Design of Portable Electromyography (EMG) System for Clinical Rehabilitation

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ABSTRACT The surface electromyogram was found very useful in muscle activity scanning and diagnosis purposes. With the high demand from the physiotherapist and neurophysiologist, electromyography (EMG) has been developing rapidly to meet the needs. The quantitative analysis of the EMG signal is required to provide particular characteristics of the EMG signal. In this paper, the EMG signals system's design is presented, and the proposed portable EMG system design concept is discussed to improve the current difficulties of EMG signal collection. The sampling frequency of the EMG signal is between 20-500Hz. The EMG signal is received effortlessly using the wired devices during the contraction of the muscle. The portable non-invasive EMG system was successfully reducing the interference of the signal whereby the movement of the muscle can be easily detected during the data collection.

KEYWORDS: Electromyography; EMG; Rehabilitation; Signal Acquisition; Classification
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Design Study

INTRODUCTION

The first study of the electromyogram (EMG) has begun in the year 1666 by Frabcesco Redi (Huynh *et al.*, 2020). The EMG signal is the electrical bio-signal generated by the neuromuscular activity. Initially, the EMG signal is obtained using the invasive electrodes and oscilloscope to record the movement. With the EMG's sustainable development in the clinical requirement, surface electromyogram (sEMG) was first introduced in 1960. The researchers have found that sEMG is very useful in muscle activity scanning and further develops EMG apparatus (Cram *et al.*, 1998). With emerging technology, the EMG signal can be utilized in many applications to improve our daily needs. However, the signal obtained using the sEMG was not as perfect as invasive EMG. The invasive EMG places the electrode needle under human skin to collect the data, which requires professional personnel to complete the routine. In addition, needle placement is caused uncomfortable to the patient, and it is needed a longer time to complete the procedures. However, invasive EMG is able to produce a more accurate signal collection. In contrast, the sEMG has several drawbacks, including noises and offset issues. It is required a high-performance data collection circuit and filter to obtained accurate weak muscle signals.

With the high demand from the physiotherapist nowadays, the electromyography has been developed and improve rapidly to meet the needs. An electromyography is a device used to diagnose and assess an individual (Chan *et al.*, 2013). The device has been used to evaluate biofeedback or ergonomic purposes, research and development in clinical, biomedical engineering, neuromuscular physiology, and many other related applications. Today an appropriate number of innovative EMG applications are commercially presented and assist in weak or older adults. The physiotherapist conducted a complex clinical analysis of neurological and neuromuscular to diagnose the illness. This clinical analysis commonly shows in the hospital or laboratories. The trained physiotherapist usually uses gait laboratories for ergonomic or biofeedback evaluation. The physiotherapist will analyse, track, and identify the human motion base on the data collected in the gait laboratory (Chan *et al.*, 2018).

In medical sciences, myopathy and amyotrophic lateral sclerosis (ALS) is a muscular disease associated with muscle damage and the organ system's impairment that causes the muscle fibers not to function correctly (Dharmadasa & Kiernan, 2018). Both conditions required an accurate essential diagnosis to prevent diseases from deteriorating. The physiotherapist helps the patients maintain function as much as possible and adapt to changes over time as muscle weakness progresses. Traditionally, a neurophysiologist can detect the abnormalities with reasonable accuracy by acquired the EMG signal using invasive electrodes. The neurophysiologist diagnoses the abnormalities through the EMG signal. However, the diagnosis method and the procedures are complicated and required the specialist to handle them. Moreover, the invasive electrodes would cause uncomfortable to the patient during the data collection. Besides, it may not be sufficient to describe less obvious deviations or mixed abnormalities signals. Quantitative analysis of the EMG signal was required to provide detailed information on the muscle. The changes in the movements consist of their particular characteristics. An artificial intelligence method would be employed in the diagnosis and predict neuromuscular disorders. The feature extraction, including amplitude and the shapes of the signal, will be taken into consideration. Then the features will be classified into several classes and determine the diseases.

In this paper, initial design of portable non-invasive electromyography system device for clinical rehabilitation is proposed and discussed. The concept and some of the signal collections of this design will be emphasized in this paper. The device's development would help the neurophysiologist and physiotherapist determine the muscle's abnormalities in the future.

REVIEW OF PREVIOUS WORKS

Electromyography is the technique of obtaining the bio-signal generated from the muscles. The muscle generates the random frequency bio-signal in the range of 0 – 500Hz. The EMG signal is in a petite range, which is in micro to millivolt. The EMG signal can be said to vary according to time. The model of the EMG signal can be represented as in Equation (1).

$$x(n) = \sum_{r=0}^{N-1} h(r)e(n-r) + w(n) \quad (1)$$

where, $x(n)$ is the EMG signal, $e(n-r)$ is the firing impulse of the signal, $h(r)$ is the motor unit action potential (MUAP), and $w(n)$ represents the zero-mean additive white Gaussian noise. Meanwhile, the N is represented the number of motor unit firing (Amrutha & Arul, 2017).

There are two methods of Electromyograph signal measurement, including invasive and non-invasive measurement (Wong *et al.*, 2015). Invasive measures require a professional physiotherapist or neurophysiologist to place a needle under the human skin to collect the data. In contrast, the non-invasive measurement has placed the electrodes on the skin to detect the muscle signal under the respective skin area (Seng & Wong, 2012). The essential EMG signal acquisition consists of several sections, including instrumentation amplification, noise filters, and isolation filter, as shown in Figure 1. The instrumentation amplification is essential due to the extremely low signal voltage from the electrodes, approximately micro to millivolt (Li *et al.*, 2010). Moreover, an accurate amplification circuitry must tackle the signals' changes concerning time and frequency, which will improve the signal analysis.

The signal filtering is critical in design and implementation in the EMG circuitry development (Saad *et al.*, 2015). The signals are required to be processed to eliminate the unwanted external signal and high-frequency signal. Furthermore, signal filtering is essential to processes other possible artifacts. A study of the researchers has found that the useful signal frequency of the muscle using the electrodes is between 10-200Hz. The overall system's frequency response must be dominated by the lowest response of any piece of interfaced equipment (Gilmore *et al.*, 1983).

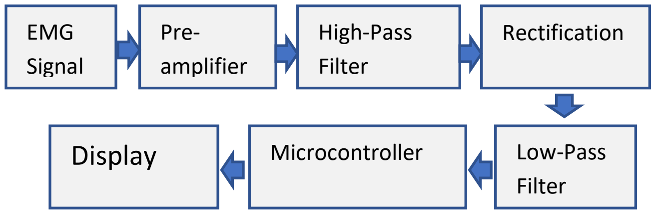


Figure 1. Conventional EMG signal acquisition

The signal analysis can be classified into time and spectrum analysis. The sEMG is a random signal. However, the variance changes insignificantly with the signal intensity in the time domain analysis. The EMG signal characteristics can be extracted according to the friction, integrated electromyogram, root mean square, average electromyography, and zero-crossing rate (Ren *et al.*, 2012). On the other hand, the spectrum analysis is related to the frequency produced from the movement power received using the EMG electrodes. The spectrum analysis consists of the power spectrum, spectrum, and characteristic parameter. The previous design for the clinical study did not involve signal classification and analysis. An analytical expression for the EMG signal classification helps the clinical personnel analyse the muscle signal. Moreover, the previous design is not accurate due to linear approaches are often used for EMG signal classification. There are some noises embedded in the system, which causes the complexity of the signal classification (Aceves-Fernandez *et al.*, 2019).

Feature extraction is used to reduce the size of the raw data and develop a new feature from the data collected by different methods. The feature extraction in the electromyography signal is used to classified the characteristics of the EMG signal. Choosing the significant features for seemly classification is essential due to the acquire EMG signals' intricate signal characteristics (Saikia *et al.*, 2019). The functional parts have to be separated from lending a high and accurate classification rate. The features are extracted, including mean absolute value, waveform length, average, absolute maximum, etc., in the time domain (Tsenov *et al.*, 2006). The classifier is the essential technique to categorize the signals. The most popular EMG features extraction is using the mean absolute value $(Mean_{Abs})$. $Mean_{Abs}$ defined the average absolute value as shown in Equation (2).

$$Mean_{Abs} = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{2}$$

The Root Mean Square (RMS) is used to extract the features of the muscle force and non-fatigued contraction. The expression of RMS is shown in Equation (3).

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} x_i^2} \tag{3}$$

For the Wavelength $(Wave_{Length})$method, it is using the cumulative time length of the waveform as shown in Equation (4).

$$\sum_{k=1}^{N-1}|x_{k+1} - x_k| \tag{4}$$

N represents the signal analysis window's length, k is the iteration of the EMG sample, and x_k is the amplitude of the EMG signal for all the expressions (Too *et al.*, 2019).

The quality is significant to the classifier, and there are several types of feature extraction available, including Wavelet Analysis, Principle Component Analysis, Histogram of Oriented Gradients, etc. The accuracy of the feature extraction depends on the classifier and the type of signals (Chowdhury *et* *al.*, 2010). The classifier is using the deep learning algorithm to assign the training data into a particular data point. The most common classifiers have been used, including K-Nearest Neighbour (KNN), Support Vector Machine (SVM), and SVM Kernel Trick. KNN classifier is using a similar differential technique of humans to identify the object. The use of KNN could ease the interpretation of the data, calculation time, and predictive power. On the other hand, the SVM is used to provision multiple classes. The accuracy of the SVM can be improved by providing a supervised learning method to the SVM. Instead, the SVM kernel trick classifier is more toward the complicated assignment. The complication of the example, such as the target, cannot be identified between two or multiple classes (Paul *et al.*, 2017).

DEVICE CONCEPT

The overall design of portable wireless non-invasive electromyography system device for clinical rehabilitation is shown in Figure 2. The proposed system can be classified into five sections, including signal collection, dataset training (classification training), raw data collection, real-time processing and classification, and internet of things and processed data storage. In this paper, the initial design of the EMG signal collection will be emphasized. Five channels of reusable electrodes are proposed to be used in the data collection. The reusable electrodes would help to reduce waste and more eco-friendly. Due to wireless data transmission, the reusable electrodes will be modified and attached to the pre-amplifier circuit. The modification could avoid the wires connected between humans directly to the device. The wireless transmitter is integrated with the amplifier circuit. Further discussion of the circuit will be elaborated in the Circuit Design section. Raw data collection is the main section to collect the signal collected from the transmitter. All the data collected from the same user will be compressed into the same dataset. The dataset training will use the dataset from the raw data storage to determine the classification model (Jain & Garg, 2019). The classification model will then feed to real-time signal processing to determine the EMG signal classification. The classification results will forward to the data storage centre for further analysis by a neurophysiologist or physiotherapist in the hospital.

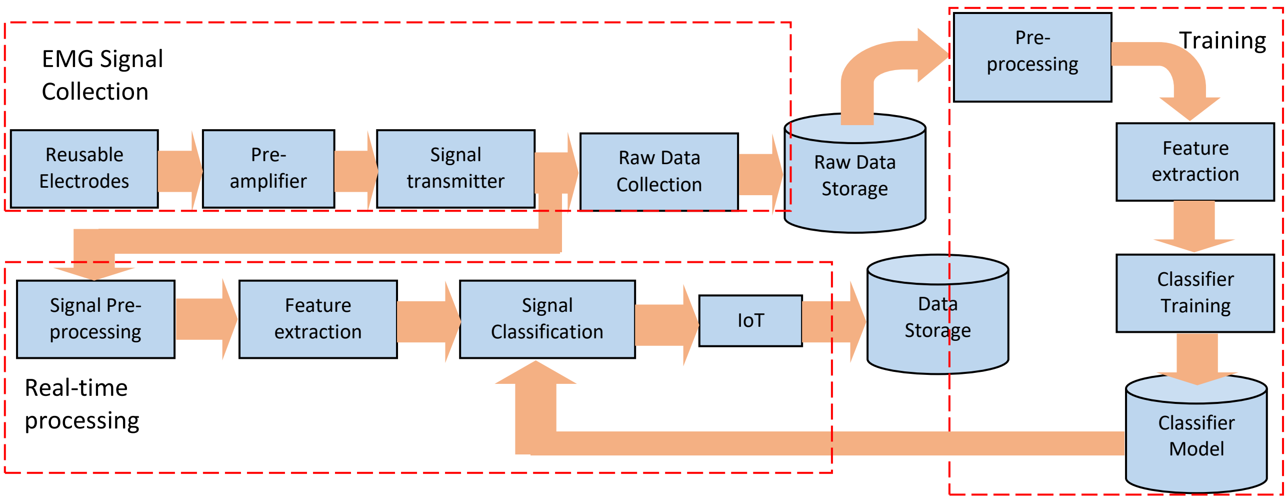
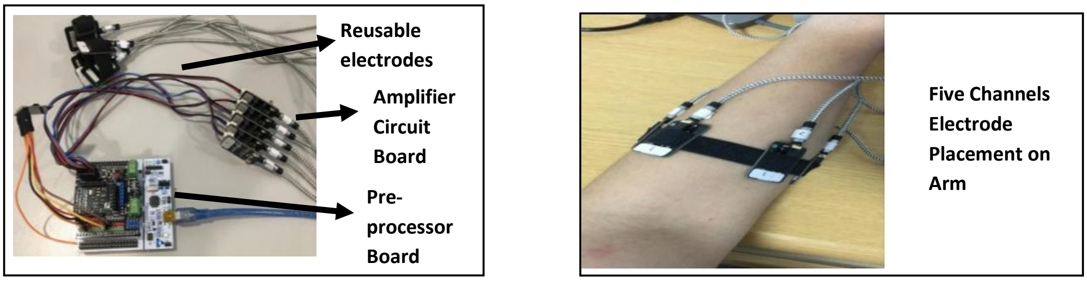


Figure 2. Portable Wireless Electromyography System Diagram

CIRCUIT DESIGN AND ELECTRODES PLACEMENT

Before commencing the development, a preliminary test has been conducted to ensure the wired product's stability and functionality. Figure 3(a) and Figure 3(b) show the hardware connection and the electrodes' placement on the hand, respectively. From Figure 3(a) and Figure 3(b), it can be observed that the electrodes and amplifier circuits are connected with wires. The messiness of the wires could cause interference issues during data transmission (Amrutha & Arul, 2017). Moreover, it could cause uncomfortable to the users during the data collection (Alseed *et al.*, 2019).



(a) (b)

Figure 3. (a). Hardware connection between electrodes, pre-amplifiers, and pre-processor board. (b). Electrodes placement on forearm for EMG signal collection.

Hence, the electrodes will be refined and integrated with the pre-amplifier circuits to avoid interference issues and enhance the user-friendly experience. The preliminary design of the wireless electrode circuit is shown in Figure 4. The system is integrated with the signal pre-processing board, wireless data transmission module, and electrodes. With the integration of the wireless module with the electrodes, it will reduce the uncomfortable issue during the EMG signal collection. Besides that, the wireless electrodes could enhance the data collection especially during the data collection for movement.

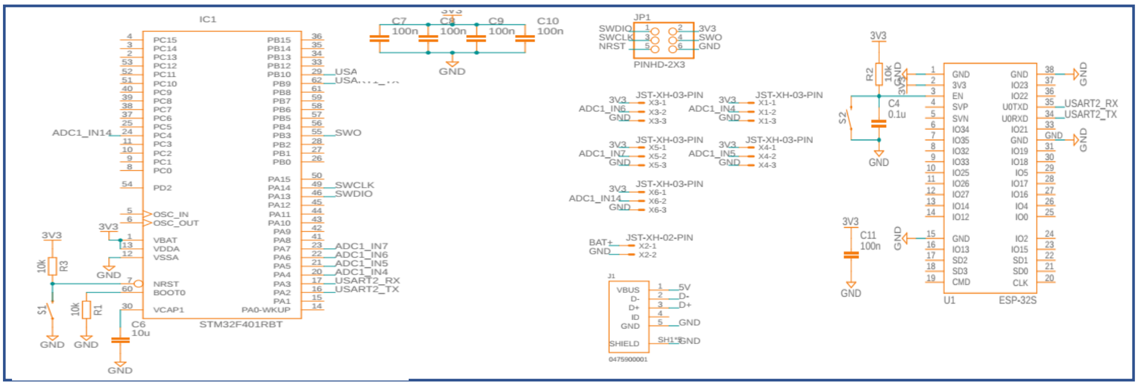


Figure 4. Preliminary design of integration wireless electrode with the pre-processing board.

DEVICE PERFORMANCE AND ANALYSIS

The preliminary design and performance of the portable device were obtained and discussed in this section. Figure 5 shows the signal collected using the circuit shown in Figure 3. The sampling frequency was initially set to 1kHz. From the signal observed, the data collected was clipped due to the overshot amplitude. The sampling frequency was then assigned to 200 Hz, and the signal was recorded as shown in Figure 6.

As observed from Figure 6, the EMG signal obtained using the sampling frequency was not distorted. It is proof that the sampling frequency of the EMG signal should less than 1kHz to avoid the distortion of the signal. The range of the sampling frequency has been discussed in. The sampling frequency of the EMG signal should be between 20-500 Hz. The initial action of the forearm is relaxing. However, there is some noise obtained. This could be due to surrounding noises or the interference of the wires. The noise could be reduced by using the wireless electrodes and algorithms-based filter to eliminate the noises. EMG amplitude has changed during the forearm movement, as observed in Figure 7. and Figure 8. The multiple signals obtained due to electrodes received muscle signals all around the forearm. However, different directions of the forearm will lead to the various signals obtained. The additional signals shown in Figure 8. have different amplitudes and frequencies. The noises need to be eliminated to improve the signal extraction and classification in the next stage.

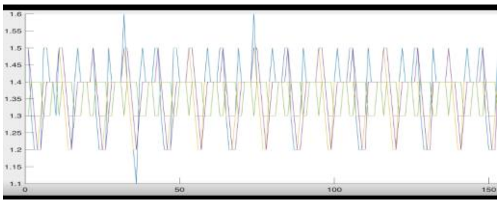


Figure 5. EMG Signal collected using sampling frequency of 1kHz

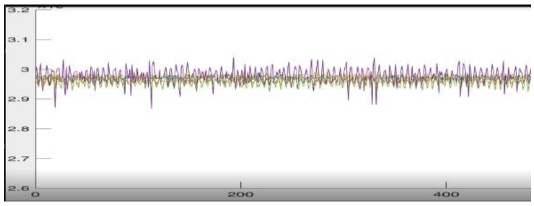


Figure 6. EMG signal collected using sampling frequency of 200Hz

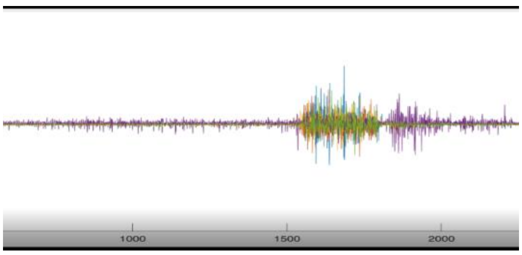


Figure 7. Multiple EMG signals were obtained during hand movement

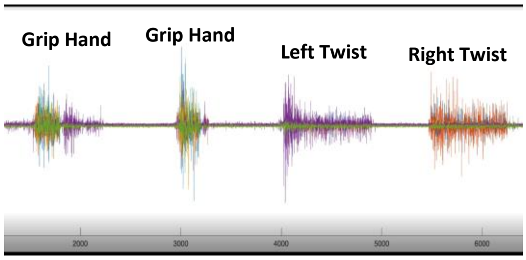


Figure 8. Multiple direction movement of the forearm

CONCLUSION

The preliminary test of the wired non-invasive electromyography system has been successfully tested. In this paper, the difficulties of the hardware have been identified. It was found that the wired device produces the interference of the signal and causes uncomfortable to the user during the data collection. Moreover, the sampling frequency needs to be fixed between 20-500Hz to receive an EMG signal. As a result, the signal receives effortlessly during the forearm movement and different hand movements. The sensitivity of the device in detecting the EMG signal is high which is provided better data collection platform for the physiotherapist in the future.

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