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Estimation of Hand Grasp Force based on Forearm Surface EMG*

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***Abstract* - In the force control of multi-functional prosthetic hands, it is important to extract grasp force information besides mode specifications directly from the myoelectric signals. In this paper, a force sensor is adopted to record the hand's enveloping force when the hand is performing several grasp modes, synchronously with 6 channels surface electromyography (EMG) which are extracting from the subject's forearm. Three pattern regression methods, locally weighted projection regression (LWPR), artificial neural network (ANN) and support vector machine (SVM) are used to find the best representative relationship of these two kinds of signals. Experimental results show that the SVM method is better than LWPR and ANN, especially in the case of cross-session validation. Also, the force regression performance is better when grasping within several specific modes than grasping randomly. Based on these results, an efficient online prediction of the hand grasp force is present finally, with an accuracy of around 0.9 in squared correlation coefficient (SCC) and 5~10N error over a range of 60N. It can be utilized for the prosthetic hand's control to provide a reasonable exerting force reference.**

Index Terms - Prosthetic Hand; EMG Control; Pattern Regression; Support Vector Machine

I. INTRODUCTION

The electromyographic signal is composed of the action potentials from groups of muscle fibers organized into functional units called motor units (MUs). This biomedical signal, measures electrical currents generated in muscles during its contraction representing neuromuscular activities, can be detected with sensors placed on the surface of the skin (non-invasive) or with needle or wire sensors introduced into the muscle tissue (invasive).

Accurate and reliable estimation of joint force from observation of the surface EMG (sEMG) can provide a safe, non-invasive tool for the control of cybernetic prostheses, as well as for the study of human movement and biomechanics. But, so far in literature, so many researches tended to classify several EMG patterns of single or joint muscle contractions rather than the exerting force of the hand. These methods generally combined feature extraction (AR model [1], wavelet transform [2]) with pattern recognition techniques (HMM [3], SMO [4], SVM [5, 6]), can efficiently discriminate particular finger motions or specified hand gestures. Then, these classified EMG modes was mapped into prosthetic hand's motions through a simple way: relevant finger(s) moved to a pre-defined position with a fixed or optimized velocity and force. Because of merely compressing the resourceful EMG signal into a few muscular contraction modes (<10), the identify accuracy rate can reach to a relatively high level (>90%). But, this control scheme has insufficient information about how much the force should be applied exactly on the object. Although making use of sensitive tactile sensors and sophisticated grasp strategies, stable grasp functionalities can be achieved [7]. But for the anthropopathy prosthetic hand, a typical human-machine interaction device, more endeavors should be put on how to trace the grasp force information directly from the human body. It will be beneficial to enhance the extended physiological proprioception (EPP) [8], i.e., to make the prosthetic hand feels like a real part of the body.

The relationship between surface EMG and the muscle exerting force (joint torque) has been studied deficiently on the hand grasp for prostheses uses. This paper adopts a 6 dimensional force/torque sensor to directly record the enveloping force of several hand grasp modes, collects surface EMG signals through 6 commercial electrodes mounting on the subject's forearm, and utilizes three regression methods (LWPR, ANN, and SVM) to find the best representative relationship between these two kinds of signals. Different grasping strategies (grasp within specified modes or randomly) are also discussed. Straightforward regression makes the online prediction system efficient and easy-to-use, thus be available for the prosthetic hands' force control when grasping objects.

II. MATERIALS AND METHODS

A. EMG Setup

There are two different ways to acquire EMG signals: in invasive or non-invasive. For the prosthetic hand's control, non-invasive method is widely used and accepted by the amputees because it is easy to configure and needs no surgeries. Danion [9] investigated the relationship between the surface EMG of the extrinsic flexors of the hand and

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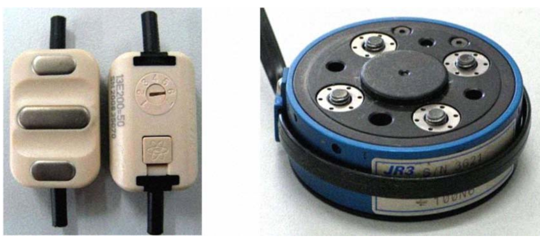
individual fingertip force during multi-finger force production tasks. Multi-variable regression method was used to describe the flexor EMG as a linear function of individual fingertip force. Thus, type of bipolar active surface EMG electrodes can be treated as force detector although they usually have large volumes and are placed on extrinsic muscles.

We finally chose the double differential Otto Bock 13E200=50 model [10] (Fig. 1-a) as our EMG sensor, because of its fine output property (amplified, filtered and rectified). The output signal can be directly used for the EMG pattern recognition and regression. The amplification factor was set to 6 (nearly 14,000 times) to ensure a high signal sensitivity. The electrodes were mounted on the subject's left forearm using pieces of medical adhesive band with appropriate bonding force making sure that the electrodes' active faces are tightly adhering to the forearm skin.



(a) (b)

Fig. 1 EMG and force sensors, (a) Otto Bock 13E200=50 surface EMG electrodes. (b) JR3 6 dimensional force/torque sensor.

The electrodes' position is crucial in EMG studies, because the muscles where the electrodes are putted on have their own functions. In our previous study [11], a total of 18 hand gestures can be classified effectively using 6 Otto Bock electrodes mounted on several forearm muscles. The configuration retained in this paper is for the research continuity, i.e., to identify EMG modes and extract the grasp force simultaneously [12]. Fig. 2 illustrates each electrode's position on the forearm. Note that, there are 2 electrodes placed on different position of flexor digitorum superficials, taking charge of detecting index finger and the rest three (middle, ring and little) fingers' flexions respectively. It is according to the facts that, the flexor digitorum superficialis (FDS) can be subdivided into functional and anatomical compartments serving individual fingers (Serlin and Schieber 1993 [13]; Bickerton et al. 1997 [14]).

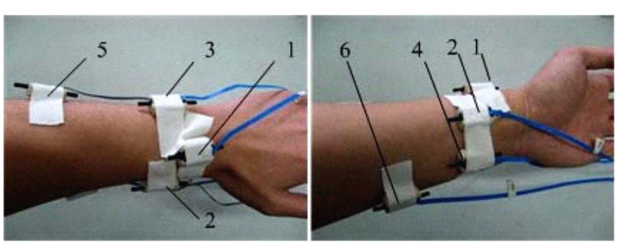


Fig. 2 Placement of the surface EMG electrodes on the forearm, 1.Extensor pollicis brevis, 2.Flexor pollicis longus, 3.Extensor indicis proprius, 4.Flexor digitorum superficialis (distal), 5.Extensor digiti quinti proprius, 6. Flexor digitorum superficialis (proximal).

In additional, an additional self-made interface model with electrodes power supplying (5V) and a commercial multi-functional AD acquisition card PCI-9118HR (ADLINK, Taiwan) [15] were used to transmit the EMG signals into a power PC (Intel dual CPU E2140, 2G RAM).

B. *Force Sensor Configuration*

JR3 6 dimensional force/torque sensor [16] (Fig. 1-b) is widely used in laboratory for human-robot interaction researches. Here we used it for detecting the hand grasp force. Its effective detecting scope is within 0~200N (Fz) on a resolution of about 0.015N, thus totally satisfies to our study. A standard PCI data acquisition card was used for the force data collection. All the data (EMG waveforms and the grasping force) is scaled in the same scope for regression operation and analysis. One dimension of the force/torque signals (Fz direction, which is the force applied oppositely on the two biggest circular faces) was used to represent the whole enveloping force of the hand.

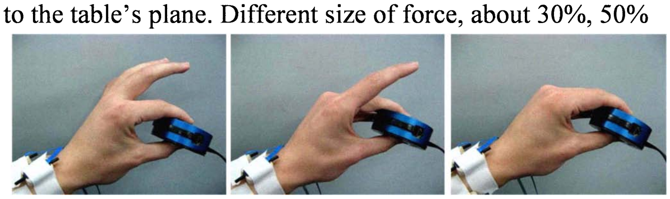
C. *Software*

The EMG and force signals were synchronized in LabVIEW 8.0 software environment, also with a front panel graphical user interface (GUI) for real-time data display. The EMG data was acquired through an ADLINK plug-in sub-VIs package for LabVIEW named DAQ-LVIEW-PnP 1.30 [17], while the force sensor was activating via an ActiveX JR3PCI [18]. Both sampling rates were set to 100 Hz. For the data analysis, toolboxes of libsvm 2.84 [19] and lwpr 1.2[20] were embedded into Matlab, also with the Matlab inner ANN algorithms, to implement the SVM, LWPR and ANN regression methods.

D. *Hand Grasp modes*

A statistical research about human hand's grasp [21] indicated that, the thumb and index finger plays a relatively important role than the others in most daily hand grasp modes. Therefore, only three hand grasp modes were considered in this paper (Fig. 3), i.e., 1, grasp by opposing thumb and index finger; 2, grasp by opposing thumb and rest three (middle, ring and little) fingers; 3, grasp by opposing thumb and all other fingers. Furthermore, another grasping mode, 4, grasp by random fingers with random force, was checked that if it can acquire even or better result in the force regression.

Every mode was performed when the test forearm was keeping still and relaxed on a table with the palm orthogonal to the table's plane. Different size of force, about 30%, 50%



(a) (b) (c)

Fig. 3 Hand grasping modes applied on the force sensor. (a) grasp by opposing the thumb and index finger, (b) grasp by opposing the thumb and the rest 3 fingers, (c) grasp by opposing the thumb and all the fingers.

and 80% of every mode's maximum voluntary contraction (MVC), and different grasping velocity were used under an isometric dynamic contraction condition. When grasping, the acting fingers were tightly attached to the big face of the sensor, thus the fingertip force applying on the sensor can be mapped into the sensor's Fz direction which represents a whole exerting force of the hand.

E. Data Analysis methods

1) Artificial Neural Network: A feed forward neural network with 6 inputs, 15 hidden neurons (transfer function: $\log\text{sig}(x) = 1/[1+\exp(-x)]$) and a linear output unit ($\text{purelin}(x) = x$) was used for the force regression from 6 channel EMG signals. The Levenberg-Marquardt algorithm [22] was adopted as the training method. To avoid network overfitting, the mean squared error (MSE) between the target and the predicted signal (as a ceasing criteria of learning) was set to 0.1.

2) Locally Weighted Projection Regression: LWPR [23] is an effective regression method especially targeted for high-dimensional spaces with redundant and irrelevant input dimensions. We chose to use the RBF (Radial Basis Function) kernel and meta-learning, performed 4-fold cross-validation and found the initial values of the distance metric for receptive fields by grid search (finally set to 1).

3) Support Vector Machine: SVM [24] has been proved to be an efficient tool for both classification and regression. Here we used the epsilon-SVR ($\varepsilon = 0.1$) and RBF kernel function and compares it with the fore two methods. We also used a cross-validation operation with a grid search to find the best pair of penalty parameter C and kernel function parameter γ . Experiential results showed that the value of 32 and 0.01 was the best combination in most of our studies.

III. EXPERIMENTAL EVALUATION

In this section, we illustrate how to prepare experiments and how to get appropriate data sets to evaluate our methods. Also, some useful regression results by using each machine learning method (ANN, LWPR, and SVM) and different training strategies are present here.

A. Experiment general setup

All of our experiments were executed under a typical laboratory surroundings (temperature: 20℃, humidity: 50%, normal electromagnetic interference and radiant intensity), which is similar to a general living environment to approve the prosthesis application. A subject (male, 27 years old) without any forearm neuromuscular diseases was tested in all of our experiments. Before any test group, the subject was introduced to the details of the experiment, i.e., the aim, the proceeding, and the grasp modes of the hand. Then his left forearm was degreased using 95% medicinal alcohol to ensure a nice interface between the skin and the electrodes. Generally, several grasping rehearsals need to be performed by the subject before the actual data acquisition until the subject is quite familiar with the experiment's paradigm.

Two independent test groups were executed within a day. Each group was composed of 4 test sessions. The electrodes were removed from the forearm for an hour and re-placed before the second test group, but is kept still for half an hour across sessions in each group. In every session, the subject was introduced to grasp the force sensor by complying with each grasp mode (see section II, *D*) for continues 10 seconds respectively. Different grasp force size and velocity should be encountered within the time spans. Two type signals, EMG and the grasp force, were collected under the LabVIEW software environment at the same time with a sampling rate of 100 Hz. Thus we can get 40 seconds (4 grasp modes, every 10 second) 7 channel signals (6 for EMG and one for the force) in every session.

B. Data preparing

For total 40 seconds length data in every session, we separated them into two different training strategies, one was called the specific mode (grasp modes of 1, 2, 3), and the other, random mode (grasp mode 4). The EMG data was without any feature extraction, normalized or filtering operations. We expected, by directly extracting the force information from the raw EMG signal, it can efficiently reduce the system's cost. For the force data, every sample's value was linearly scaled into the EMG signal's scope (electrode output range, values 0~5) for regression calculations.

C. Regression analysis

We used every session's data to train, and the other sessions' data to validate. For example, we took the first session's total 4000 samples to train under both specific mode and random mode, then to predict the rest data within rest sessions by the trained regression machines (LWPR, ANN and SVM). Through these operations, we can get not only the training effect of each method, but also the cross-session validation results, which are more important to practical applications.

Two indicators of regression performance, mean squared error (MSE) and squared correlation coefficient (SCC) in their standard definitions were used to compare the appearances of the methods of LWPR, ANN and SVM. Fig. 4 shows the results of total 8 sessions' training and validation under specific mode. The index of the sessions (1~8) is arranged in chronological order.

It is apparent from the Fig. 4 that, on the diagonal of each shape, where the test sessions are exactly the training sessions, the validation accuracy is very high, MSE: 0.07~0.08, SCC: 0.92~0.93. The LWPR method performs slightly better than ANN and SVM (MSE: 0.0705±0.0153, SCC: 0.9316±0.0142) on these elements. But if we consider the remaining elements of the pixel matrix, which represents the cross session (or group) validation results, SVM performs the best (MSE: 0.2118±0.1403, SCC: 0.8612±0.0551). In detail, within each group, the cross session MSEs are 0.1329±0.0233 (group 1) and 0.1004±0.0321 (group 2), and the SCCs are 0.9063±0.0147 (group 1) and 0.8985±0.0329 (group 2).

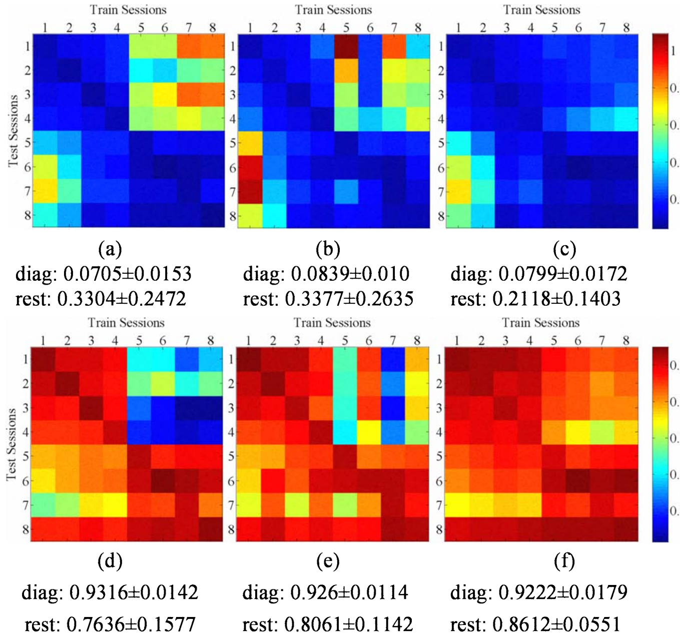


Fig. 4. Cross session validation under specific mode, MSE (up) and SCC (down), using methods of (a) (d)LWPR, (b) (e)ANN, (c) (f) SVM

Similar to Fig. 4, we also get validation results of the total 8 sessions under random mode. The SVM method performs still better than LWPR and ANN, taking the cross session (or group) performance into account. So, we only talk about its performance bellow, see Fig. 5.

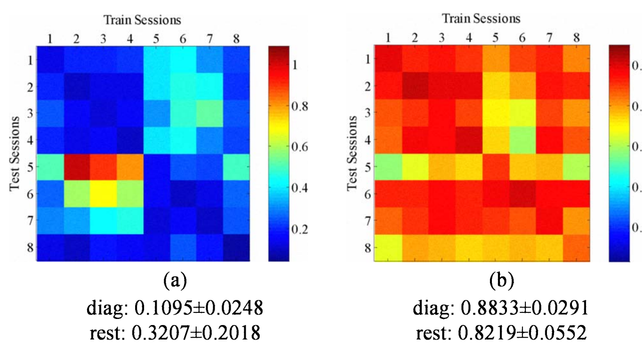


Fig. 5. Cross session validation under random mode using SVM method, (a) MSE, (b)SCC.

We can see a clear performance decrease when training under the random mode, whatever the predictions of training data itself (diag) or cross session validations (rest). In detail, for the cross session validation results, MSEs jump to 0.1753±0.0399 (group 1) and 0.2173±0.105 (group 2), and SCCs reduce to 0.8655±0.0232 (group 1) and 0.8131±0. 0541 (group 2).

Because fewer samples are used under the random mode (totally 1000 samples in 10 seconds span) than specific mode, it seems to be reasonable for the performance declining. But even adopting more training sessions, for example, 3 sessions for train and the rest session for validation in each group (on this setting, the number of training samples is equal to 3000, the same to specific mode), we still get a relatively bad result of cross session validations, MSE: 0.1401±0.0299 (group 1), 0.1628±0.0379 (group 2), SCC: 0.8822±0.0149 (group 1), 0.8413±0.0432 (group 2).

D. *Online force prediction*

Based on the results above, we propose here an online procedure for hand grasp force estimation:

1) Acquire data: Under the grasp mode 1, 2 and 3, collect 10 seconds length EMG and force data with a sampling rate of 100 Hz respectively. Different size of force and grasping velocity should be applied on the force sensor.

2) Training: Using the total 30 second EMG and force data as training samples and targets to train the SVM (epsilon-SVR), $\varepsilon = 0.1, C = 32, \gamma = 0.01$.

3) Online estimation: Input real-time EMG samples to the trained SVM and get the predicted grasp force value. Note that, the grasp modes should also be complied with as in the training sessions.

Given this configuration, the grasp force prediction rate can be achieved above 1000 Hz, with accuracy of around 0.9 (SCC, 30 seconds data length), that is, 5~10N over a range of 0~60N. Fig. 6 shows a series of online grasp force prediction results.

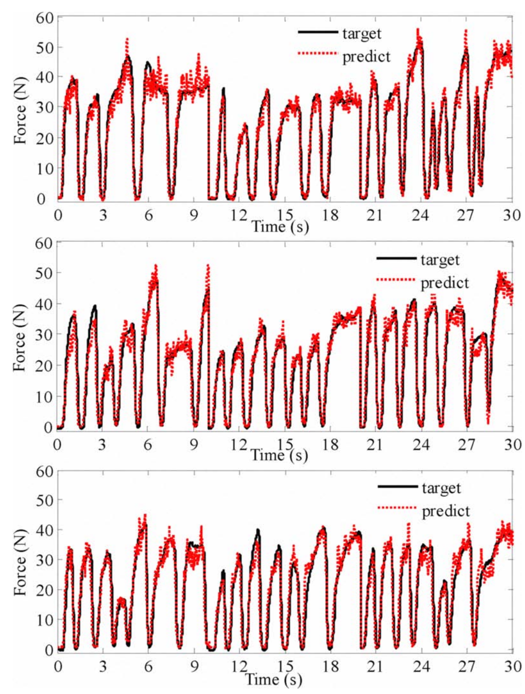


Fig. 6 Several online prediction results of the grip force comparing with their force targets

IV. Discussion

The number of the EMG electrodes is redundant in our study. Fewer electrodes, for example, three on the surface of the front forearm, are sufficient for an acceptable accuracy as well. A principal component analysis (PCA) shows that these three channel signals are more dominant than the other ones. It is reasonable, because the relative muscles on the front forearm are responsible for fingers' flexions. If we want to classify more hand gesture modes rather than grasp ones, for examples, the thumb, index and middle fingers' extension actions, more electrodes should be placed on the back forearm. Fingers' motion modes (not related in this paper) combined with necessary grasp force information should be involved in the prosthetic hand's control simultaneously.

In this paper, only one dimensional force (Fz of the sensor) is used to represent the whole hand grasp force. It is unable to predict each finger's exerting force when the hand is grasping or operating with a single finger. High performance devices (data-glove for force estimation) or intelligent algorithm (multi-targets regression) will well promote our study.

No filtering operations are executed on the forecasting force signals. Such digital filters, IIR or FIR, can effectively reduce the signal's peak noise, but it will increase the predicting system's time delay in a real-time control and decrease the subject's EPP sensitivity.

Moreover, to the subject's proprioception of the grasp force, it can be accomplished by the feedback of hierarchical electric stimulation, which makes the subject appreciatively know the size of the force applying on the object.

V. Conclusion

This paper presents an online estimation of hand grasp force directly from the forearm surface electromyography through some machine learning approaches. The system's configuration is totally non-invasive, easy to setup and can get good results within several minutes' training. Our experiments, performed with 3 regression methods (LWPR, ANN and SVM) and 2 different grasp training modes (specific and random), reveals that, the SVM method is better than the others, especially on the cross session validation. And the system's performance is better when the hand is grasping complying with several specified modes than grasping randomly. An average accuracy of about 0.9 (SCC) with an error of about 5~10N over a range of 0~60N can be achieved.

Future work will be focus on applying this approach in the closed loop of the prosthetic hand's force control and experimenting on disable patients.

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