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sEMG Signal and Hill Model based Continuous Prediction for Hand Grasping Motion

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***Abstract* - This paper is aimed at the continuous hand grasping motion prediction during all fingers flexion and extension. Only sEMG signals recorded from flexor digitorum superficialis and extensor digitorum of forearm are used to predict the flexion and extension motion. In order to find the relation between sEMG signals and hand grasping motion, a Hill model is used to represent the force value of the muscles. Some assumptions are also made for simplicity in calculating the association. A simple and efficient motion recording system using flex sensor, Mtx sensor and a glove is designed for the purpose of recording fingers motion. The motions are voluntary finger flexion and extension with no load. Acceptable results are achieved. The purpose of this paper is to provide a method for continuous hand grasping motion prediction based on sEMG signals. Although some assumptions are made to simplify the problem and indeed these assumptions brought prediction errors in the experiment, the method shows itself an alternative way to use sEMG signals for hand motion prediction.**

Index Terms – Surface Electromyography (sEMG) signal, Hill model, hand grasping motion, continuous prediction

I. Introduction

With the development of robot technology, the biorobots are compelling during recent years [1]-[4]. After the discovery of electromyographic (EMG) signal, it has been widely used in biorobots control and some other fields such as rehabilitation, human body motion detection and athlete training. The nature feature of the EMG signal, which directly represent for the activation potentials of skeleton muscle, makes it very convenient and direct in representing status of muscles. Many researchers are working on EMG-based devices design, such as the EMG-driven exoskeleton hand robotic training device, which is mounted on patient's impaired hand and detected sEMG signals are used as the driven signals [5]; the EMG-driven musculoskeletal model of the ankle, which combines the Hill-model and sEMG signals to estimate the forces of the triceps surae muscle and Achilles tendon [6]. Also some others are using EMG signal to predict human body motions, such as Artemiadis et al [7] used a switching regime model to predict the motion of arm based on 11 channels of EMG signals.

There are mainly two kinds of EMG signals measurement: the surface EMG signals detection method using non-invasive surface electrodes and the invasive EMG signals detection method using fine wire electrodes. The surface EMG signals measurement is widely used in researches because of its non-invasive characteristic. But the low signal to noise ratio (SNR) is an unavoidable problem, at least under present electromyography technology in this measurement. Many factors result in this issue, such as the condition of the skin, the thickness of the fat tissue under the skin, the crosstalk between muscles, and the different recruitment level in motor unit action potentials. Because of the low SNR and crosstalk in muscles, many researchers are focusing on the method to increase the recognition accuracy, such as Tang et al [8] used two developed methods to extract features of EMG and designed a novel cascaded-structure classifier to achieve hand pattern recognition. Although some method can achieve high recognition accuracy for special motions, it is far beyond enough in whole human motion, especially in hand motion detection. The crosstalk between EMG signals and the coordination of small muscles on the forearm make the recognition extremely complicated. Also many of these studies separate motions into different patterns and deal with problem as pattern recognition, thus the continuous prediction is also a main issue.

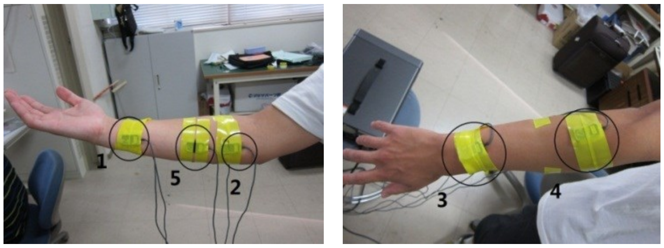
In this paper, sEMG and Hill-model based continuous hand grasping motion prediction method is represented. sEMG signals recorded from flexor digitorum superficialis and extensor digitorum of forearm are used to predict the fingers flexion and extension motions. The Hill model is used to represent the force value of the muscles. Three assumptions are made to simplify the situation. Acceptable results are achieved after experiments on three subjects.

II. Design of Continuous Prediction Method for Hand Grasping Motion

In this paper, the grasping movement is flexing and extending of all fingers at the same time. EMG signals are recorded from flexor digitorum superficialis and extensor digitorum of forearm. Then the Hill model is used to calculate the force value of muscles according to activation level of EMG. Under three assumptions, a prediction is calculated according to the force value of muscles.

A. EMG Recorded from Forearm

The crosstalk and coordination between the small muscles of forearm is one of the reasons making the prediction of hand motion extremely complicated. It is very ideal to find each muscle involved in the flexion and extension for each digit separately but from the point of view in anatomy, there may not be a separate muscle or a group of muscles affording the



a). Electrode placement on front side of forearm

b). Electrode placement on back side of forearm

Figure 1. Electrode placement on forearm

flexion or extension force for each finger because of the phenomenon of fingers coordination. It is very difficult to move each finger freely without involving other fingers. Also in experiment, it is not easy or maybe impossible to find a proper placement to detect EMG signals presented single finger movement.

In this paper, flexor digitorum superficialis and extensor digitorum of forearm are selected to detect EMG signals from. The placement of the electrodes around the forearm is shown in Fig.1, where electrodes 1, 2 and 5 are placed on three different surfaces upon flexor digitorum superficialis belly, which takes charge with flexion of middle phalanges at proximal interphalangeal joints of medial four digits. After compared the effects of the EMG signals, electrode 2 is selected for experiment. And electrode 4 is placed on the surface of extensor digitorum, which takes charge with extension of medial four digits at metacarpophalangeal joints. Electrode 3 isn't included in this time.

Although the crosstalk between these muscles can be easily observed from the experimental results, the performance of these muscles is of coincidence of defined finger motions.

B. *Hill Model*

The Hill model simulating the biomechanics of muscle is one of the conventional and classical models to predict the muscle behaviour. The model (Fig.2) contains a pair of elements arranged in series: the passive serial element (SE) and the active contractile element (CE); and a passive element (PE) arranged in parallel to the previous two. The Hill model calculates the force of muscle using the activation level, muscle length and shortening velocity. Some researcher calculated the muscle length and moment arm given the joint angles and limb kinematics. The equations [9]-[10] used to calculate the force are shown as follows:

$$F_{PE,SE} = \left[\frac{F_{max}}{e^{S}-1}\right]\left[e^{\left(\frac{S}{\Delta L_{max}}\Delta L\right)}-1\right] \tag{1}$$

$$\begin{cases} F_{CE} = u \cdot f_l \cdot f_v \\ f_l = \exp\left(-0.5\left(\dfrac{\frac{\Delta L_{CE}}{L_{CE_0}}-0.05}{0.19}\right)^2\right) \\ f_v = \dfrac{0.1433}{0.1074+\exp\left(-1.3\sinh\left(2.8\frac{V_{CE}}{V_{CE_0}}+1.64\right)\right)} \\ V_{CE_0} = 0.5(u+1)V_{CE_{max}} \end{cases} \tag{2}$$

$$F_T = F_{CE} + F_{PE} \tag{3}$$

$$a(u) = \left(e^{AuR^{-1}}-1\right)/\left(e^{A}-1\right) \tag{4}$$

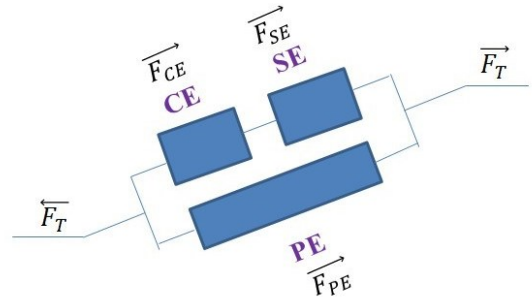


Fig. 2 Schematic of Hill-model with CE, SE and PE elements

where ΔL is the change in length of the element with respect to the slack length, S is a shape parameter, F_{max} is the maximum force exerted by the element for the maximum change in length ΔL_{max}, and $F_{PE,SE}$ is the passive force generated by the PE or the SE element depending on the set of parameters used. F_T is the total force exerted by the muscle. $a(u)$ is the activation level of a muscle.

The parameters such as length of muscle fiber and fiber length change velocity are difficult to record through conventional measurement. Some researchers used indirect method such as change in joint angles to calculate the change in muscle fiber length, or used the data from other project to represent for a mean value. To simplify this situation, three assumptions are made in the following section.

C. *Assumptions for Simplicity*

In this paper, subjects performed the experiments with their hand holding nothing, in other words, there is no extra force exerted by the muscle to conquer the external load. Thus, only voluntary isotonic contraction is considered in this time. So in first assumption, the force exerted by muscle is considered to be only coordinated with the joint angle of fingers. The Hill model calculates force exerted from muscle mainly by muscle activation level, muscle length and shortening velocity. Because of considering isotonic contraction, $\frac{\Delta L_{CE}}{L_{CE_0}}$ or $\frac{\Delta L}{\Delta L_{max}}$ is defined as proportional to the activation level of muscle in second assumption. And the third assumption is that the velocity of CE element is considered to be zero, because experimentation is performed at a very slow speed, subjects performed the entire process in about 10 seconds.

D. *Motion Detection Device*

Two flex sensors (Spectrasymbol com.) are mounted on proximal interpharangeal joint (PIP) and metacarpophalangeal joint (MCP) of a rubber glove, as shown in Fig.3. The electric resistance of the flex sensor is changing with the shape bending. A simple OP circus is used to record the data of the sensor. A 3DoF inertial orientation tracker (MTx sensor, Xsens Technologies B.V.) is applied to calculate the association between the change of resistance and the degree of the shape bending. In the experiment, the MTx sensor is sticked on the flex sensor and both the data from the MTx sensor and flex sensor are recorded through data acquisition system (USB4716, Advantech Co. Ltd.) at the same time, while operator bended the flex sensor from 0° to 90°, as shown in Fig.4. Then a curve fitting toolbox (MathWorks Co. USA) is used to generate a function $y = f(x)$, where x is the change of resistance and output y is the degree of the joint mounted with the flex sensor.

E. Experimental Protocol

Three healthy volunteers aged from 22-26 years, all male, one left-handed and two right-handed, participated in the experiment. Before electrodes are placed that are aligned parallel to muscle fibers over the belly of the muscle and positioned following recommendations, the skin is shaved and cleaned with alcohol in order to reduce skin impedance. The subjects are asked to wear on the glove and keep their forearm relaxed vertically. The EMG signals from this position are observed in order to guarantee no extra movement interfering the hand motion. Because the motion velocity must be low enough, the subjects are asked to practice the flexion and extension movement several times before experiment. The entire process took about 10 seconds and subjects had a 30 seconds rest after one process.

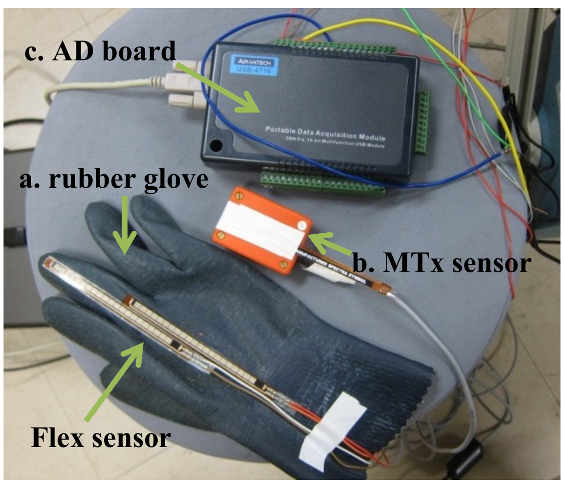


Fig. 3 Experimental setup detecting motions of fingers. a) rubber glove with flex sensor; b) flex sensor attached on MTx sensor; c) AD board

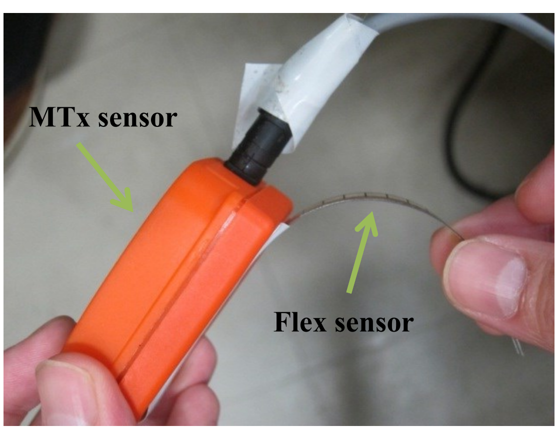
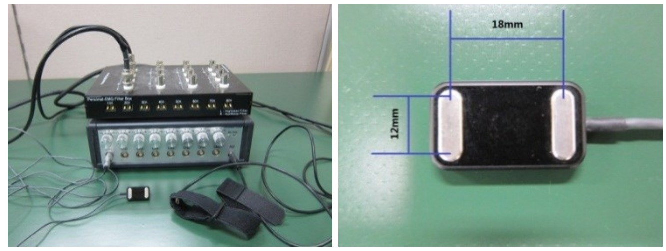


Fig. 4 Experiment to calculate function between changes in voltage and joint angle



a). sEMG Filter box b). Electrode

Figure 5. sEMG recording devices

F. EMG Recording Setup

sEMG signals are collected using bipolar surface electrodes 12mm long, located 18mm apart, as shown in Fig.5. The sampling rate is 3000Hz with differentially amplified (gain 1000) and common mode rejection (104dB). This sampling rate is sufficient because the most frequency power of EMG signals is between 20 to 400Hz. Sampling data are pre-processed with a commercial filter box (Oisaka Electronic Device Ltd. Japan.) before being recorded in the control program through an AD board.

III. Experimental Results

A. Recording of Finger Motions

The sampling rate of recording the data from flex sensor and MTx sensor is 1KHz. The data from flex sensor is voltage and from MTx sensor is pitch degree. The experimental result is shown in Fig.6

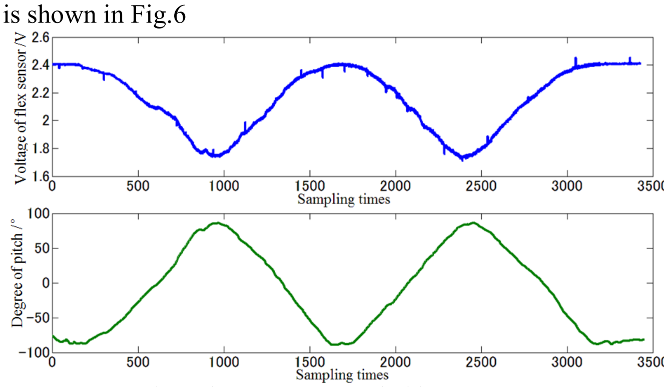


Fig. 6 Flex sensor compared with MTx sensor

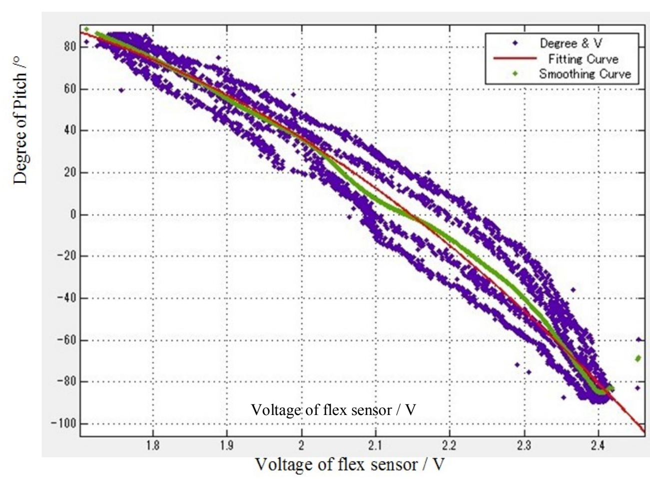


Fig. 7 Curve fitting process of flex sensor

The quadratic function is implemented to represent the coordination between voltage and degree in curve fitting method. The function is written in Eq.5, and the fitting process is shown in Fig.7, where the dots represent the original data, the green line is calculated by smooth method, and the red line is the fitting curve. Coefficient of determination is 0.97, which is sufficient for finger motion record.

$$f(x) = -176.2x^2 + 481.7x - 222.1 \tag{5}$$

B. EMG Signals Processing Results

The EMG signals are filtered with band passed (20-450Hz), 5 order Butterworth filter, full wave rectified. Following shows one experiment result from one subject, where the above two are the EMG signals from extensor digitorum and flexor digitorum superficialis separately, and the two below are degree changes of MCP and PIP joints. It can be indicated that the flexor digitorum superficialis activated in flexion movement, and the activation level increased with MCP joint degree increasing. The extensor digitorum activated in two periods: first at the extension period (from 0 to 1000 and 4000 to 5000 in Fig. 8), and second at the flexion period (from 1500 to 3000 in Fig. 8). The movement of finger is from the entire extension to entire flexion and back to the entire extension. Thus the extensor digitorum activated at the beginning and at the end of the movement. Although it is natural that the extensor digitorum activated at the finger extension period, activation at flexion period is considered as coordination at this time and the contribution of this part is eliminated.

The processed EMG signals are calculated using root mean square (RMS) via a 50ms window. The value of RMS is then used as input of (4) to get the activation level of a muscle and the activation level is put into (1) and (2) to calculate the force of the muscle, which is considered proportional to the degree of finger joint. Fig.9 shows the result of calculation using Hill model, and the PIP and MCP data are resampled via a 50ms time window. The RMS value of extensor digitorum is ignored when the activation level of flexor digitorum superficialis is exceeded 10% of maximum because this part is considered as coordination at this time.

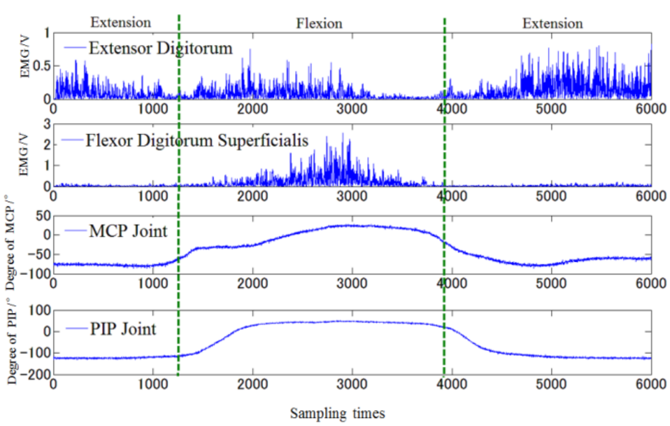


Fig.8 Recorded EMG and flex sensor data from one subject in one experiment

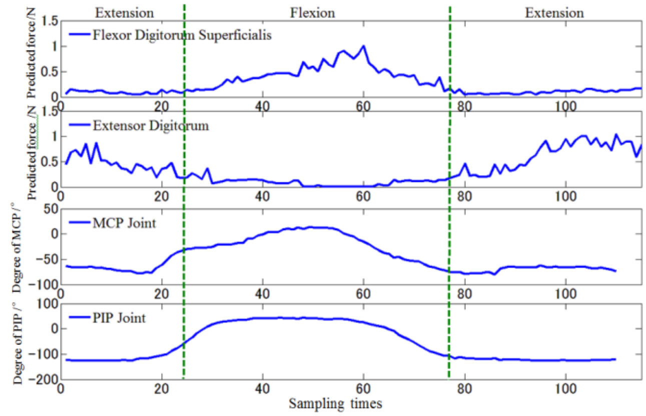


Fig. 9 Predicted forces compared with angles of joints

The non-linear relationship between the predicted force and the recorded angles of joints can be indicated from Fig.9. At the beginning part (from 0 to 15) and the end part (from 90 to 110) the value of force level keeps upon a threshold indicating an un-movement motion, and the muscle status at these two parts is more like isometric contraction. A curve fitting method is implemented to find a preliminary function to predict the motion of finger via force value calculated by Hill model. The MCP and PIP joints are predicted separately. The functions are described as follows:

$$f_{mcp}^1 = 3533x^5 - 9568x^4 + 9257x^3$$
$$-3785x^2 + 634.3x - 44.01 + C_{mcp}^1 \tag{6}$$

$$f_{mcp}^2 = -4106x^5 + 9357x^4 - 7211x^3$$
$$+2038x^2 - 128.8x + 71.66 + C_{mcp}^2 \tag{7}$$

$$f_{pip}^1(x) = 730x^3 - 1761x^2 + 1383x - 306.5 + C_{pip}^1 \tag{8}$$

$$f_{pip}^2(x) = -1032x^3 + 1973x^2 - 1215x + 130.5 + C_{pip}^2 \tag{9}$$

Where f_{mcp}^1 and f_{mcp}^2 are used to predict the flexion and extension motion of MCP joint and f_{pip}^1 and f_{pip}^2 are used for PIP joint. Especially, f_{mcp}^1 and f_{pip}^1 are used when flexor digitorum superficialis is activated and f_{mcp}^2 and f_{pip}^2 are used when extensor digitorum is activated. Coefficients of determination for f_{mcp}^1 and $f_{mcp}^2$are 0.61 and 0.65 separately. And towards f_{pip}^1 and f_{pip}^2, they are 0.80 and 0.75 separately. Fig.10 and Fig.11 show the prediction results compared with the records from flex sensors where the solid blue lines are the prediction results and dot lines are records from flex sensors.

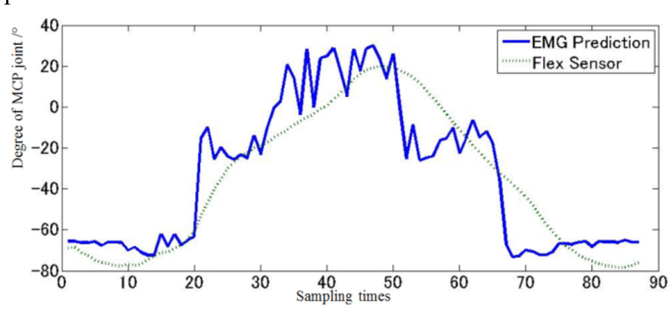


Fig. 10 EMG based MCP joint motion prediction

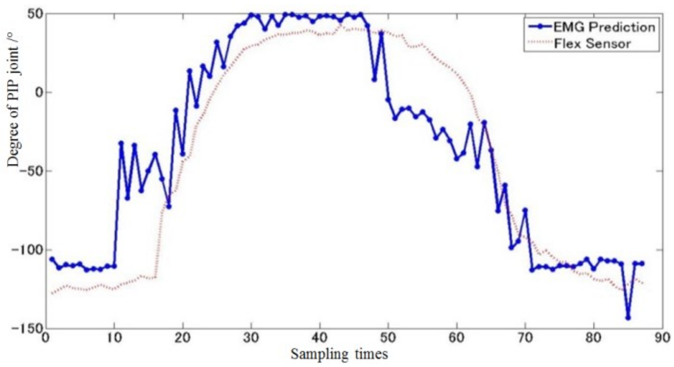


Fig. 11 EMG based PIP joint motion prediction

IV. Discussion

The objective of this study is to develop a hand grasping motion continuous prediction method based on EMG signals and Hill model. Although it is convenient and direct to use EMG signals to represent muscle status, the unstable and non-stationary features make it intricate in EMG-based implementation. Sometimes only rough recognitions can be achieved or some perplexing algorithms are needed.

In order to record the motion of MCP and PIP joint, flex sensors are used. Although it will be more precise to use MTx sensor directly recording the joint motion, the inertia of MTx sensor will bring some errors into the prediction, because more force needs to be exerted from the muscle to conquer the extra torque which will lead the value of EMG higher than in a free condition. The flex sensor is much lighter (0.40g) than MTx sensor (37.80g) and the inertia interference is much smaller.

The three assumptions used for simplifying the implementation of Hill model will indeed bring errors to the prediction of force. Although the experiment is performed by subjects in a very slow velocity, it is of cause not zero. And the isotonic contraction can only be kept by subjects subjectively. It is hard to guarantee every subject can keep isotonic movement in every second, especially at the beginning and end of the movement. One of the controversial issue in EMG signals prediction is that not only the defined motion can lead to the EMG signals changes but other motions especially the isometric contraction can lead to the same EMG behavior for a muscle compared to the isotonic contraction. One of the feasible methods to solve this problem is to use more electrodes to detect other muscles EMG behavior because in isometric contraction, not only target muscle contracts but other coordinate muscles. In this time, two electrodes are used to record EMG signals from flexor carpi radiais and extensor digitorum, no other muscles are involved. The association between the changes of muscle length and the EMG amplitude is of cause non-linear. The changes of muscle length during the experiments are not easy to record, thus the assumption of proportion to muscle activation is made, according to isotonic contraction.

The EMG signals are individual independence. In this paper, the subjects had their own prediction functions and the effect is also individual independence. Some coefficients needed to be regulated after the re-setup of the experiments. And the placements of the electrodes also contributed to this inconvenience. It took some times to find suitable placements for electrodes, even we took photos of every subject's forearm for reference.

V. Conclusion and Future Works

In this paper, a continuous finger motion prediction method using EMG signals and Hill model is presented. A flex sensor is used to record the angle changes of MCP and PIP joints. Three subjects participated in the experiments. Although there are many precise methods to detect the motion of fingers, most of them need to attach extra sensor or equipment on fingers, which may affect the natural motion of fingers or bring some uncomfortable feeling to subjects. In this paper, two electrodes are attached on flexor digitorum superficialis and extensor digitorum of forearm, bringing no extra burden to fingers.

More details in Hill model are needed to be confirmed and detected, such as changes of muscle length and velocity. A furthermore dynamic model describing the relationship between force calculated from Hill model and the changes of finger joints angle is also needed.

Acknowledgment

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