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EMG Pattern Recognition and Grasping Force Estimation: Improvement to the Myocontrol of Multi-DOF Prosthetic Hands

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***Abstract*—The multi-DOF prosthetic hand's myocontrol needs to recognize more hand gestures (or motions) based on myoelectric signals. This paper presents a classification method, which is based on the support vector machine (SVM), to classify 19 different hand gesture modes through electromyographic (EMG) signals acquired from six surface myoelectric electrodes. All hand gestures are based on a 3-DOF configuration, which makes the hand perform like three-fingered. The training performance is very high within each test session, but the cross-session validation is typically low. Acceptable cross-session performance can be achieved by training with more sessions or fewer gesture modes. A fast rhythm muscle contraction is suggested, which can make the training samples more resourceful and improve the prediction accuracy comparing with a relative slow muscle contraction method.**

For many precise grasp tasks, it is beneficial to the prosthetic hand's myocontrol if we can efficiently extract the grasp force directly from EMG signals. Through grasping a JR3 6 dimension force/torque sensor, the force signal applying to the sensor can be recorded synchronously with myoelectric signals. This paper uses three methods, local weighted projection regression (LWPR), artificial neural network (ANN) and SVM, to find the best regression relationship between these two kinds of signals. It reveals that the SVM method is better than ANN and LWPR, especially in the case of cross-session validation. Also, the performance of grasping force estimation based on specific hand gestures is superior to the performance of grasping with random fingers.

I. Introduction

THE electromyographic signal is a biomedical signal that measures electrical currents generated in muscles during its contraction representing neuron-muscular activities. Detection and analysis of the EMG signal with powerful and advanced method is a hot topic today in biomedical engineering, especially in the prosthetic hand's myoelectric control.

Myoelectric control has been widely used in commercial prosthetic hands for several decades. Take Otto Bock SensorHand [1] for example, one or two electrodes are used to capture the EMG signals generating from muscles on the surface of the forearm. Then, after extracting some time domain features of these signals and mapping these features to the hand actuator's rotation direction and velocity, the hand can be instructed to grasp (or release) an object with typical velocity and force. The myo-type prosthetic hand, which is activated by the amputee's residual muscular activities, can be recognized as a simple replication of the human hand. But, the myohand is not widely accepted by disabled people because of its clumsy appearance and deficient functions [2]. Advanced development has been done to improve the dexterity degree and the grasping functionality by increasing the degrees of freedom (DOF) of the artificial hand, as shown from the novel Cyberhand [3] or i-limb [4]. But new problems of the EMG control policy appeared at the same time. The signal obtained by the surface EMG electrode is a summation of motor unit action potentials (MUAPs) beneath the electrode, which represents a comprehensive effect of many motor units' activations. It is quite difficult to acquire kinematics information of each joint of the human hand from raw EMG signals.

However, by using advanced machine learning algorithm, such as SVM and ANN, to extract useful information from multi-channel EMG signal, a novel EMG control of multi-DOFs prosthetic hand can be achieved.

This papers focus on the myocontrol of a 5-DOF prosthetic hand based on a powerful pattern recognition algorithm SVM, presents some detailed results of predicting 19 hand gestures using six-channel EMG signal based on different muscle contraction rhythms. It also clarifies the performance of estimating hand grasping force from the EMG signals under several specific hand gesture modes.

II. Background and Related Works

A novel prosthetic hand, named HIT/DLR Prosthetic Hand, has been developed by the State Key Laboratory of Robotics and System of China. Its five fingers can move independently and its volume is just 75% as a real human hand (Figure 1). For its myoelectric control, our previous work [5] combined auto- regressive (AR) model parameters with neural network (Levenberg-Marquardt learning), can successfully identify the fingers' respective flexion actions of the thumb, the index and the middle. It used only two electrodes placed on the forearm to acquire proper EMG signals. However, this method has some obvious drawbacks: firstly, the control strategy is not similar with that of a human hand and only three motions can be classified; secondly, only a single finger can be controlled at a time.

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Fig. 1. The proposed prosthetic hand (left) and a volume comparison to a human hand (right).

Transient EMG signals can be utilized to recognize combining finger actions, such as pinching and holding [6]. But, methods of using this kind of signals discarded precious steady-state information of EMG signals. This deviation of EMG usage will make the recognition system only be able to predict the hand's motions, but not real-time hand gestures.

Kevin Englehart [7] investigated the different usage of transient EMG and steady-state EMG thoroughly, and indicated that high classification success rate can be also achieved by using steady-state EMG features to train the learning machines. Moreover, if we can predict every particular hand gesture from moment to moment, and make the prosthetic hand follow the human hand's postures, there will be an improved intuitive feeling of the amputee about his/her prosthetic hand (extended physiological proprioception, EPP [8]). Continuous prediction of hand gestures based on steady-state EMG signals ensures the EPP feelings and enables the myocontrol system more responsive and usable.

For raw EMG signals, a slide window is commonly established to extract time-frequency domain features at a certain length, such as wavelet coefficients [9], RMS [10], etc. Pattern recognition methods (such as GMMs [11], SVM [10], etc) are acting on these different feature groups for EMG pattern predictions. Sometimes, in order to identify the patterns more accurate and avoid some bad effects caused by pattern switches, it needs to overlap some decision points together within a typical length of decision stream using majority vote. But the prediction delay caused by the decision overlapping should be also considered. At the same time, the inertia of a prosthetic device will serve to smooth the stream of class decisions and ignore a few error transition states [7].

Crawford [10] proposed an SVM-based approach for EMG classification using 7 surface electrodes. It can distinguish 8 different gestures of the hand with an accuracy of 92-98%. But half of their discussing gestures were based on the arm being pronated or supinated. That made the system less useful for the multi-DOF prosthetic hand's applications. Bitzer [12] used ten electrodes to classify six different finger motions, i.e., the flexion and extension of the thumb finger, the index finger and the remaining fingers, respectively. He also discussed some performance differences under several conditions, such as different arm gestures (relaxation, pronation) and cross-session validations. For his study, it is hard to implement some hand grasps which need fingers to cooperate with each other. Castellini [13] also used ten electrodes and focus on four grasping modes, i.e., grasping by opposing the thumb and index finger, grasping by opposing the thumb and middle, grasping by opposing the thumb and ring, and grasping by opposing the thumb and all other fingers. Originally, the regression performance from EMG signals to the grasp force of these gesture modes was discussed.

Among them, Crawford and Bitzer adopted a probability estimate to the current classifying class. It can improve the recognition system's reliability by setting its acceptance threshold to a high value (0.95). However, we should not ignore the existence of idle mode (where all fingers are relaxed). For example, errors will occur if some active modes' signals are too similar to the idle mode's ones. Also, the calculation of posteriori probability is so complex that, for real-time pattern recognition, it will increase the system's time delay, especially for some embedded applications.

III. METHODOLOGY

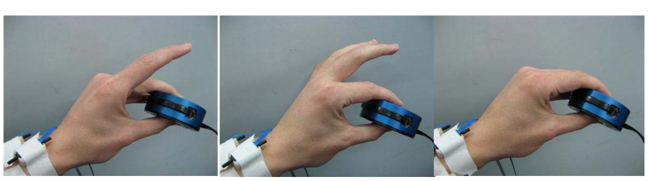
A. *Hand Gestures*

A research on human hand's grasp function [14] indicated that the thumb, index and middle fingers play a relatively important role than the others (the ring and little) in most of our daily-life hand grasp modes. Although the new generation of HIT/DLR Prosthetic Hand has five independent moving fingers, it was intentionally configured into a three-fingered (three-DOF) type for its EMG control. Because our study found it was very difficult to recognize each finger's motion only based on several surface EMG electrodes. Specifically, we made the thumb finger, the index finger, and the rest fingers (the middle, ring and little) move respectively, similar to the design of a fore generation HIT/DLR prosthetic hand [15]. Considering about their different state of relaxation, flexion and extension, there will be a total of 27 different hand gesture modes (Figure 2).

If we use 0, -1 and 1 to represent the three DOFs' different states respectively, the precise grip, which the thumb and index are opposite from different orientation, can be written as (-1, -1, 0), and the power grasp can be written as (-1, -1, -1), and so on. Figure 2 shows all the 27 modes divided into 4 groups (basic, extended I-III) with varying degree of performing difficulty. There is also an index (from 1 to 27) indicating the training sequence of these modes. This arrangement improves the training efficiency in experiments and reduces the mental burden of the testers during training. Not only single but also joint fingers' movements are included in these modes, which further improve the hand's grasping funcion by EMG controlling. In this paper, some hard performing modes which are rarely seen, such as the group of extended III, in which the modes need a subject to keep the three DOFs with three different states, were eliminated from our study. Therefore, a total of 19 modes needed to be classified in this paper (include “all relax” mode (0, 0, 0), namely the idle mode). The index order of the modes was kept still for training, and that made the acquisition of the training samples more stable and reliable.

Fig. 2. All hand gesture modes under three-DOF configuration. Note that the modes of 5, 6, 12, 13, 14, 17, 21, 22 (lower contrast) is not discussed in this paper.

For the estimation of grasping force from EMG signals, three closed gesture modes of the hand (index of 16, 25 and 26) were utilized. Figure 3 shows these three different modes while the subject is grasping a force sensor.



(a) (b) (c)

Fig. 3. Hand grasp modes applied on the force sensor. (a) grasp by opposing the thumb and the rest three fingers (-1,1,-1). (b) grasp by opposing the thumb and index finger (-1,-1,0). (c) grasp by opposing the thumb and all the other fingers(-1,-1,-1).

B. *Data Acquisition Set up*

The EMG sensors used in this paper were six surface EMG electrodes 13E200=50 [16], which were made by Otto Bock company in Germany. The electrodes were connected to an AD acquisition card (ADLINK PCI-9118HR), which was embedded in a computer’s PCI slot, via a self-made power supply connector. For the grasping force detection, a type of 6 dimensional force/torque sensor, made by JR3 [17] was adopted. The force sensor’s output is between 0~200N (Fz), which is larger than a human hand’s grasp force. When the force sensor was grasped, the force signal was import into the PC via a standard PCI card. The signals of two different sensors (EMG and force) were collected synchronously in LabVIEW environment with a sample rate of 100HZ. In order to facilitate analysis and comparison, we also linearly scaled the force AD data into the EMG output range (0~5V).

C. *Electrode Placement*

The placement of the electrodes seriously infects the recognition of EMG patterns. Comparing with Bitzer’s research, fewer electrodes were used in this paper. It needs to prepare the electrodes’ position more carefully. The fingers’ flexion or extension motions need different muscles’ or muscle groups’ contractions. We chose some muscles where the electrode signals can mostly represent their own basic gesture modes (Table I) and hardly interfere with the others. Based on this criterion, five muscles on the forearm were adopted and six electrodes were put upon the bellies of these muscles. Specially, we chose the flexor digitorum superficials (the same muscle but different position) to take charge of both the index’s and the rest fingers’ flexions. Figure 4 and Table I shows exactly the electrodes’ placement and corresponding muscles and modes.

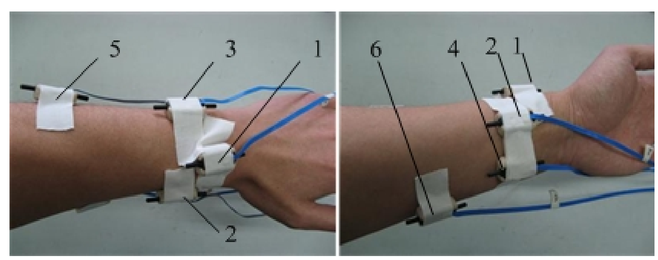


Fig. 4. The placement of surface EMG electrodes on the forearm.

TABLE I
The related muscles and corresponding basic modes

	Name of the muscle	Corresponding mode
1	Extensor pollicis brevis	Extend thumb (1,0,0)
2	Flexor pollicis longus	Flex thumb (-1,0,0)
3	Extensor indicis proprius	Extend index (0,1,0)
4	Flexor digitorum superficialis (distal)	Flex index (0,-1,0)
5	Extensor digiti quinti proprius	Extend rest (0,0,1)
6	Flexor digitorum superficialis (proximal)	Flex rest (0,0,-1)

D. *Support Vector Machine*

The SVM [18] has proved to be a powerful and efficiency tool for classification tasks. It has so many applications in the field of artificial intelligence. We used a type of classification SVM named C-SVM to recognize the EMG patterns stated before. We chose RBF as the kernel function, and used one-against-one method to solve multi-mode classification. A regression method, ε-SVR with RBF kernel function, were used for the estimation of hand grasping force. For the optimization of a pair of parameters, the penalty parameter C and kernel function coefficient γ, we made an exponential grid research with 4-fold cross validations.

E. Experiment Set up

We split our experimental research into two different topics. One aimed to get the cross-session classification performance with two different training strategies (slow and fast rhythm muscle contraction), and the other discussed the regression performance from EMG signals to grasping force under several grasp modes. A healthy subject was selected for our tests. The 'session' meant a period of EMG data acquisition, in which each concerned hand gesture were performed by the subject for a typical length of time (in this paper, 10 seconds).

For the first topic, the experiment was combined of four test groups. The six electrodes were removed from the forearm for about two hours and placed again in the group intervals. Each group was composed of 3-4 test sessions (4 sessions each in the first two groups and 3 sessions each in the last two groups). Among these sessions, the subject got half an hour rest without the electrodes being removed. In each session, we collected a total of 360 seconds EMG data, i.e., 10 seconds data for each hand gesture (not include the idle mode), respectively on two different muscle contraction rhythms (nearly 0.3Hz and 2Hz). We expected that the fast rhythm contraction would raise the muscle fatigue easily, thus makes the training samples more plentiful. The subject's forearm for test was put on a desk with the palm orthogonal to the desk's plane. This posture was persisted for performing all hand gestures.

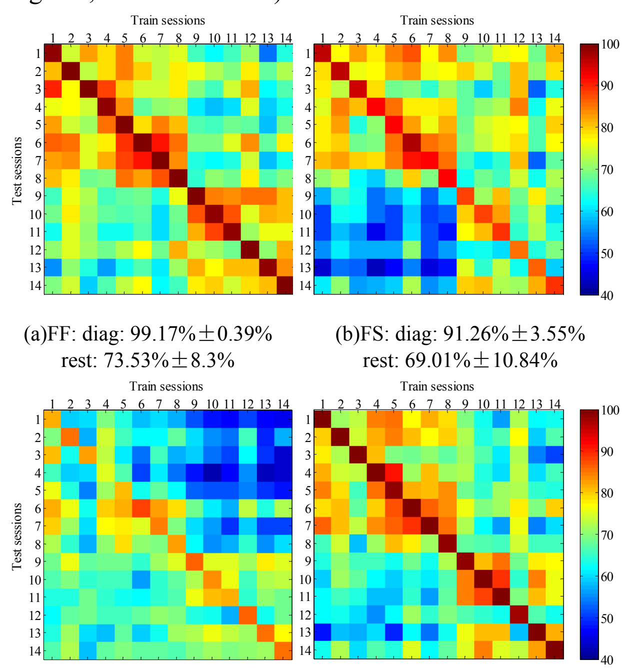
The eight sessions of experiment group 1 and group 2 was accompanied by force data collection. The subject was notified to grasp the force sensor's two large faces (Figure 3), complying with the grasp modes, for nearly ten times with different scale of grasping force (0-60N, Fz direction). We also discussed a regression performance of another grasping strategy, in which the subject randomly grasps the sensor without specific modes. So, a total of four grasping modes (three from Figure 3 and a random grasping with random fingers and force) were concerned, and each of them lasted 10 seconds in every session.

IV. EXPERIMENT RESULTS

A. EMG Pattern Recognition

For the total 14 sessions, we used each session's EMG data to train a C-SVM (C=32, γ=0.125), and used the C-SVM to predict the EMG modes of all sessions (that is called cross-session validation). All training and predicting were acted on the threshold dataset, which was defined as a subset of the acquired EMG data (360 second in length). The subset only contained the sampling points whose element (or elements) exceeded its own threshold. The threshold was set to the EMG value range's 1/5 of its corresponding channel. Based on this operation, for a 6-dimension EMG signal vector, if all element values are bellow their own channel's threshold, the date point will be treated as idle mode (0, 0, 0) and not used for training and predicting. Here we define that the success rate is the sum of right predict points divided by total points' number in each session's threshold dataset. Figure 5 illustrates the success rates of both training within session and predicting cross-sessions. FS means training with fast rhythm (2Hz) data, but validating with slow rhythm (0.3Hz) data. Similar expression can be seen from FF, SF, and SS.

From Figure 5, we can see that the training success is very high (nearly 99%), both on the condition of fast and slow rhythm muscle contraction. But the cross-session validation success rate is typically low (70%), especially in different groups which the electrodes were reconfigured. The validation from the same group is relatively high (80%). The fast rhythm training is better than slow rhythm training according to the cross-session performance (FS diagonal>SF diagonal, FF rest >SS rest).



(a)FF: diag: 99.17%±0.39%
rest: 73.53%±8.3%

(b)FS: diag: 91.26%±3.55%
rest: 69.01%±10.84%

(c)SF: diag: 83.58%±3.34%
rest: 64.29%±9%

(d)SS: diag: 99.16%±0.56%
rest: 70.82%±9.27%

Fig. 5. Cross-session validation of success rate within 18 gesture modes,(a) FF: using Fast rhythm for training and Fast rhythm validation, (b)FS, (c)SF, (d)SS.

B. Grasping Force Estimation

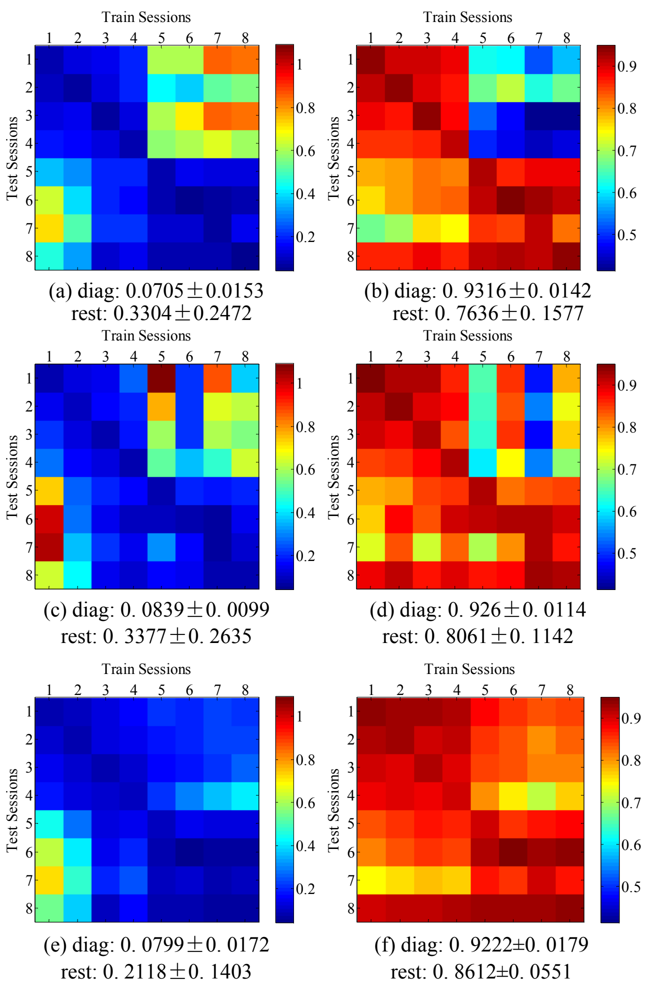
We adopted an ε-SVR algorithm (C=32, γ=0.01, ε=0.1) for the regression from EMG signal to the grasp force. Methods of LWPR and ANN were also used for comparing with the ε-SVR method. For the ANN, we used a feed-forward neural network with 6 inputs, 15 sigmoidal hidden units, and 6 linear outputs. The training method was Levenberg-Marquardt algorithm [19], and the learning stopping criteria, mean squared error (MSE) of the training target and prediction result, was set to 0.1 to avoid over fitting of the network. For the LWPR, We chose the RBF kernel and meta-learning, performed a 5-fold cross-validation, and found the initial values of the distance metric for receptive fields by grid search (0.5 is perfect for our research).

Because there were two different grasp strategies, i.e., grasp complying with gesture modes in Figure 3 and grasp with random fingers and force, we constructed two regression machine models (LWPR, ANN and ε-SVR, respectively), for these two different situations. That is, using each session's 30 second length EMG-force data (regularized gesture modes) to train the first model, and using the remaining 10 second length EMG-force data (randomized grasping) to train the other model.

Figure 6 shows the regression performance of the first models training within sessions and estimating cross sessions with two standard indicators of performance:

1) The mean squared error (MSE) in its standard definition;

2) The squared correlation coefficient (SCC) between the training target and the predicted force result.



(a) diag: 0.0705±0.0153 rest: 0.3304±0.2472

(b) diag: 0. 9316±0. 0142 rest: 0. 7636±0. 1577

(c) diag: 0. 0839±0. 0099 rest: 0. 3377±0. 2635

(d) diag: 0. 926±0. 0114 rest: 0. 8061±0. 1142

(e) diag: 0. 0799±0. 0172 rest: 0. 2118±0. 1403

(f) diag: 0. 9222±0. 0179 rest: 0. 8612±0. 0551

Fig. 6. Cross-session validation of MSE (left column) and SCC (right column) using LWPR (a, b), ANN (c, d) and ε-SVR (e, f).

In each group, there is no clear validation out-performance of the three methods, only the SVM cross-session validation is slightly better. But if taking the cross-group performance into consideration, SVM method is obviously better than the other two methods. As a whole, using SVM can achieve an acceptable cross-session performance as MSE: 0.1329 ±0.0233 (group 1) and 0.1004±0.0321 (group 2), SCC: 0.9063±0.0147 (group 1) and 0.8985±0.0329 (group 2).

For the second ε-SVR model, the system's cross-session SCC reduced to 0.8655±0.0232 (group 1) and 0.8131±0.0541 (group 2) respectively, MSE increased to 0.1753±0.0399 (group 1) and 0.2173±0.105 (group 2). The ANN and LWPR performed even worse in cross-session and cross-group situations.

V. Discussion

Only SVM method was used to identify the EMG hand gesture modes in this paper. Because so many researches revealed that the SVM method outperformed some general pattern reorganization methods, especially in the multi-mode and few training sample tasks. Even so, for the 18 active EMG modes, the cross-session performance is relatively low, not because of only the EMG signal's random and time-varying properties, but also insufficient training samples. We attempted to use more training sessions in every group, for example, three sessions for training and the rest for validation, a higher success rate (nearly 93%) can be gotten. Moreover, by reducing the modes (only basic modes and grip (-1,-1, 0), total 9 active modes), the cross-session success rates are 85.88%±8.34% (inter-group) and 93.1±5.1% (intra-group). Training with fast rhythm muscle contraction also outperforms training with the slow rhythm in all of these cases.

For the estimation of the grasping force, because the training data of two grasp strategies are different in size (30 seconds and 10 seconds), we tried to use more sessions to train the second ε-SVR model. For example, using three sessions' data to train and the rest session's data to validate, we can get a performance of 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), which is still worse than the first ε-SVR model's achievement. But, if we construct an independent ε-SVR model for each hand gesture mode in Figure 3 (that is, three modes for three hand gestures in each session, respectively), the validation performance is better in some gesture modes (Figure 3-a, Figure 3-b), which is shown in Table II.

TABLE II
Force regression performance of cross-session validation within three gesture modes from Figure 3

gestures	Figure 3 (a)	Figure 3 (b)	Figure 3 (c)
MSE:			
group 1	0.1489±0.0535	0.0818±0.0344	0.2618±0.1262
group 2	0.1058±0.0483	0.0889±0.0340	0.1646±0.0785
SCC:			
group 1	0.9137±0.0123	0.9236±0.0180	0.8826±0.0418
group 2	0.9182±0.0151	0.9156±0.0328	0.8573±0.0888

VI. CONCLUSIONS

Throughout our study, the fast rhythm training (1 Hz muscle contraction) method will get better cross-session performance than slow rhythm (0.3 Hz). Using C-SVM method, the recognition of 18 active gesture patterns can achieve at 82.5%±5.4% (validation the success rate within each group). More training sessions or fewer gesture modes can increase the success rate to 93% (three sessions for training 18 modes, or one session for training 9 modes). Because of low validation success rate cross groups (60%~70%), it is recommended that re-training the SVM when the electrodes' positions are changed. Our grasping force regression study shows that: training with grasp modes is better than without modes; hand gesture performed by fewer fingers achieves better results; and the SVM method outperforms ANN and LWPR with a strong generalization capability.

Based on this paper, an intelligent EMG control scheme can be implemented to recognize the hand's gesture and grasping force simultaneously. That makes a big improvement to current multi-DOF prosthetic hands' myocontrol. Future work will concentrated on validating this method on patients.

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