Design of a real time portable low-cost multi-channel surface electromyography system to aid neuromuscular disorder and post stroke rehabilitation patients

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***Abstract*— Surface and needle-based electromyography signals are used as diagnostic markers for detecting neuromuscular disorders. Existing systems that are used to acquire these signals are usually expensive and invasive in practice. A novel 8 channel surface EMG (sEMG) acquisition system is designed and developed to acquire signals for various upper limb movements in order to evaluate the motor impairment. The real time sEMG signals are generated from the muscle fibre movements, originated solely from the upper limb physical actions. Intuitively, sEMG signals characterize different actions performed by the upper limb, which is considered apt for assessing the improvement for post stroke patients undergoing routine physical therapy activities. The system is designed and assembled in a view to make it affordable and modular for easier proliferation, and extendable to motor classifying applications. The system was validated by recording realtime sEMG data using six differential electrodes for various finger and wrist actions. The signals are filtered and processed to develop a machine learning (ML) model to classify upper limb actions, and other electronic systems are designed in the portable form around the patch electrodes. A classifier was trained to predict each action and the accuracy of the classifier was assessed across different usage of channels. The accuracy of the classifier was improved by optimizing the number of electrodes as well as the spatial position of these electrodes. The sEMG circuit designed has the capacity to characterize wrists, and finger movements. The improvement observed in the sEMG signals should benefit the physiotherapists to plan further protocols in the prescribed rehabilitation program.**

***Clinical relevance*— A portable and low-cost sEMG system allows patients to have easy access to motor functionality assessments as well as aid physiotherapeutic exercises. Ready access to such a system will not only allow physicians to perform motor impairment studies but also help to quantify and gauge the rehabilitation progress through periodic and frequent assessments of the motor system.**

I. INTRODUCTION

Extremely low electric currents are generated from the muscle fibres due to the physical movement of human body driving the muscle movements [1]. These low currents are observed to have a pattern for different movements, and are commonly measured non-invasively by placing electrodes over the skin. The signal acquired by the electrodes are known as surface Electromyography (sEMG) signals that ranges from μV to mV at the surface of the skin, and is usually observed at 50-150 Hz frequency spectrum band. Surface EMG is widely accepted in medical fraternity due to its hassle free application of electrodes on the patients under investigation, and minimum turn around time to determine the signals. The motor functionality of muscles can be ascertained using the sEMG signal, as the amplitude and other characteristics of the signal measured are directly correlated with the muscle activity [2], [3]. Hence sEMG is commonly used to evaluate motor functionality of post stroke patients and assess the degree of impairment [4], [5]. Accurate motor impairment assessments could help physicians understand the type and severity of the impairment, which will help in better planning of physiotherapy. Periodic motor assessments would help in gauging the motor improvement and helps guide further course of rehabilitative measures [6].

Commercially available sEMG system allows multi-channel and raw-data collection, and are usually either expensive, bulky, or sparsely available, leading to highly inaccessible to the patients under need. A two channel low cost EMG signal acquisition and processing circuit is described in [7], [8], however picking all possible muscle signals from two channels is not adequate to characterize upper limb actions, hence multi-channel sEMG signal acquisition and processing system in a compact form is required. An ultra low power microcontroller was considered for implementing EMG signal processing algorithms and evaluate muscle signals as reported in [9], hence a similar system for multi-channel, with additional characterization of upper limb actions is needed.

In the past, correlating muscles for specific activities are reported [10], [11], [12], however the finer movements of the upper limb are still not characterized efficiently, hence a multichannel sEMG signal with spatial positioning of electrodes for picking specific muscle movements needs thorough investigation. Characterization of finer movements will assist in recovery of partially deformed parts of the upper limb, especially for patients suffering from specific parts of fingers, or wrist. A wearable system with dry electrodes to measure EMG signals was also investigated in the past for measuring the agility index [13]. Again the system lacked the characterization of finer movements, hence the system may not be directly applicable for rehabilitation of post stroke and neuromuscular disorder patients.

EMG signal is inherently stochastic in nature and contains noise, hence special signal processing technique with prior feature extraction is generally a preferred method [14].

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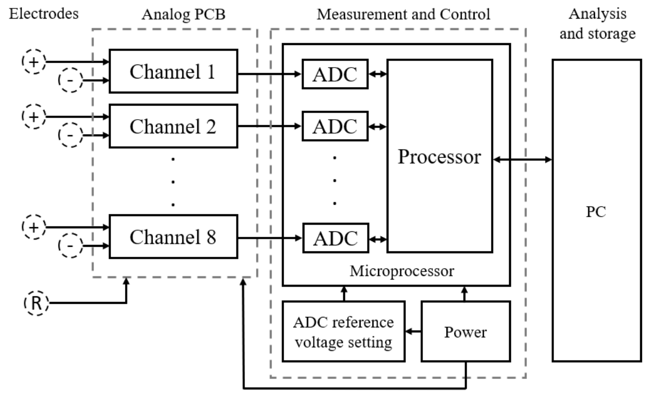

Fig. 1: Block diagram of the EMG signal acquisition system

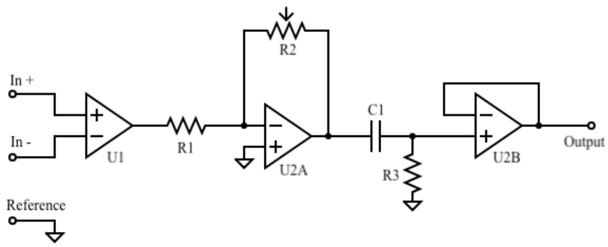

Fig. 2: Circuit diagram of a single channel EMG amplifier

The paper proposes not only a circuit for EMG signal acquisition, but also a real time classifier technique for characterizing upper limb movements. Classifier techniques in the form of Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) were applied for similar upper limb movements [15] and accuracy for five channels EMG system were reported earlier. However the spatial arrangement of patch electrodes towards higher accuracy are not studied in the past, hence an optimized number, and spatial position of electrodes to cover all upper limb actions is much needed and critical for a robust system design. In this paper, an 8-channel sEMG system is proposed, with real time classification capability, and an optimized placement of electrodes to acquire signals and characterize upper limb actions are presented. The device is envisioned as a sensory system applicable towards domestic rehabilitation assessment for post stroke patients, considered an alternative to the supervised assessment currently practiced. The physicians can modify the prescribed set of therapy based on the sEMG signal assessment report, and chart a plan towards complete recovery of upper limb.

II. DESIGN

The sEMG signal acquisition system was designed to be modular, with 8 separate channels, and the overall fabrication of the system was made cost effective. Major components of the system are: the electrodes in the form of patch connected to front end analog design for signal amplification and conditioning, followed by signal digitization and last stage consisting of storage, and analysis, as shown in the Figure 1.

In the design, bipolar electrode architecture was preferred over the unipolar architecture due to the following reasons. Bipolar architecture allows the strategic electrode placement on various muscle groups with different spatial configurations, allowing the choice of acquiring differential signal between two distinct points along the length of a muscle fibres. In addition, bipolar system favourably rejects common mode noise better than the unipolar configuration. Single use gel adhesive electrodes (3M Red Dot Sticky Gel 2560) were used in the design as they are affordable in the order of 10 cents per electrode, and are widely available. These electrodes provide a very high signal quality while requiring minimal to no skin preparation. Alligator clips connected these electrodes to the front end circuitry. Ideally the wires carrying signal from the electrodes to the circuitry should be shielded to reduce noise. The wires were designed to be short in length and the differential pairs were twisted together to avoid noise.

The analog circuitry was designed to accommodate eight simultaneous differential channels. The analog system was designed with an intention to use minimal circuitry. An instrumentation amplifier was used as the first stage to amplify the differential signal, that rejects common mode noise, while preserving and amplifying differential signal. Hence a differential amplifier with a high common mode rejection ratio was chosen. A natural choice would be to use an instrumentation amplifier (Fig 2 U1 INA106U/2K5) such as the INA106 series, which meets the required specifications. The gain of this instrumentation amplifier is fixed. This signal was further amplified in a second stage (Fig 2 U2A LM358DT) which has a variable gain controlled by a potentiometer and passed to an active high pass filter (30Hz cutoff frequency) circuit as shown in the Figure 2. The buffered output (Fig 2 U2B: LM358DT) of the filter is directly digitized and stored using an ADC. The instrumentation amplifiers and the active filters are housed on a PCB. The overall setup with 8 channel electrodes are shown in the Figure 3(a). The PCB was fabricated using a additive PCB printer, where conductive ink was deposited onto the PCB, then appropriate SMD components were reflowed to get the printed circuit as shown in the Figure 3(b). The filtered analog signal was then used as an input to the analog to digital converters in a suitable microprocessor such as the Atmel SAM3X8E ARM Cortex-M3 board. The reference of the ADC was adjusted to convert complete analog signal swing to digital. The microprocessor sampled all 8 channels data at the preset sampling rate, and transferred data to a system where it is stored and processed further. A snapshot showing ARM cortex microprocessor and potentiometer to adjust ADC level is shown in the Figure 3(c).

The EMG signal is dominant between 50 Hz to 150 Hz. The system samples the signal at 20kHz frequency, which more than satisfies the requirements of EMG recording. The acquired signal is processed to remove any DC component and noise using digital filters. Two major filters were designed: a notch filter to remove any AC power noise around 50 Hz and a band-pass filter from 30Hz to about 300Hz

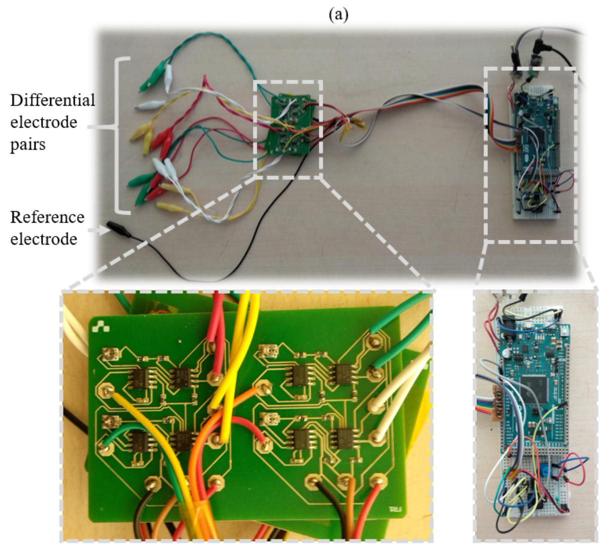

Fig. 3: Prototype showing (a) sEMG signal acquisition system with electrodes, (b) Image of sEMG printed circuit board, (c) Image of microprocessor and ADC setup that is interfaced to the acquisition system.

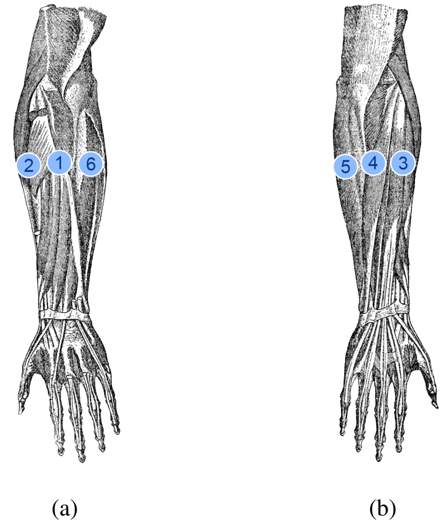

Fig. 4: Schematic representing placement of six electrodes with (a) three electrodes on the posterior side of the arm, and (b) three electrodes patched on the anterior side. Image redrawn from [16]

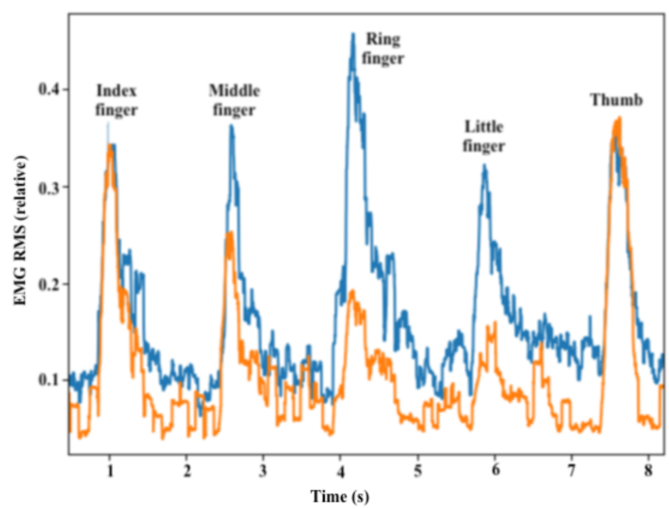

Fig. 5: EMG signal response for individual finger movements, using two channel system.

to eliminate other signal noise. In this processed signal, any EMG signal would appear as an oscillating wave with changing amplitude. For further analysis, the processed EMG signal is passed through a moving window RMS calculator, to estimate energy of the signal at discrete time points. The moving window RMS calculator depicts the strength of the EMG signal for different upper limb actions performed over time.

III. Experimental Analysis and Results

The overall sEMG setup was applied to record wrist movement, and flexion action of the fingers. Six channels from the eight designed channels were used and mounted radially on the arm as shown in the Figure 4. Six pairs of electrodes completely covered the circumference of the forearm, where the electro-muscular activity was detected. On posterior side of the arm, the muscle density is less when compared to the anterior side, hence only two electrodes were patched on the sides, that provided adequate signal level. The individual fingers of upper limb were actuated for flexion action, and signal response was experimentally acquired by the EMG acquisition system.

A. *Principle of operation*

Figure 5 shows RMS response of the sEMG signal for two channels over time, characterizing the flexion action of individual fingers. Both channels show a sharp rise in the signal level, attributing to the movement of the individual fingers. The amplitude of the signal is different for each of the channel, which is fundamentally related to the source of the EMG signal generated due to the muscle fibres at different locations, away from the placed electrodes. The generation of the EMG signals at varying locations leads to the difference in the magnitude of signal recorded at each electrode. As observed in the Figure 5, the amplitude signature is used to estimate the origin of the muscle set signal, and characterize the performed action. Similar change in signal level is detected for all six channel based EMG system when placed on arm. The change in signal level is detected in each of the six electrodes when each of the fingers were actuated. If each action is repeated exactly by the person, the performed action is actuated using a set of muscles fibres and the amplitude of signal picked up by the electrodes has a unique fingerprint. However, every time an action is performed, the generated EMG signal is different, due to various factors including difference in force applied, sets of muscle fibres used, and muscle fatigue [17]. Hence to overcome this issue, the absolute value of the EMG signal is seldom used. Instead, the EMG data is normalized and then used for further analysis.

B. Feature extraction

The proposed method when applied for every action, RMS waveform for all six channels were generated, with maximum value of RMS from the six channels were considered as absolute valued feature vector. A fixed-length moving rectangular window was used for calculating the RMS value. The length was determined by trail and error to maximise the RMS energy difference between actuation and relaxation. Vector consisting of six RMS values were further normalized and reduced to vector of length five, by considering the ratio of RMS of each of five channels to one chosen channel RMS value. Vector of length five is utilized in the classifier to predict the upper limb actions. The choice of one of these RMS values as the normalization factor is also a variable, which heavily affects the classifier accuracy.

C. Action classification and model accuracy

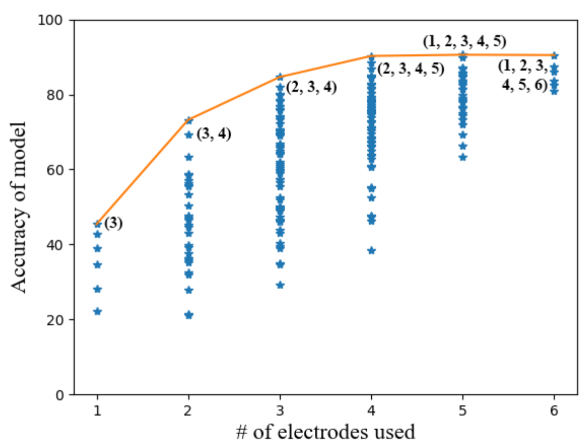

Fig. 6: EMG signal classification accuracy for 4 fingers vs. the number of electrodes used. (*, *, ..) represents the electrode combination corresponding to that accuracy.

sEMG signal was collected for all the actions including finger flexion and the wrist movements from an individual. In total 331 actions were captured and the features were extracted and normalized. The data was divided into 80% training and 20% testing classes. The training features were then used to train support vector machine (SVM [18]) based classifiers. Several permutations and combinations were tried to get the optimal feature creation and find the maximum testing accuracy with minimum number of electrode usage. Model for different target classes were investigated. One such case is the prediction model for 4 finger classes, in which data pertaining to only those 4 finger movements were used to calculate the accuracy. Next, all possible variable states were tried to attain maximum accuracy. The classifier model was also investigated for different number of electrodes being used. It was felt that using only a subset of electrodes may achieve a higher testing accuracy. In order to investigate the same, all combinations of electrode choices were considered in the experiments. For example, in one such case, electrodes 1, 3, and 5 as a combination is used to generate features and calculate accuracy. Further among the chosen electrode subset, the choice of the electrode used for normalization is also a variable. The result of one such experiment with 4 target finger actions is shown in Figure 6, where each data point (blue star) represents a unique variable set of electrode subset and normalizer choice, which resulted in certain accuracy. The orange line shows the maximum possible accuracy achieved for respective number of electrodes used.

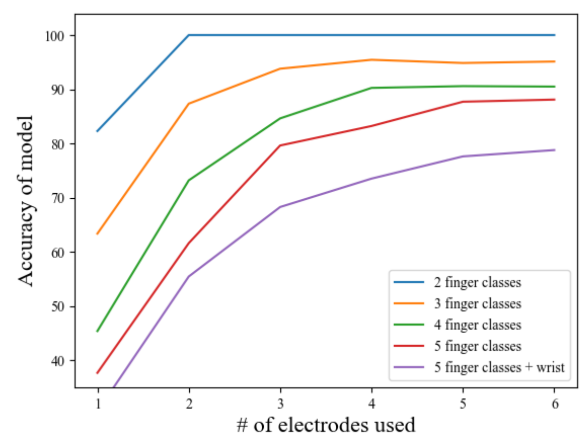

Fig. 7: EMG signal classification accuracy for N fingers versus the number of electrodes used

D. Optimal number of electrodes

Figure 7 contains the data of model accuracy for various target classification sets as the number of electrodes, used were changed. If one requires to only differentiate between two finger actions, then two electrodes was adequate to serve the purpose as more number of electrodes does not change the accuracy of the model. Similarly if one required to differentiate between 5 finger classes, than 5 electrodes usage was recommended. In general it was observed that the number of electrodes required is same as the distinct number of classes one targets to predict.

E. Optimal spatial placement of electrodes

From the Figure 6, the highest data point (blue star) for each electrode subset number represents an optimal combination of electrode choice which yields highest model accuracy. It was observed that this choice of electrode subset followed a pattern. It was found that electrode #3 was always top choice or within 5% accuracy of the top choice, followed in order by the electrodes #4, #2, #5, #1 and then #6. The experimental results indicated that if one wanted to use the system with 3 sets of differential electrodes, it is optimal to place them at positions of #3, #4, and #2. This is also biologically intuitive as most of the flexor muscles lie directly beneath those areas as also shown graphically in Figure 4(b). The closer the electrode to the target muscle group, the higher signal quality is achieved hence allowing a better classification accuracy.

F. Realtime action classification

The proposed system was designed to render a realtime classifier. The model was trained on an individual and then tested in real time. The system constantly measures EMG signals, and detects possible muscle actions when it sees an increase in EMG signal energy corresponding to an increase in RMS value of the signal. As soon as an action is detected, EMG data is collected and using a classifier the target action is predicted. The EMG data from start and end of the action is used to generate a feature vector which is used as input to the classifiers. It was generally found that the system collected data for about a hundred milliseconds and generate a prediction, within a span of tens of milliseconds. The reduced latency of the realtime classifier system can be further utilized to various other upper limb actuation systems including prosthetic hand and wearable exoskeleton devices.

G. Overall cost of the system

It was observed that the overall cost of this system was around USD 200. The majority of the cost being the instrumentation amplifier ICs, that can be replaced with more affordable options. The cost of the entire system could be further reduced by employing bulk manufacturing techniques. The simplicity and modular nature of the design allows for employing cheaper manufacturing techniques as well as allowing swapping of modules.

IV. CONCLUSION

A novel portable low-cost eight channel sEMG signal acquisition system was designed, fabricated, and tested as a proof of concept. To validate the system, the sEMG signals for single finger actuation and wrist actuation was acquired multiple times. The collected data was processed and was used to train an SVM model with relative RMS voltage peaks as multiple features. The acquisition system characterizes the five finger flexion movements with an accuracy of 85% in real time. From the data collected and analysed it was concluded that the optimal number of electrodes to be used is roughly equal to the number of target classification classes. Further, the most optimal placement of these set of electrodes is as close as possible to the muscle group of interest. The system was thus shown to be capable of identifying the action performed and the intensity of the action performed. The developed sEMG signal acquisition circuit automatically collected signal over time from an individual, that will provide insight into the rehabilitation progress of the individual. Thus avoiding tedious manual evaluation of the individual and provide personalized exercise and physiotherapy plans.

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