J Intell Robot Syst (2014) 76:427–441
DOI 10.1007/s10846-014-0037-6

Experimental Study of an EMG-Controlled 5-DOF Anthropomorphic Prosthetic Hand for Motion Restoration

Dapeng Yang · Li Jiang · Qi Huang · Rongqiang Liu · Hong Liu

Received: 29 August 2012 / Accepted: 7 February 2014 / Published online: 29 May 2014

Abstract In this paper, we attempted to evaluate the performance of an electromyography (EMG)-controlled 5-DOF prosthetic hand on ten transradial amputees. The proposed prosthesis is composed of a five-fingered hand, a passive wrist, and a customized socket for each subject. The EMG control methods included both a commonly used pattern recognition-based scheme (DD-SVM) and a novel digital encoding strategy (double-channel template matching (DCTM)). A virtual 3D hand platform was developed for training the subjects and rapidly testing the control methods. For each subject, the performance of the EMG control methods was firstly measured by off-line classification accuracy; then, according to the accuracy, a particular control method was selected and embedded in the EMG controller for further validation on ordinary daily life activities. Our experiments were conducted to test not only the hand's grasp ability but also other multifinger cooperation skills. The result indicated that the subjects of rich control experience can accomplish several intuitive motion control over their hands. However, the kinds of the motions and their relative recognition accuracy may depend on some individual differences, such as the amputation level, the activity of the residual nerve-muscle system, and the richness of control experience. Meanwhile, the proposed digital encoding method, DCTM, which only utilized two channels of EMG, was necessary for those amputees with few available control signals. This paper suggested that the EMG control method should be differently considered according to the particular condition of each subject.

Keywords Prosthetic hand · EMG control · Pattern recognition · Virtual reality

Mathematics Subject Classification (2010) 68T40

1 Introduction

At present, most commercial prostheses possess only one or two degrees of freedom (DOF), such as hand close/open and wrist rotation. This lack of dexterity largely impedes the hand's rehabilitation efficacy, making customers rarely use them during the activities of daily living (ADLs) [1].

In order to better restore the hand function, many multi-DOF prosthetic hands [2–8] have been developed. However, only a few of them are clinically evaluated. One big obstacle of putting these hands into practice is their control method. It becomes even more difficult when the control source, electromyography (EMG), is highly restricted on the stumps

D. Yang · L. Jiang (✉) · Q. Huang · R. Liu · H. Liu
State Key Laboratory of Robotics and System,
Harbin Institute of Technology, 150080 Harbin,
Heilongjiang, People's Republic of China
e-mail: jiangli01@hit.edu.cn

of the amputees. Although the targeted muscle reinnervation (TMR) technology [9], which redirected severed nerves to the muscles on the chest for providing sufficient EMG control signals, has been proved useful through multisubject clinical experiments, the complexity, and cost of this surgery are still relatively high, which may lead to low acceptance by the patients.

Commercial multi-DOF prosthetic hands, such as Touch Bionics i-LIMB hand [10] and RSL Steeper Bebionic hand [11], have been available since 2007. These dexterous hand prostheses have superior anthropomorphic features when compared with conventional prosthetic grippers [12]; however, their functionality is highly limited by using the current coding-type methods. This type of methods generally adopts the EMG amplitude information for driving the hand. For example, by using "0" to represent the low EMG amplitude and using "1" to represent the high EMG amplitude, the hand gesture can be switched from one to another under a typical coding mechanism (that is, a serial code consists of 0 and 1 mapping into the hand gestures, such as "111"-hand open, "110"-hand close, like the Morse code). This method may cost much time on motion selection and thus largely reduces the response speed of the hand. In addition, since the control dexterity of the hand is highly related to the number of the coding patterns, the user generally needs more training time when higher hand dexterity is needed.

During the last decade, several anthropomorphic prosthetic hands (Harbin Institute of Technology-German Aerospace Center (HIT-DLR) prosthetic hand, prototypes I∼III) [13–15] have been developed in our laboratory. These hands are all five-fingered; each finger has three phalanxes. For the newest one (prototype IV) [16], five DC motors are integrated in the palm, making all fingers individually actuated. A large variety of sensors for measuring the position and torque of the fingers and a feedback channel of electrical stimulus [17] are integrated in the hand. As to the EMG control method, a refined control scheme [18] is adopted based on the research of [19], in which the support vector machine (SVM) is used as the classifier. By carefully arranging six electrodes on particular muscle groups and introducing a threshold for purifying the EMG samples, it shows that at most 18 finger motions (individual or jointed-DOF motions, according to the 3-DOF configuration as digit I, digit II, and digits III–V) can be precisely deciphered on healthy people with accuracy of about 95 %. This method was evaluated first on hand prototype III [15], in which the DOF configuration of the motions was the same to the mechanical hand.

For developing a prosthetic hand, sufficient experiments on patients should be conducted to fully validate the hand design. The motivations of this paper were to provide a clinical evaluation for the newly developed HIT-DLR prosthetic hand prototype IV and to verify if the amputees, without any surgical intervention, can operate the multi-DOF prosthetic hand freely by means of their EMG signals. Two different EMG control strategies, termed as double-decision SVM (DD-SVM) and double-channel template matching (DCTM), on the basis of pattern recognition scheme and digital encoding, respectively, were both used. In terms of classification accuracy, the performance of these methods with respect to each subject was quantified. Then, several daily life activities were performed to further evaluate the control methods and the hand design. These results will help to design appropriate prosthetic hand systems for individuals, which will provide increased hand dexterity and will be efficiently controlled by EMG signals.

2 Materials and Methods

2.1 Subjects

Ten patients, seven men and three women, with forearm amputation, two bilateral and eight unilateral, were tested. Some major information of the subjects is shown in Table 1.

For the subjects with bilateral amputation (PQT and SCC), the dominant side was tested. The cause for amputation included cold injury, car accident, electric strike, and machine injury. The subjects were with different amputation conditions, such as stump length and amputation history. The usage experience of the prosthetic hand was also different: five were already equipped with commercial EMG-controlled hands, one wore a cosmetic hand, and the rest four had no prosthetic hand yet. The commercial EMG hands were traditional prostheses with 1-DOF (or 2, including an active wrist) that is controlled by no more than two channels of EMG signals.

Ahead of experiments, all subjects were given a short description about the system configuration, the

Table 1 Information of the subjects

Index	Name	Gender	Age (years)	Height (cm)	Weight (kg)	Amputation cause	Stump length (cm)	Year of amputation	Prosthesis in use
1	PQT	Male	50	171	65	Electric shock	16.8/R	2001	2-DOF myohand
2	KXD	Male	46	170	80	Machine	19.8/R	2007	2-DOF myohand
3	ZYQ	Male	42	172	80	Machine	21.8/R	2011	1-DOF myohand
4	LB	Male	40	173	65	Car accident	12.3/R	2011	2-DOF myohand
5	WXM	Female	35	160	55	Machine	9.5/L	2009	1-DOF myohand
6	WTF	Female	63	160	52	Machine	13.7/R	2002	None
7	CXY	Female	42	162	60	Machine	13.3/R	1992	Cosmetic hand
8	ZQS	Male	40	172	79	Machine	12.5/L	2006	None
9	SCC	Male	39	180	90	Cold injury	21.5/R	2011	None
10	ZXZ	Male	36	170	80	Machine	19.5/L	2000	None

For privacy consideration, the names of the subjects are not fully given. The length of the stump is measured from the extensor condyle of the humerus to the end of the stump
R "right hand"; *L* "left hand"

EMG control methods, and the main experimental procedure. All subjects voluntarily participated in the experiments. All experiments were supervised by an expert from a professional rehabilitation center and were approved by the local ethics committee.

2.2 Hardware Configuration

2.2.1 The 5-DOF Prosthetic Hand

A total of ten hand prototypes (HIT-DLR prosthetic hand IV), using the same hardware configuration, were developed. The hand is 79 mm wide, 159 mm long, and 21 mm thick, as shown in Fig. 1a. The hand weighs about 420 g, including five motors and necessary mechanical and electrical elements. The hand has five fingers; each finger is actuated by a DC motor. The motion of the rest two phalanxes of the finger is kinematically coupled with the proximal joint (transmission ratio nearly 1:1) through a four-bar linkage [16]. These three phalanxes of the finger have superior grasp adaptability with comparison to those of rigid body. The hand can grasp a large variety of objects: the minimum diameter of a sphere object the hand can pinch is about 5 mm, while the maximum diameter of a cylinder object the hand can hold is about 90 mm. The designed output force on the fingertip is about 10 N.

A set of position and force sensors enabling low-level control schemes is integrated in the finger, as shown in Fig. 1b. Motor encoders are used in the base joints of the thumb finger, index finger, and middle finger for measuring the speed and turning direction of the motors. Absolute angle sensors developed based on giant magnetoresistance (GMR) are also integrated in the base joints of the fingers. For getting knowledge of the force applied on the object, a strain-based torque sensor (1D) is built on the driving bar of the linkage mechanism. The precision of the position and the force sensor can reach to 0.04 rad and 0.2 N, respectively, which meet the prosthesis usage. Integrated circuits for signal modulation are totally embedded in

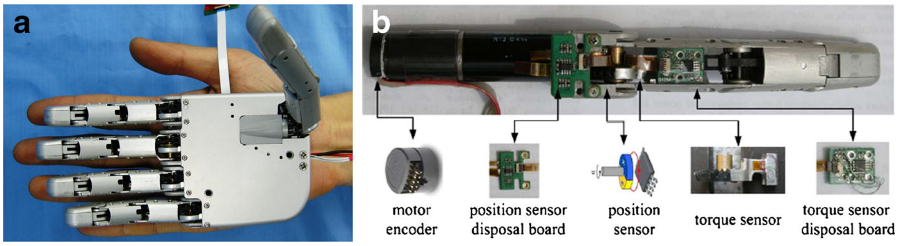


Fig. 1 The multi-DOF prosthetic hand and finger sensory system: **a** overview of the prosthetic hand and **b** sensory configuration of the finger

the finger knuckle. The signals are transferred via flex PCB and then fed into the A/D modular of the motion controller in the palm, which is constructed on a high-speed digital signal processor (DSP, TMSF2810). The on-chip controller area network (CAN) is adopted for communicating with the EMG controller in the socket (for acquiring top-level motion commands). Only four wires are introduced from the hand: two for CAN and the other two for power supply. The high-speed DSP and its peripheral facilities (CPLD, sRAM, H-Bridge, etc.; more information were presented in [17]) provide the hand with a large variety of control schemes, such as proportional-integral-derivative (PID) and impedance control.

2.2.2 Data Acquisition Configuration

A set of commercial EMG electrodes (Otto Bock, 13E200 = 50) [20] was adopted to measure the EMG signals of the amputees. On account of the signal's sensitivity and stability, the Otto Bock electrode has been widely accepted in the literature [13, 19, 21]. This type of electrode can directly output an envelope signal of the raw EMG signal (after amplification, filtering, and rectification). Most of the signal energy is concentrated in a lower frequency band (0∼50 Hz) with comparison to the raw EMG signal (0∼500 Hz). The amplification factor of the electrodes was set to grade 6 (the magnification factor is nearly 14,000), and the output amplitude of the signal was within 5 V.

The electrodes were directly wired to an EMG controller in the hand socket, which was constructed based on a DSP TMSF2812. The EMG data acquisition was accomplished using the on-chip A/D conversion module (with 12-bit resolution). Besides the prosthesis system, a computer-based virtual hand system was developed for testing the control methods in advance, in which a multifunctional A/D card (ADlink, 9118HR, 16-bit resolution) was used for sampling the EMG signal. The difference of the data resolution between these two systems was found bringing no significant variance in classification accuracy. The sampling frequency was set to 100 Hz on both systems, which was suitable for our study.

2.2.3 The Socket Design

In the socket, there was an EMG controller running various control methods. According to the variety condition of the subjects, it was difficult to find a universal control method. It was typical for the pattern recognition-based methods, since the number of controllable patterns and the electrodes may be remarkably different. Instead of validating a control method across all subjects, this paper intended to perform an overall validation of the hand. For doing this, we tended to find the optimum EMG configuration from all candidates for each subject and then compared the hand performance across both subjects and methods. Therefore, according to each subject, not only the shape of the socket but also the control method embedded in the EMG controller was separately considered.

The socket was designed according to the shape of the stump and the subject's body parameters. The constitution of the socket included an inner socket, an outer socket, an EMG controller, a rechargeable lithium battery, and two LED lights, as shown in Fig. 2a. The inner socket was used to hold the stump and attach the EMG electrodes (Fig. 2b). The number and position of the electrodes were determined after evaluating the control method by using the computer-based virtual hand system (detailed in the following sections). A passive wrist joint was mounted on the

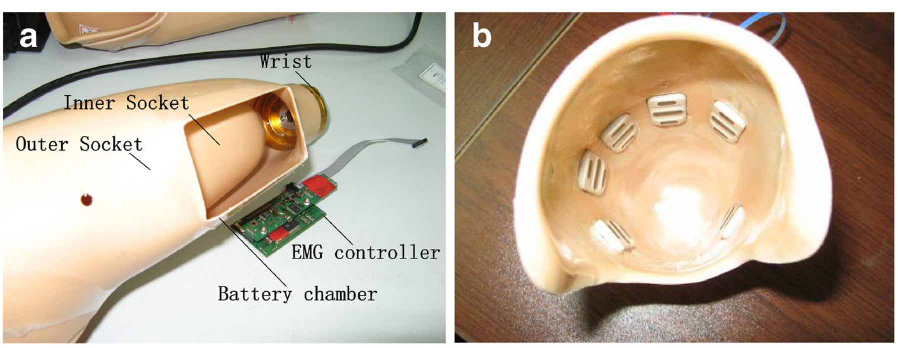


Fig. 2 The socket design: **a** the EMG controller integrated in the socket and **b** the electrodes mounted on the surface of the inner socket (from inside)

end of the outer socket for restoring the wrist rotation. The EMG control algorithm was implemented in the EMG controller. As referred before, the embedded data acquisition was also accomplished in the controller, which supported at most eight channels. A large-capacity lithium battery (2,500 mAh, rated voltage of 8.4 V, peak current of 5 A) supplied the power of the hand system. A prior experiment showed that the battery can support continuous operation for nearly 3 h. The LED lights were used for indicating the working status (training, suspending, or running) of the hand.

2.3 Virtual Hand System

The virtual reality (VR), a computer-based environment that simulates the real physical sense, has been widely used in the fields of medical therapy and rehabilitation training. It has been already shown that the virtual hand system can help to train the patients with different control methods [9]. Another study also found that, with a long-term training, the virtual training system can even contribute to neural rehabilitation [22]. In this paper, a 3D virtual hand was developed, as shown in Fig. 3, for testing our algorithm and training the patients in an efficient way. The simulated prosthetic hand that appears on the screen is controlled by algorithms realized with high-level languages in the computer and provides an intuitive tool for examining the control methods. It must also be noted that such a simulation tool is an ideal solution for training patients before deploying the real prosthetic hand.

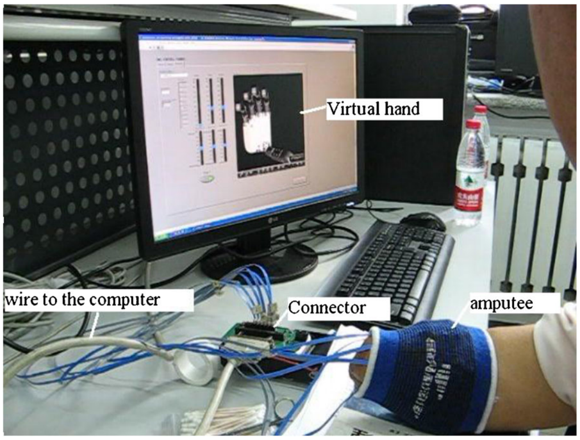


Fig. 3 The virtual hand control platform

The virtual reality model language (VRML) was used to construct the emulated environment of the hand. The 3D models of the hand presented in the Cortona Viewer (Parallel Graphics) were integrated in the LabVIEW's front graphic panel though ActiveX. Each proximal joint of the fingers had a property node that can be adjusted in the program's background panel. Similar to the mechanical design, the remaining two joints of the fingers were coupled. Position limitations of the fingers were also considered. On the basis of the software rendering method (Cortona Client), a frame frequency of 100 Hz can be granted. It is sufficient for an EMG control method with decision latency more than 10 ms. A proper constant coefficient DEG (rad) was defined to control the motion speed υ (rad/s) of the finger:

$$\upsilon = \text{DEG} \times f_c \tag{1}$$

where f_c (Hz) is the decision frequency of the motion.

2.4 Algorithms

2.4.1 Double-Decision SVM

For a typical pattern recognition-based EMG control method, it contains two procedures: feature extraction and pattern classification (an overview can be found in [23]). After extracting signal features in real time and feeding them into a beforehand classifier trained offline, the algorithm can recognize the ongoing motion pattern. In this paper, because the EMG electrodes output DC-type signals, no extra feature extraction method was used. Instead, the multichannel EMG signals were directly sampled as time-domain (TD) features. To collect proper samples for training the classifier, a proper threshold was applied on the amplitude of the EMG signals to extract the useful signals from raw signals. When conducting online recognition, we adopted two decisions: one for the detection of the motion onset (onset decision) and the other for the recognition of the motion type (pattern decision). This method collected the transient EMG signals and steady-state EMG signals together for training a classifier that can better recognize the motion with high accuracy and small latency [24].

For the classifier, there are many alternatives, such as linear discrimination analysis (LDA) [9, 25], artificial neural network (ANN) [26], Gaussian mixture model (GMM) [27], hidden Markov model (HMM) [28], and so on. Among them, support vector machine (SVM) has a sturdy theory background from statistical learning and can achieve a superior generalization ability based on insufficient number of learning samples. Our previous study showed that the classifier has a superior ability in recognizing multiple (at least 18 types) hand motions [15]. Other meaningful investigations [19, 21, 29, 30] also verified the classifier's effectiveness on EMG pattern classification, especially when integrating with TD EMG features, such as root-mean-square (RMS) or maximum absolute value (MAV). Also, since we used the Otto Bock EMG electrode, which produces DC-type EMG potentials that are similar to the signal's TD feature, we finally decided to adopt SVM to achieve a TD feature-SVM configuration. For clarity, we hereafter name the method consisting of the double decisions (onset decision and pattern decision) and support vector machine as the DD-SVM.

In specific implementation, a standard SVM with RBF kernel [31] and one-against-one scheme for multiclass problem [32] was adopted. For determination of the parameters (penalty parameter C and kernel parameter γ) of the classifier, the grid search method was adopted, in which a fourfold cross-validation was performed on all training samples (typical value, $C = 64$, $\gamma = 0.01$).

Note that the classifier should be trained to carry out further predictions. At first, a proper number (200∼400) of EMG samples belonging to each motion were collected. Then, a software package named LIBSVM [33, 34] was utilized to train the classifier both in LabVIEW (version in 8.0) and Matlab (version in R2012a) environments. In the embedded EMG controller, the algorithm was implemented using standard C language.

On the side of hand control, once a motion was recognized, the motion-related fingers of the virtual hand will move DEG degrees (1° or 2°) to a predefined position. Otherwise, the hand will move to its predetermined neutral position. This control scheme was also adopted for controlling the prosthetic hand, with the EMG controller generating top-level motion command (motion class) and the hand's motion controller realizing low-level motion control scheme (PID control) .

2.4.2 Double-Channel Template Matching

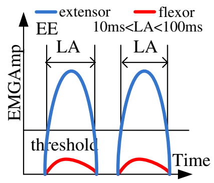
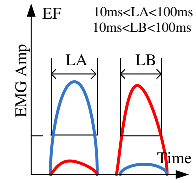
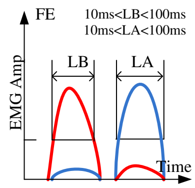
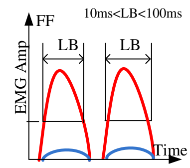
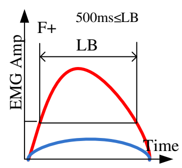
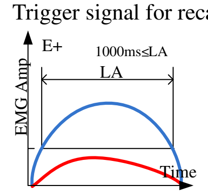
In addition to the DD-SVM, another digital EMG encoding method (DCTM) was proposed for the amputees having limited EMG control sources. This method was implemented both in the computer-based and the embedded prosthesis system. It needed only two electrodes separately placed on a pair of agonist/antagonist muscles. By denoting the extensor activity as "E" and denoting the flexor activity as "F," a sequential two-bit code can generate, as shown in Table 2. It had four templates, or patterns, as "EE," "EF," "FE," and "FF." We matched these templates to four general hand motions as indexing motion (IM), lateral pinching (LP), power grasping (PG), and tripod grasping (TP), which covered many daily activities of the hand. The long durations of flexor activity and extensor activity, denoted as "F+" and "E+," were used for enabling and disabling the pattern, respectively. Once a pattern was enabled, the extension (or flexion) motion of related fingers can be controlled proportionally via the activities of the extensor (or the flexor). It was similar to the on/off control scheme of a traditional 1-DOF prosthetic hand. This control mode kept effective unless a disabling signal E+ was activated. For motion transition, a trigger signal (E+) for recalling the state of pattern selection was firstly actuated; then, following the pattern selection signal (EE, EF, FE, or FF), a trigger signal for activating the selected pattern (F+) was required. This control method provided a supplemental method for the DD-SVM method. The patient should be trained well for understanding the algorithm and being skillful to generate the control signals. In the experiments, this procedure would last 2∼3 h.

2.5 Experimental Protocol

2.5.1 Virtual Hand Control

In this experiment, the subjects were requested to control the virtual hand at first without wearing the prosthesis. The subjects sat suitably beside a desk with his/her arm lying on the desk. Their forearms were degreased using 95 % medical alcohol and then cleaned with warm water. Then, we attached the EMG electrodes on the surface of the stump by using pieces of medical adhesive tapes. The number of the electrodes was determined based on the level of the muscle

Table 2 The double-channel template matching (DCTM) method

Pattern	Indexing motion (EE)	Tripod pinching (EF)
Signal		
Function	Index direction, operate a keyboard, click a button, etc	Pinch a pill, cap, nut, earphone, etc
Pattern	Lateral pinching (FE)	Power grasping (FF)
Signal		
Function	Grasp a handle, lift a case, nip a key, credit card, etc	Grasp a bottle, cup, ball, etc
Pattern	Trigger signal for activating the selected pattern (F+)	Trigger signal for recalling the pattern selection (E+)
Signal		
Function	After this signal, the motion of the hand, according to an activated pattern, is controlled by the muscle extension and flexion activities	After this signal, the hand is on a standby state that switched from of the pattern selection signals (EE, EF, FE, FF) to another.

The blue curve and red curve show the change of the EMG amplitude of the extensor and flexor, respectively. "LA" is the duration of the extensor activity beyond the threshold. "LB" is the duration of the flexor activity beyond the threshold. The length of LA and LB is different in "F+" pattern and "E+" patterns

activities, which are tested by an experienced expert. Initially, the electrodes were evenly placed around the stump. Then, after fine adjustment, they were relocated on the most active muscles nearby. At most, eight electrodes are used. For bilateral amputees, they were requested to do their best to image the hand motion along with the muscle contraction. Meanwhile, for the unilateral amputees, intended motion should be performed on both sides of the body at the same time.

The subjects were instructed to move his/her fingers according to a given motion. The motion types included hand close (HC), hand open (HO), thumb extension (TE), thumb flexion (TF), index finger extension (IE), index finger flexion (IF), middle finger extension (ME), middle finger flexion (MF), ring finger extension (RE), ring finger flexion (RF), little finger extension (LE), little finger flexion (LF), extension of the digits III–V (R3E), flexion of the digits III–V (R3F), extension of the digits II–V (R4E), and flexion of the digits II–V (R4F). For the duration of each motion, a total of 400 EMG samples were collected. Sometimes, it needed the subject to repeat the motion several times. The threshold used for triggering the collection was determined based on the quality of the EMG signal. Typically, a threshold of 0.5 V for each channel was applicable, with response latency less than 100 ms for the motion onset detection [24]. This data collection procedure would cost several minutes.

The acquired data was split into two groups: one for training the classifier and the other for validating the classification accuracy, which was defined as the percentage of the correctly classified samples on all motions. An online virtual hand control experiment was conducted, while proper classification accuracy was obtained. This online validation method was executed on three subjects (PQT, KXD, and ZYQ), for those who had been well trained and had plenty experience on EMG control.

All subjects with exceptions of PQT and KXD evaluated the DVTM method. The subjects were asked to attempt a functional signal (EE, EF, FE, or FF) several times as fast as possible. The classification accuracy was defined as the number of the correctly activated patterns divided by the number of the total test trials in percentage.

2.5.2 Prosthetic Hand Control

After virtual hand experiments, the suitable EMG control method (DD-SVM and DCTM), the number of the motions, and the number of the electrodes were found and customized for each subject. We marked the position of the electrodes and transferred the subject to a local prosthesis center, where the shell of the socket was fabricated. The manufacture procedure of the sockets was similar to those of a traditional EMG-controlled prosthetic hand, with special consideration of the placement of the electrodes, battery, and the EMG controller.

While using the multi-DOF hands, all subjects conducted several daily tasks to further validate the prosthetic hand. Besides the motion control, operational grasping control was also considered. A collective box containing a set of daily life objects was provided, as shown in Fig. 4a. The objects were of different sizes, shapes, and textures, including a cylindrical cup, a spherical ping-pong ball, a bottle of water, a slender toothbrush, a key, a credit card, a cell phone, and so on. The subjects were requested to grasp and move the objects one by one, by using different hand control strategies, from one box to another (Fig. 4b). A proper distance between the two boxes was provided for measuring the grasp stability of the objects. Once the object was dropped on the way, it should be replaced in the first box and transported over again. The completing time of all objects, as well as the drop times, was recorded to examine the fast response and grasp stability of the new prosthetic hand. For convenient comparison, a normalized statistical index termed as drop probability was used to quantify the grasp stability, which was defined as the drop times divided by the total transporting times in percentage.

The second part of the hand control experiment was to test the fine operation ability of the hand, in which the subjects were required to control their hands to perform more complex tasks, such as mouse dragging/clicking, tying, door-handle operation, lighter operation, and so on. For the tasks the subjects can achieve, the accomplishment time was recorded and compared with the traditional prosthetic hand. On the other hand, for the tasks the subjects cannot achieve, an improved design scheme of the hand would be given.

3 Results

3.1 Virtual Hand Control

The subjects had different feelings and control abilities over their phantom fingers. For example, the subject PQT felt the existence of the thumb, the ring, and the little finger, while the subject KXD only perceived the existence of the thumb finger and little finger. It was a general phenomenon across all tested patients. This diversity may originate from the different anatomic structures and atrophy levels of the residual neural-muscular system. For endowing each subject with suitable EMG method based on their

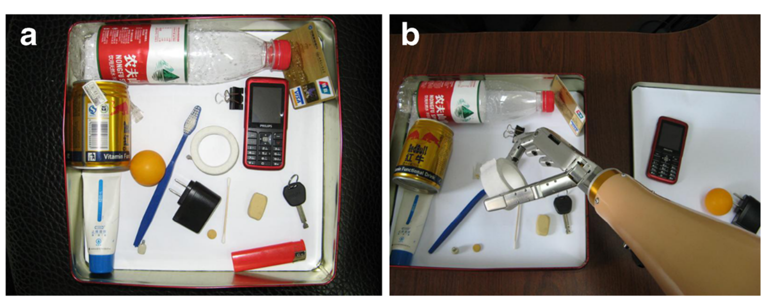


Fig. 4 The grasp-release experiments: **a** a collection of daily life objects and **b** the prosthetic hand grasps and relocates the objects from one box to another

control abilities, various EMG configurations were tested. By using the EMG samples collected in the experiment, the classification accuracy of the DD-SVM method and the precision of the DCTM were estimated, as shown in Table 3.

These preliminary results showed that the muscle activities on the stumps remained relatively high for the subjects who had plenty of EMG-controlled experience, such as the PQT and KXD. Some subjects (PQT, KXD, and ZYQ) claimed that they had intensive control feelings about several finger motions, such as the thumb flexion/extension and hand close/open. On that condition, if a number of electrodes (four to six) were used, a variety of finger motions (six to nine classes, multimode DD-SVM method) could be classified at a high precision (nearly

Table 3 Accuracy of the DD-SVM and DCTM methods

No of electrodes	Num. of patterns	Types of motion	Classification accuracy		
Subject PQT					
8	9	HO, HC, TE, TF, IE, IF, ME, MF, R	84.6 %		
8	9	HO, HC, TE, TF, RE, RF, LE, LF, R	93.5 %		
6	*9*	*HO HC TE TF RE RF LE LFR*	*92.5 %*		
6	6	HO, HC, TF, IF, MF, R	89.4 %		
6	5	HC, TF, IF, MF, R	95.5 %		
4	7	HO, HC, TE, TF, R4E, R4F, R	92.6 %		
4	5	HC, TF, IF, MF, R	93.5 %		
Subject KXD					
8	7	HO, HC, TE, TF, R4E, R4F, R	82.5 %		
8	5	HO, HC, TF, R4F, R	93.5 %		
6	7	HO, HC, TE, TF, R4E, R4F, R	80.2 %		
6	*5*	*HO HC TF R4F R*	*92.3 %*		
4	7	HO, HC, TE, TF, R4E, R4F, R	74.2 %		
4	5	HO, HC, TF, R4F, R	82.5 %		
Subject ZYQ					
6	9	HO, HC, TE, TF, IE, IF, ME, MF, R	73.2 %		
6	7	HO, HC, TE, TF, R4E, R4F, R	76.3 %		
6	*6*	*HO HC TF IF MF R*	81.3 %		
4	7	HO, HC, TE, TF, R4E, R4F, R	63.2 %		
4	5	HO, HC, TF, R4F, R	77.5 %		
2	4	IM, LP, PG, TP (DCTM)	95 %		
Subject WXM					
4	7	HO, HC, TE, TF, R4E, R4F, R	55.2 %		
4	5	HO, HC, TF, R4F, R	74.5 %		
2	*4*	*IM LP PG TP (DCTM)*	*90 %*		
Subjects of LB, WTF, CXY, ZQS, SCC, ZXZ					
4	7	HO, HC, TE, TF, R4E, R4F, R;	LB: 48.2 %	WTF: 50.3 %	CXY: 60.7 %
			ZQS: 54.3 %	SCC: 44.3 %	ZXZ: 54.3 %
4	5	HO, HC, TF, R4F, R;	LB: 51.3 %	WTF: 62.3 %	CXY: 70.4 %
			ZQS: 64.2 %	SCC: 50.2 %	ZXZ: 62.2 %
2	4	*IM LP PG TP*; (*DCTM*)	*LB:80 %*	*WTF:85 %*	*CXY:95 %*
			ZQS:95 %	*SCC:90 %*	*ZXZ:85 %*

The italicized rows are the final selection of the EMG configuration for the subject

90 %). The subjects could control the finger (or fingers) as they will, or could, drive their hands according to a given motion as fast as they can (no obvious control lag was found), which showed great control intuitiveness. For example, for the subject PQT, in total of nine motions (HO, HC, TE, TF, RE, RF, LE, LF, R) can be well accomplished at a classification accuracy of 92.5 %, using six electrodes. For subjects KXD and ZYQ, a relatively low-grade (but still usable) EMG configuration could be found, such as six electrodes and seven patterns for KXD (HO, HC, TE, TF, R4E, R4F, R, 80.2 %) and six electrodes and six patterns for ZYQ (HO, HC, TF, IF, MF, R, 81.2 %).

There were also several subjects who claimed that they could not perceive their lost hands anymore (in other words, they had totally lost the feeling of their hand). For these subjects, the pattern classification accuracy was relatively low and unstable (70∼80 %). This low accuracy may be caused by the similar samples within the motions which were unconsciously introduced by the subject. It is not clear if the unavailable feelings can be restored by rehabilitation training or some other surgical operations. In practice, according to the importance of the fingers, some unimportant finger motions were mapped into the other ones which are more significant. For example, the motion of the ring finger was mapped into the one of index finger, and the motion of the little finger was mapped into one of coupled middle-ring-little fingers. Since most daily life activities can be accomplished by the thumb, index, and middle fingers, this finger reconfiguration may show a higher operation ability of the hand.

After receiving the classification accuracy of the motions, the online control experiment was performed to fully validate the control method. It was realized by using the virtual hand platform referred above. The subjects were informed to pay attention to the virtual hand's motion and were allowed to adjust his/her EMG outputs according to the intended motion. It was found that with the help of the virtual hand feedback, the subject can somehow correct his/her EMG signals. The longer time the subjects spent on the control, the more effective was the interaction. After several training sessions, wrong motions tended to be reduced, and the classification accuracy was improved. Thus, for those subjects (like ZYQ) who had relatively active residual stumps, the virtual hand system provided an effective way for training them to recall their control abilities over multi-DOF prosthetic hand.

The online control experiment also showed that a large amount of misclassifications appeared in the transition and beginning stages of some particular hand motions, such as the flexion of the four digits II∼V (R4F) or the extension of the rest three digits III∼V (R3E). For achieving these motions, generally, more than two fingers (multiple muscle co-contractions) were involved. It is common that a particular finger will move ahead of the others, resulting in a number of pseudo-samples (crossover samples) being collected within a specified movement window and thus affecting the classification. On this situation, a large threshold (0.5∼1 V) was preferred to improve the purity of the training samples, introducing a relative large detection delay (less than 300 ms).

It was also found that, for those subjects who had long-term amputation and little rehabilitation training experience, the classification accuracy was very low even using more electrodes (40∼70 %). This may be due to the fact that the subjects had rare feeling about their fingers. As a supplement, the DCTM method applied to these people, with the impedance control method [35] integrated in the main hand control system, showed an effective control performance. After getting familiar with the DCTM method, the subjects can give correct control signals as requested and control the hand grasp/release according to a given motion pattern. The overall accuracy after training was around 90 % for all subjects. The activation signal consumed comparably longer time (300∼500 ms) than the DD-SVM, with reducing some control effectiveness of the hand. However, it should be noticed that once after a pattern was activated, the action of the hand was actually controlled by the real-time EMG signal.

3.2 Prosthetic Hand Control

After determining the individual EMG configuration, each subject was equipped with the multi-DOF prosthetic hand, as shown in Fig. 5. High anthropomorphic appearance, i.e. the length, size, shape and weight, without discomfort and allergic symptoms, were found in the usage.

At last, the DD-SVM method was chosen for the subjects PQT, KXD, and ZYQ; the DCTM method was selected for the rest of the subjects. The time for completing the object-grasping experiments with drop possibility was recorded, as shown in Table 4. For

Fig. 5 Hands equipped on the amputee subjects

the subject with available commercial prosthetic hand, comparative results were also given.

The result showed that, by using the multi-DOF prosthetic hand with the new EMG control methods, the grasping rapidness and stability was significantly improved. Under similar experimental condition, the new prosthetic hand system can grasp objects quickly, by saving time nearly 30 %. It was also found that the dropping possibility, which was defined as the number of dropping times divided by the total transporting times, was considerably reduced. Low drop possibility of multi-DOF hand may attribute to the independency of the fingers and their unique enveloping features. Nevertheless, since the subjects were requested to move the objects as fast as possible, some objects were early released before reaching to the second box. The single-DOF hand with fixed-shape fingers acted like a mechanical gripper; thus, it cannot easily grasp the tiny, thin, or complex-shaped objects. Some subjects (nos. 4, 6∼10) received high drop possibility because they were novices to the EMG-driven multi-DOF prosthetic hand. Apparently, they still need long-term training.

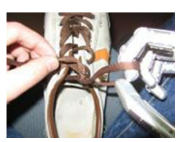
For examining the hand function on daily life behaviors, several operational tasks were performed by the subjects, with main results shown in Table 5. Comparative results obtained by the traditional 1-DOF hand are also presented in the table.

Table 4 Time and drop possibility for the object grasp/release experiment

Subject	Time (s)		Drop possibility (%)	
	Multi-DOF hand	SingleDOF hand	Multi-DOF hand	SingleDOF hand
1 PQT	105	123	0	6.3
2 KXD	90	118	7.7	15.4
3 ZYQ	75	102	0	8.3
4 LB	91	135	13.3	20
5 WXM	89	115	7.1	14.3
6 WTF	136	N/A	11.8	N/A
7 CXY	83	N/A	21.4	N/A
8 ZQS	84	N/A	12.5	N/A
9 SCC	76	N/A	15.4	N/A
10 ZXZ	115	N/A	18.2	N/A

Note that the number and variety of the objects may be different for each subject

Table 5 Results for complicated operational tasks

Tasks	Description	Multi-DOF hand	1-DOF hand	Notes
1. Keyboard	Typing the 26 letters arranged in alphabetical order as fast as possible. Retype the mistaken one.	 38.4s	 41.4s	The new hand can individually operate the index finger thus a precise position can be achieved. The amputee even attempted to press the buttons using different fingers of the hand.
2. Mouse	Clicking and dragging 10 files into a given folder on the desktop	 28.5s	 N/A	The new hand can drag and click the mouse simultaneously; while, the old hand can only drag the electrical mouse.
3. Handle	Grasping the door handle with proper gesture, and rotating it to open the door.	 5.6s	 4.2s	The new hand can accomplish a better enveloping quality. While, because this operation is heavily wrist dependent, the 2-DOF hand wins due to its power.
4. Gearlever	Operating the gearlever of the car, enveloping the handle and pressing the button.	 3.2s	N/A	The new hand can hold the handle well and drag it with pressing the button; while, the old hand can hardly grasp the gearlever.
5. Lighter	Holding the lighter and pressing the button.	 N/A	N/A	The thumb finger cannot arrive at the button. Abduction motion is needed.
6. Shoe lace	Cooperating with the healthy hand for knotting a knot.	 34.5s	N/A	Dexterous motion of the wrist is needed, as well as the precise finger cooperation.

Note that it was just a preliminary study and concentrated on validating the hands functionality; best results of the subject were presented instead of the general statistics

It can be seen from Table 5 that the multi-DOF hand had relatively high operational abilities as the fingers were being individually controlled. It had a superior enveloping ability over objects with comparison to those of 1-DOF hands. Special tasks involved multiple finger collaborations, such as pinching, crushing, pressing, knocking, and holding, and can be easily accomplished. Besides, a large variety of hand gestures can also be realized for nonverbal communication.

4 Discussions

The experimental results suggest that when compared with traditional prosthetic hands, our five-fingered multi-DOF prosthetic hand possesses superior features with regard to its grasping ability, flexibility, and dexterity. However, there are also some limitations of the hand. First, the hand had no skin. The rigid contact between the hand and the object largely degraded the grasping stability. The little sliding friction of the contact interface between the fingertip and the slippery object made the grasp hard to accomplish. The subjects sometimes had to try many times to successfully pick up the object. Second, the hand had no sense of touch. It was difficult to detect whether the hand was contacting with the target and how much force was applied on the object. In our future design, these problems could be solved by covering an advanced artificial skin on the hand. The skin has a human-like color, texture, and flexibility. As well, it can sense the pressure force applied on its surface [36].

A limitation was also found in the thumb design: the finger had no abduction/adduction motion. Instead, this motion was combined into the extension/flexion motion of the trapeziometacarpal joint (TM), making the thumb grasp along a cone surface as a natural one [16]. As found in the experiments, this fixed motion trajectory cannot well accomplish some hand operations, such as lateral pinch and hook grasp. A passive degree of motion mounted on the base joint of the thumb, as designed in i-LIMB hand and Bebionic hand, can largely promote the grasp functionality. Some patients also claimed that the thumb finger was relatively too long when comparing with a natural hand. This vision illusion can be relieved by covering the hand with an anthropomorphic glove.

In the experiment, the feedback from the hand to the user was highly limited. To accomplish a complex operation, more information such as the contact point and applied force should be provided to the user. This information could be transferred by means of mechanical vibration or electric stimulus on proper sites of the user. Although the transmission rate is still too low when comparing with human afferent nerves, these surface feedback channels indeed play an important role in the control scheme, especially for the user with bad sight condition (a blind person) or in a dark environment.

In the experiment, the classification accuracy was found to be unstable during long-term usage (say, 2∼3 h). There were many factors, such as the changes of temperature and humidity, sweating, skin impedance, the electrochemistry interface between the electrodes and the surface, and the fact that the positions of the electrodes on the muscle might be altered, modifying the electrodes' signal quality. Even the EMG signal, the control source of the prosthesis, was a nonstationary signal that changes from time to time. Influence of these factors became aggravated when more electrodes were involved. Thus, an online, self-adaptive procedure is a prerequisite for a successful application of the multimode DD-SVM control method. Meanwhile, accuracy degradation was not found in DCTM method. It was not sensitive to slight signal changes, which made it relatively more robust than DD-SVM. This result shows consistency to the study of [37], in which the authors suggest that a multigrasp EMG control method needs only a single calibration over a 1-month trial period.

5 Conclusions

A primary work on the clinical evaluation of a multi-DOF prosthetic hand is presented. Ten amputees equipped with the hand prototypes are tested. Two distinct EMG control schemes, on the basis of pattern recognition and digital encoding, respectively, are examined. These two methods, termed as double-decision SVM classification (DD-SVM) and double-channel template matching (DCTM), are chosen according to EMG control abilities of the subjects. Experiments on virtual hand control and real prosthetic hand control show that the new hand system, together with the EMG control methods, has superior grasping ability and motion dexterousness than traditional gripper-type prosthetic hands. However, only a small proportion of the patients who have relatively more active residual muscles and full control experiences is able to deploy the DD-SVM method. At the same time, the DCTM method especially designed for patients with severe amputations and limited EMG signals is still an indispensable alternative for controlling the multi-DOF prosthetic hand. Future work will focus on ameliorating the design of the thumb, developing a tactile glove for the hand, and introducing biological feedbacks, such as a mechanical vibration device or electrical stimulation electrodes, for providing the real-time sensation (position and force) of the hand to the users. Finally, stable EMG control methods for long-term usage of the prosthetic hand should be also considered.

Acknowledgments This work is in part supported by the National Program on Key Basic Research Project (973 Program, Nos. 2011CB013306 and 2011CB013305), the National Natural Science Foundation of China (No. 51205080), the China Postdoctoral Science Foundation Funded Project (No. 2013M540276), and the Self-planned Task of State Key Laboratory of Robotics and System (HIT, No. SKLRS201201A03).

References

1. Atkins, D.J., Heard, D.C.Y., Donovan, W.H.: Epidemiologic overview of individuals with upper-limb loss and their reported research priorities. J. Prosthet. Orthot **8**(1), 2–11 (1996)
2. Zollo, L., Roccella, S., Guglielmelli, E., Carrozza, M.C., Dario, P.: Biomechatronic design and control of an anthropomorphic artificial hand for prosthetic and robotic applications. IEEE-ASME T Mech. **12**(4), 418–429 (2007)
3. Cipriani, C., Controzzi, M., Carrozza, M.C.: Objectives, criteria and methods for the design of the SmartHand transradial prosthesis. Robotica. **28**(6), 919–927 (2010)
4. Dalley, S.A., Wiste, T.E., Withrow, T.J., Goldfarb, M.: Design of a multifunctional anthropomorphic prosthetic hand with extrinsic actuation. IEEE-ASME T Mech. **14**(6), 699–706 (2009)
5. Fite, K.B., Withrow, T.J., Shen, X., Keith, W.W., Jason, E.M., Michael, G.: A gas-actuated anthropomorphic prosthesis for transhumeral amputees. IEEE T. Robot. **24**(1), 159–169 (2008)
6. Palli, G., Borghesan, G., Melchiorri, C.: Modeling, identification, and control of tendon-based actuation systems. IEEE T. Robot. **28**(2), 277–290 (2012)
7. Arieta, H., Katoh, R., Yokoi, H., Wenwei, Y.: Development of a multi-DOF electromyography prosthetic system using the adaptive joint mechanism. Appl. Bionics Biomech. **3**(2), 101–110 (2006)
8. Gaiser, I., Pylatiuk, C., Schulz, S., Kargov, A., Oberle, R., Werner, T.: The Fluidhand III: a multifunctional prosthetic hand. J. Prosthet. Orthot. **21**(2), 91–96 (2009)
9. Kuiken, T.A., Li, G., Lock, B.A., Lipschutz, R.D., Miller, L.A., Stubblefield, K.A., Englehart, K.: Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms. JAMA-J Am. Med. Assoc. **301**(6), 619–628 (2009)
10. Christine, C.: Prosthetic hands from touch bionics. Ind. Robot: An Int. J. **35**(4), 290–293 (2008)
11. Medynski, C., Rattray, B.: Bebionic prosthetic design. In: Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium. Fredericton, Canada, August 14–19 (2011)
12. Belter, J.T., Dollar, A.M.: Performance characteristics of anthropomorphic prosthetic hands. In: Paper presented at the 2011 IEEE International Conference on Rehabilitation Robotics, Zurich (2011)
13. Zhao, J., Xie, Z., Jiang, L., Cai, H., Liu, H., Hirzinger, G.: Levenberg-Marquardt based neural network control for a five-fingered prosthetic hand. In: Proceedings of IEEE International Conference Robotics, Barcelona, pp. 4482-4487 (2005)
14. Hai, H., Yong-Jie, P., Li, J., Shao-Wei, F., Xin-Qing, W., Hong, L.: Underactuated hand dynamic modeling, its real-time simulation, and control. Int. J. Hum. Robot. **7**(4), 609–634 (2010)
15. Yang, D., Zhao, J., Gu, Y., Wang, X., Li, N., Jiang, L., Liu, H., Huang, H., Zhao, D.: An anthropomorphic robot hand developed based on underactuated mechanism and controlled by EMG signals. J Bionic. Eng. **6**(3), 255–263 (2009)
16. Wang, X., Liu, Y., Jiang, L., Yang, D., Li, N., Liu, H., Huang, H.: Design and control of a coupling mechanism-based prosthetic hand. J Shanghai Jiaotong Univ. (Sci.) **15**(5), 571–577 (2010)
17. Li, N., Jiang, L., Yang, D., Wang, X., Fan, S., Liu, H.: Development of an anthropomorphic prosthetic hand for man-machine interaction. Lect. Notes Comput. Sci. **6424 LNAI(PART I)**, 38–46 (2010)
18. Yang, D., Zhao, J., Gu, Y., Jiang, L., Liu, H.: EMG pattern recognition and grasping force estimation: improvement to the myocontrol of multi-DOF prosthetic hands. In: Proceedings of IEEE/RSJ International Conference Intelligent and Robotic Systems, St. Louis, Oct. 11–15, pp. 516–521 (2009)
19. Bitzer, S., Van der Smagt, P.: Learning EMG control of a robotic hand: towards active prostheses. In: Proceedings IEEE Internation Conference on Robotics and Automation, Orlando, pp. 2819–2823 (2006)
20. Otto Bock MYOBOCK 13E200=50 electrodes, http://www.ottobock.com/cps/rde/xchg/ob_us_en/hs.xsl/16573.html?id=16607
21. Castellini, C., Van der Smagt, P.: Surface EMG in advanced hand prosthetics. Biol. Cybern. **100**(1), 35–47 (2009)
22. Sveistrup, H.: Motor rehabilitation using virtual reality. J. NeuroEng. Rehabil. **1**(1), 1–10 (2004)
23. Oskoei, M.A., Hu, H.: Myoelectric control systems—a survey. Biomed. Signal Process Control **2**(4), 275–294 (2007)
24. Yang, D., Zhao, J., Jiang, L., Liu H.: Dynamic hand motion recognition based on transient and steady-state EMG signals. Int. J. Hum. Robot. **9**(1), 1250007.1-1250007.14 (2012)
25. Englehart, K., Hudgins, B., Parker, P.A.: A wavelet-based continuous classification scheme for multifunction myoelectric control. IEEE Trans. Biomed. Eng. **48**(3), 302–310 (2001)

26. Au, A.T.C., Kirsch, R.F.: EMG-based prediction of shoulder and elbow kinematics in able-bodied and spinal cord injured individuals. IEEE Trans. Rehabil. Eng. **8**(4), 471–480 (2000)
27. Huang, Y., Englehart, K., Hudgins, B., et al.: A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses. IEEE Trans. Biomed. Eng. **52**, 1801-1811 (2005)
28. Chan, A.D.C., Englehart, K.: Continuous myoelectric control for powered prostheses using hidden Markov models. IEEE Trans. Biomed. Eng. **52**(1), 121–124 (2005)
29. Shenoy, P., Miller, K.J., Crawford, B., et al.: Online electromyographic control of a robotic prosthesis. IEEE Trans. Biomed. Eng. **55**(3), 1128–1135 (2008)
30. Oskoei, M.A., Hu, H.: Support vector machine-based classification scheme for myoelectric control applied to upper limb. IEEE Trans. Biomed. Eng. **55**(8), 1956–1965 (2008)
31. Cortes, C., Vapnik, V.: Support-vector network. Mach. Learn. **20**(3), 273–297 (1995)
32. Hsu, W., Lin, C.J.: A comparison of methods for multi-class support vector machines. IEEE T Neural Netw. **13**(2), 415–425 (2002)
33. Chang, C.-C., Lin, C.-J.: LIBSVM: a library for support vector machines. ACM Trans Intell. Sys. Tech. **2**(3), 27:1-27:27 (2011). Software available at http://www.csie.ntu.edu.tw/∼cjlin/libsvm
34. Fan, R.E., Chen, P.H., Lin, C.J.: Working set selection using the second order information for training SVM. J Mach. Learn. Res. **6**(12), 1889–1918 (2005)
35. Zhang, T., Jiang, L., Liu, H.: A novel grasping force control strategy for multi-fingered prosthetic hand. J Cent. South Univ. Tech. **19**(6), 1537–1542 (2012)
36. Zhang, T., Liu, H., Jiang, L., Fan, S.W., Yang, J.: Development of a flexible 3-D tactile sensor system for anthropomorphic artificial hand. IEEE Sens. J. **13**(2), 510–518 (2013)
37. Dalley, S.A., Varol, H.A., Goldfarb, M.A.: Method for the control of multigrasp myoelectric prosthetic hands. IEEE T. Neur. Sys. Reh. **20**(1), 58–67 (2012)