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Finger Joint Continuous Interpretation based on sEMG Signals and Muscular Model

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***Abstract* - The human hand is very dexterous and can perform various of gestures in activities of daily living. Only dividing the motions of hand into several types and applying pattern recognition method for implementation of manipulation control may result in low dexterity and delicacy. In this paper, a novel finger joint interpretation method based on sEMG signals and muscular model is presented. The motion of finger is flexion and extension without any external resistant force and at a natural movement velocity. sEMG signals are recorded from flexor digitorum superficialis and extensor digitorum of the forearm. The Hill-based muscular model is used to calculate the force of muscles according to sEMG signals. In this paper, we assume that the changing of force corresponds directly to the motions of fingers given the circumstance that the subjects hold nothing in their hand and keep the movement velocity. The curve fitting method and Kalman filter are implemented to calculate the relation between force and basic movements of digits. Five subjects participated in the experiment to evaluate the efficiency of this method.**

Index Terms – sEMG, finger motion, muscular model.

I. INTRODUCTION

The dexterity of human hand makes it very convenient and accurate to complete delicate manipulation. Some devices, which mimic the motion of human hand, have been developed for the purpose of achieving new manipulation method, such as HIRO[1], a human-finger like grounded-type haptic interface robot, which can provide high-precision three-directional force at the five human fingertips and the Rutgers Master II-ND glove[2], which was designed as an exoskeleton device, providing about 16N force to fingertips. Although these devices can provide haptic or accurate manipulation method, the size of these devices limit the application and mounting apparatus on hand may result in unnatural feeling to operators. Even using camera, operators have to stand in the scan range, which constrains the users' movement space. Alternatively, implementation of electromyographic (EMG) signal may bring some new convenience to manipulation.

After its discovery, EMG signal has been widely used in biorobots[3]-[6] control and some other fields such as rehabilitation[7], human body motion detection [8] and athlete training. The nature feature of the EMG signal, which directly represents the activation potentials of skeleton muscle, makes it very convenient and direct in representing the status of muscles. Many researchers are working on EMG-based device 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 [9] and Artemiadis et al [10] used a switching regime model to predict the motion of the upper limb arm based on 11 channels of EMG signals.

The individual differences and various unstable factors affecting the behavior of the EMG signal prevent the implementation of such kind of muscular signals. Many researchers use pattern recognition methods to predict the motions of body[11]-[14], such as Tang et al [15] used two developed methods to extract features of EMG and designed a novel cascaded-structure classifier to achieve hand pattern recognition. It seems to have a bit long way to go to implement the recognition results in a reliable control or clinical purpose, although the recognition accuracy is very high in many cases. Also dividing the movement into many patterns may result in missing the details in motion and reducing dexterity for control purpose.

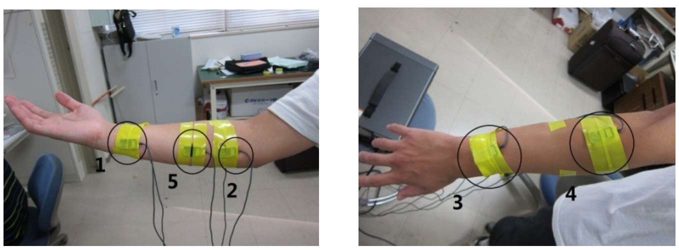
In this paper, a novel finger joint continuous interpretation method based on sEMG signals and muscular model is presented. Surface EMG (sEMG) signals recorded from flexor digitorum superficialis and extensor digitorum of the forearm are used to calculate the force of the two muscles via the Hill-based muscular model. Then the curve fitting method is used to build the relationship between digits flexion and extension movements and the forces. To prove the efficiency of this method, several hand gestures are selected to be interpreted using the finger joint interpretation method in the experiments.

II. DESIGN OF FINGER JOINT INTERPRETATION METHOD

A. Placement Selection for Electrodes

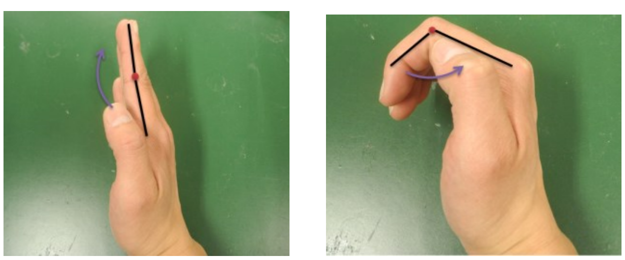
Finding the right surface places upon the aimed muscles to record EMG signals is the guarantee for efficient motion interpretation. It is very ideal to find consistent muscle involved in the motion of flexion and extension for each digit separately and from the perspective of anatomy there may be a single muscle or a group of muscles affording the flexion or extension force for each digit. But in experiment, it is impossible or not easy to find a proper placement on the surface skin to detect EMG signals from the aimed muscles because some of these muscles are in the deep or intermediate level of the forearm. Besides, phenomena of crosstalk and muscle co-activation are more distinct in forearm because of the complexity of the forearm muscles constitution. In the other researches[16], many muscles in the forearm have been used to detect the motion of the hand, such as extensor pollicis brevis, extensor pollicis longus, extensor indicis, flexor digitorum superficialis, extensor digitorum and flexor digitorum superficialis. Among them, the flexor digitorum superficialis (FDS) takes charge with finger flexion at proximal interphalangeal joints, and the extensor digitorum (ED), as an antagonist of FDS, takes charge with finger extension. As a classic method for simplifying the analysis of muscle-joint systems is to lump synergistic muscles into "equivalent" agonist and antagonist muscles, the pair of FDS and ED is very suitable for finger motion detection.

Because the flexor digitorum superficialis is at the intermediate level of forearm, three placements upon its belly were selected (as shown in Fig.1(a)) to find a proper place to detect the EMG signals. And electrode 4 was placed on the surface of extensor digitorum.



(a) Electrode placement on front side forearm (b) Electrode placement on back side of of forearm

Figure.1 Electrode placement on forearm



(a) Gesture of "Rock" (b) Gesture of "Paper"

Figure.2 Gestures of "Rock, Paper, Scissors"

B. Muscular Model

The tendons of flexor digitorum superficialis attach to the anterior margins on the bases of the middle phalanges of digits and the tendons of extensor digitorum are inserted into the middle and distal phalanges of digits. In this paper we assume that these tendons are so stiff that there is no stretch during muscle activation. Consequently muscle contraction directly involves the changes of PIP joint angle θ (as shown in Fig.3 up). Actually, these two muscles are not the only ones take charge with digits flexion and extension. However, we assume that the function of each muscle is proportional under voluntary motions during a certain period of time. And the association between feature extracted from these two muscles and the joint angle θ is invariable under a certain period. We chose force as the muscle feature in this paper. The force was calculated via the Hill-based model.

The Hill model simulating the biomechanics of muscle is one of the conventional and classic models to predict the muscle behavior. The model (Fig.3 below) 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 researchers calculated the muscle length and moment arm given the joint angles and limb kinematics. The equations [17]-[18] used to calculate the force are shown as follows:

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

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

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

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

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 $\Delta L_{\max}$, 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 root mean square (RMS) method was used to calculate the feature (u as shown in Eq.4) of EMG signals with a time interval of 50ms. Then the Kalman filter was applied to smooth the results. Each subject completed a MVC

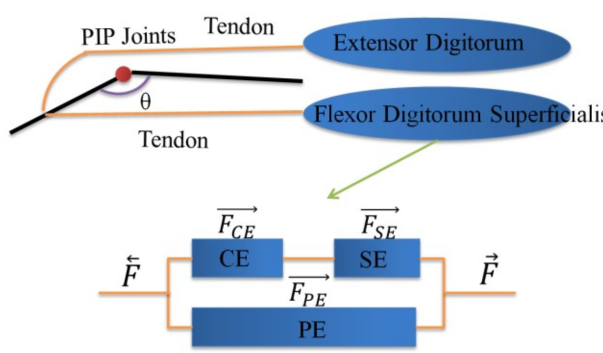


Figure.3 Muscular structure of digit and Hill-based muscle model with CE, SE and PE elements

test to get the value of R separately. 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, the only voluntary isotonic contraction is considered during the experiments. For simplification, $\Delta L / \Delta L_{max}$ is defined as proportional to the activation level of muscle.

C. *Finger Joint Interpretation*

The association between the force of muscles and finger motion is calculated using curve fitting method via MATLAB. A quadratic function (with the form of Eq.5) is implemented to represent this association and each subject gets his own quadratic function individually. In Eq.5, the input $f(u)$ is the muscle force calculated using RMS of EMG and the output θ is the joint angle of digit. Forces from Flexor digitorum superficialis and extensor digitorum are calculated separately.

$$\theta = \sum_{i=0}^{2} a_i f^i(u) \qquad (5)$$

The relaxed position of subject's hand is decided when the EMG signals from FDS and ED stay "un-activated". Because of the existence of muscle co-activation, a state switching part is developed to decide which muscle behaviors as a major factor and the major muscle is used to calculate the finger joint angle.

The muscle activation level ($a(u)$ calculated by Eq.4) of FDS and ED is different during the motion of flexion and extension separately. Although muscle co-activation exists, the division d of $a_{FDS}(u)$ and $a_{ED}(u)$ is different, where $a_{FDS}(u)$ means the activation level of FDS and $a_{ED}(u)$ means the activation level of ED. When $d > a_T$ (a_T means a certain threshold decided experientially), it indicates that the FDS behaviors as a major factor and the finger is in a flexion motion. And when $d < a_T$, it means finger extension oppositely. The state switching part uses this division as an input and decides in which motion the finger is. In this paper, we define that θ is equal to 0 when digit fully extends and equal to 90 when fully flexes. Fig.4 represents the schematic of this process.

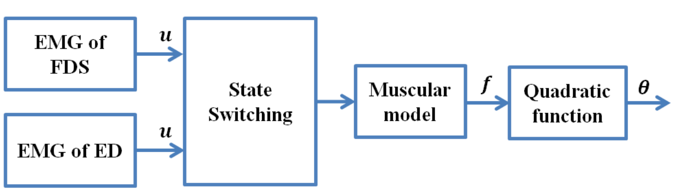
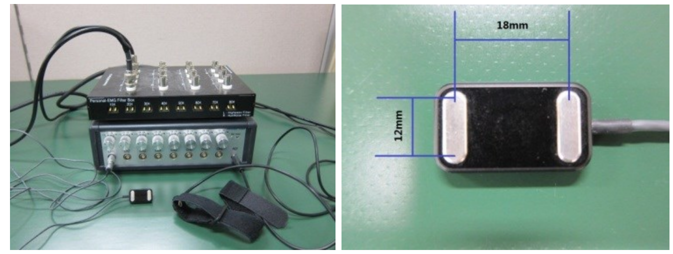


Figure.4 Schematic of gesture interpretation method

D. *Experimental Setup and Protocol*

sEMG signals were collected using bipolar surface electrodes 12mm long, located 18mm apart (as shown in Fig.5). The sampling rate of the filter box was 3000Hz with differentially amplified (gain 1000) and common mode rejection (104dB). sEMG signals were pre-processed using a 4th order Butterworth band-pass filter with 20Hz lower cut-off frequency and 400Hz upper cut-off frequency.

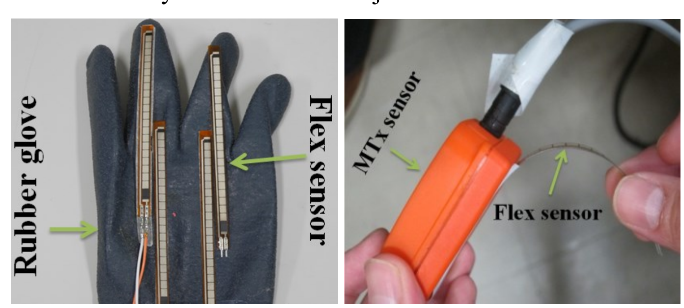


(a) sEMG Filter box (b) Electrode

Figure.5 sEMG recording devices

Two flex sensors (Spectrasymbol com.) mounted on proximal interpharangeal joint (PIP) of 2 and 3 digit of a rubber glove (as shown in Fig.6a) are used to detect the joint angle of fingers. The electric resistance of the flex sensor is changing with the shape bending. A simple OP circus is used to detect the resistance changings as a function of voltage. A 3DoF inertial orientation tracker (MTx sensor, Xsens Technologies B.V.) is applied to find the association between the change of resistance and the degree of the shape bending.

Five healthy volunteers (age: 24.60±1.67, height: 1.70±0.07(m), weight: 67.66±9.54(kg), all male, one left-handed and four right-handed) participated in the experiment. Before electrodes were placed, the skin was shaved and cleaned with alcohol in order to reduce skin impedance. The subjects kept their forearms relaxed vertically on a table and were asked to perform MVC test firstly for three times. The EMG signals were observed in order to guarantee no extra movement interfering the hand motion. The average values of EMG and force were recorded. Then the subjects were asked to wear on the rubber glove attached with flex sensors and perform full finger flexion and extension five times. Because the motion velocity must be kept around a static value (at about 45°/sec), the subjects are asked to practice the flexion and extension movement several times before the experiment. The quadratic functions were calculated off-line using MATLAB. After that, the subjects performed the "Rock, Paper, Scissors" gestures to evaluate the efficiency of this method. The steps of this evaluation experiment were: 1).performing one gesture 2).back to the relaxed position and 3).performing the next gesture. The sequence of the gestures was random by the will of the subjects.



(a) Rubber glove with flex sensors (b) Flex sensor attached with MTx sensor

Figure.6 Digits motion detection setup

III. Experimental Results

A. Finger Joint Interpretation

Fig.7 and Fig.8 depict PIP joint kinematics (joint angles), and the forces calculated via muscular model as a function of time. The joint angles were detected by flex sensor attached at the PIP joint of digit 2. The sampling rate was 1000Hz, the same as EMG signals. During the motion of finger flexion, the force of FDS increases gradually and causes the joint flexion angle increasing (as shown in Fig.7 from 2s to 4s). The co-activation of ED also can be observed (as shown in Fig.7 from 3s to 7s). While the finger extends to the relaxed position, the force of FDS decreases gradually and the force of ED increases slightly (as shown in Fig.7 from 6s to 8s). The increasing part of the ED force (as shown in Fig.7 from 9s) is caused by the subject over-extends from the relaxed position. During the motion of digit extension, the behaviour of these two muscles changes (as shown in Fig.8).

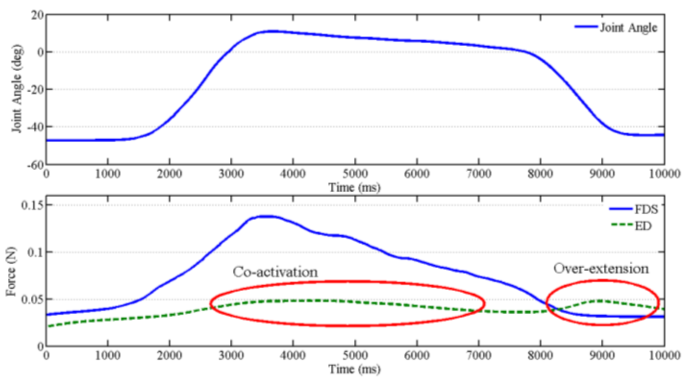


Figure.7 Joint angle and interpretational force changes during the motion of digits flexion

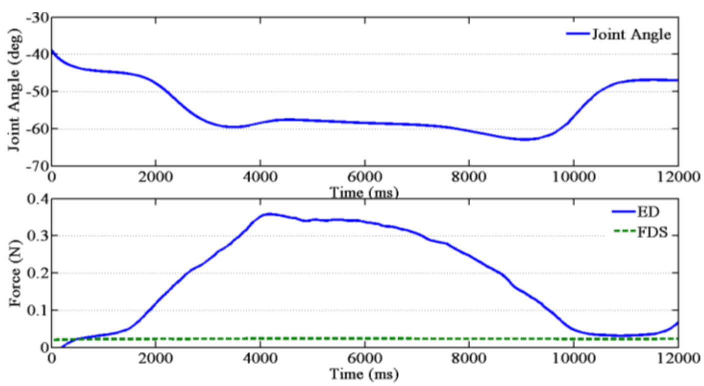


Figure.8 Joint angle and interpretational force changes during the motion of digits extension

Fig.9 and Fig.10 depict interpretation results of flexion and extension motion from one subject separately. The time lag between interpretation curve (solid line in Fig.9 and Fig.10) and detected motion curve (dotted line) can be explained by the phenomenon of electromechanical delay (EMD) and algorithm of RMS, but the error brought in by the interpretation function can't be ignored. Each subject repeated the experiment five times and the results of correlation coefficient are shown in Fig.11 and Fig.12.

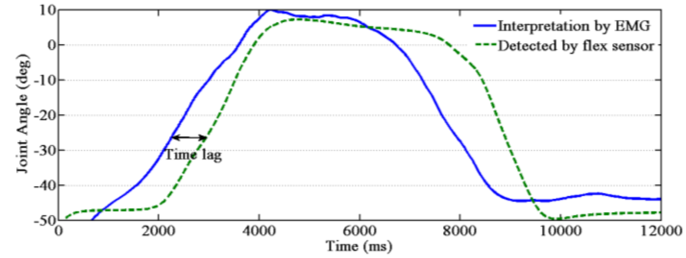


Figure.9 Interpretation results compared with detection result in the motion of digits flexion

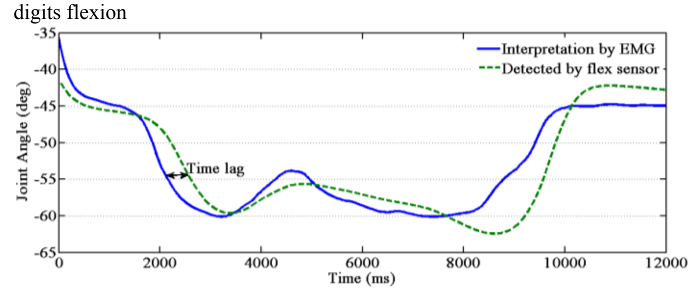


Figure.10 Interpretation results compared with detection result in the motion of digits extension

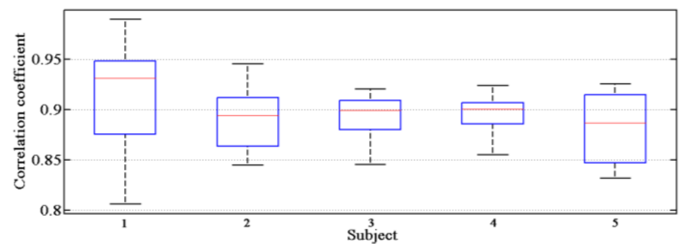


Figure.11 Box plot of correlation coefficient of digit flexion interpretation

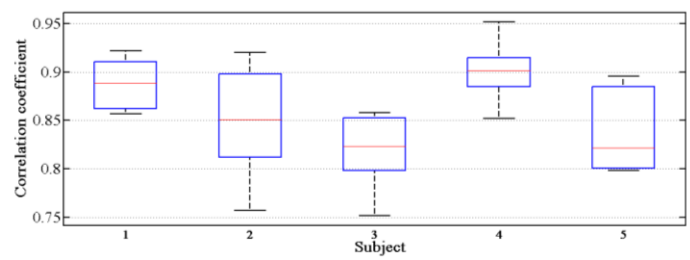


Figure.12 Box plot of the correlation coefficient of digit extension interpretation

B. Hand Gesture Interpretation

To evaluate the efficiency of this finger joint angle interpretation method, a hand gesture interpretation was performed on-line. During the motion interpretation process, the results of the joint angle calculated from FDS mainly indicate the degree of digit flexion, where in this paper we define that, such as the degree ranging from -40° to -30° means a "light" flexion and -30° to -5° means a "medium" flexion and from -5° to 10° means a "full" flexion. On the other hand, the degree of extension is indicated by results from ED, and the ranges are: -40° to -45° means "light"; -45° to -50° means "medium" and -50° to -60° means "full". The definition is different between individuals.

Fig.13 depicts the interpretation result during the motion of "Paper" of one subject. The joint angle decreased to -60°

according to the activation of ED (EMG signals from ED), indicating the “full” extension of digits and FDS kept almost nonactivated in this motion, indicating the “null” flexion of digits. The result corresponds to the motion of “Paper”. Fig.14 depicts the interpretation result during the motion of “Rock” of one subject. The joint angle increased to 20° (full flexion) according to the activation of FDS (EMG signals from FDS) and ED kept almost non-activated in this motion, corresponding to the motion of “Rock”. Fig.15 depicts the result during the motion of “Scissors”. Both the ED and FDS activated and the result indicated that the digits not only flexed but extended at the same time (as shown from 2s to 8s) which interpreted 3 and 4 digits “full” flexed while 1 and 2 digits “full” extended in the motion of “Scissors”.

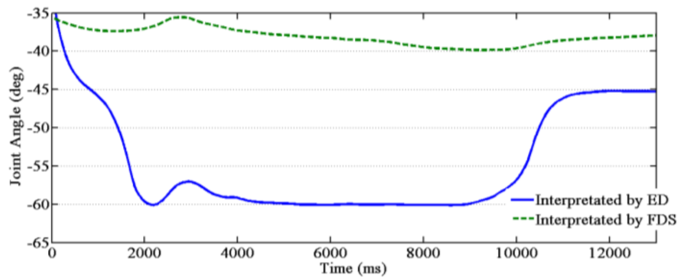


Figure.13 Interpretation results during the motion of “Paper”

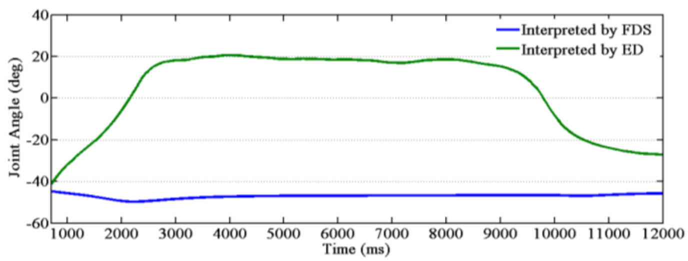


Figure.14 Interpretation results during the motion of “Rock”

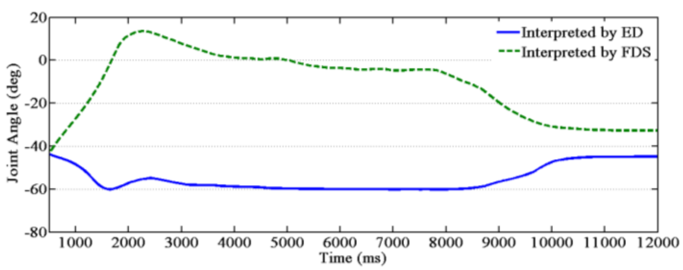


Figure.15 Interpretation results during the motion of “Scissors”

The subjects were asked to perform gestures of “Rock, Paper, Scissors” randomly for 30 times. The results both from flex sensor (standard results) and EMG interpretation (being verified results) were recorded and the accuracy rate was 0.913±0.038 (mean±SD).

IV. Discussion

A. Factors involved the muscular model

The load force and digit movement velocity, which mean the rotary inertia (I) and angular velocity ($\dot{\theta}$) separately, were constrained in this paper. In the muscular model, the different rotary inertia (I) and angular velocity ($\dot{\theta}$) mean that FDS or ED should provide different force or torque at the same joint angle (θ). A different quadratic function compared with Eq.5 should be re-built (with different coefficients a_i' and different force function $f^{i'}(u)$) or there will be a large error compared to the standard result (as shown in Fig.16).

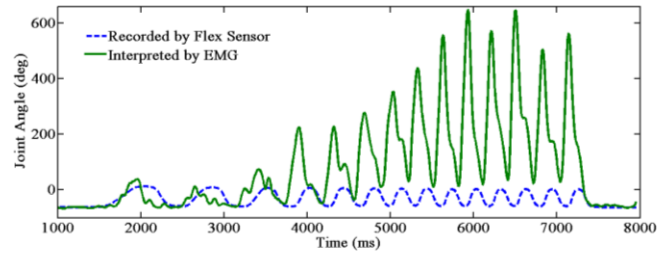


Figure.16 The interpretation results with a sequence of step-increasing velocity of digit movement

The interpretation results became higher than the value recorded from flex sensor with the increasing of digit movement velocity. Because these two parameters (load force and digit movement velocity) involve the results, it is important to constrain the experimental condition and subjects were asked to do practices before experiment. But for an application in daily life, such as manipulation, it will be far from enough if these parameters are ignored and too many constraints are made.

B Coactivation in Muscles

The proposed method is also effected by the phenomenon of co-activation in muscles. Fig.17 and Fig.18 depict two of the experiment results during one subject performed gestures of “Rock” and “Paper”. In the gesture of “Paper”, the co-activation of FDS brings some error interpretation for digit extension motion, which makes it like gesture of “Scissors”. And the same phenomenon happens in the gesture of “Rock”. Besides, the co-activation phenomena are different between different subjects. Although a range or threshold can be used for the purpose of gesture interpretation, these un-continuous divisions result in clumsiness in manipulation or motion interpretation. On the other hand, a low level of range or threshold may give rise to many faulty interpretation results. In evaluation experiments, subjects felt the performance of the method became too sensitive if the range or threshold was set too low and felt the method too hard to give an interpretation if the range or threshold was set too high.

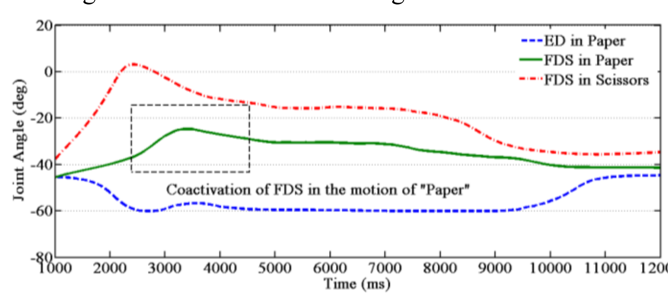


Figure.17 Muscle coactivation during the motion of “Paper”. Blue solid line represents the coactivation of FDS. Red dotted line represents the activation of FDS during the motion of “Scissors”, as a comparison

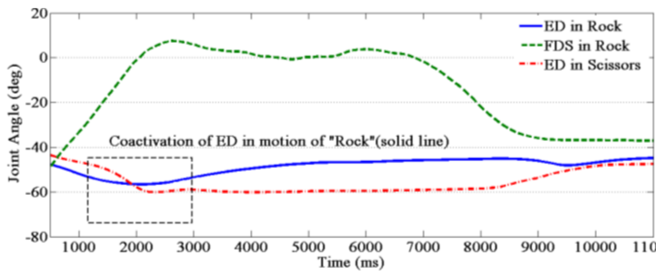


Figure.18 Muscle coactivation during the motion of "Rock". Blue solid line represents the coactivation of ED and red dotted line represents the activation of ED during the motion of "Scissors", as a comparison

C Individual Differences

One of the individual differences is the joint angle at relaxed position(-50.2°±7.9). Some subjects' relaxed positions are near their full extension positions. And EMG signals, especial the one from extensor digitorum, were observed as activated in most of this circumstance although some subjects said that their hand stayed relaxed. This phenomenon results in unstable interpretation between relaxed motion and extension motion. This phenomenon doesn't involve the interpretation results for gestures quite much because we can set a high level of threshold value, despite the low sensitiveness of the performance of the method. But it gives rise in unstable interpretation during the entire motion of extension.

Another difference is the EMG amplitude value changes during the same motion at different times of one subject. The amplitude value of EMG is different between subjects of course, but it also changes differently during the same motion in one subject, the standard deviation is from 0.0257 (13.8% of mean value of one subject) to 0.0908(26.1% of mean value of one subject) between subjects. The higher standard deviation proportion means the larger errors during the motion interpretation.

V. Conclusion and Future Works

A novel finger joint angle interpretation method based on sEMG signals and muscular model is presented in this paper. The purpose is trying to interpret the motion of digits in a continuous and smooth way via EMG signals only. Compared with the exoskeleton devices or grounded-type devices, the EMG signals can provide a more easeful way for manipulation. A finger muscle-skeleton model is built according to the structure of the forearm. The forces produced by FDS and ED are calculated via the Hill-based muscular functions. A quadratic function was designed using curve fitting tool to represent the relationship between forces and digit basic flexion and extension motions based on the digit muscle-skeleton model. The final gestures interpretation was implemented via the results from the basic digit flexion and extension motions.

Furthermore, the velocity and force will be taken into account in the muscular model to reinforce the robustness of this method. The standard deviation of the amplitude of EMG signals in individual will also be used as a control reference to improve the accuracy of this method.

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