# Home Switch Control using Electromyograph and AVR Microcontroller

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#### ARTICLE INFO

#### ABSTRACT

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#### Keywords

Electromyograph Moving Average Tresholding On-off Control The increasingly rapid development of technology in the field of biomedical engineering, one of which is applying EMG (Electromyograph) signals to move mechanical devices. Various studies have been carried out with various methods tested. The research entitled "Home Switch Control using Electromyograph and AVR Microcontroller" is directed at EMG signals in the arm muscles as input to actuate several switch devices which are usually used in homes or hospitals. The results of placing electrodes at 3 points, namely Bicep Brachii, Tricep Brachii, and Wrist Flexor, produce an EMG signal which has 2 different truth values during contraction after extraction using a moving average and thresholding algorithm, so that the final result produces an on-off control system for 1 switch.

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# 1. Introduction

In this research, a device was designed that takes EMG signals to actuate a simple mechanic (on-off switch). This device is designed to help subjects who are unable to operate on\_off manually due to physical weakness or being unable to reach the on off switch location. In several previous studies, EMG signals were still a research trend. Huang and Chen [3] developed a "myoelectric discrimination" system for a multi-degree prosthetic hand. They used Back Propagation Neural Network (BPNN) to separate several feature sets. From this separation system the average success rate reaches 85% for off-line tests and 71% for on-line tests.

Karlik [3] classified EMG signals for multifunctional prosthetic device control using 3 layers of Back Propagation Neural Network (BPNN). BPNN input is the result of EMG signal segmentation using Auto Regressive (AR), namely a1, a2, a3, a4, and power signals. This research has an average accuracy rate of 97.6% for 6 movement categories (R: Resting, EF: Elbow Flexion, EE: Elbow Extension, WS: Wrist Supination, WP: Wrist Pronation and G: Grasp) with 5000 iterations.

Tsuji et al. [6] introduced a neural network called "Recurrent Log Linearized Gaussian Mixture Network" (R-LLGMN) to classify time series signals, more specifically for EEG signals. The accuracy rate obtained was 94.4%.

Angkoon Phinyomark [10] obtained a novel EMG signal feature extraction for accurate EMG signal pattern recognition. From the journal entitled "A Novel Feature Extraction for Robust EMG Pattern

Recognition" it has been learned that MMNF (Modified Mean Frequency) feature extraction is the best feature extraction for the EMG pattern recognition process. It is stated that MMNF has an average error of 6% on contraction EMG signals and 10% on weak EMG signals. This value is still considered the best compared to the 16 other feature extractions that were tried.

# 2. Literature Review

In human muscle tissue, there is a neural network which is schematically shown in Figure 1. It can be seen in the picture that the force of movement exerted by muscles is the result of the coordination of a motor unit (consisting of motoneurons and muscle fibers).

Electromyogram is a technique for evaluating and recording muscle signal activity, which is the sum of several muscle fiber potential (MFP) signals into a Motor Unit Potential (MUP), then figure 1.



Figure 1. Schematic of Basic Motor Control Mechanism and Motor Unit and its components [5]

From an MUP will issue Motor Unit Potential Trains (MUPT) as shown in figure 2. In measurements carried out with surface electrodes, an Electromyograph signal will be obtained which is a combination of MUPTs and also allows noise signals to enter.



Figure 2. Electromyogaph resulting from several Motor Unit Potential Trains (MUPTs) signals[1]

The elbow joint consists of the humerus, radius and ulna bones. The two main actions at the elbow are flexion and extension. The wrist joint consists of the distal ends of the radius and ulna and the carpal bones of the hand. The two main actions of the wrist are flexion and extension.



# Figure 3. (a) Elbow Joint (b) Wrist Joint

The dominant muscles when the elbow and wrist joints work are as shown in the following table 1.

Action of the Elbow and Wrist	the Action	Primary Muscles
Elbow flexion	Bend your elbow	Biceps brachii
Elbow extension	Straighten your elbow	Triceps brachii
Wrist flexion	Bend your palm toward your forearm	Wrist flexors
Wrist extension	Bend the back of your hand toward your forearm	Wrist extensors

# Table 1. Muscle Movement Elbow and Wrist

# 3. Method

# **EMG Signal Electrodes**

The EMG signal detection point is taken from the human arm, namely the Bicep Brachii muscle, Tricep Brachii muscle and Flexor muscle. Data were collected from the three muscles using a surface electrode, as shown in Figure 4 as follows.



Figure 4. Placement of EMG Signal Electrodes

The system as a whole can be depicted in a block diagram as shown in Figure 5 as follows.



Figure 5. Block diagram of the overall system

The working principle of the system as a whole includes collecting data at 3 electrode sensor points installed in the biceps, triceps and flexor muscles, using 3 AD8232 instrumentation amplifiers. The output from the AD8232 is input to the 3 channel ADC microcontroller ATXMega128U1, after it becomes digital data, the data will then be processed by a digital filter with a notch type filter with a cut off frequency of 50 Hz and a high pass filter type with a cut off of 0.3 Hz, and a low pass filter with a cut off. off 400 Hz to get EMG data without noise. Next, the filter output will be processed by Linear Envelope to become an EMG signal that is easier to threshold. In the final process the microcontroller will carry out signal classification based on thresholding data to carry out the ON/OFF process on the desired relay.

# **Instrumentation Amplifier**

The instrumentation amplifier circuit used is the AD8232 which has a special function as a biopotential Instrumentation Amplifier. Another advantage of the AD8232 is that it has a radio frequency noise filter and a gain of up to 58 dB. The AD8232 block diagram and module are as shown in the following figure 6.



Figure 6. Block Diagram of AD8232

#### **Data Acquisition System**

The ADC used is the internal ADC of the ATXMega128U1 microcontroller with 10 bit resolution. The ADC sampling rate is 4 ksps, using interrupt timer1 with an interrupt time every 250 uS. Setting interrupt timer1 at OCR timer value 1. Design the interrupt timer and ADC setup as shown in Figure 7.



Figure 7. Interrupt Time and ADC Setup

# Filters

The filter used is a digital filter programmed in the ATXMega128U1 microcontroller. The filters used are Low Pass Filter, High Pass Filter and notch filter.

The cut off frequency of the Low Pass Filter is 400 Hz with the Butterworth Filter type



Figure 8. Frequency Cut off

Transfer Function of the Butterworth Filter as shown in equation 1.

$$|H(j\Omega)| = \frac{1}{\sqrt{1 + \left(\frac{\Omega}{\Omega_c}\right)^{2N}}}$$
 (1)

The High Pass Filter cut off frequency is 0.3 Hz, while the notch filter is 50 Hz.

# **Rectifier Signal**

In EMG signal processing, a "Rectifier Signal" feature extraction method is required. This method is used so that the results of EMG data processing are positive and there are no negative signals. The formula for the signal rectifier is as follows.

y[i] = |x[i]| .....(2)

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# **Linear Envelope**

In the linear envelope process, the MAV (Moving Average) and Zerolag equations are used. From the Linear Envelope Signal you will get the peak level of the EMG signal. The Linear Envelope Equation is. The M value used is 30.

$$LE[i] = \frac{1}{M} \sum_{j=0}^{M-1} x[i+j]$$
.....(3)

In the LE process, a signal phase shift occurs, so to restore this shift, Zerolag is used. The Zerolag equation is:

#### Threshold

The threshold value for each person can be different, but is always between 5 - 10 mV. To determine the threshold value, an initial trial is required to record the subject's threshold value.

#### Relay

The relay used is the SPDT (Single Pole Double Through) type. The Relay Circuit uses an optocoupler at the relay input and a relay driver transistor, as shown in the following figure 9.



Figure 9. Driving Relay Circuit with optocoupler

# 4. **Results**

Some tests include EMG signal recording, Filter testing, Linear Envelope testing, motion classification testing and relay output.

1) The result with Low Pass Filter (LPF)

LPF 4th order specifications for a cut off frequency of 400 Hz and tested using a standard function generator signal. The plotting graph output produces the following test.



Figure 10. Low Pass Filter Response Frequency 400 Hz result

# 2) The result with High Pass Filter (HPF)

HPF 4th order specifications for a cut off frequency of 0.3 Hz and tested using a standard signal function generator, produces the following test.



Figure 11. High Pass Filter Respon Frequency 0.3 Hz result

# 3) The result with Band Reject Filter (BRF)

BRF order 4 specification type Butterworth, cut off frequency 50 Hz, tested with a standard function generator and produces the following frequency response:



Figure 12. Band Reject Filter Respon Frequency 50 Hz result

# 4) Result with EMG Signal Record

The AD8232 functions to change the dual input EMG signal into a single output as shown in the following image:





The EMG signal data from the AD8232 is analog data recorded using an oscilloscope (figure 10) and carried out with relaxed movements and flexion and extension contractions. Next, the EMG signal is input to the ATXMega128U1 ADC with a sampling rate of 4 ksps and filtered using a notch type, low pass and high pass digital filter.

The EMG signal recording process uses a 3 channel ADC designed by the simultaneous ADC ATXMega128U1 and recorded by a GUI created using VB as verification of the extraction process carried out. The GUI created is as shown in the following image:

	_				
Iana Peccibaan Data				STOP	
Paring Savetat Dear Door	Junio	Palet			
ko npa		~	CH 50	010	DHE

Figure 14. Menu Parsing data from 3 ADC channels

5) The result the rectifier and linear envelope signal EMG

Testing of the Rectifier and Linear Envelope EMG signal processes is carried out on the GUI and recording is carried out to verify the correctness of the formula used. Below are the results of plotting the Rectifier and Linear Envelope in Figures 15 (b) and (c).







Figure 15. (b) Display of EMG Signal Rectifier Process Results



Figure 15. (c) Display of EMG Signal Linear Envelope Process Results

# 6) The result 3 point EMG signal thresholding

The 3 points in question are the Biceps Brachii muscles, Triceps Brachii muscles, and Wrist Flexor muscles. The data for the 3 points is as shown in Figure 11 below. From these three muscle points, wrist flexion and wrist extension movements are detected. After thresholding at a value of 2.27 mV in the Wrist Extension, 0.43 mV in the Biceps Brachii Muscle, and 0.64 mV in the Triceps Brachii Muscle, the thresholding of the EMG signal is as shown in Figure 16.



Figure 16. EMG raw signal and thresholding signal results

Table 2. Relay ON/OFF Experiment ON Subject A					
Subject Movement	Wrist Flexor Muscle Logic	Biceps Brachii Muscle Logic	Triceps Brachii Muscle Logic	Relay Status	
Wrist Resting	Low	Low	Low	OFF	
Wrist Flexion	High	High	High	ON	
Wrist Extension	Low	High	High	OFF	

From an experiment in subject A above, signal classification data with the target ON / OFF Relay is produced as shown in table 2 below:

The muscle logic generated by the thresholding process results in the decision to drive the relay. However, the success of this research still needs to be further developed with more precise algorithms such as neural networks. This needs to be done because muscle logic is greatly influenced by the muscle strength of each subject, so the thresholding value and time duration are quite different for each subject.

As has been done in subject A, the time duration data for the experimental results are as shown in table 3 below:

Table 3. Logic High Time Duration ON Subject A						
Subject Movement	Wrist Flexor Muscle Logic	Biceps Brachii Muscle Logic	Triceps Brachii Muscle Logic			
Wrist Resting	Low	Low	Low			
Wrist Flexion	High (7.02 -8.00 s)	High (5.25 – 8.00 s)	High (6.02 – 7.75 s)			
Wrist Extension	Low	High (9.51 – 10.27 s)	High (8.50 – 10.25 s)			

#### 5. Conclusion

From this research it can be explained that a truth table can be created from human muscle movements. Simple signal processing such as linear envelope and thresholding is able to provide data that can be classified as ON and OFF output on the relay. However, the diversity of EMG signal forms needs to be handled by a more precise algorithm. This research has not been completed with 5 relays but still uses 1 relay. Diversity of output will require better algorithms such as Neural networks.

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