Using Palpation for Identification and Discrimination of Optimal Points for EMG Harvesting on the Lower Forearm Muscles

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***Abstract*—The calibration process of the EMG input system is often not straightforward because it requires knowledge of muscle anatomy. The lack of a guide makes it difficult for untrained users to perform the calibration. This paper proposes a systematic method for identifying muscles in the lower forearm for EMG input for a control system. Palpation was used on a single subject to identify the major muscles and their locations. A coordinate system was then used to record the positions of the muscles. Seven major muscles which are considered robust to electrical interference and skin shift were identified, and their coordinates recorded.**

***Index Terms*—palpation, EMG, human machine interface, synthetic system**

I. Introduction

EMG is commonly used as an input for machine control. In the category of machine control, the EMG has been widely applied as a control signal for prosthesis for amputees [1]. For able bodied operators, EMG provides an alternative input for teleoperation of robots and machines [2] and [3]. Regardless of the end application of EMG, the underlying reason behind EMG is to provide a method of input to a computing system. In relation, EMG has also been explored as a wearable input interface for computing devices [4] and [5].

Traditional HMI such as joysticks, buttons and levers have provided reliable input. However, in cases where the operator needs to be mobile and hands-free, these input methods may not be optimal. With the development of sensors and software, surface Electromyography (EMG) is emerging as a potential alternative to traditional HMI. Over the last decades, EMG has gained a lot of attention since it is a non-invasive interface. Since EMG signals are electrical signals harvested from the contraction of muscles, the operator can be free from physical control the machines.

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Despite the development of algorithms to decode and process EMG signals, the quality of the raw input signal remains an important issue. The EMG signal is physiological in nature and thus, subjected to subject variation [6]. Variations can take place as difference in size and origin-insertion points of muscles, and the characteristics of the EMG signal it produce. As a result, the procedure of calibrating an EMG input system is often not as straight-forward as desired. A system created for a single user can take up to 30 minutes of calibration [2]. Precision also comes at a cost. While it is possible to obtain precise control from individual fingers, the setup requires placement of up to 10 electrodes, some laid over deep muscles [7]. Pronation and supination causes considerable shift to muscle locations of the thumb and extensor indicis [8].

II. Methodology

An operator of the EMG interface will need an intimate anatomic knowledge of the muscular system if he were to do his own setup. The setup procedure is impractical for real-world applications such as a machine operator in a manufacturing environment, or an electronic product consumer. In this case, this user would desire a wearable sensor device that is simple to setup and robust to ambient electrical noise. Therefore, we aim to address the problem by designing an EMG sensing sleeve that targets major muscles which are less prone to rotation shift, and minimize the number electrodes, while maximizing the usable muscle area.

It is worthwhile to look into the aspect of the muscles that are responsible for the EMG signals. The main objective of this work is to identify and discriminate the muscles in the forearm. The approximate location of the muscles in the forearm was recorded with a coordinate system introduced in [9]-[11]. The benefit of marking the muscles by a coordinate system is two-fold. First, users with little anatomic knowledge can perform the electrode placement setup and calibration quickly, and second, the

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muscle locations recorded with the coordinate system can be used to construct a wearable sensor device.

Emphasis was placed on identifying the center and end of the muscle bulk, as it will give the highest EMG signal. Gestures that were studied include flexion and extension of the wrist, ulnar and radial deviation of the wrist, and flexion and extension of fingers and thumb, shown in Fig. 1. Muscles that shift during pronation and supination are considered complex and therefore not viable for simple EMG electrode placement. Thus, the focus of the experiment is to determine the muscles that are significant, and thus easy to identify.

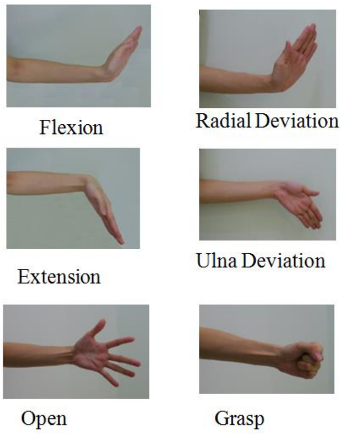
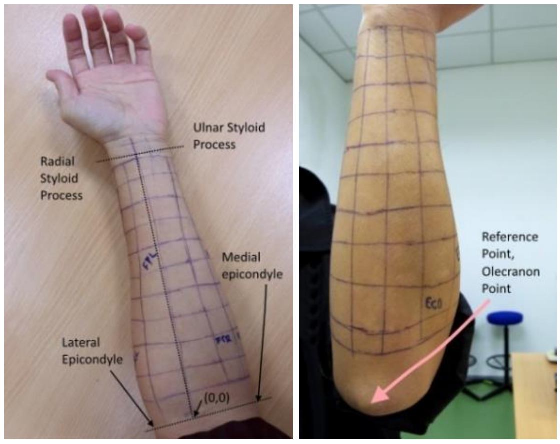


Figure 1. Gestures made by muscles of the lower forearm.

There are 15 muscles in the human forearm [12]. From a mechanical viewpoint, the human forearm is redundantly over-actuated. For example, there are five muscles that flex the wrist. In practice however, over-actuation provides additional strength to the action.

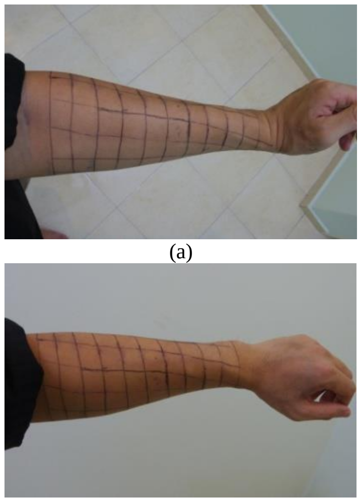
For the experiment, a healthy, male subject was examined. First, palpation was used in conjunction with muscle contraction. The subject was asked to perform gestures while the muscles were palpated. The area of skin where the muscle bulks most during the action represents the muscle belly.

A coordinate system to map the muscle locations was specified where the forearm was segmented with a grid. The place where the corresponding muscle showed the most contraction was marked. Fig. 1 shows the grid with the optimum locations of the FCU, FCR and FDS muscles. There are two reference points that were defined, also shown in Fig. 2(a) and Fig. 2(b). The first is an origin defined by a center line that is defined as the midpoint of the medial and lateral epicondyle, which intersects with the midpoint of the ulna-radius styloid. The size of each grid is 2cm×2cm. Since the skin stretches during action, a second stationary reference point is required. This point is defined by the olecranon point of the elbow, and its location is (6, -1) from the grid origin. The grid was established when the forearm is in a supinated position, which is accepted as neutral in anatomy sense. Fig. 3(a) shows the amount of skin shift in neutral position, while Fig. 3(b) shows further deviation during forearm pronation. The skin and underlying muscles closer to the elbow are less prone to shifting during rotation.



(a) (b)

Figure 2. Location of the grid (a) origin and reference point (b).



(a)

(b)

Figure 3. Deviation of the forearm skin in neutral (a) and pronated position (b).

Wet electrodes were used to acquire the resulting EMG waveforms during the six gestures. The gestures were performed with the wrist in neutral position, pronation and supination. The signals were recorded with the GW Instek GDS 2104A digital storage oscilloscope and Matlab was used to reconstruct the signals.

III. RESULTS

A total of seven significant muscles has been found by palpation. Tendons will slide while muscles will bulk while muscles will be more apparent with load. These muscles are larger and do not shift considerably during pronation and supination of the forearm. Although FPL and APL can be found by palpation, they were found to shift during pronation and supination. Therefore, electrode placement cannot be considered to be robust. The PLG, FDS, EDM, EPL and EI muscles that control the thumb, index finger and little finger are difficult to distinguish by palpation. This is because these muscles are anatomically proximate to each other. Moreover, thesemuscles have origins in the middle of the ulna and radius, which shifts under the skin layer during pronation and supination of the forearm.

TABLE I. RESULTS OF PALPATION AND MUSCLE COORDINATES

Muscles not prone to shift during rotation of the forearm, α		Significant Muscles affected by rotation of the forearm, β		Muscles insignificant to palpation, γ	
FDS	(3,6)	FPL	(-1,6)	PLG	insignificant
FCR	(3,2)	APL	(-4,6)	FDP	(3,6)*(FDS)
FCU	(2,2)			EDM	Insignificant
EDT	(-3,3)			EPL	(-4,6)*(EPB)
ECRL	(-2,1)			EXI	insignificant
ECRB	(-2,1)*(ECRL)			EPB	(-4,6)*(EPL)
ECU	(-4,1)				

All major muscles and their coordinates are listed in Table I. These coordinates were found to be in agreement with [13]. The algorithm of gesture can be generally defined as G = (α+β+γ) where G is the action while α, β and γ are the muscle groups, as defined in Table I. Therefore, the algorithm of the gestures associated to all forearm muscles can be defined in (1). The "+" sign is a logical OR operator.

$$G = \left\{ \begin{array}{l} (\text{Wrist\_flex}, W_f = FCR + FCU + FDS + FDP + PLG), \\ (\text{Wrist\_extend}, W_e = ECRL + ECRB + ECU + EDT \\ \qquad + EDM + EPB + EXI), \\ (\text{Wrist\_abduct}, W_b = FCR + ECRL + ECRB + APL + EPL), \\ (\text{Wrist\_adduct}, W_d = FCU + ECU), \\ (\text{Fingers\_flex}, F_f^{<P,M,D>} = FDS + FDP), \\ (\text{Fingers\_extend}\; F_e^{<P,M,D>} = EDT + EDM + EXI), \\ (\text{Thumb\_extend}, T_e^{<T,P,D>} = EPB + EPL + APL), \\ (\text{Thumb\_flex}, T_f^{D} = FPL), \\ (\text{Thumb\_adduct}\; T_a = APL) \end{array} \right\} \tag{1}$$

We define the gesture of *Hand_open* and *Hand_close* in (2) as a function of the fingers and thumb.

$$\left. \begin{array}{l} \text{Hand\_open}, H_o = F_e + T_e^{<T,P,D>} \\ \text{Hand\_grasp}, H_g = F_f + T_f^{P} + T_a \end{array} \right\} \tag{2}$$

In addition, since the ECRL and ECRB are physically close to each other and essentially similar function-wise, we combined their functions in (3). This simplifies the number of variables and also increases the surface area of the muscles.

$$ECR = ECRL + ERCB \tag{3}$$

The complexity of the equations can be reduced if the muscles defined in β and γ are omitted with elimination defined as Y={G|G(α\β\γ)}, or simply Y={α}. This yield to:

$$\left\{ \begin{array}{l} (\text{wrist\_flex}, w_f = FCR.FCU + FCU.FDS + FDS.FCR), \\ (\text{wrist\_extend}, w_e = ECR.ECU + ECU.EDT + EDT.ECR), \\ (\text{wrist\_abduct}, w_b = FCR + ECR), \\ (\text{wrist\_adduct}, w_d = FCU + ECU), \\ (\text{hand\_open}, h_o = F_e = FDS), \\ (\text{hand\_grasp}, h_g = F_f = EDT) \end{array} \right\} \tag{4}$$

As a result, we have defined six gestures that are potentially easier to harvest and also robust to rotation. The gestures are listed in Table II.

TABLE II. GESTURES THAT POTENTIALLY PRODUCE GOOD EMG SIGNALS

Hand Open	Hand Grasp
Wrist Flex	Wrist Extend
Wrist Abduct	Wrist Adduct

From the table, there are six major actions that can be classified without major deviations due to muscle shift caused by rotation of the forearm. Due to the larger usable area of the muscles, we expect the design of the EMG sleeve to be simpler. In addition to the six major actions, it is possible to expand the range of actions by defining several actions with signals tapped from a single channel. Kim *et al.* has shown that signals from a single channel can be utilized to define up to four actions [3].

A biopotential amplifier circuit, shown in Fig. 4 has been developed in order to acquire the EMG signals. The circuit was designed to have a gain of 650 and a bandpass region of 20-700Hz. The EMG signals were recorded with a Digital Storage Oscilloscope (DSO) and later reconstructed with Matlab.

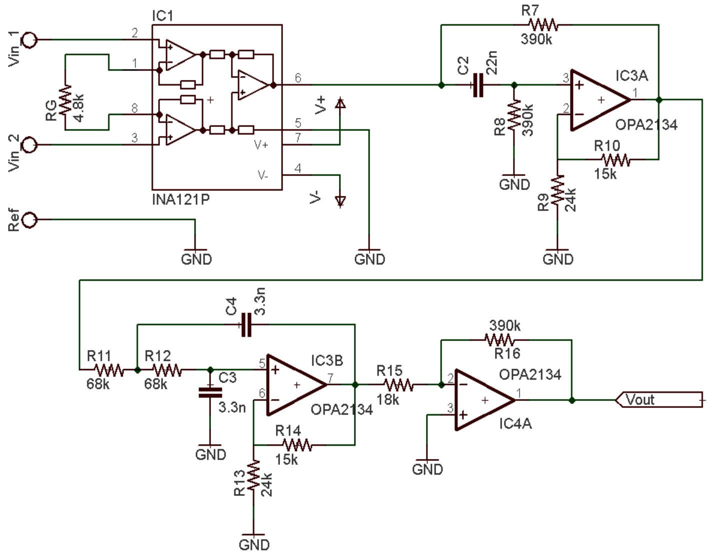


Figure 4. EMG sensing circuit.

The proposed grid layout was tested for signal fidelity of the gestures when forearm rotation is introduced. A sample of wrist adduction (radial deviation) recorded over the FDS at location (2, 2) is shown in Fig. 5.

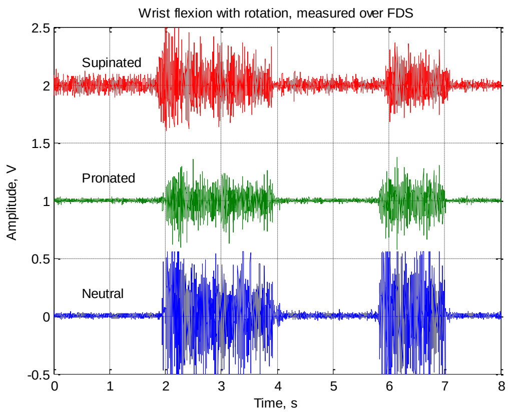


Figure 5. Result of EMG signals during wrist rotation test.

A visual observation shows that general maintained fidelity during the pronation and supination. This shows that the targeted muscle was still above the electrode even during wrist rotation. However there is some minor variation in term of the amplitude of the EMG signal, and its baseline noise. The same trend was observed over the other muscles in the test. The measured RMS in the individual channels is provided in Table III.

TABLE III. RMS AMPLITUDE OF WRIST FLEXION

Position	RMS (V)
Neutral	0.1174
Pronated	0.0793
Supinated	0.0648

Although the proposed electrode grid showed general robustness during rotation, crosstalk is still an issue. Fig. 6 shows the EMG recording for wrist extension acquired over the EDT muscle. Although the gesture of wrist extension is due to the extensor muscles, some EMG signals are picked up in the flexor muscles. However, crosstalk is completely responsible for the signal duplication. In reality, the flexor and extensor muscles work in an agonist-antagonist pair. Most gestures require contraction of both muscles to maintain position.

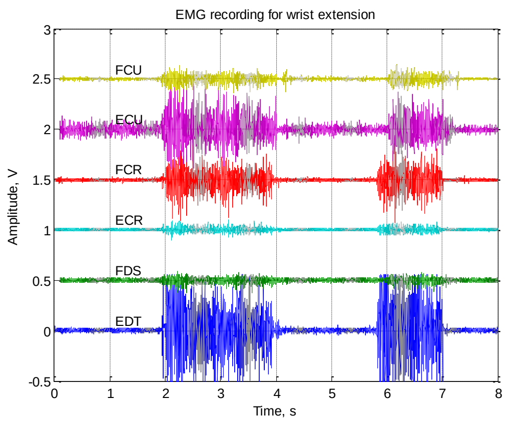


Figure 6. Crosstalk of EMG signals during wrist extension.

Fig. 7 shows the EMG result of radial deviation. Although the muscle activity appears to be crosstalk, close inspection will reveal that the signals across the channels are not entirely identical, suggesting there indeed is muscle activity. For the radial deviation, we expected dominant muscle activity in the radialis muscles, however, the data showed almost equal.

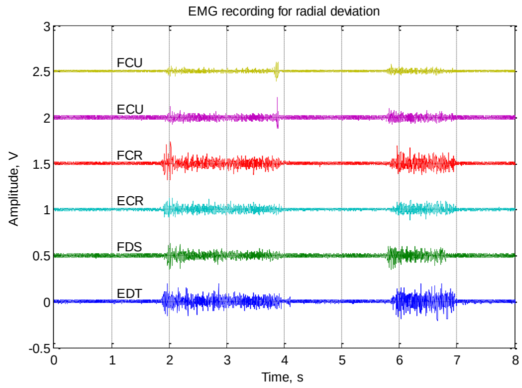


Figure 7. Crosstalk of EMG signals during wrist extension.

IV. CONCLUSION AND FUTHER WORKS

This paper proposes a method for locating muscles for surface EMG harvesting, which we hope will simplify the calibration process of an EMG input system. A grid system was used and the major muscles were found. We were able to define six gestures that we consider robust to noise and muscle shift.

The test results show that EMG distortion due to pronation and supination can be generally avoided with the proposed guidelines. However crosstalk between channels cannot be averted because the surface EMG acquisition method covers a large area and EMG signals can be picked up easily from nearby muscles. The main issue found in this research is that a gesture can be a result of more than one muscle in contraction.

Future research will be directed to studying the cause and effects of crosstalk, and how it can be minimized. A larger sample of users will be used, with use of test equipment. If the muscles defined by the coordinate system are repeatable for other users, then we can explore the possibility of realizing a wearable sensor device for multiple users.

NOMENCLATURE

Flexor Capri Radialis (FDS), Flexor Capri Ulnaris (FCU), Flexor Digitorum Superficialis (FDS), Palmaris Longus (PLG), Flexor Pollicis Longus (FPL), Flexor Digitorum Profundus (FPL), Extensor Capri Radialis (ECRL), Extensor Capri Brevis (ECRB), Extensor Digitorum (EDT), Extensor Digitorum Minimi (EDM), Extensor Capri Ulnaris (ECU), Abductor Pollicis Longus (APL), Extensor Pollicis Longus (EPL), Extensor Pollocis Brevis (EPB), Extensor Indicis (EXI), proximal, middle and distal phalanx of finger <P,M,D>, metacarpal, proximal and distal phalanx of thumb <T,P,D>.

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