Interaction Force Transfer for Characteristic Evaluation of Touch Motion

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Abstract - The prediction and transfer of interaction force between operator and environment is an interesting and important issue. This paper proposed an interaction force of touch motion transfer method from operator to observer. Compared with the conventional implementation of force sensor, the desired force is predicted by electromyography signals detected from the operator. Given the different muscle-tendon condition, the experiments are divided into vertical gesture part and horizontal gesture part. Three muscles in the forearm are selected to record the EMG signals. A forearm muscle-skeleton model is developed and a dynamic equation is defined to predict the interaction force. To calibrate the coefficients of the dynamic equation, a least-squares-like method is implemented to find a local optimal solution. Compared with the other complicated parameter calibration methods, this method can provide sufficient prediction results for our particular case. The predicted interaction force is repeated by Phantom Premium on the observer's side. The proposed interaction force transfer method is aimed for the purpose of characteristic evaluation of touch motion.

Index Terms – Interaction force, EMG, touch downward motion, muscular model, Phantom Premium.

I. INTRODUCTION

To measure and transfer the interaction force between subject and environment is one of important issues in human-machine interface (HMI) and teleoperation [1], [2]. Using force sensors is a very direct way. Tawil et al [3] used an electrical impedance tomography based skin to mimic human touch identifying. Jain et al [4] developed a whole-arm tactile sensing control method to perceive clutter and maneuver within it while keeping contact forces low. A. M. Okamura et al [5] used a feature definitions and local exploratory procedures to identified features’ type and geometry based on a three DoFs robotic finger with a spherical tactile sensor. Additionally, some vision assist methods are also developed. H. T. Tanaka et al [6] proposed a vision-based haptic exploration approach toward an automatic construction of reality-based virtual space simulator.

However, it is not very convenient to mount a force sensor on the surface of environment or on the tip of end-effector especially when humans perform the operation. Alternatively, electromyography (EMG) signals can be another choice aimed for the purpose of kinematic and dynamic analysis of human arm. The nature feature of the EMG signal, which directly represents the activation potentials of skeleton muscle, makes it very convenient to represent the status of muscles [7]. Fukuda et al [8] used this biologic signal to control a developed manipulator. Ajoudani et al [9] used EMG signals from eight muscles around operator arm to derive stiffness information and sent this stiffness information together with the position command to a slave robot to achieve a tele-impedance control.

For the purpose of musculotendon force estimation, there are some physiological models, such as Hill-type model [10] and Huxley-type model [11], [12]. To calculate musculotendon force, EMG signals are used to represent the muscle activation level and then this activation level is implemented to obtain the desired force value together with other parameters in the musculoskeletal model [16], [17]. Compared with the complexity of Huxley-type model, Hill-type model is more computationally viable. Cavallaro et al[13] developed a Hill-type model based myoprocessor to predict joint torque. Seven muscles around upper limb were recorded and a genetic algorithm was implemented for the purpose of tuning the parameters of the model. Manal et al [14] also used the Hill-typed model to calculate muscle force and implemented a forward dynamics approach to estimate joint angle. They used an optimal controller to map the relationship between measured joint moments and predicted joint moments. However the muscle-tendon system is so extreme complex that it is very difficult or sometimes seems to be impossible to estimate the musculotendon force accurately. Fortunately some research results indicated that there is a linear or subsection linear relationship between muscle activation level and musculotendon force under isometric contraction circumstance [15].

The purpose of this paper is to transfer the interaction force of touch downward motion from operator to observer. The operator is the one who perform the touch motion with the environment and the observer is the one who hold the handle of Phantom to “observe” or feel the same interaction force of the environment and the observer is the one who hold the handle of Phantom to “observe” or feel the same interaction force of the environment. For simplicity, the movement is constant touch downward motion which is under the isometric contraction circumstance. EMG signals were recorded from flexor carpi radialis (FCR), extensor carpi radialis longus (ECRL) and extensor carpi radialis brevis (ECRB). A muscle-
skeleton model of forearm was developed to calculate the interaction force between the operator's hand and environment. For the consideration of different muscle-tendon status, two kinds of gestures which are vertical gesture and horizontal gesture were tested.

II. DESIGN OF THE TOUCH-DOWNWARD INTERACTION FORCE TRANSFER METHOD

A. Experimental setup and protocol

Two volunteers (both male, right handed, age 28 and 26, weight: 61kg and 84kg, height: 165cm and 177cm) participated in the experiment. One volunteer performed as the operator and the other was the observer. Three muscles which are FCR, ECRL and ECRB were selected to record EMG signals. These muscles act to flex and extend the hand around wrist joint. Actually there are other muscles together with the selected three muscles to take responsibility for hand flexion and extension. But some of them lie in the deep level of forearm. As we used non-invaded surface electrodes to record EMG signals, it is inconvenient to record the EMG signals from these deep level muscles and we ignored them in this paper. Furthermore we assumed, in this paper, that the contribution of all muscles involved in a certain motion is invariant under certain circumstance individually because of the control of central nervous system. As a consequence, ignoring deep level muscles had little influence on the experimental results.

On the operator’s side, a link-supporter was made to mark the forearm gesture for the operator (as shown in Fig.1). Link 1 and link 2 were fixed corresponded to the operator’s forearm gesture when the operator performed the motion of touch downward voluntarily and comfortably. A singular gesture was tried to avoid during performing the two gestures. Two MTx sensors (Xsens Technologies B.V. USA) were attached on operator’s hand and elbow joint to record the real gesture. During the performance, the operator was asked to touch the centre of the load cell. The EMG signals were recorded using bipolar surface electrodes with 12mm in length, located 18mm apart. The raw EMG signals were pre-processed by a filter box (Personal-EMG, gain 1000, common mode rejection 104dB, Oisaka Development Ltd.). All the EMG recording apparatus are shown in Fig.2.

On the observer’s side, Phantom Premium was used to represent the interaction force from the operator. As a commercial product, Phantom Premium is easy to be used and set a desired torques in the horizontal and vertical plane. The observer held the handle of Phantom Premium and observed or felt the interaction force transferred from the operator’s side.

The experiment was divided into two part: the vertical part and the horizontal part. In each part, the operator was asked to perform the motion of touch downward in five groups. Each group is with a increment of 5 N. As a result, the range of the touch downward interaction force is from 5 N to 25 N. The operator put his hand on the load cell with the middle finger touching the centre surface of the load cell and tried to find a comfortable gesture with a attention of avoiding singular point. In our particular case, the anatomic angle between hand and forearm is around 29.8° to 42.7° in vertical part and around -6.78° to 3.21° in horizontal part for the operator. Then the link-supporter was fixed following the gesture of the operator. The operator was asked to finish 10 trials in each group and there was a 1 minute rest between each trial. For one trial, the operator performed the task following the link-supporter and observed the display of the strain amplifier to hold the required force.

B. Muscle-skeleton Model

Generally, there are three DoFs around forearm which are pronation/supination in forearm, radial/ulnar deviation around wrist and palm flexion and extension. For simplicity, only palm flexion and extension is concerned in this paper. The sketch of the muscle-skeleton model of the forearm is shown in Fig.3.
The FCR acts to flex the hand around wrist joint and ECRL and ECRB act to extend the hand. F is the interaction force which is desired. The gravity force derived by the weight of hand is mg. During the motion of touch downward, both flexors and extensors are activated to maintain the stiffness of wrist joint. As the motion is constant, the dynamic function can be written as:

\[ \tau_{FCR} - \tau_{ECRL} - \tau_{ECRB} + \tau_{mg} = F \tag{1} \]

where \( \tau \) is the torque derived by the corresponded force. The friction between the joint is ignored in this paper.

As the interaction force is desired to be calculated by EMG signals of FCR and ECRL/B, the singular point of the wrist joint should be avoided. In singular condition, the direction of the interaction force pass through the wrist joint. Under this circumstance, the main function of flexors and extensors in forearm is to maintain the stiffness of wrist joint. And other muscles around upper arm or shoulder acts to balance the torque of interaction force. This situation is beyond the discussion in this paper.

According to Hill-type model, the main factors which involves the function of muscle force generation are muscle activation level, muscle length, and muscle length changing velocity. The Hill-type model can be described as follows:

\[ F_{PE,SE} = \left( F_{\text{max}} / e^{S} - 1 \right) \left[ e^{\left( 0.5/0.05 \right) \left( \Delta L_{\text{max}} \right)} - 1 \right] \tag{2} \]

\[ F_{CE} = u \cdot f_{i} \cdot f_{r} \]

\[ f_{i} = \exp \left( -0.5 \left( \left( \Delta L_{CE} / L_{CE} \right) - 0.05 \right) / 0.19 \right) \]

\[ f_{r} = 0.1433 \left( 0.1074 + \exp \left( -1.3 \sinh \left( 2.8 \frac{V_{CE}}{V_{CE_{\text{max}}}} + 1.64 \right) \right) \right) \]

\[ V_{CE} = 0.5(u+1)V_{CE_{\text{max}}} \]

\[ F_{T} = F_{CE} + F_{PE} \tag{4} \]

where \( \Delta L \) is the change in the length of the element with respect to the slack length, \( S \) is a shape parameter, \( F_{\text{max}} \) is the maximum force exerted by the element for the maximum change in length \( \Delta L_{\text{max}} \), 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. \( u \) is the activation level of a muscle. As the motion can be considered as isometric contraction, the \( f_{i} \) term can be regarded as constant and the force derived by the muscle can be defined as:

\[ F_{m} = f(u, L) \tag{5} \]

The muscle activation level is calculated by EMG signals while the effect of muscle fiber length is tested by different gestures.

**C. Muscle activation level calculation**

The EMG signals can directly reflect the muscle activation dynamics level (\( u \)). Usually, the raw EMG signals should be passed by a high-pass filter firstly to remove any DC offsets or low frequency noise. Then the signals should be rectified. Sometimes these rectified signals are directly transformed into muscle activation by dividing them by the peak rectified EMG value obtained during the MVC test. Some researchers also suggested that a more detailed model of muscle activation dynamics is warranted in order to characterize the time varying features of the EMG signal. In this paper, a discretized recursive filter is used.

The discretized recursive filter with a continuous form of a second-order differential equation shown as following is implemented:

\[ u(t) = M \ddot{e} - e(t) + B \dot{e}(t) + Ke(t) \tag{6} \]

where \( M, B \) and \( K \) are the constants that define the dynamics of (6) and \( e(t) \) is the processed EMG signal. This equation can be presented as a discrete form using backward differences:

\[ u(t) = \alpha e(t - d) - \beta_{1}u(t - 1) - \beta_{2}u(t - 2) \tag{7} \]

where \( d \) is the electromechanical delay and \( \alpha, \beta_{1} \) and \( \beta_{2} \) are the coefficients that define the second-order dynamics. Selection of the values for \( \alpha, \beta_{1} \) and \( \beta_{2} \) should follow the following restrictions:

\[ \beta_{1} = \gamma_{1} + \gamma_{2} \tag{8} \]

\[ \beta_{2} = \gamma_{1} \times \gamma_{2} \tag{9} \]

\[ |\gamma_{1}| < 1 \tag{10} \]

\[ |\gamma_{2}| < 1 \tag{11} \]

\[ \alpha - \beta_{1} - \beta_{2} = 1 \tag{12} \]

in order to guarantee the stableness of the equation and the neural activation does not exceed 1.

The calculation results are usually processed by a low-pass filter (with a cut-off frequency of 3-10 Hz) because the muscle naturally acts as a filter resulting in that force changing frequency is much lower than EMG. In our particular case, the cut-off frequency was set even lower which was around 0.5-1 Hz.

**D. Interaction force prediction**

As the motion is isometric contraction, the torque derived from a muscle can be represented as a linear relation with the musculotendon force. And in isometric condition, the musculotendon force has a linear relationship with muscle activation level. As a consequence, the dynamic equation of (1) can be rewritten as follow:

\[ k_{FCR}(L)u_{FCR} - k_{ECRL}(L)u_{ECRL} - k_{ECRB}(L)u_{ECRB} + C(L) = \tau_{f} \tag{13} \]

where \( k(L) \) is the corresponded coefficient with a parameter of muscle-tendon length \( L \). Equation (13) can be represented in a form of matrix:

\[ K(L)U = \tau_{f} \tag{14} \]

where \( K(L) \) is with the form of \( (k_{FCR} k_{ECRL} k_{ECRB} C) \) and \( U \) is with the form of \( (u_{FCR} u_{ECRL} u_{ECRB}) \). In this paper, \( K(L) \)'s are calculated or calibrated off-line using experimental data recorded from different gesture performances respectively.
the issue of parameters calibration when dealing with the problem of musculotendon force calculation, there are some compelling research results. As a distinct linear relationship between the muscle activation level and output interaction force can be indicated (this will be shown in the experimental results section), a least-squares-like method was adopted in this paper, for the purpose of simplicity. Assuming that $S$ is the off-line experimental data set, $U \in S$ is the data set which is used to calculate the coefficient matrix $K(L)$ and define the cost function as

$$ f = \sum_{i=1}^{n} (K(L)U_i - \tau_p)^2, (U_i \in S, \bar{U}_i \neq U) $$

And the least-squares-like problem is to find the proper $U$ in the entire data set $S$ which minimizes the natural logarithm of cost function $f$.

**E. Schematic of the proposed method**

The schematic of the proposed method is depicted in Fig.4. Firstly an off-line experiment is conducted to calibrate the parameters using proposed least-squares-like algorithm. After calibrating the coefficient matrix, an on-line experiment was performed by the operator. The predicted interaction force was calculated in real-time and sent to the observer side via TCP/IP communication protocol. The observer hold the handle of Phantom Premium to observe or feel the same interaction force as the operator did.

**III. EXPERIMENTAL RESULTS AND DISCUSSION**

**A. Off-line coefficients calibration**

Fig.5 depicts one set of experimental results from vertical touch downward motion with the interaction force around 15 N. All the data were plotted together with the hand anatomic angle. It can be indicated from Fig.5 that the entire motion can be divided into four parts: relaxation part (0s-5s, no muscle activation), extension part (5s-10s, eccentric contraction), touch part (10s-30s, isometric contraction) and flexion part (30s-35s, concentric contraction). In the extension part, the operator only extended the palm and put his hand onto the load cell. During this period, there was no obvious output force detected by load cell. The ECRL and ECRB contracted to extend the palm and maintain the gesture. The FCR also contracted to assist the extension motion or maintain wrist stiffness. In the touch part, the activation levels of all the three muscles increased. The phenomenon of increase activation level of antagonist muscles is believed to have relationship with the maintaining of joint stiffness.

Fig.6 depicts all the experimental results of muscle activation levels of FCR, ECRL and ECRB with a function of interaction force. The results were calculated with the mean value of stable period in each trial. The brown lines represent the linear relationship between the muscle activation levels and interaction forces. For vertical gesture, the correlation coefficients are 0.87, 0.71 and 0.83 for FCR, ECRL and ECRB respectively and for horizontal gesture, they are 0.85, 0.78 and 0.69 respectively. It should be noted that the correlation coefficients which are listed above are calculated
ingorning most of the points in relative high interaction force area (as shown by pentagram shape). As indicated by some of other research results, the relationship between muscle activation level and musculotendon force is beyond linear when the musculotendon force is in a relative high level (such as with a level of up to 70% MVC). In our particular case, the maximum interaction force which was tested is above 27 N. As a consequence, the range of the pentagram shape points are around 60 to 70%. If the pentagram points are included for calculation, the linear correlation coefficients are 0.78, 0.53 and 0.69 for FCR, ECRL and ECRB respectively for vertical gesture and 0.75, 0.63 and 0.57 for horizontal gesture. Another interesting result is that the slope or the changing rate for ECRL and ECRB is different. They are 0.0011 and 0.0025 for ECRL and ECRB respectively for vertical gesture and 0.0021 and 0.00114 for horizontal gesture. As both of the two muscles act to extend the hand at wrist joint, the ECRB seems to be more active than ECRL in vertical case and seems to be less active in horizontal gesture.

The off-line parameter calibration procedure is plotted in Fig.7. The value is the natural logarithm of cost function. It can be indicated in Fig.7 that the parameters calibrated by the 7th or 8th trial data fitted the entire experimental results best in the local ten trials for vertical gesture and the 5th is the best for horizontal gesture. It can also be indicated that, for vertical gesture, when the force is near or above 60% of MVC in which the relationship between muscle activation level and musculotendon force is not linear, the absolute error increases compared with the other situations. This phenomenon is not obvious in horizontal gesture motion. As a contrast, prediction accuracy in a relative high force condition is better than which in a low force condition.

B. On-line experiment

In on-line experiment, the operator performed five trials in each group. Fig. 8 depicts one of the on-line interaction force prediction results compared with the data recorded by load cell. The prediction results followed the detected ones quite well. The root mean square error for this case is 2.98 N. The detailed experimental results of on-line interaction force prediction are listed in Table I.

It is interesting that as we only used the mean values of stable period (such as 15s to 25s in Fig. 8, (a)) in each trials to calibrate the parameters, the prediction results can fit the entire touch motion well (although not quite good in relaxation part). It may be indicated that, in our particular case, during the transient period of musculotendon force setup, the relationship between transient muscle activation level and transient musculotendon force is also linear-like. But still during relaxation part, the proposed interaction force prediction method makes unstable or relative large error results. And for high level musculotendon force case (as indicated by 25N case), the RMS errors are higher than the ones in a relative low level cases.

The average computation time for one loop in on-line experiment is 1.872 ms, in which 0.012 ms is for data pre-processing, 0.800 ms is for data transfer and 1.060 is for force prediction. As the data are processed with the window-length of 50 ms, this time consumption is sufficient for a real-time application.
An interaction force of touch downward motion is predicted and repeated by Phantom Premium in this paper. Com-pared with the conventional force detection method, such as using a force sensor, the desired force is predicted only by EMG signals detected from the operator. A muscle-skeleton model and a Hill-type musculotendon model are implemented to obtain the dynamic equation for the target motion. In order to calculate or calibrate the coefficients in the dynamic equation, a least-squares-like parameter optimal algorithm is developed. Compared with the other complicated parameter calibration methods, the proposed algorithm is easy for implementation and the prediction results are sufficient (with RMS error around 3.72N, ignoring the relative high force case). Even that the coefficients are calibrated with a mean value of the stable period in each trial, they can also fit the transient period well. But in relaxation part, the behavior of this dynamic equation are not good (with RMS errors around 5.87N).

As mentioned above that, even under an isometric contraction, not only muscle activation level but the other parameters, such as muscle length involve the musculotendon force. In this paper, two gestures with different muscle-tendon conditions were tested. In the future more gestures will be considered and a more completed dynamic equation will be developed in order to obtain the desired force under a more freedom condition.

### IV. CONCLUSION AND FUTURE WORKS

An interaction force of touch downward motion is predicted and repeated by Phantom Premium in this paper. Compared with the conventional force detection method, such as using a force sensor, the desired force is predicted only by EMG signals detected from the operator. A muscle-skeleton model and a Hill-type musculotendon model are implemented to obtain the dynamic equation for the target motion. In order to calculate or calibrate the coefficients in the dynamic equation, a least-squares-like parameter optimal algorithm is developed. Compared with the other complicated parameter calibration methods, the proposed algorithm is easy for implementation and the prediction results are sufficient (with RMS error around 3.72N, ignoring the relative high force case). Even that the coefficients are calibrated with a mean value of the stable period in each trial, they can also fit the transient period well. But in relaxation part, the behavior of this dynamic equation are not good (with RMS errors around 5.87N).

As mentioned above that, even under an isometric contraction, not only muscle activation level but the other parameters, such as muscle length involve the musculotendon force. In this paper, two gestures with different muscle-tendon conditions were tested. In the future more gestures will be considered and a more completed dynamic equation will be developed in order to obtain the desired force under a more freedom condition.

### REFERENCES


### ACKNOWLEDGMENT

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### TABLE I

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<thead>
<tr>
<th>Gesture</th>
<th>RMS Errors (N)</th>
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Fig.8 On-line experimental results