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Finger Movement Identification Using EMG Signal on the Forearm

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ABSTRACT

Finger movement identification is an important innovative interfacing method which has countless possible applications. It can be used to create a new age in human computer interfacing (HCI) devices. It can also be applied to medical applications, such as in the development of a more advanced prosthetic hand. The current research for this purpose includes methods such as computer vision and detecting finger motion through mechanical vibrations from skin surface. They have the limitation of being restrictive, in terms of the degree of movement that the hand is allowed from a certain optimum position, as well as being susceptible to environmental factors. In this study, the surface electromyography (sEMG) of the forearm from skin electrodes is developed and interfaced with computer. The response at the flexor carpi radialis muscle of the forearm is plotted for a group of subjects to observe the qualitative responsiveness of the sEMG to different types of finger movements. The results show that finger movement generates a corresponding response on the EMG electrodes. For the particular muscle being studied, the greatest individual digit amplitude response was observed for the ring finger (digitus annularis) across the subjects. In future studies, this research could be made more quantitative in nature by observing the frequency content of a variety of hand gestures across a sample of subjects.

Keywords: Human computer interfacing; finger detection; surface electromyography; finger movement; flexor carpi radialis; digitus annularis.

1 Introduction

Recently, detection of finger movement has been gaining increasing attention as a new method for human computer interfacing (HCI) [1]. Examples of areas where this can be applied are augmented reality, active prosthetics, playing video games, and controlling particular devices. They can be improved to have a more user friendly implementation through new and novel methods of HCI such as finger gesture recognition [2-4]. Humans interact with computers in different ways, amongst which, the mouse is one of the most widely used methods. The mouse has, in essence, a very simple mechanism, which does not really require the array of complex motions that many of the studies related to finger detection

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exhibit. An alternative to the mouse could be simple as individual finger detection. For this, surface electromyography (sEMG), in particular, of the forearm, is an important avenue of research to classify and differentiate each digit of the hand and can then be used by users to communicate with devices.

Kulshreshth et al. used Microsoft Kinect as an input device to track fingers in real-time. The image was processed through algorithms to detect fingers by matching them to various templates to classify them [5]. The technique's accuracy was restricted by the limited resolution of the Kinect, which meant that accuracy of the finger detection decreased as the user moved his hand away from the Kinect. Aside from this issue, the orientation of the hand was also limited, as it needs the hand to be parallel to the camera plane with the fingers at a distance from each other.

Kishi et al. applied accelerometers to detect mechanical vibration patterns to detect finger motion while fingers were tapping [6]. Sensors are placed on the forearm of the subject. The difference between each finger in amplitude and frequency was indiscernible, so they then used template matching method to identify each digit of the hand. The success rate of identifying finger motion was relatively high; however, use of accelerometer sensors would be heavily prone to external artifacts, such as an external force applied on the forearm could disturb the readings. A big limitation of this method is that the finger motion detected is limited to finger tapping, which limits the degree of freedom for the hand.

Using electromyography to detect finger movements is not a new idea; rather, it is something that has been done in a variety of ways before as well. Previous studies used an EMG sensor device to integrate changes in muscle potential due to finger movement to a computer interface [7-11]. These can be in varying arrangements with different methods of classification such as using neural networks to train and classify a system to correctly identify a particular finger according to the data received from the EMG device.

In this study, the data from previous work is considered and brings up the question of whether the classification of the fingers can be achieved using only a single pair of electrodes rather than using a multiple sensor configuration. Also, if this can be achieved without the use of algorithms, neural networks and other such methods. In this study, an EMG sensing device using a single pair of surface electrodes was designed first, and then, finger movement is detected by placing the surface electrodes on the flexor carpi radialis muscle of 11 subjects. This was done to observe the response of different finger movements across the different subjects. The site of electrode placement was chosen as superficial area above the belly of the flexor carpi radialis muscle. The electrode distance was kept constant in all subjects as 25 mm. The subjects were prompted to do opening (extension) and closing (flexion) finger movements and the resulting sEMG signals were recorded and stored on a computer.

2 Methodology

The various system components for sensing changes in sEMG signal are shown in Figure 1. After acquiring a sEMG signal, qualitative observations of the sEMG signals of 11 subjects is taken while they open and close different fingers when prompted.

2.1 Electrodes

In this work, three disposable EMG surface electrodes are used per subject. Two of the electrodes are placed at the muscle of interest (flexor carpi radialis) at a distance of 25 mm from each other. The placement of the electrodes was within the range of inter-electrode distance used for kinesiological electromyography [12]. The electrodes are placed at the same muscle across all the subjects [4, 13]. A reference electrode is placed on the styloid process of the radius [12].

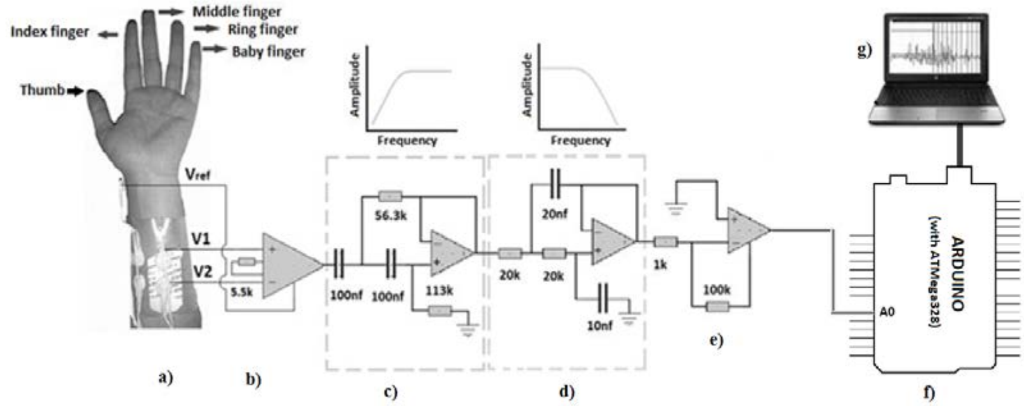

Figure. 8: System Components. (a) Forearm with electrodes placed on muscle of Interest. (b) Pre-amplifier. (c) High-Pass filter. (d) Low-pass filter. (e) Gain amplifier (f) Microcontroller. (g) Computer with software for plotting and storing EMG data.

2.2 Preamplifier

The human body has high impedance. This requires a preamplifier so that current is not drawn from the body. In this study, an instrumentation amplifier, INA114 [14], is used to amplify the incoming signals from the electrodes by a factor of 10 before the filtering phase.

2.3 Filter

For surface EMG, the frequency contents are generally considered anywhere in between the range of 0 to 500Hz [12, 15]. In this work, we implement a second order; band-pass filter from 20 to 500Hz using LM358 [16], the lower cut-off frequency is considered 20Hz, rather than 0Hz to remove baseline noise. A notch filter for the 50 Hz power line is not used as experts discourage its use, as it removes important EMG information along with the noise [15].

2.4 Amplifier

Without any conditioning, sEMG signals amplitude range from ± 5mV [12]. Although, preamplifiers amplify the signal, dedicated amplifier stages are used to amplify the signal with a much higher gain setting. A two-stage amplifier using LM358 [16], with an overall gain of 100, is used in this work to bring the conditioned EMG signal to range across 0 to 5V.

2.5 Data Acquisition

To Interface the signals with the computer and to convert the signal from analog to the digital form, an ATMega328 is used [17]. ATMega328 has a 10-bit analog to digital converter. In this experiment, pin 23 of this microcontroller is used to provide analog to digital conversion of the data. By itself, the microcontroller can't relay the data to the computer, so, it is used in conjunction with an Arduino Uno board. The Uno board allows for interfacing with a computer and even emulating a virtual COM port for serial communication over USB using an ATmega16U2 on board. Programming of the microcontroller was done using the Arduino IDE, which has C-language based syntax.

2.6 Data Display/Storage

Serial communication through USB is used to relay data to the computer. Communication is done at a Baud rate of 115200 bits per second. The visualization of data and storage is possible through a graphical program built in the processing IDE. The program emulates an oscilloscope taking the amplitude at each sample and plotting it as a graph. It also saves the data for further processing offline.

After development of this sensor circuitry and interfacing it with signal graphing program, we have taken observations on 11 male subjects aged between 22 – 25 years, who have electrodes placed on their left arms. The muscle being studied in this work was the flexor carpi radialis and an inter-electrode distance was fixed at 25 mm. The electrodes are placed at the belly of the muscle [18]. Each subject is prompted to perform flexion and extension of each finger one by one. The data is visually displayed in real time on the computer and then, every 10 seconds the EMG data of the subject is saved.

3 Results and Discussions

The sample graphical results for one of the subjects using our sEMG sensing circuit are shown in Figure 2. In Figure 2(a), it can be seen that the thumb shows no response. This is due to the muscle that can be studied to detect flexion of thumb finger, the flexor pollicus longus is quite distant from the flexor carpi radialis muscle and has no contact with it either, making it isolated, leading to the no response readings in each subject. The index finger showed a relatively low response, as seen in Figure 2(b). This can be explained, as the muscles responsible for flexion of index finger, the flexor digitorum superficialis is distant from the site of electrode placement, but can still have some effect as it is surrounding the muscle being observed in this study. A mid-level response is observed for the middle finger shown in Figure 2(c). This can be explained as the location of electrode placement is extremely near to the muscles in question, which is responsible for detection of flexion of the middle finger, the flexor carpi radialis and palmaris longus. Figure 2 (d) shows the subject highest relative response with ring finger contraction. This was because of the flexor carpi radialis muscles directly responsible to detect the flexion of the ring finger [4]. Like this, the baby finger shows a relatively low response, on average, as can be noted in Figure 2 (e). Similar to the index finger, the muscle responsible for flexion of baby finger, the flexor carpi ulnaris is also distant from the site of electrode placement, but can still have an effect on the electrodes placed on flexor carpi radialis.

In studies like this, quantitative data collection of the EMG signals of each subject is unfeasible, as many factors make it impossible to reproduce the same results in subsequent trials. For example, one factor is electrode placement, which is difficult to get at the exact same location and even minute changes in position or inter distance can change the amplitude of the signal greatly. As such, even on the same subject, if the subject is tested once, and then, at a later time, examined again, quantitatively, the results will not be the same due to the factors mentioned previously. As such, the better option is to take qualitative observations of the signals at the muscle site to check the trend of the EMG signal amplitudes is done. These readings are observed and noted down, which can be studied in Table 1.

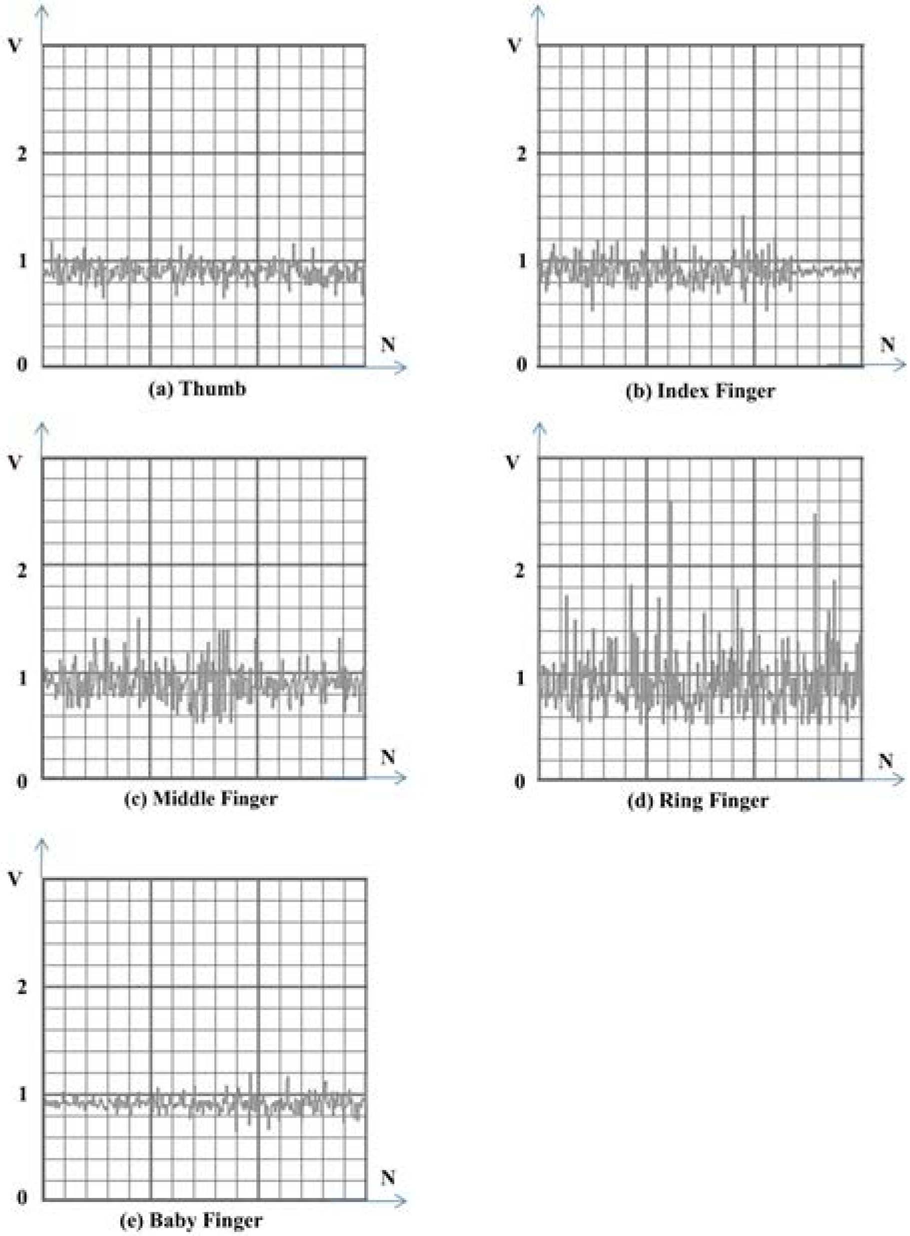

Figure.9.sEMG graphs corresponding to Finger movement with x- axis shows the number of samples taken in N, and y-axis shows the voltage in V

Table 1 listed the relative amplitude intensity of each individual digit of the different subjects. Table 1 shows some fluctuations in the readings, in particular, the readings of the index, middle and baby finger. This variation from subject to subject can be explained by minute differences in electrode placement. It is humanely impossible to get the same exact position for each subject, due to human error, differing arm size, amongst other factors. As such, the electrodes can be placed at a position in which the main muscle being studied is still detected correctly, however, the surrounding muscle which also have effects on the sEMG signal observed are not picked up as well by the electrodes, when moving from subject to subject. The observations revealed that amongst all the samples taken for each subject, flexion of the ring finger (Digitus annularis) consistently managed to have the highest amplitude relative to the other digits of the hand. The middle finger was relatively constant amongst the subjects, giving a response that could be easily distinguished from the higher amplitude ring finger and the other digits. The thumb gave no visible response whatsoever, whereas the index and baby fingers gave a low level response. This confirms that the flexor carpi radialis muscle is responsible for detection of ring finger flexion primarily. Also, the muscles surrounding it, which are also responsible for finger detection can, also have a resultant effect, although of a much lesser amplitude.

Table 1: Relative amplitude intensity of each individual digit of the different subjects

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Sample	Thumb	Index	Middle	Ring	Baby
A	No response	Low	Intermediate	High	Low
B	No response	Intermediate	Low	High	Low
C	No response	Low	Low	High	Low
D	No response	Low	Intermediate	High	Low
E	No response	Intermediate	Intermediate	High	Low
F	No response	Low	Intermediate	High	Low
G	No response	Low	No response	High	No response
H	No response	No response	Intermediate	Intermediate	No response
I	No response	Low	Intermediate	High	Low
J	No response	Low	Intermediate	High	No response
K	No response	Intermediate	Intermediate	High	Low

Where; No Response = No response, Low = Low amplitude response, Intermediate = Intermediate level response and High = High level response.

The observations show that even while using a single pair of electrodes, the different fingers respond differently when flexed. Visually, they can be distinguished by the amplitude intensity each digit exhibits when closed, which is different for each finger. At the flexor carpi radialis, the highest response was observed for ring finger, which was constant across all the subjects. Whereas there was some variation between the results for the other fingers when changing from subject to subject, on average it could be determined that the thumb showed no response, the index and baby fingers gave low level responses and the middle finger gave an intermediary response. Amongst the index and baby fingers, the maximum amplitude reached is similar between the two, which would be hard to distinguish from each other for the devices. Also since thumb gave no response, it cannot be determined at the particular site we chose to place electrodes on. However, it is quite feasible to distinguish the other fingers due to the intensity difference amongst the fingers.

4 Conclusions

In this study, the finger movements of different subjects were observed and analyzed by plotting their sEMG at the forearm, using a single pair of electrodes, placed above the flexor carpi radialis. It was noted that different fingers gave different EMG amplitude in response to finger movement when monitored from the same electrode site. However, the change in amplitude in detecting the different fingers flexion was relatively same throughout the study. At the Flexor carpi radialis muscle, the ring finger gave the highest individual finger response. Other fingers also showed responses, albeit, less intense as compared to that of the ring finger. This study could be made more comprehensive by taking signal analysis on different forearm muscles or by repeating the study while having an array of electrode pairs around the forearm, integrating the information from each electrode pair during gesture detection for a more detailed response analysis to each individual finger. It can be further improved by implementing digital filters to remove noise and artifacts better. In the future, a study using frequency analysis of the signals could give more detailed information on classifying fingers using EMG, as the information gathered by frequency analysis can be studied quantitatively and can then be further assessed to formulate a strong relationship which can correlate the response that each finger flexion generates to the site of electrode placement. By applying all these modifications and future advancements, a collection of gesture templates can be generated, starting from simple single finger gestures to complex gestures, involving all the fingers. These templates can then be used to reliably detect a multitude of different gestures, using sEMG signals.

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