XIX IMEKO World Congress
Fundamental and Applied Metrology
September 6–11, 2009, Lisbon, Portugal

ESTIMATION OF RELATIVELY COMMANDED FORCE FROM EMG AND ITS APPLICATION TO HUMAN-MACHINE INTERFACES

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Abstract – In this paper we present a novel calibration method for an electromyogram (EMG) based human-machine interface which estimates force. EMG based interfaces need a calibration process in which musculoskeletal model parameters are determined for each individual user. Most conventional calibration methods which relate EMG signals to force magnitude require not only EMG measurement devices but also force sensors. Our goal here is to develop a calibration method that requires only EMG measurement devices. In our method, users are asked to apply stepwise force indicated by visual or auditory information. With a multiple linear regression model, the EMG magnitude is then related to that of the indicated force, instead of the force being measured by force sensors. With the users showing strong ability to exert linearly graded force, the force estimations of the linear regression model fit well with the indications, and estimated force correlated well with that of actual measured force.

Keywords: force estimation, electromyogram (EMG), human-machine interface

1. INTRODUCTION

Surface EMG signals are non-invasively sensed from the muscles by electrodes. Low-pass filtered EMG signals represent a motor command from brain. We can estimate our motion such as muscle's tension, joint torque and stiffness by using a musculoskeletal model [1][2]. In this paper we focus on a force estimation method for a human-machine interface. Many researchers proposed human-machine interfaces using EMG [3][4]. Most of these interfaces need a calibration process because EMG patterns depend upon individual users. So the parameters of an EMG-force model must be adjusted before using the interface. Fig.1 shows a conventional EMG interface calibration flowchart. Calibration refers to an adjustment of the EMG-force model to balance measured force and estimated force. In the conventional method, a force sensor measures absolute magnitude of actual force [5][6]. In the proposed method, we substitute a relative force command for actual force as shown in Fig.2. If interface users control the force according to the command, we can calibrate the model parameters without a force sensor. In the following sections we describe the methods used to acquire the EMG data, determine the EMG-force model parameters and the experimental tasks for evaluation.

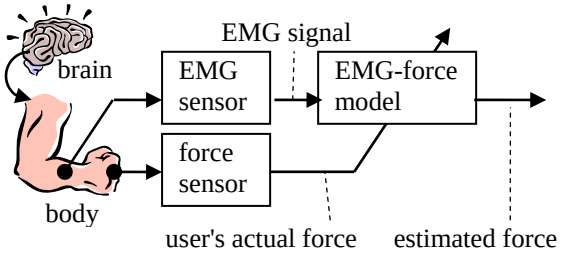

Fig.1 Current calibration method

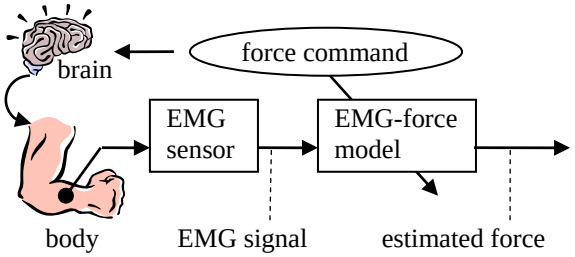

Fig.2 Proposed calibration method

2. EXPERIMENT

The purpose of this study is to validate that the proposed calibration method provides a feasible force input interface. The experiments were conducted to determine the feasibility of achieving the following goals:
Goal 1: The estimated force corresponds well with the commanded magnitude.
Goal 2: The time-series of the estimated force correlates well with that of the actual force.

ISBN 978-963-88410-0-1

2.1 Experimental design and apparatus

Eleven healthy subjects (10 male, 1 female) performed isometric contractions composed of flexion and extension about the wrist. The subject's right forearm was fixed to a cuff, as shown in Fig.3. They were asked to control their wrist according to the experimenter's force magnitude command.

The command was randomly selected from the following three magnitude labels:

Label1: base magnitude, which was determined for each subject

Label2: twice lablel1's magnitude

Label3: 3 times label1's magnitude

All subjects were asked to concentrate on the force magnitude during the experiment. In each trial, subjects were asked to keep the force magnitude constant from start to stop, as shown in Fig.4. The notification of label, start and stop were given verbally. Experiment was composed of 180 trials: 3 labels x 30 trials/label x 2 directions (flexion/extension). The first 30 trials of flexion and extension were used to calibrate the EMG-force model and remaining trials were used for evaluation.

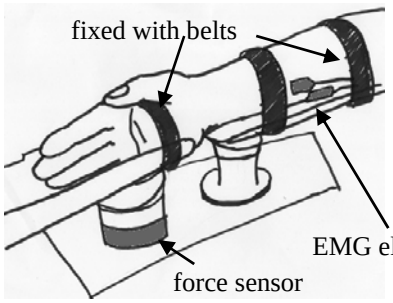

Fig.3 Experimental setup

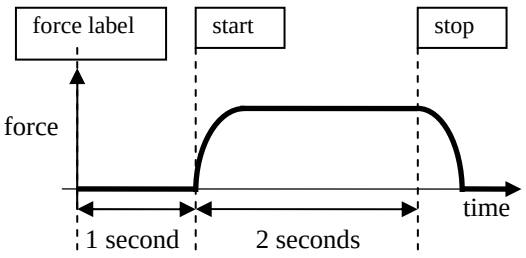

Fig.4 Protocol of force input task

2.2 Data aquisition

EMG signals were recorded at 2000 Hz from four electrodes attached to the surface of the subject's right forearm. Measured muscles were the flexor carpi ulnaris (FCU), flexor carpi radialis (FCR), extensor carpi ulnaris (ECU) and extensor carpi radialis longus (ECRL). Subjects' actual force was recorded at 200 Hz from a force sensor mounted under the cuff.

2.3 EMG-force estimation model

In this study we used a simple linear model to estimate force from EMG as shown in Equation (1), where b_0 is a bias, b_1 to b_4 are conversion coefficients and x_1 to x_4 are low-pass filtered EMG signals (x_1: FCU, x_2: FCR, x_3: ECRL, x_4: ECU).

$$\hat{y} = b_0 + \sum_{i=1}^{4} b_i x_i \tag{1}$$

We used a multiple regression algorithm to determine conversion coefficients. Since the subject's actual force shape is unknown, we had to detect the timing for when the subject's output reached commanded magnitude. We assume the peak EMG of mean agonist muscle as the timing shown in Fig.5.

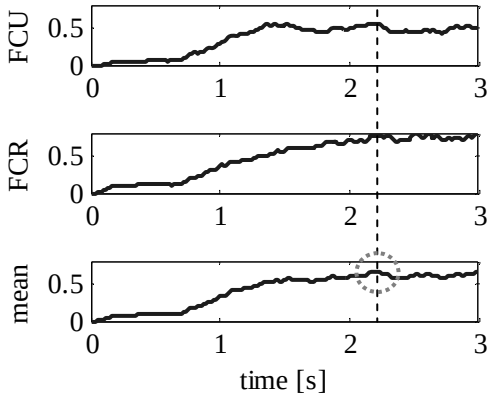

Fig.5 Selection method of EMG data for regression

2.4 Evaluation

Due to the commanded force being a relative value, we could not compare estimated and measured force directly. So we used the following two indexes for evaluation. The first index is relative error defined as Equation (2), where y_c is commanded force and $\hat{y}$ is estimated force. Small relative error indicates achievement of Goal 1. The second index is correlation coefficient which represents the time-series similarity of estimated force to that of measured force. The value of correlation coefficient equalling one indicates achievement of Goal 2.

$$e = \frac{|y_c - \hat{y}|}{|y_c|} \tag{2}$$

3. RESULT

Fig.6 shows relative error. As the number of trials per label increased, mean relative error decreased and converged to about 0.35. Fig.7 shows correlation coefficient. Mean correlation coefficient reached 0.9 when the number of trials equaled two, then increased gradually. After the number of trial reached 5, mean correlation coefficient changed little.

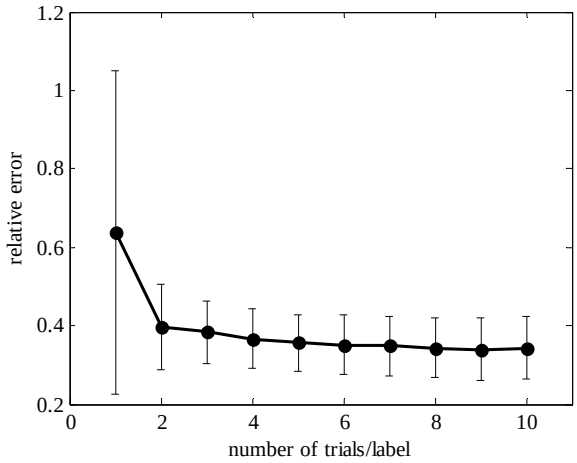

Fig.6 Relative error with varying number of trials/label

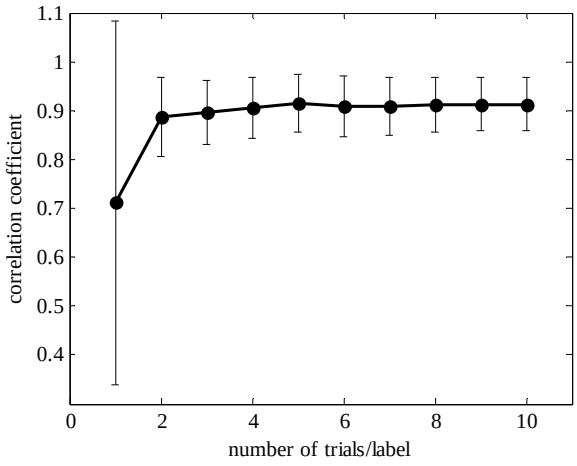

Fig.7 Correlation coefficient with varying number of trials/label

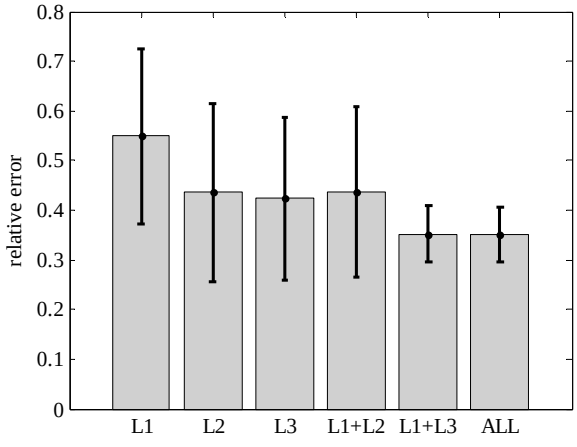

Fig. 8 Relative error with varying number of labels

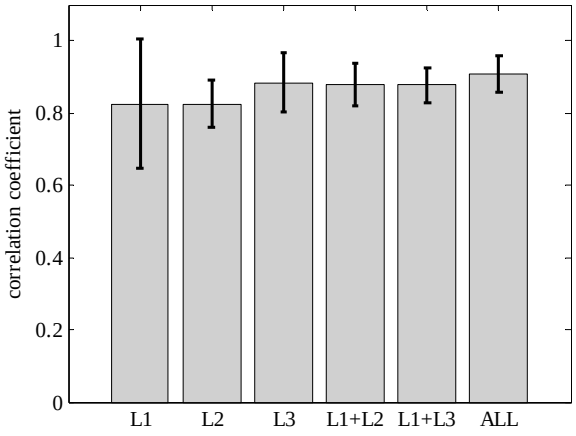

Fig.9 Correlation coefficient with varying number of labels

Fig.8 and Fig.9 show relative error and correlation coefficient with the number of trials fixed to 5. As the number of labels increased, the mean and S.D of relative error decreased. Fig.9 shows that correlation coefficient improved with the number of labels, just relative error did.

4. DISCUSSION

4.1 Appropriate number of labels and trials

Fig.8 and Fig9 suggest that a calibration with 2 or 3 labels is better than a single label calibration, which is similar to 100% maximum voluntary contraction (MVC) calibration. The indexes of estimation accuracy increased with the number of labels. But it is difficult to increase the number of labels. Fig.10 shows mean magnitude of measured force. The magnitudes were converted to relative values because the mean magnitudes of label 1 were different among individuals. As the labels increased, mean force magnitude differed from commanded magnitude and the variance increased. Thus if we used over 3 labels the estimation accuracy would be worse.

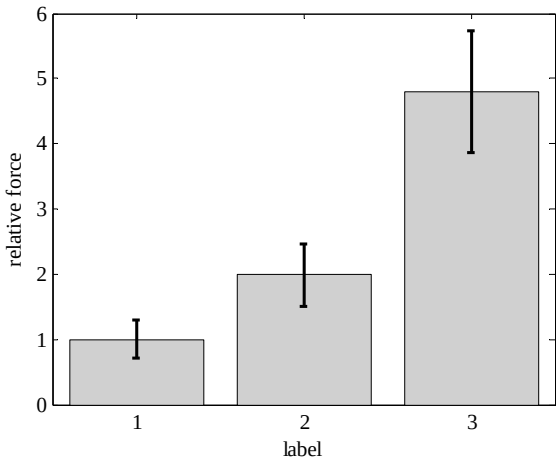

Fig.10 Relationship between commanded label and measured force

4.2 Effect of co-contraction

If we applied this method in practical use, a shorter calibration time would be beneficial. To shorten the time, one solution is to reduce the number of trials. Fig.6 and Fig.7 show the accuracy of estimation converged when the number of trials was around 5. For the number of labels, 3 is the best, according to standard deviation of relative error and correlation coefficient.

Obtained parameters are illustrated in Table 1. b_3 and b_4 which are the extensor parameters normally take negative values. Seeing as the number of trials was small, there were sometimes parameter misfittings such as too big a value or an inversion of sign. This suggests that the first trial's data was inappropriate for regression. If the subject co-contracted muscles, actual joint torque would decrease against high EMG activity. So this contrariety might cause an error in parameter adjustment. Fig.11 shows normal EMG activity. The horizontal axis donates force in [N] and positive values indicate flexion. The vertical axis donates EMG activity normalized by 100% MVC. Flexor activities were high during flexion and low during extension. This appeared in the plots as asymmetric L-shapes. In contrast, symmetric V-shape patterns appeared in a co-contracting subject's plot shown in Fig.12. Activities of FCU and ECRL were high during flexion and extension. Therefore eliminating co-contracted trials would reduce the number of trials.

5. CONCLUSION

We proposed a novel calibration method for an EMG-force model without a force sensor. In this method, an interface user is commanded a force magnitude relatively, then the system determines the musculoskeletal model parameters using a multiple linear regression algorithm. We used agonist muscle EMG signals to detect the timing for when the user input the commanded force magnitude. Estimated force represented original force well. 3 labels and 5 trials were needed to obtain sufficient estimation accuracy for all subjects. Elimination of bad data may shorten the calibration process.

ACKNOWLEDGMENTS

This work has been partially supported by a Grant-in-Aid for Scientific Research on Priority Areas "Emergence of Adaptive Motor Function through Interaction between Body, Brain and Environment" and Strategic Promotion Program for Brain Science Research from MEXT, and the JST CREST Program to Y.SAKURAI.

REFERENCES

[1] Y.Koike, M.Kawato, Trajectory Formation from Surface EMG Signals Using a Neural Network Model, The transactions of the Institute of Electronics, Information and Communication Engineers, 77, pp.193-203, 1994

[2] Y.Koike, M.Kawato, Estimation of dynamic joint torques and trajectory formation from surface electromyography signals using a neural network model, Biological Cybernetics 73, pp.291-300, 1995

[3] H.Kawamoto, Lee Suwoong, S.Kanbe, Y.Sankai, Power assist method for HAL-3 using EMG-based feedback controller, Proceedings of IEEE International Conference on Systems, Man and Cybernetics, Vol.2, pp.1648-1653, 2003

[4] E.Costanza, S.A.Inverso, R.Allen, P.Maes, Intimate interfaces in action: assessing the usability and subtlety of emg-based motionless gestures, Proceedings of the SIGCHI conference on Human factors in computing systems. Tangibility, pp.819-828, 2007

[5] C.J.Gatti, L.C.Doro, J.E.Langenderfer, A.G.Mell, J.D.Maratt, J.E.Carpenter, R.E.Hughes, Evaluation of three methods for determining EMG-muscle force parameter estimates for the shoulder muscles, Clinical Biomechanics 23, pp.166-174, 2008

[6] M.J.M.Hoozemans, J.H.van Dieén, Predictrion of handgrip forces using surface EMG of forearm muscles, Journal of Electromyography and Kinesiology 15, pp.358-366, 2005

Table 1 Obtained coefficients of subject I

trials	b_0	b_1	b_2	b_3	b_4
1	0.415	2.889	20.629	-30.888	-1.951
2	0.021	1.684	10.943	8.967	-9.055
3	-0.087	2.743	6.934	14.954	-10.252
4	-0.121	3.111	6.064	16.799	-10.265
5	0.036	5.297	9.956	-4.701	-7.077

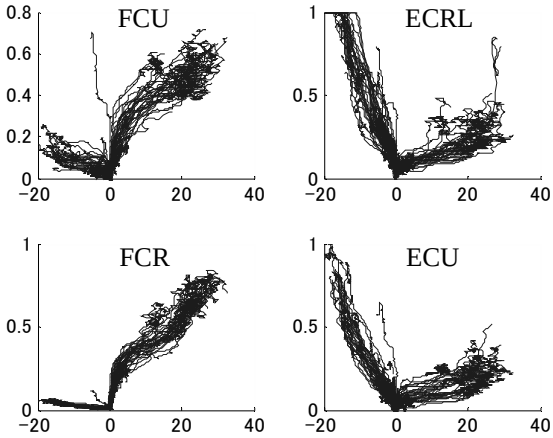

Fig.11 An example of normal EMG activity

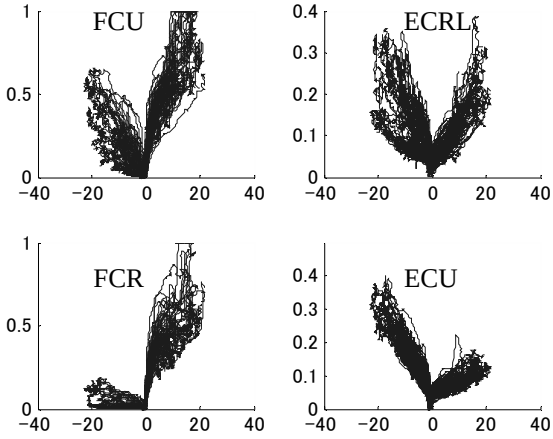

Fig.12 An example of co-contraction