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Preliminary Study on Proportional and Simultaneous Estimation of Hand Posture Using surface EMG Based on Synergy Concept

Shunchong Li, Xingyu Chen, Xinjun Sheng and Xiangyang Zhu

***Abstract*— Most of current myoelectric prostheses are using sequential and on-off control strategy within pattern classification framework, which is of robustness. But it is not a natural neuromuscular control scheme. On the other hand, there are two difficulties to control the prosthesis proportionally and simultaneously. First, human hand is high dimensional with more than 20 degrees-of-freedom (DOFs); Second, extracting such control information from EMG is hard due to signal crosstalk and noises. This paper is aimed at proposing a new method for proportional and simultaneous myoelectric control, taking advantage of synergy concept. The hand motion and corresponding forearm EMG signals were collected simultaneously. Principal component analysis (PCA) is used to reduce hand motion dimension. And support vector regression (SVR) is adopted to build the connection between hand posture and EMG. Offline analysis validated the effectiveness of this method, and preliminary and positive results have been obtained.**

I. INTRODUCTION

Surface EMG signals (sEMG) contain abundant information about motion intention, it is very promising in serving as a new kind of human machine interface and thus benefiting amputees. There have been many researches extracting control information from sEMG signals for prostheses, and most of them take advantage of pattern classification. In this approach, the pattern recognition system is capable to classify sEMG signals into several preset classes, and then turn on or off a function of the prosthetic hand [1].

However, such control strategy is mainly limited in two aspects. First, the outputs of the system are constrained by the preset classes, and only one class can be selected at one point. Second, a function of the prosthesis is simply turned on or off. On the contrary, natural neuromuscular control is proportional and simultaneous [2].

Recently, some researchers have changed the focus to extracting proportional and simultaneous control information from sEMG signals. Jiang et al. proposed a generative model to obtain proportional and simultaneous control information for a 3-DOF wrist prosthesis, and positive results have been achieved [3]–[5]. Some other researchers have also obtained satisfying achievements [6], [7].

The most direct idea for extracting control information for prosthetic hand control is increasing the number of patterns to approximate, but this results in more complex classifiers and reduction of classification accuracy, since human hand is highly dexterous and has more than 20 DOFs.

Fortunately, according to neuroscience researches, human nervous system does not control each joint of hand directly. Instead, it controls only a parameter set with a much smaller dimension [3]. It is similar to the control of a marionette. The number of wires is less than that of puppet's body parts (See Fig.1). Different DOFs are coupled, synergetic and can be dimensional reduced. In [8] a linear method, principal components analysis (PCA), was used to obtain hand postural synergies and the result turned out that the first 2 principal components (PCs) take up to more than 80% of the variance, which imply that control of hand posture involves a small number of variables.

In this paper, a new myoelectric control method for prosthetic hand is proposed which based on synergy concept. It acts as a bridge from sEMG signals to proportional and simultaneous estimation of hand motions. The DOFs of hand motions are dimensional reduced by PCA. And the relationship between hand postural and sEMG is established using support vector regression (SVR).

II. METHOD AND MATERIALS

A. Experimental Protocol

Two subjects were involved in this preliminary experiment. They were fully informed of the details of the experimental procedure and agreed through an informed consent.

In the experiment, subjects were asked to grasp twelve objects with different size and shape. These twelve objects are listed as follow:

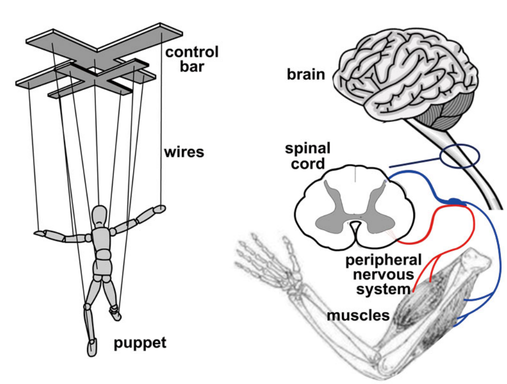

Fig. 1. Synergy concept implies in the control of a marionette. The control wires are less than the parts of puppet's body. The neural system possibly works in a similar fashion, using a few synergies to control the highly dexterous multi-DOF hand.

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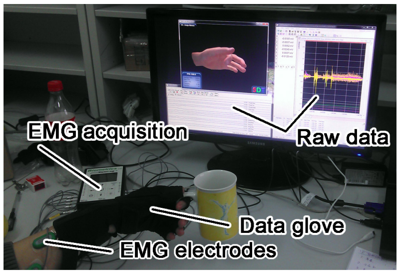
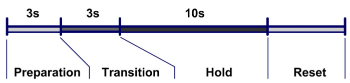
Shunchong Li, Xingyu Chen, Xinjun Sheng and Xiangyang Zhu are with State Key Laboratory of Mechanical System and Vibration, Shanghai Jiao Tong University, 200240, Shanghai, China (Email:evenfourphyfan@hotmail.com)



(a)



(b)

Fig. 2. (a) Experimental setup (b) The experiment comprises four phases: preparation, transition, holding and reset

1.Apple 2.Matchbox 3.Pop can 4.500ml bottle
5.Mouse 6.Tea caddy 7.Box 8.Cellphone
9.Key 10.Pen 11.Cup 12.Spanner

The hand posture and sEMG signals from forearm skin are collected simultaneously. (See Fig.2(a))

The hand posture was recorded with a data glove (Data Glove 14 Ultra, 5DT Ltd.). Fourteen hand joint angles were recorded, including angles of MCP and PIP of four fingers, MCP and IP of the thumb and four angles between adjacent fingers (Thumb/Index, Index/Middle, Middle/Ring, Ring/Little). The sampling rate of hand motion was 55Hz.

Surface EMG signals were collected using a biosignal acquisition device(DataLOG, Biometrics Ltd.). Six channels of signals were involved and the corresponding muscles were:

1.Palmar longus 2.Flexor digitorum superficialis
3.Flexor digitorum profundus
4.Extensor digitorum communis
5.Extensor digiti minimi 6.Extensor pollicis longus

The sampling rate of sEMG was set to 1kHz.

The experiment includes four phases: preparation, transition, holding and reset phase, as shown in Fig.2(b).

1) Preparation: After the command of start, the subject keeps his hand about 10 cm away from the object and waits for the next phase. Recording is started at the beginning of this phase.
2) Transition: After the end of preparation phase, the subject is asked to move his hand to grasp the object. This phase lasts 3 seconds. Note that the subject can often finish grasp task within 1–2 seconds before the end of this phase.
3) Holding: The subject is asked to keep the hand posture after getting the object. Data recoding is stopped at the end of this phase.
4) Reset: After the holding phase, the subject is asked to put down the object and move the hand back. In this phase, the subject can take a break to avoid muscle fatigue.

For each object, the subject repeats three times to grasp in order to ensure subjects' familiar patterns grasping the object.

B. Posture Dimensional Reduction Using PCA

In fact, the angles of joints of human hand do not vary independently. Therefore, PCA is an ideal linear method to find out the patterns in data of such high dimension. It is a useful statistical technique to reduce dimension of high-D data, and is defined in such a way that the first PC has the largest possible variance, and each succeeding PC in turn has the highest variance. More detailed explanation about PCA can be seen in [9].

The mathematical form of PCA based hand posture decomposition is:

$$P = PC \times Q + \bar{P} \tag{1}$$

Here P is a hand posture. PC is a principal component matrix, and Q is a weight vector. $\bar{P}$ is the average posture in the entire data set.

Equation 1 can be expanded as:

$$\begin{aligned} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} = & q_1 \times \begin{bmatrix} pc_{11} \\ pc_{12} \\ \vdots \\ pc_{1n} \end{bmatrix} + q_2 \times \begin{bmatrix} pc_{21} \\ pc_{22} \\ \vdots \\ pc_{2n} \end{bmatrix} + \cdots \\ & + q_m \times \begin{bmatrix} pc_{m1} \\ pc_{m2} \\ \vdots \\ pc_{mn} \end{bmatrix} + \begin{bmatrix} \bar{p}_1 \\ \bar{p}_2 \\ \vdots \\ \bar{p}_n \end{bmatrix} \end{aligned} \tag{2}$$

Here, p_i represents the ith joint angle.

If we use the first 2 PCs to reconstruct hand posture, then

$$P \approx \tilde{P} = q_1 \times PC_1 + q_2 \times PC_2 + \bar{P} \tag{3}$$

Through dimensional reduction using Equation 3, the hand postures in high-D original space can be mapped into a 2-D space of the first two PCs.

C. Extracting Control Information Using SVR

Once the PCs have been found, the estimation of hand posture becomes a problem of estimating the values of the selected PCs. EMG signals contain abundant information about motion, hence building the connection between these PCs and corresponding sEMG signals is desired. The sEMG signals are preprocessed with a 300*ms* wide window, and the slide increment is 100*ms*.

Support vector machine (SVM) is a supervised machine learning model that uses a hypothetical space of linear functions in a high-dimensional feature space, which is used for regression here (so-called SVR) to construct a mapping from sEMG signal to hand postures. As regards to regression, the LIBSVM [10] is used in the matlab, and radial basis function (RBF) is choosen as a kernel in the SVM. Five fold cross validation is adopted for grid search and finding optimal parameters.

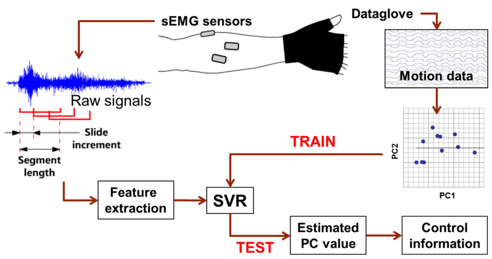


Fig. 3. The support vector regression (SVR) machine is firstly trained with the values of selected principal components and corresponding EMG signals. After training, the SVR can output the values of principal components if given EMG signals and obtain proportional and simultaneous control information.

The process of estimation is divided into two phases: training phase and testing phase.

In training phase, the values of selected principal components and the time domain feature (Mean Absolute Value, Slope Change, Zero Cross) set of corresponding sEMG signals are fed to SVR to get the learning machine trained.

In testing phase, the features of EMG signals are sent to the trained SVR and the output is the estimated value of principal components. To examine the effectiveness, the results given by estimation are compared with the data from data glove. The difference between these two results can be the judgment of the performance. The process flow is shown in Fig.3.

It is noted that since the change of angles of joints is slight during the holding phase, the data of the hand postures is considered constant and averaged during this period.

III. Results

A. Principal Components Analysis

For the two subjects, the contribution of each PC is given in TABLE I. And the amount of information increases monotonically up to at least the 8th PC (See Fig.4). The first 2 PCs make contribution of more than 75% of the variance, which can be seen as a information transmitted rate.

TABLE I

The contribution made by each of the first five PCs

	PC_1	PC_2	PC_3	PC_4	PC_5
Subject.1 (%)	58.9	16.1	7.6	5.6	5.0
Subject.2 (%)	65.2	13.9	10.7	5.1	2.6

The difference between the estimated and the actual values of the weights (q_i in Equation 3) for the first 2 PCs is evaluated by index – R^2, which is defined as follow:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - y_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{y})^2} \tag{4}$$

Here, Y_i is estimated value and y_i is actual value, and i represents different objects that are grasped. The R^2 is between 0 and 1. If the value is close to 1, then the difference is small.

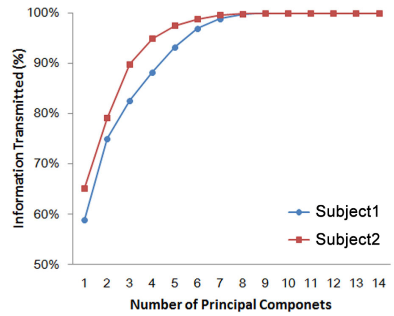


Fig. 4. This figure shows how each additional PC increases the total information transmitted rate.

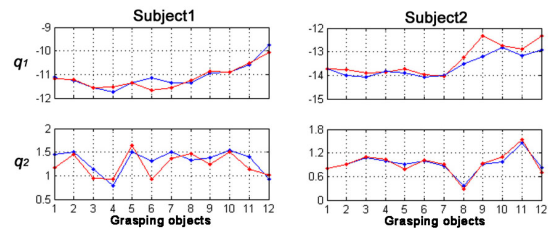


Fig. 5. The estimated and the actual values of the weights (q_i in Equation 3) for the first 2 PCs. This result is obtained by averaging the results of testing data. The red lines are actual values and the blue lines are estimated values. The horizontal axis represents 12 grasping objects, and the vertical axis represents the weights of the PCs.

The result of using the first 2 PCs to reconstruct hand shape is shown in TABLE II. The average of R^2 is 0.63.

B. Hand Posture Estimation Using SVR

In order to train and evaluate the SVR machine, the first half of the recorded sEMG signals are used for training, and the other half are used to test the feasibility of this method. The performance of estimation is shown in the Fig.5, which shows the difference between the estimated values and the actual values.

A typical restoration of the hand posture using EMG signals is given by Fig.6. The restoration uses the first two principal components. The root mean squared residual is 0.07, which is 7% of the range of the scaled angles. The difference between the estimated posture and the actual one is slight.

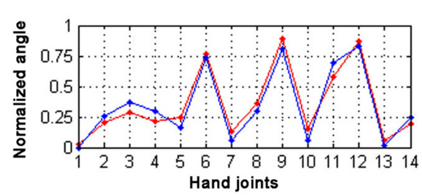


Fig. 6. The horizontal axis represents the fourteen joints and the vertical axis is the angle of each joint (scaled). The red line is actual angles of the joints and the blue line is estimated ones.

TABLE II

THE PERFORMANCE OF HAND POSTURE RECONSTRUCTION USING THE FIRST TWO PCS

Joint	T_{mcp}	T_{ip}	T/I	I_{mcp}	I_{pip}	I/M	M_{mcp}	M_{pip}	M/R	R_{mcp}	R_{pip}	R/L	L_{mcp}	L_{pip}	*Aver.*
Subject.1 R^2	0.47	0.20	0.95	0.83	0.87	0.23	0.85	0.64	0.22	0.91	0.52	0.55	0.82	0.77	0.63
Subject.2 R^2	0.71	0.49	0.52	0.58	0.95	0.68	0.93	0.63	0.22	0.93	0.63	0.51	0.94	0.83	0.68

*T stands for thumb, and I for index finger, etc. T/I, I/M, M/R, R/L stand for the angles between the two fingers.

IV. DISCUSSION

In this preliminary study, a matrix decomposition algorithm–PCA is adopted to reduce **human hand motion** dimension, and a regression method–SVR **instead of traditional pattern classification** to create a mapping from sEMG to hand motion. The results mentioned above demonstrate that proposed approach is feasible and potential.

For Subject.1, the IP joints of the Thumb, Index/Middle and Middle/Ring joint are not well reconstructed. And the same situation happened in the Middle/Ring joint of Subject.2. The different results may relate to different habits of grasping the objects, but in fact these joints do not greatly influence the hand shape of grasping. It can be concluded that it is feasible to use a small number of variables to represent human hand posture.

An interesting phenomenon is when adding more PCs to reconstruct hand posture, the contribution is not the only factor to be considered. Some principal components are crucial to the reconstruction of the angles of some joints. For Subject.1, although the 5th PC only contributes 5% to the variance, we find it is critical in rebuilding the angles of Index/Middle and Middle/Ring. And the 3rd PC greatly improve the performance of reconstruction the angle of IP of the thumb. Hence which principal components should be selected to reconstruct hand posture is a problem needed to be deliberately studied.

Since most of forearm muscles involved in hand motions are located in intermediate or deep layer, it is difficult to use surface electrodes to collect EMG of these muscles without influence of crosstalk and noise. It is a main factor that reduce the estimation accuracy. We consider that two approaches may solve this problem. First and also the direct one is using invasive electrodes. And second is high density multi-channel surface electrode array which may be a much better choice. In fact, obtaining EMG signals of intermediate or deep layer muscles using surface electrodes would be a blind source separation (BSS) problem. If the number of sensors are sufficient and conductive model of EMG signal in human tissue is explicit, this problem can be solved theoretically.

V. CONCLUSION AND FUTURE WORKS

This paper introduces a new method that is able to use sEMG signals to reconstruct the hand posture. Principal component analysis (PCA) is used to reduce dimension of the multi-DOF human hand motion, and support vector regression (SVR) machine is used to establish the connection between sEMG signals and low-D transformed hand posture. Preliminary experiments were taken to examine the feasibility of this method. Positive results have been obtained through data analysis.

Since the estimation of the PC values adopts SVR machine which is able to output a result that is continuous, this method reveals a new way to the proportional and simultaneous estimation of hand postures. What we desire is that the trained system can predict those hand postures which are not contained in the training data set. Although the results in this experiment are not very satisfying, we will improve the performance of hand motion estimator in future works.

Different algorithms will be tried out to pursue the desired results. These works may include blind resource analysis to eliminate the influence of crosstalk and thus trying to find some more obvious relations among muscle contractions, EMG signals and hand motions.

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