Classification of Five Finger Movement, based on a Low-cost, Real-time EMG System

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Abstract: Researchers commonly use myoelectric signals to study the electrical activity produced by skeletal muscles for the control of prosthetic arms, hands and limb replacement devices. Additionally, to the application in prostheses, a myoelectric control system for multiple finger movements has the potential to develop commercial products including advanced human-computer interfaces. The objective of this work is to implement a set of low-cost active electrodes for the decoding of finger movement via time-domain analysis, with an auto-gain adjustment technique. Different people will have different EMG amplitudes; therefore, it is difficult to determine the gain required prior performing further signal processing. In this work, an auto-adjustable gain amplifier circuit processes the maximum EMG signal amplitude and adjusts the gain stage accordingly, without the need of any user interaction. This ensures that the gain is always automatically adjusted to get the most effective performance from the data acquisition or analogue to digital converter (ADC) module since the signal will be neither too low in amplitude to cause inefficient use of the ADC resolution, nor too high to cause saturation of the signal. Through extensive experiments, the developed low-cost EMG data acquisition system achieves reproducible and repeatable results for the detection and classification of the five finger movements.

1 INTRODUCTION

This paper is an extension of the work originally presented in NGCAS conference (Seguna, 2018). Electromyography (EMG) signal acquisition is a medicine technique used for recording and analysing the electrical activity produced by skeletal muscles. EMG systems detect the electrical potential generated by muscles when they are neurologically activated (Tsuji, 2000). The EMG signal can be used to obtain several information related to muscle activity, such as detecting medical abnormalities, muscle activation levels, or to analyse the biomechanics of the human. It is also used as a research tool for studying kinesiology, which can then be used to control prosthetic devices such as prosthetic arms, hands and lower limbs. This is possible since muscles in the remaining part of the limb function in a normal way, enabling the EMG signals extracted from them to be used in limb replacement devices. The benefit of this technique is that the signal is acquired from the patient's remaining limb muscles, which after appropriate processing can be used to control motors. These motors can be used to control several applications, including the control of motorised wheelchairs and the control of prosthetic devices which can be worn by amputees and activated by their own EMG signals (Sudarsan, 2012), (Osamu, 2003), (Jingpeng, 2013), (Côté, 2015) provided. EMG studies in general are useful for assessing the health of the neuromuscular system, since certain diseases, such as multiple sclerosis, suppress or even slow down normal nerve and muscle firing. Surface EMG (sEMG) signal is the product of all the action potentials which are picked from the muscles below skin surface electrode. The amplitude of sEMG signals is stochastic (random) in nature and hence the reason why appropriate signal processing is required for interpreting and using the signal. Although the amplitude is random, it can be reasonably represented by a gaussian distribution function. The typical EMG amplitude varies from microvolts to the low millivolts range (with the maximum amplitude being around 10mV peak-to-peak). The amplitude depends on the force applied since the bigger the force, the more action potentials will be stimulated which will trigger the contraction of more muscle fibres (Naeem, 2012).

The more the action potentials are in reach of the surface electrodes, the bigger the product result and

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therefore the higher the amplitude. The frequency of EMG signals can range from a few hertz up to the lower kilohertz range, but the frequencies below 20 Hz and above 200 Hz are usually not considered to contain any useful physiological information. For this reason, EMG acquisition systems normally filter these frequencies out. Since the 50 Hz power line frequency is within this range and can contribute to interference in the EMG data being analysed, it is sometimes recommended to set the cut-off frequency of the low-pass filter at 50 Hz to attenuate most of the power lines interference, or else apply a notch filter at that particular frequency (Khoshaba, 1990), (Ahmad, 2017). The EMG signal can also contain small DC contents producing an EMG signal with a non-zero baseline. The DC content is eliminated in the EMG acquisition circuitry, usually by using an instrumentation amplifier (IA) or a high-pass filter (Hong Quach, 2017).

Table 1: Applications of EMG (Côté, 2015).

Medical research	**Rehabilitation**	**Ergonomics**	**Sports Science**
Orthopedic	Post-surgery	Analysis on Demand	Biomechanics
Surgery	Neurological Disorders	Risk Prevention	Movement Analysis
Functional Neurology	Physical Therapy	Ergonomics Design	Athletes Strength Training
Gait & Posture analysis	Active Training Therapy	Product Certification	Sports Rehabilitation

Common EMG analysis techniques include amplitude analysis, time duration analysis, frequency analysis and time-frequency analysis. The amplitude of the EMG signal expresses the level of the muscle activity and it changes with the amount of electrical activity detected by the electrodes. EMG acquisition systems usually make use of techniques to smoothen the raw EMG signal amplitude and form a better representation with respect to time. The most common techniques are the Root Mean Square (RMS) followed by the Mean Absolute Value (MAV). The RMS technique is considered to be the most meaningful since it provides a measure of the power of the raw EMG signal (Tijssen, 2000).The ability to correlate EMG amplitude with muscle force allows one to determine whether the respective muscle is inactive or active. When a muscle is inactive, the EMG amplitude is effectively at 0 V and when the muscle is active, the amplitude gets greater than 0 V. When a muscle is active, one can also determine the time duration of the muscle being active. This is achieved by simply measuring the time when the amplitude exceeds a pre-set threshold. Frequency analysis applies Fast Fourier Transform (FFT) technique to obtain meaningful frequency information, for a fixed stationary time-domain data segment. This factor makes frequency analysis not the ideal method when fast data processing is required, such as for the use of prosthetic limbs. On the other hand, this type of analysis is ideal for studying muscle fatigue since in various studies it has been proven that the mean frequencies of the EMG signal will decrease with time during tasks that induce muscle fatigue. The frequency analysis can also be used for detecting interfering frequencies in the raw signal, such as power line frequencies. Time-Frequency analysis comprises the study of EMG signal in both the time domain and the frequency domain simultaneously. As already discussed, both the time domain and frequency domain analysis can be used to extract specific muscle activity. For this reason, many researchers have combined the two to benefit from information the two types of domains can offer. This type of analysis is sometimes used to achieve multiple classifications from the same EMG signal, such as the angle and the force applied at a joint. This is because the muscle force show more change in the time domain, while any change in the joint angle is more visible in the frequency domain of the EMG signal (Clancy, 2008). During the process of EMG signal acquisition one must follow certain steps to prevent unwanted factors that may influence the process. Although the human body is a good conductor of electricity, there are still many aspects that effect the conductivity level. Tissue conductivity level can vary with the type, thickness, physiological changes and even with temperature. These conditions will vary from one person to another and sometimes may even vary within the same person when the test is performed at different time. Additionally, the human body has approximately 640 skeletal muscles which are close to one another, it is difficult to monitor signals originating from a single muscle when using surface electrodes. Neighbouring skeletal muscles may produce signals which will eventually be picked from the electrodes together with the wanted signals. This is known as cross-talk, and normally it does not exceed 15% of the overall signal contents. Electrocardiography (ECG) signals can also interfere the EMG signal recording. This is especially common when performing EMG monitoring near the upper trunk or the shoulder muscle. Another factor that may alter EMG reading is when the distance between the skeletal muscle belly (origin of the signal) and the surface electrode changes during the signal acquisition process. This normally happen when the patient moves which causes the electrode to change position. To prevent this from happening, one must secure the surface electrodes and any wires that may cause them to move during signal monitoring. The EMG signal whose amplitude is between 0-10mV, when passing through various tissues, is contaminated by various noises (Amrutha, 2017), (De Luca, 2010), (Guohua, 2009).Therefore, it is vital to understand the properties of various unwanted electric signals. EMG signals are very sensitive to external noise and artifacts, mainly due to the signal ranging from a few microvolts. Inherent noise present in all electronic equipment cannot be eliminated but can be reduced drastically through intelligent circuit design. Additionally, the silver/silver chloride electrode are electrically stable and as their size increases, the impedance decreases. Most of these interferences may be filtered out using active or digital filters, by preparing the skin and placing the electrodes properly. If proper skin preparation and proper electrode placing is not fulfilled signal quality is deteriorated. The electrode cable and interface will also cause movement artefacts, where such artifacts can be reduced significantly using recessed electrodes. Further to this, between the surface of the skin and the electrode-electrolyte interface, a conductive gel layer is applied. Electrical noise causes EMG interference since most of the electronic components generate electrical noise (known as Johnson–Nyquist noise) whose frequency can range from few hertz to thousands of hertz. Such electrical noise can be reduced drastically by using quality components and through the implementation of a well-designed circuit. Ambient noise is the main source of electromagnetic radiation whose amplitude is sometimes one to three times greater than the desired EMG signal.

The surface of the human body is constantly flooded with electromagnetic radiation. To prevent these interferences, one must use an IA with a high CMRR. This will attenuate any common mode noise at the inputs of the electrodes. Another technique to reduce ambient noise is to use the shortest possible leads. If long leads are used, they will serve as an antenna which will pick any ambient noise in the vicinity. The leads should also be shielded to reduce the possibility of noise from being picked. If noise problems persist, the EMG acquisition circuit can be covered by a Faraday cage. This will shield the circuit from any Electromagnetic interference (EMI). When the Faraday cage is grounded, the electric field energy is drained away without affecting the circuit performance. EMG instrumentation can pick various types of influences that one may not even be aware of, which include emotions and thoughts. These factors can cause skeletal muscles to slightly contract since humans tend to tighten up with certain emotions or thoughts. These influences are better known as involuntary activities which are picked by an EMG measuring equipment (Bekir, 2014). There are various techniques used to process and classify EMG signals. Researchers make use from both the amplitude and the spectral properties of the raw EMG signals to supplement information on the muscle activity which is used to increase the classification accuracy. Following are some of the commonly used techniques for signal acquisition, processes used and algorithms for eliminating unwanted artefacts, process the raw EMG signals and for classifying different muscle movements. EMG signals can be picked up using surface electrodes in two different configurations, these being the monopolar and the bipolar. The monopolar configuration makes use of two surface electrodes, where one is placed on the belly of the muscle and the other electrode is placed as a reference on an electrically neutral tissue (such as joints or other bony areas). The difference of the two electrodes is then compared and processed for further filtering and smoothing (Hudgins, 1993). The other technique is the bipolar. This configuration makes use of two electrodes (known as the detecting electrodes) which are both placed on the belly of the muscle. The detecting electrodes are typically kept one to two centimetres apart. Another electrode is used as a reference and must be placed on an electrically neutral tissue. The advantage of using this configuration is that the common noise can easily be eliminated, something which is not possible to achieve with the monopolar configuration. When eliminating the common noise or any interference, one will achieve a better signal-to-noise ratio and hence a clear raw EMG signal can be obtained. The pre-amplification is one of the most important aspect when it comes to processing very low signals such that of EMG. This is because the components used in this stage must be of high precision and produce the minimum noise possible, or else the noise can be interpreted as the wanted signal. The most common pre-amplification component used in EMG devices is the instrumentation amplifier. Instrumentation amplifiers are used to amplify the difference between two inputs, which are connected to the two detecting electrodes. They are designed to reject any signals that are common to both inputs and therefore, are used where precision and gain accuracy must be maintained within a noisy environment, and where large common-mode signals are present. After reviewing the literature, it was found that the most commonly used instrumentation amplifiers for EMG devices are the INA126P, INA128, INA141, AD8221, AD8421, AD623 and the AD642. Some papers suggest that the IA gain must not be set too high or else it may amplify the noise components together with the wanted signal. Most of the EMG devices set the instrumentation amplifier reference pin to half the supply voltage (virtual grounding), while other devices keep the output of the IA at a zero volts baseline and then rectify the EMG signal prior entering the ADC input. An experiment conducted by the University of Utah includes the use of precision rectifiers (super diodes) to rectify the raw EMG signal prior inputting it to the IA. Other techniques were used in other studies, which include the use of three separate operation amplifiers that form the IA which permits more flexibility in the selection of parameters.

After the pre-amplification stage, most devices perform filtering to remove unwanted signal prior further processing. Different EMG devices divide this section into different stages, with some using separate circuit for the low-pass and high-pass filtering, others make use of a band-pass filter circuit and other devices perform this task either on a microcontroller or desktop computer. Digital filtering is usually performed using Infinite Impulse Response (IIR) filtering structure or Finite Impulse Response (FIR) filtering structure, with the latter being the most popular since it is more stable and less likely to introduce non-linear phase distortions.

Most of the existing devices which make use of hardware filtering, achieve this by using active filters based on operational amplifiers or by using dedicated filter ICs. Some EMG data acquisition implementations make use of a combination of a low order hardware filtering stage, which is then followed by a higher order software filter. This is usually done so that the hardware filtering can perform the first stage filtering, prior the signal is inputted to an analogue to digital converter (ADC). Another technique would be the use of an adaptive noise cancellation. Such technique can be implemented using the Least Mean Square algorithm and has been proved to be reliable and efficient (Phinyomark, 2012).

This will contribute to better ADC processing since it will eliminate any major baseline drift and high amplitude noise. Further filtering of the EMG signal is then achieved by a second stage digital filter. Some existing devices also make use of notch filters to attenuate any frequencies that may interfere with the wanted signal, with the most common being the 50 - 60 Hz power line frequency. This type of filtering is not suggested by some researches since the frequencies in the 50-60 Hz range can contain useful information on the muscle contraction. They suggest that a high-end instrumentation amplifier with a high CMRR should be used instead. This should attenuate any common power line distortion picked up by the human body.

Although many studies agreed that the low-pass filter (LPF) cut-off frequency should be set to around 15 to 50 Hz, it was noted that when it comes to the high-pass filter (HPF) cut-off frequency, different papers used different values with the range varying from 150 Hz up to 800 Hz. Some of the papers recommend that a high cut-off frequency for the HPF is preferred so that any rapid on-off bursts of EMG activity will not be filtered out. EMG devices which perform hardware smoothing need to first rectify the signal. Some existing devices use half-wave rectification, but the most popular is the full-wave rectification. Devices that use full-wave rectification have the advantage of maintaining all of the raw EMG signal information, unlike half-wave rectification where the negative cycles are completely blocked. The common technique used for the signal rectification is through the use of a precision rectifier (also known as a super diode) which is a circuit that acts as an ideal rectifier.

The stage following the EMG rectification, is usually the signal smoothing stage which is normally achieved through an integrator circuit or a low-pass filter. A similar technique which is also commonly used is the envelope detector circuit, which gives a similar output effect as the integrator and the low-pass filter circuits. There are other techniques which are sometimes used instead of root-mean square (RMS), these being the Absolute Mean Value (AMV), the Difference Absolute Mean Value (DAMV) and the Variant Value (VAR) (Garavito, 2016). A study entitled “Evaluation of EMG processing techniques using Information Theory” shows that the RMS technique provides the most meaningful information out of the EMG signal.

More complex EMG processing devices can make use of different algorithms to achieve better results. Some of the commonly used algorithms are the Neural Network, the Support Vector Machine and the Euclidean Distance. The last two algorithms are typically used when monitoring and recording finger movements. They are used to isolate individual finger movements to be able to control individual outputs, such as prosthetic limbs. On the other hand, Neural Networks (Subasia, 2006), (Gutiérrez, 2011) algorithms are artificial intelligence networks that can acquire any non-linear mapping of trained data through learning. This algorithm is normally used to achieve successful classification for non-stationary

EMG signals. Euclidean distance is used to determine the distance of the input data points from a set of predefined target points. Based on the distance acquired, the system will check if the new data input lies within a pre-defined target border and is used to classify the data related to a particular muscle activity into the desired group of channels.

The concept of autoregressive modelling is to assume that the real EMG can be approximated by what is known as the AR process. With this assumption settled, the order and parameters of the appropriate autoregressive model are chosen in a way to fit the acquired EMG signals as closely as possible. In turn, for every particular autoregressive model, the power spectrum of the corresponding AR process can be analytically determined. Thus, the AR method provides an alternative way for EMG spectral properties estimation. The work entitled “Real-Time Computer Control using Pattern Recognition of the Electromyogram” claimed a 95% accuracy in classification was achieved when using the Autoregressive modelling technique.

2 ANALYSIS OF EMG SIGNALS

Analyses of various EMG signals was done using a pair of electrodes placed over the palmaris longus muscle, which is mostly active when the ring finger is contracted. The raw EMG signal was processed through root mean square calculation. Figure 1 illustrates the result of the processed signal where it is observed that the amplitude increases relatively proportional with every 10 N of extra force applied. This signal feature can be utilized in prosthetic hands to apply variable force depending on the EMG amplitude.

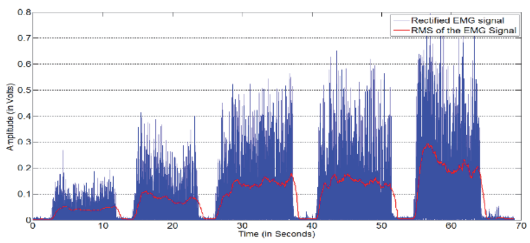


Figure 1: RMS of the EMG bursts with different forces, starting from a force of 1 kg and increasing the force by 1 kg with every burst.

The amplitude and frequency components of the ring finger being closed at different angles were analysed. Figure 2 illustrates the EMG signals obtained at different angles, starting from 0 degrees (finger fully opened) up to an angle of 180 degrees (fully closed), with intervals of 45 degrees. The rectified EMG signal amplitude increases quasi-proportional with the angle of the finger. This feature can be utilised for prosthetic hands for adjusting individual finger angle. A test was conducted to analyse the EMG signal pattern with respect to muscle fatigue. The setup used is shown in Figure 3.

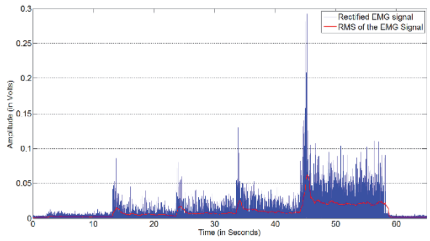


Figure 2: Rectified EMG amplitude signal at various finger angles, starting from angle 0 degrees (finger fully opened) up to an angle of 180 degrees (fully closed).

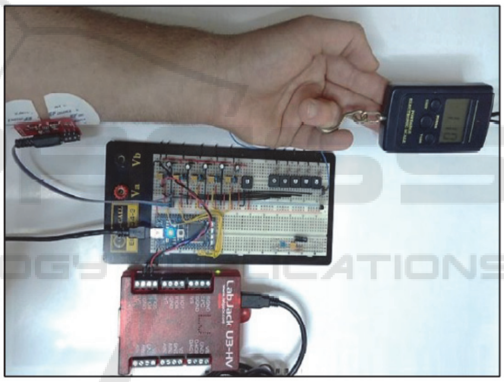


Figure 3: Setup for analysing EMG signal pattern with respect to muscle fatigue.

The EMG signal for this test is shown in Figure 4. The RMS equivalent is illustrated in Figure 5 showing the profile of an EMG signal obtained for the ring finger when a constant force of 5 kg for a period of 60 seconds was exerted. As shown in Figure 5 the amplitude of the EMG signal increases slightly with muscle fatigue when applying a constant force of 5 kg. Therefore, since the difference in amplitude is minimal the signal was then analysed in the frequency domain where it was noticed that the frequency of the EMG signal shifts to the lower side with muscle fatigue as shown in Figure 6.

The amplitude frequency spectrum was performed on a raw EMG signal at various angle position of the finger. Figure 7 illustrates the magnitude frequency spectrum plots obtained for four different ring finger angles. From the results obtained, the magnitude of the

100 Hz frequency bin increased with angle position. Frequency domain analysis could be challenging to apply with accuracy due to problems such as frequency resolution, magnitude accuracy at steady state, and more generally, due to data processing.

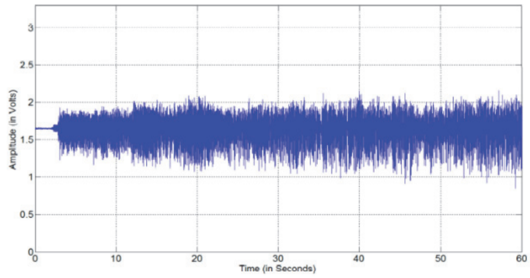


Figure 4: EMG signal pattern with ring finger exerting a constant force of 50 N.

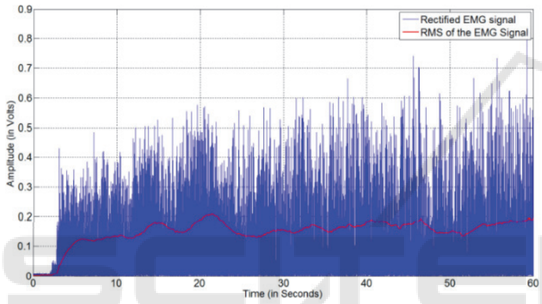
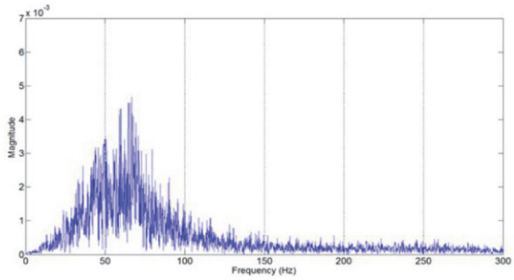
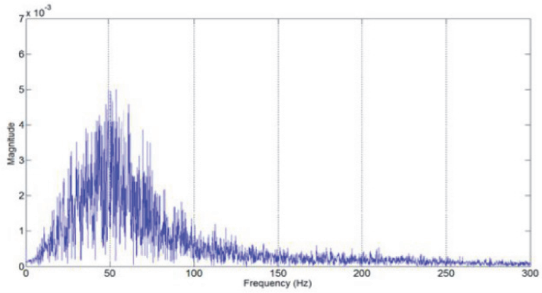


Figure 5: RMS of the EMG signal with the ring finger exerting a constant force of 50 N.

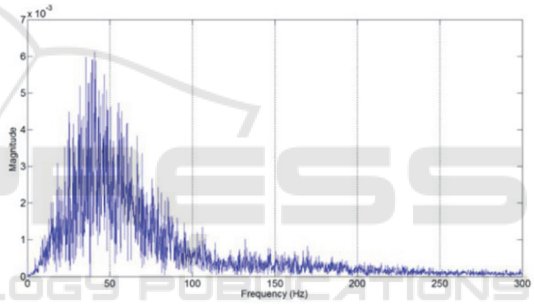
The time domain feature analysis is concerned with the extraction of various EMG signal features in time domain. Time domain features such as mean absolute value, root mean square and wavelength were the most popular in EMG pattern recognition because of high processing speed in classification. The mean absolute value of an EMG signal is defined as the average of the total absolute value, while root mean square is the amplitude modulated Gaussian random process related to muscle force and contraction Time domain features can easily and efficiently be used for the recognition of an EMG pattern recognition. On the other hand, frequency domain features can be used to estimate the EMG power spectrum in frequency form. In addition, the frequency domain spectrum is commonly used in muscle fatigue and muscle force estimation. Therefore in this work the classification of finger movement was performed through the time domain analysis rather than frequency spectrum.



(a)



(b)

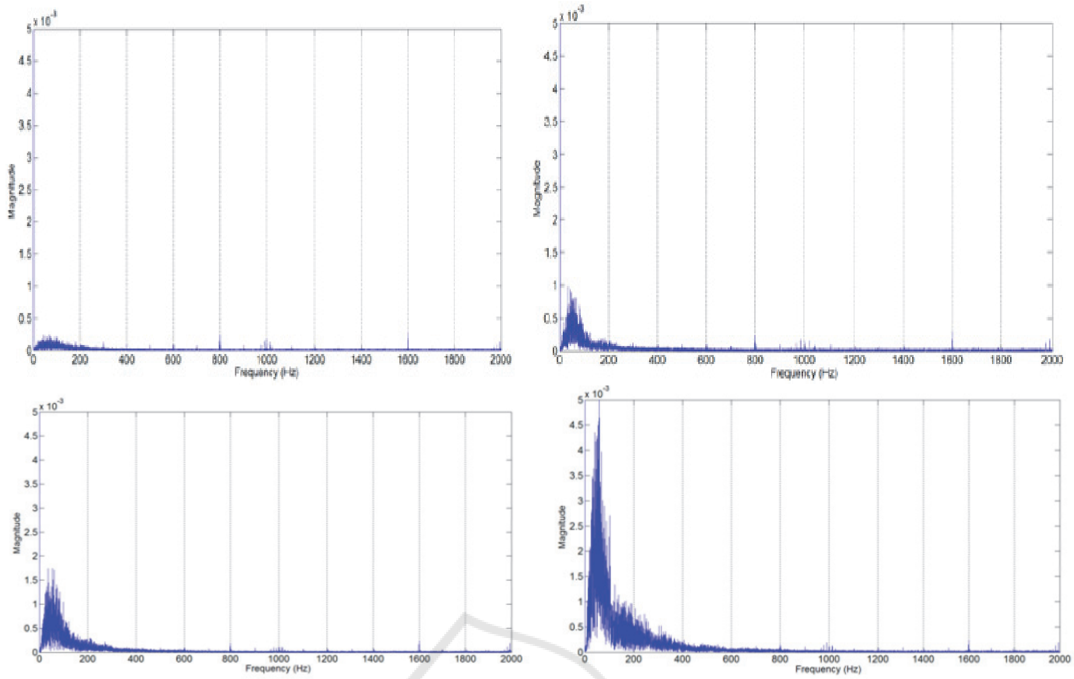


(c)

Figure 6: Frequency spectrum shifting to the lower side of the spectrum with muscle fatigue for various time durations (a) 5-15 (b) 15-25 (c) 35-45 seconds.

3 CLASSIFICATION OF FINGER MOVEMENT

H124SG muscle sensor surface electrodes were placed at a particular area on the hand as shown in Figure 8. The forearm has nineteen major muscles responsible for the flexion, extension and other movements of the fingers, wrist and elbow. Reviewing the anatomy of the muscles, it was concluded that the muscles used for the contraction of the fingers are mostly exposed at the lower part of the forearm Muscles responsible for finger movement include the flexor digitorum superficialis (responsible for flexing all fingers -primarily at proximal interphalangeal joints), flexor digitorum profundus



(c) (d)

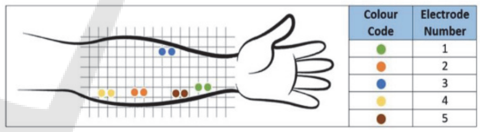
Figure 7: Frequency magnitude spectrum of an EMG signal for (a) 0°, (b) 90°, (c) 135°, and (d) 180° ring finger angle position.

(responsible for flexing the distal and proximal interphalangeal joints) and flexor pollicis longus (responsible for flexing the thumb).

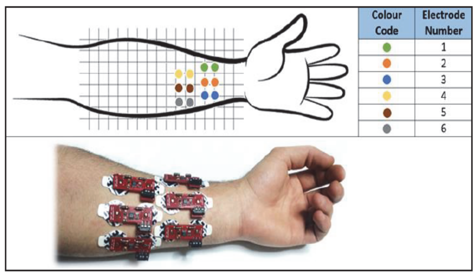
This work covered two different experiments. In the first experiment the electrodes were placed along various muscles as shown in Figure 8a, while in the second experiment six electrodes were placed on the lower part of the forearm. The first experiment did not show repeatable results from person to person. This was mainly caused by the fact that not every person has the same muscle anatomy and not every person has the same amplitude peaks for the same muscle. The physical factor of the person also played a big role in the lack of consistency. When the system was used on overweight people, it was noticed that it is difficult to get finger movement classification. This is due to the constantly changing physical distance between the surface electrodes and the muscles being monitored.

To avoid the use of complex algorithms and other additional signal processing for isolating finger movements from other unwanted muscle activities, such an area was selected. Calibration process followed electrode placement. This process consisted of contracting each finger multiple times one at a time.

With each contraction, the amplitudes acquired from all electrodes being recorded. This process was repeated for a pre-defined amount of repetitions so to establish the required thresholds. EMG bursts were monitored and processed so to evaluate the upper and lower thresholds for each finger contraction, with the highest monitored amplitude being set as the upper threshold and the lowest amplitude being set as the lower threshold. The maximum and minimum amplitudes detected at each electrode after the raw square algorithm.



(a) First Experiment



(b) Second Experiment

Figure 8: Electrode placement for (a)1st and (b) 2nd Experiment.

Ten EMG bursts were recorded during this calibration procedure. From the plots shown in Figure 9, it is observed that the thresholds for each finger contributed to a unique pattern thus enabling EMG signals were processed using the root mean- the possibility of classifying various finger movements.

4 ACTIVE ELECTRODES FOR ECG

Most EMG devices use of passive electrodes. In this work active electrodes were used because they tend to perform better for applications where very low signals need to be acquired. Active electrodes contribute to a have high input impedance with minimal stray-capacitances at the inputs and low output impedance contributing to a low cable movement artifact. As shown in Figure 10 the main front-end component for the developed active electrode module is the LT1167 instrumentation amplifier (IA). The LT1167 operates with a single or dual rail supply voltage of ±2.3 V, common-mode rejection ratio (CMRR) of 126 dB, and input impedance of 1000 GΩ, thus contributing to less attenuation in the input signal. Such parameters satisfy the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) standard. To minimize the gain error and achieve best CMRR the REF pin of the LT1167 was connected to a 1.25 V supplied by the REF3312AIDBZT voltage reference IC. This IC required low supply current (typically 3.6 μA), has low temperature drift and has an internal accuracy of ±0.15%. The maximum output impedance does not exceed 0.1Ω, assuming the output of the REF3312 is not switching at high frequencies. This integrated circuit is also suggested for use in medical applications. A 4.7 μF and 1.5 μF supply bandpass capacitors are connected to the input and output of the REF3312 respectively for better stability of the input and output signal. A 604 Ω resistor is used to set a fixed gain of 83. Note that this gain will only amplify the raw EMG signal to around 500 mV peak-to-peak as per requirement. The two 5.1 kΩ resistors connected in series to each input of the instrumentation amplifier input. These resistors are made from carbon composition which can withstand large short-term pulses and high voltages when compared to other resistor types. Although these resistors will contribute to higher noise at the inputs of the IA, they are necessary to protect the IC from any ESD.

The filtering stage consists of a 2nd order Butterworth high-pass filter with a cut-off frequency of 15 Hz, a 5th order low-pass filter with a cut of frequency of 500 Hz. A digital amplifier followed the filtering stage.

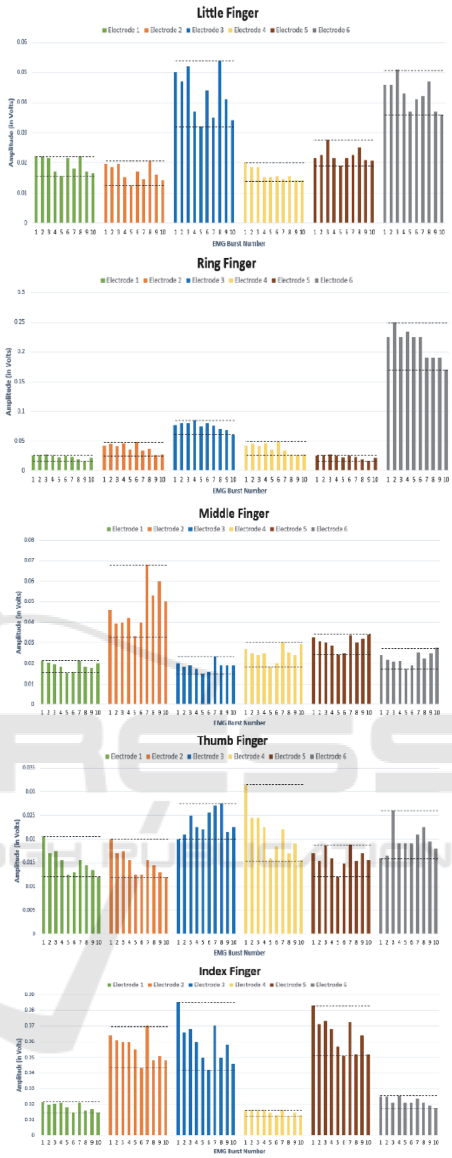


Figure 9: RMS and threshold plots for various finger movements.

The high-pass filter is required so that the baseline drift will not affect the ADC performance. The operational amplifier for the active high-pass filter selected is the MCP604, which is a single supply, rail-to-rail, unity gain stable CMOS quad op-amp IC. Such component has a Butterworth response and can operate at 3.3V, while consuming maximum current of 1.2mA. The input of the filter comes directly from the electrode, which pre-amplifies the raw EMG gain accordingly. DS1804-050 is a 50kΩ potentiometer that has 100 tap-points. The DS1804-050 can operate from 3V or 5V.

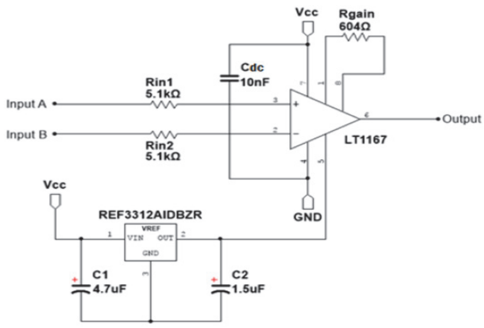


Figure 10: Schematic diagram for the front-end component interfaced with active electrodes.

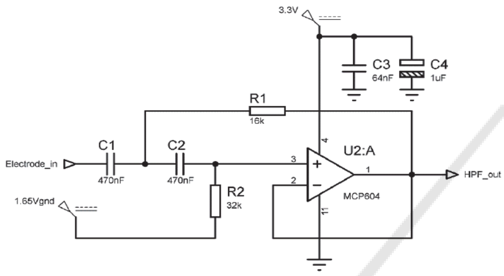


Figure 11: Low-pass filtering stage based on the MAX7414 5th order LPF.

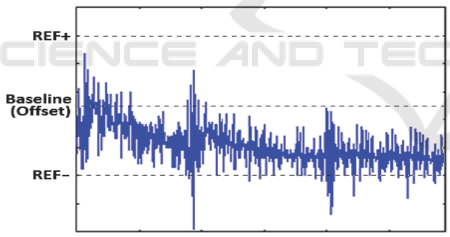


Figure 12: Baseline drift causing the EMG signal to be saturated by the ADC references.

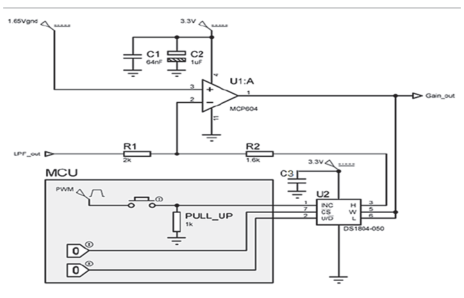


Figure 13: Digital Potentiometer.

This digital potentiometer also has a built in EEPROM to store the wiper position even when the supply is disconnected. This is useful so that the system will not have to be re-calibrated every time the supply is turned off. The DS1804 is specified to provide an absolute linearity of ±0.60 LSB, which is irrelevant for this application. It has a -3dB cut-off frequency of 200 kHz. Since the EMG frequencies are low, 200 kHz are enough for this application. Developed software monitors the signal amplitudes from each electrode and adjust the gain accordingly through the digital potentiometer. Such technique will not require the user interaction. The digital amplifier circuitry consists of the DS1804-050 and the MCP604 operational amplifier (same op-amp IC used for the high-pass filter). The op-amp is configured as an inverting amplifier, which can vary the gain from 1 (unity) up to 25. The MCP604 can be supplied with a single rail supply between 2.7 V to 5.5 V. The inverting configuration was used, so to implement a linear gain amplification, by incrementing the feedback resistance at equal intervals. The non-inverting input of the op-amp is connected to a 1.65V reference supply to offset the output by half the supply voltage.

5 CONCLUSION

In this work, we proposed the successful implementation of an active, noise cancelling, affordable and wearable 6-channel sEMG data acquisition system for the detection and classification of finger movement. Such classification feature can be combined with other systems for myoelectric control applications. Additionally, unlike other systems the gain is auto-adjusted using a digital amplifier. Finger movement can be detected and classified easily via EMG time domain rather than frequency domain analysis. The most basic and effective algorithm for enveloping the raw EMG signals was found to be root-mean-square (RMS) with a wide averaging window of 3000 instead of 1000. RMS only requires basic mathematical calculations, which sums up in a system that requires less processing power. As a result, a wider selection of microcontrollers could be used for processing EMG signals. The classification of finger movement was done through the placement of six electrodes at the lower part of the forearm. For this experiment, there was no need for the electrodes to be placed precisely in a specific area. The forearm was selected because it has thin layer of fat, thus reducing the problem of baseline drift drastically. After studying the anatomy of the muscles, it was also concluded that the muscles used for the contraction of the fingers are mostly exposed at the lower part of the forearm. The developed active electrodes with integrated IA placed as close as possible to the input electrodes contributes a better signal to noise ratio. The use of an auto-adjustable gain stage contributed to a practical user-friendly system. This circuit monitors the maximum EMG signal amplitude and adjusts the gain stage accordingly, without any user interaction. This ensures that the gain is always adjusted to get the most effective performance from the ADC module since the signal will be neither too low in amplitude to cause inefficient use of the ADC resolution, not too high to cause saturation of the signal. A comparison of our active electrode sEMG processing system with other systems available in the literature and commercial products in terms of frequency, weight, supply voltage, wearable and other classification features is shown in Table 2. Through extensive experimentation system was tested by ten different people of various weights, size and genders with classification results observed to be repeatable and reproducible.

6 FUTURE WORK

A small footprint prototype board is currently under development and planned to be finalized by 2020. This new prototype will enable the extraction of more finger muscle movement features including finger angle and muscle fatigue. Additionally, such a wearable module will enable the processing of EMG signals wirelessly over the cloud so to help of patients suffering from conditions such as Carpal Tunnel, Diabetic Peripheral Neuropathy, Ulnar Neuropathy, Chronic fatigue syndrome, and Fibromyalgia, among others.

Table 2: Comparison with other similar systems.

	This work	Myo Armband	Biometrics Datalog	Hercules (Mert, 2018)
Classification of Finger Movement	Yes	No	No	No
Contraction Detection	Yes	No	No	Yes
Wearable	Yes	Yes	No	Yes
Bandwidth (Hz)	20-589	-	20-460	20-500
Supply Voltage	2.5V	-	3V	3.7V

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