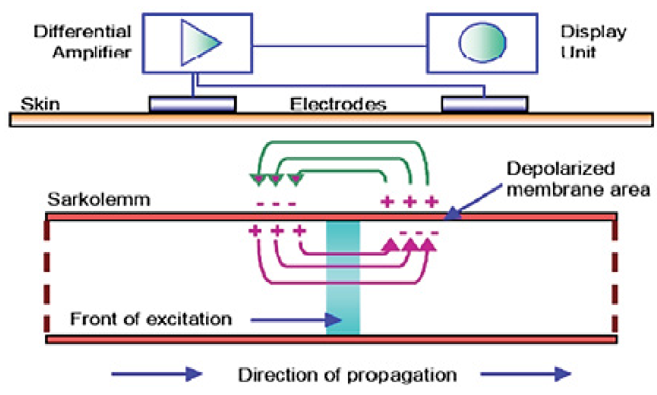

Figure 2) *A view of the potential action record [3]*

signal has an acceptable performance in movement analysis, prosthesis control, and the diagnosis of different states [22,23].

Electromyography has various techniques for detecting body movement [24,25], which are important in computer modeling and the design of

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normal movements of prostheses [26,27]. Although the role of these prosthetics in rehabilitation treatments is undeniable, due to the control of such prosthetics based on a sequential control strategy, normal movements require a long and complex process. Researches show that by relying more on EMG signals, such restrictions in these prostheses will be eliminated which require extensive research and testing [28]. The most suitable and safe way to design a variety of movements and planning to control these prostheses is to use an EMG simulator [29].

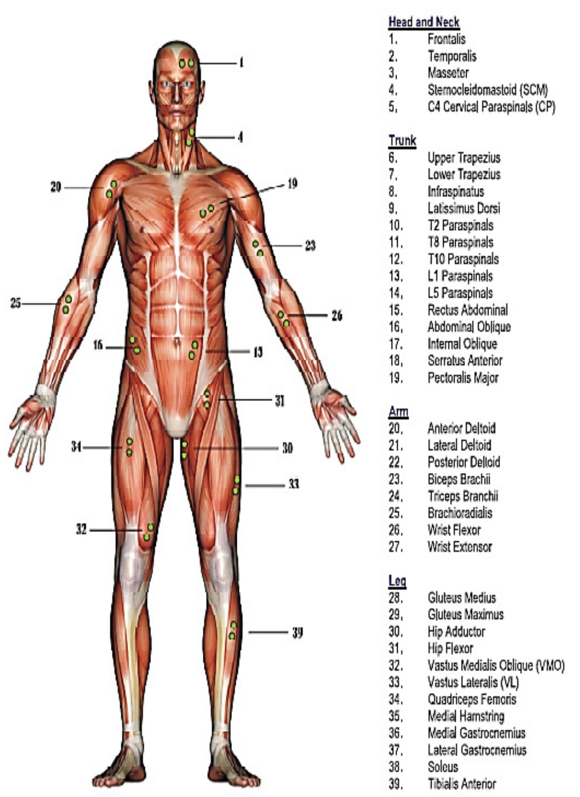

Figure 3) *The index points in recording surface electromyography (sEMG) [33]*

The Electromyogram signal is a random signal with different noises such as movement artifact and environmental noise [30,31]. Therefore, because of the complex patterns in it, its classification and analysis are very complicated and require different processing techniques [32]. Due to the interference of the EMG and noises, the real signal characteristics disappear. These specifications relate to tissue structure, skin temperature, and blood flow velocity in the target area [11]. Identifying all kinds of electromyographic noise is essential in the precise design of the simulator.

Inherent noise of electrodes

All electronic equipment generates noise at frequencies of 0 to several thousand Hz. This noise cannot be completely eliminated, but the improvement of the quality of electronic instruments and the design of intelligent circuits can greatly reduce its effect [11,33,34].

Increasing the size of the electrode, decreases its impedance. Also the quality of recorded signal and SNR greatly become better. But due to the effect of the activity of near muscles (cross-talk), during the recording signal the use of big electrode is not acceptable.

Motion artifact

In general, the motion artifact comes from two main sources. First, moving the cables connected to the electrodes and the amplifier can create this artifact. Also during the muscle activity, the length of the muscle decreases so this contraction causes the motion of skin and electrode. On the other hand, the difference between the potential of different layers of the skin can add noises to the recorded signal [35].

The frequency of these artifacts is about 0-20 Hz and recessed electrodes and a layer of conductive gel on the skin reduce their effects [35].

Electromagnetic interference

The electromagnetic sources near the EMG device cause noises in the signal, usually the amplitude of noises is greater than the original signal and their frequency is about 0-500 Hz (the most dominant is at 50 or 60 Hz (PLI) frequency) [36-38]. Off-line processing can remove this artifact [35]. Also, during signal processing, the actual signal is recognizing by the frequency of 50 Hz and its four harmonics (100,200,300 and 400 Hz) [39].

Heart electrical activity

This interference is one of the most important components of EMG interference [40], which appears more in trunk muscle electromyography [41]. Although the removal of this artifact is very difficult, its effect will be greatly reduced by determining the exact location of the electrodes and the use of high-pass filter and common-mode rejection during the recording [42-44].

Other cases of EMG noise include the effect of the activity of a muscle group (cross-talk), inherent instability and the inherent noise of the signal [11].

Importance of EMG simulator

To develop and validate bioelectric signal measurement systems, especially automated systems, there will be a realistic validation method. Although different parts of a measurement system, including hardware, software, and signal processing algorithms, are separately verified and validated, typically, the validity of the entire system as part of each phase increases reliability in the validation process. This validation requires that the sample bioelectric signals in the same way that are generated are given to the system and the output of the whole system is investigated. One of the validation methods for bioelectric systems is to use measurement cards that are controlled by the computer and highly expensive. If the system is constantly being developed, its validation in several stages will increase the cost of this test, but the costs can be significantly reduced with the help of a simple simulator. In this method, the signals recorded are modulated using a sine wave signal with a higher frequency (amplitude modulation). This modulation causes the signal frequency to be changed temporarily, which can prepare the signal to broadcast through the audio card and other audio devices. Again prior to entering this signal into the test system should be demodulated by a detector [45].

MATERIALS AND METHODS

By the graphical programming software, LabVIEW, which is known as a standard model in data collection and processing, simulation and control of various tools, we simulated an EMG Simulator. This software is a powerful and flexible tool for analyzing measurement systems. By using this software and PCs, real-time measurement systems can be simulated ritualistically.

Based on mentioned points, we designed a surface EMG simulator in LabVIEW software (Figure 4). This circuit simulates the surface electromyogram resulting from the isotonic contraction. During isotonic contraction, the length of the muscle is shortened, but the pressure on it stays constant. Isotonic contraction characteristics depend on the load on the muscle and the load inertia.

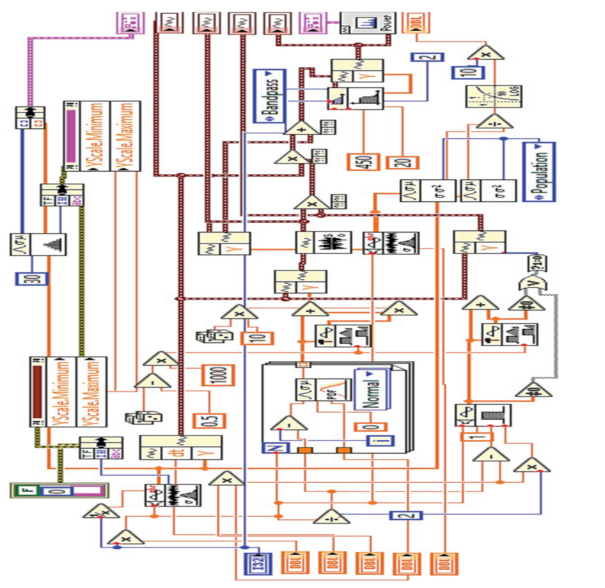

Figure 4) *Block diagram of the sEMG simulator*

In this circuit, at First a few parameters must be specified. Factors of the simulation signal including duration (s) and frequency (Hz), the modulation signal factors include the variance (in the range of 50 to 150), the alpha coefficient (in the range of 1 to 5) and sEMG signal factors including signal amplitude, noise domain variance and SNR (dB) are determined by the user. Then a Gaussian signal is produced randomly. Also, a Gaussian signal is shortened with a pulse signal to obtain suitable time intervals with smooth domain variations.

In the following, the produced signals are added to the random Gaussian signal and the sEMG signal is generated. At last this signal passes from a band pass filter. The frequency range of this filter is a bout 20 - 450 Hz.

RESULTS AND DISCUSSION

First, we investigate the output of this simulator. As expected, the output of this software is a Real-Time signal and in comparison with the real EMG, has an adequate accuracy and precision (Figure 5).

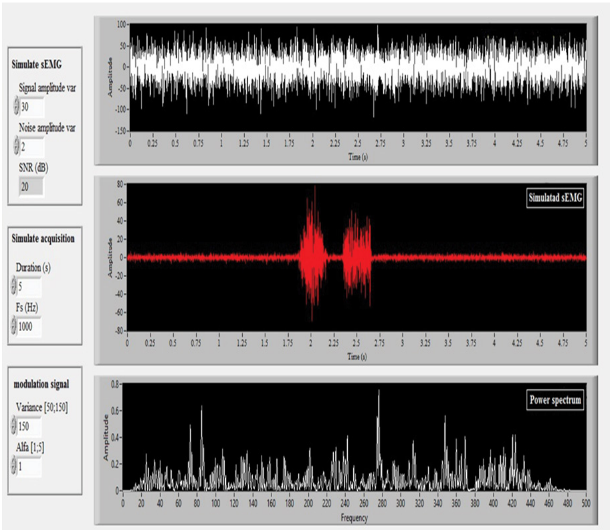

Figure 5) *The output of sEMG simulator*

With the Modbus protocol in the LabVIEW software, this simulator can be connected to the hardware and it can provide an acceptable signal for software and hardware processing such as testing and calibrating the electromyography devices or creating the proper conditions for testing the controlled prostheses with EMG signal.

Also, if needed, this software can calculate and display the various characteristics of the signal such as histogram and power spectrum diagrams.

Finally, we can do the same work with a random Gaussian signal in MATLAB software. Then the generated signals transferring to hardware through the audio cards.

CONCLUSION

Electromyogram is a biomedical signal that contains valuable information about the anatomical and physiological characteristics of the muscles. This signal has many uses in the field of diagnosis, treatment and rehabilitation. Today, by EMG signal many motion disorders and disabilities are easily diagnosed and treated. On the other hand, in recent decades, new technologies in the field of rehabilitation such as cybernetic hands have attracted much attention to EMG signal. Because the use of this signal is easy and is an effective way of obtaining control commands.

Depending on the operation of the EMG devices, may have some problems. The most common problems with this device can be the signal's obviousness, the device's electronic bugs, and definitive communication wires.

So due to the importance of electromyogram signal, accuracy and precision of the electromyography device are very important and continuous testing and calibration of this device is essential. Also, the increasing development of new technologies based on EMG requires various and extensive testing in this regard. The most efficient and safe way to carry out these items is to use the EMG simulator. Considering the costs associated with the hardware simulators, it can be said that replacement of such software simulators is very cost effective and will be readily available at any location and time.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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