sEMG Based Joint Angle Estimation of Lower Limbs Using LS-SVM

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Abstract. In this paper, a new estimation model based on least squares support vector machine (LS-SVM) is proposed to build up the relationship between Surface electromyogram (sEMG) signal and joint angle of the lower limb. The input of the model is 2 channels of preprocessed sEMG signal. The outputs of the model are joint angles of the hip and the knee. sEMG signal is acquired from 7 motion muscles in treadmill exercise. And two channels of them are selected for dynamic angle estimation for their strong correlation with angle data. Angle estimation model is constructed by 2 independent LS-SVM based regression model with radial basis function (RBF). It is trained using part of the sample sets acquired in 10s exercise duration and test by all data. Experimental result shows proposed method has good performance on joint angles estimation based sEMG. Root mean square error (RMSE) of prediction knee and hip joint angles is 3.02° and 2.09° respectively. It provide new human-machine interface for active rehabilitation training of SCI, stroke or neurological injury patients.

Keywords: sEMG, LS-SVM, Angle estimation, Rehabilitation.

1 Introduction

SEMG is the weak electrical potential recorded by electrodes from the skin. It reflects muscle activity and function accurately and objectively. sEMG has been widely used in clinical rehabilitation and sport science fields for neuromuscular disorders diagnosis and fatigue analysis. Especially in clinical rehabilitation fields, for its strong relationship with human autonomous motions, sEMG is taken as a non-invasive control means for human-machine interface devices such as prosthesis, rehabilitation robot, power assist exoskeleton. Its application greatly enhances the convenience and efficiency of these rehabilitation systems and helps reconstruct neuromuscular function for people affected by stroke and spinal cord injury (SCI).

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Clinical rehabilitation system is divided into three types: mechanical assistant devices, power feedback system and biofeedback system. Traditional mechanical rehabilitation assistance devices provide passive exercises for patients without feedback such as continuous passive motion machine. In some newly developed systems, human motion and force information are introduced as control signal. They are called power feedback system such as Lokomat [1], MIT-manus [2], MIME [3]. The last one take bio-information especially sEMG as control signal in order to excite patients' autonomous motions and promote nerve repair and regeneration. For the better effects of reconstruct motion function for patients, it arouses many researchers' interests.

In the biofeedback system, the key issue that researchers focus on is how to capture human active motion intention from sEMG signals. At present, human motion researches based on sEMG signal are divided into qualitative and quantitative analysis. The typical application of the former is motion recognition [4] [5]. Many researchers have been engaged in higher accuracy and fewer channels for qualitative motion recognition based on sEMG signal and gained remarkable achievements.

With further application research of human-machine interface (HMI) based on sEMG signal, quantitative sEMG analysis is expected to supply continuous real-time control. Javad Hashemi et al. proposed a calibration method for the amplitude of the sEMG signals collected from biceps brachii at different joint angles [6]. In Jimson's study, the parameters of muscle activation model considered electromechanical delay was taken as the input of neural network to predict finger joint angles. Results showed correlation as high as 0.92 between the actual and predicted metacarpophalangeal joint angles for periodic finger flexion movements and 0.85 for non-periodic movements [7]. In order to suppress pathological tremor effectively by exoskeleton system, Shengxin Wang et al. extracted the linear profile-curve of sEMG, and explored the relationship between sEMG signals and angle with the radial basis function neural network [8]. In many other researches, various feature extraction and classification methods are applied to quantitative analysis for sEMG signal. The essence of these researches is to capture human active motion intention from sEMG signal, and then supply continuous and real-time motion control information for assist devices.

With successful application of quantitative analysis for sEMG, there are still some disadvantages. Estimation accuracy of continuous variable is the key problem for motion control of assistant devices, and it is very important for natural motion of subjects. In this research, sEMG signals acquired from normal lower limb are used to estimate continuously hip and knee joint angle, which will be taken as control instruction for rehabilitation robot for the affected lower limb. Because in clinic, almost all persons affected by stroke or SCI have clinical manifestation of hemiplegia in varying degrees. That means unilateral limb injury for the patient. Therefore, rehabilitation training of the affected limb controlled by the normal limb is feasible and effective. It has been verified by many related researches. Continuous estimation of lower limb joint angle with high accuracy is the core of this rehabilitation strategy and also what we interested in. It contains two main key technologies, that is feature extraction meof sEMG signals for data compression and estimation algorithm for joint angles. In the following content, sEMG data acquisition and preprocess, estimation model design and experimental results will be explained in detail.

2 Methods

2.1 Data Acquisition

Treadmill exercise is a common training movement for SCI and stroke patients in clinical rehabilitation. Considering the character of unilateral injury, data were acquired from a normal volunteer in a gymnasium. As shown in Fig 1, during the treadmill exercise, sEMG signals of 7 lower limb muscles including vastus rectus muscle (VR), vastus lateralis muscle (VL), semitendinosus muscle (SM), biceps muscle of thigh (BM), tibialis anterior muscle (TA), extensor pollicis longus (EP), and gastrocnemius muscle (GM) were sampled with frequency of 2000Hz by Flexcomp, which is the production of Thought Technology Ltd., Canada. 7 pairs of Ag/Agcl electrode with glue solution were sticked on muscle belly with a distance of 2cm, where the signal amplitude is up to the maximum. sEMG is easily disturbed by environmental noise, some preparations including shaving and cleaning the skin surface should be done before experiment. The raw sEMG signal contains noise and a large amount of data. Before applying for angle estimation it must be preprocessed with the following procedure.

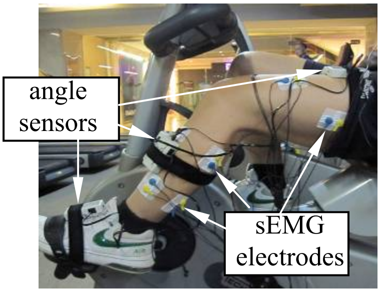


Fig. 1. sEMG and joint angle signal acquirement in treadmill exercise

2.2 Signal Processing

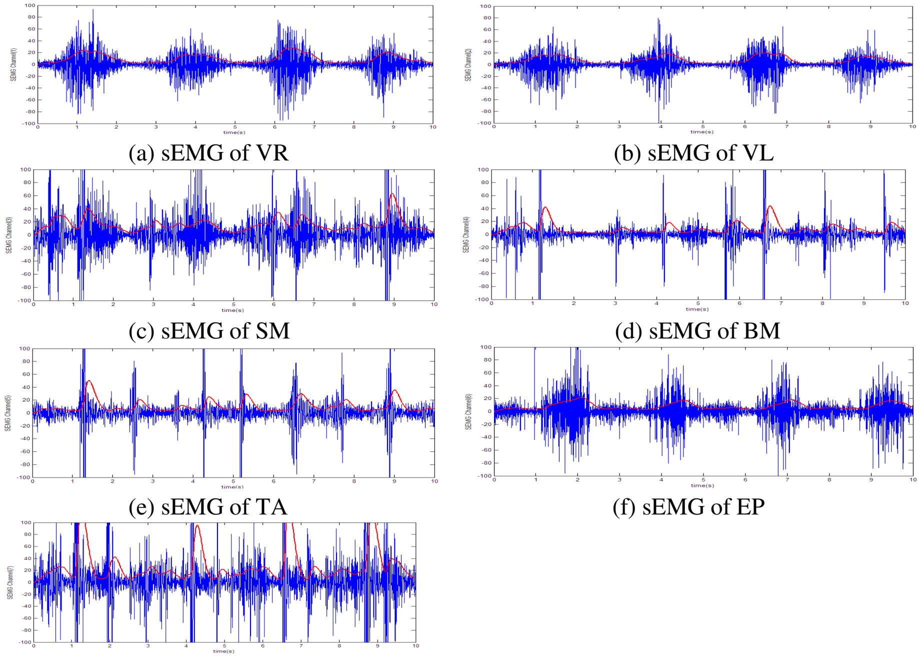
sEMG signal is very weak, non-stationary and random. It is easy to be disturbed by industrial frequency and the other environmental noise. It must de-noise and preprocess for further application. The power spectrum of electromyography mainly concentrates between 20Hz to 500Hz. Conseuquently, a notch filter with 50Hz (industrial frequency of 50Hz in China), a band-pass filter with low cut-off frequency of 20Hz and the high of 500Hz and DC component elimination are applied to the raw sEMG. sEMG after primary de-noising is sent to following two process steps:

(1) Integral absolute value (IAV) sEMG is taken as zero mean Gaussian distribution in time domain. Its amplitude is random and vibrates frequently across zero. IAV method describes the envelop characters of sEMG as

$$sEMG_I(n) = \frac{1}{W} \cdot \sum_{i=n\cdot(W-1)+1}^{n\cdot W} |sEMG(i)| \tag{1}$$

where $sEMG_I(n)$ is IAV of de-noised sEMG on the interval $i \in [W\cdot(n-1)+1, W\cdot n]$. As mentioned above, the sampling frequency of 2000Hz is higher than that of joint angle 100Hz. The integral window width is set to 20 in experiment to synchronize the frequency of sEMG and joint angle.

(2) The envelop of the sEMG signals get from last step still vibrates very much. Actually amplitude of sEMG reflects the contract level of corresponding muscle. And joint angle variation is the result of muscle contraction. So a two order low-pass Butterworth filter with cut-off frequency of 5Hz is used for data smoothing. Fig.2 shows comparison figure of raw and preprocessed sEMG signal of each muscle. The output data is applied directly for subsequent multi-joint angles estimation of lower limb.



(a) sEMG of VR (b) sEMG of VL

(c) sEMG of SM (d) sEMG of BM

(e) sEMG of TA (f) sEMG of EP

(g) sEMG of GM

Fig. 2. Raw and envelop sEMG signal of 7 channels muscles in treadmill exercises

2.3 Joint Angles Estimation

2.3.1 Least Squares Support Vector Machines (LS-SVM)

Support vector machine (SVM), the most young and practical machine learning algorithm was proposed by Vapnik and his co-workers. It has been paid wide attention in recent years for merits of small classification and approximation error, simple mathematical forms and excellent generalization performance. So it is widely used for pattern recognition and function regression.LS-SVM is an improvement model of SVM. In the model, the inequality constraint conditions are replaced by equality constraints. Consequently, quadratic programming problem was simplified as the problem of solving linear equation groups. It simplifies the complexity of calculation and accelerates solving process.

In this research, joint angle estimation based on sEMG can be regarded as a function regression problem or function fitting. That means obtaining an optimal function as follow for mapping relationship between x and y for given training set $(x_1, y_1)\ldots(x_l, y_l)$:

$$f\left(x\right)=w^{\mathrm{T}}\varphi(x)+b \tag{2}$$

where $\varphi(x)$: $R^n \rightarrow R^m$ is the nonlinear mapping from input space to high-dimension feature space. It can translate nonlinear regression to the linear. LS-SVM regression algorithm can be described solving following constraint optimization problem:

$$\text{Minimize}\quad J\left(w,e\right)=\frac{1}{2}w^{\mathrm{T}}w+\frac{1}{2}\gamma\sum\nolimits_{i=1}^{L}e_i^2 \tag{3}$$

with constraint condition $y_i = w^{\mathrm{T}}\varphi(x)+b+e_i$, $i=1,\cdots,L$, where w is the weight variable, e is the error variable, b is the offset and γ is penalty factor. Lagrange function is defined as

$$L(w,b,e,\alpha)=J(w,e)-\sum\nolimits_{i=1}^{L}\alpha_i\left\{w^{\mathrm{T}}\phi(x)+b+e_i-y_i\right\} \tag{4}$$

where α_i is the Lagrange multiplier. According to KKT conditions, Derivatives of $L(w,b,e,\alpha)$ with respect to w,b,e,α respectively is set to be 0 to get

$$\begin{cases}\dfrac{\partial L}{\partial w}=0\rightarrow w=\sum\nolimits_{i=1}^{L}\alpha_i\varphi(x_i)\\ \dfrac{\partial L}{\partial b}=0\rightarrow\sum\nolimits_{i=1}^{N}\alpha_i=0\\ \dfrac{\partial L}{\partial e}=0\rightarrow\alpha_i=\gamma e_i,\\ \dfrac{\partial L}{\partial \alpha}=0\rightarrow w^{\mathrm{T}}\varphi(x_i)+b+e_i-y_i=0\end{cases},i=1,\cdots,L \tag{5}$$

Let kernel function $K(x_i,x_j)=\varphi(x_i)\varphi(x_j)$, the optimal problem mentioned above is replaced by solving linear equations

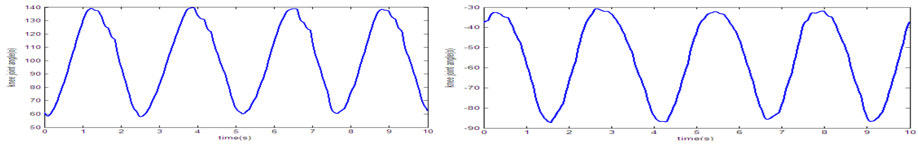
$$\begin{bmatrix}0 & 1 & \cdots & 1\\ 1 & K(x_i,x_j)+1/\gamma & \cdots & K(x_i,x_j)\\ \vdots & \vdots & \ddots & \vdots\\ 1 & K(x_i,x_j) & \cdots & K(x_i,x_j)+1/\gamma\end{bmatrix}\begin{bmatrix}b\\ \alpha_1\\ \vdots\\ \alpha_l\end{bmatrix}=\begin{bmatrix}0\\ y_1\\ \vdots\\ y_l\end{bmatrix},i,j=1,\cdots,L \tag{6}$$

Lagrange multiplier α_i and the offset b is solved from equation (6) and taken into $w=\sum\nolimits_{i=1}^{L}\alpha_i\varphi(x_i)$ to get fitting function of training set as

$$f(x)=\sum_{i=1}^{L}\alpha_k K(x_i,x_j)+b \tag{7}$$

2.3.2 Design of Regression Model

Processing result of 7 channels sEMG signal by IAV and Butterworth smoothing is shown in Fig. 2. Angle data of the hip and knee joint in Fig. 3 has a periodic change for treadmill motion. By comparing the waveform changes, it is obvious that sEMG signal of each muscle has different performance of correlation with joint angle data for treadmill motion. sEMG of VR and VL is strong correlation with angle data. sEMG of EP has some correlation with angle variation and sEMG of SM, BM, TA and GM has low correlation with angle. Accordingly, sEMG of VR and VL is utilized as the input of SVM and joint angle of the hip and knee as the output y.



(a) Angle of the knee joint (b) Angle of the hip joint

Fig. 3. Measured joint angle of the lower limb in treadmill exercises

In order to make full use of dynamic information of sEMG amplitude, a m-order model is proposed to describe the relationship of sEMG and joint angles of lower limb. That means joint angle y_k in a moment is thought be determined by sEMG signal from the present to the next follow m-k moment $\{x_k, x_{k-1}, \ldots, x_{k-m}\}$. The nonlinear relationship between sEMG and joint angles is described as

$$y_k = f(x_k, x_{k-1}, \ldots, x_{k-m}) \tag{8}$$

In experiments, two channels sEMG data strong correlated with joint angle are used to construct the input of SVM and *m* is set to 10. As a result, the input dimension of regression is 20, which is expressed as

$$x_k = \left[sEMG_k^{VR}, sEMG_{k-1}^{VR}, \ldots sEMG_{k-10}^{VR}, sEMG_k^{VL}, sEMG_{k-1}^{VL}, \ldots sEMG_{k-10}^{VL}\right]^{\mathrm{T}} \in R^{20\times 1} \tag{9}$$

The output of LS-SVM is two channels joint angle, which is

$$y_k = \left[\theta_k^{Knee}, \theta_k^{Hip}\right]^{\mathrm{T}} \in R^{2\times 1} \tag{10}$$

LS-SVM based regression model consists of two independent LS-SVMs. As Fig. 4, where LSSVM(1) maps nonlinear relationship between sEMG and the knee joint angle, and LSSVM(2) maps the relationship between sEMG and the hip joint angle.

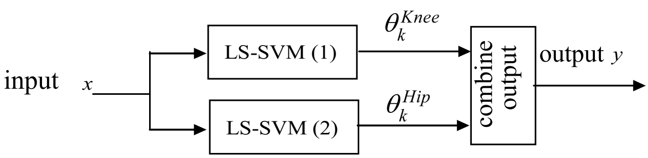
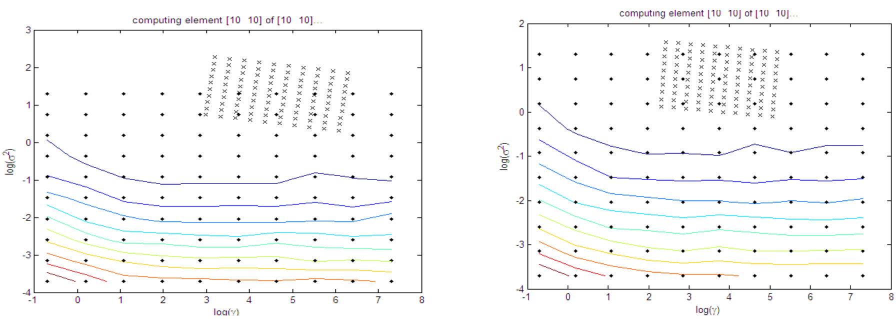


Fig. 4. The structure of LS-SVM based regression model

2.3.3 Joint Angle Estimation

Sampling frequency of sEMG after IAV preprocessing mentioned in section 2.2 is changed to 100Hz. As a result, preprocessed sEMG has the same frequency as joint angle. The sampling process lasts 10 seconds. Acquired 1000 sets of sEMG-joint angle data are sent to 10-order model (eq.9) for final 991 couples data, from which 198 couples are extracted every 5 data as training sample. All 991 sets are used to test performance of proposed LS-SVM regression model.

In this paper, Coarse-fine search with cross validation is used to determine two unknown parameters in LS-SVM, σ and γ. Search range of the kernel parameter σ^2 and penalty factor γ is set to [0.08， 12] and [0.05， 200] respectively. The logarithmic scale is employed for the parameter space (Fig.5). Each is linearly divided into 10 parts. 100 intersections of corresponding grid lines are set to the test point of parameters. On each point, cross validation method is applied to test the performance of LS-SVM. The specific steps are: All samples are randomly divided into 10 parts. 9 of them are for training and the rest is for regression performance testing. After 10 times of training and testing sets transforming for each couple kernel parameters, regression performance is evaluated by mean squared error of 10 times of test result called cross validate rate. As shown in Fig.5, grid points of coarse search for kernel parameters are highlighted with black “ • ”. Error contour of cross validation rate describes different parameter performance and determines the scope of optimum parameters. Based on the result, the search range is reset for fine search. Grid point is highlighted with “×” in Fig. 5. Its number is still 100 and the search process is the same as cross validation method. The result of optimum parameters are listed in table 1. Then, all 198 samples are used to calculate their Lagrange multiplier α and unknown parameter b .



(a)Parameter optimization of LS-SVM(1), (b)Parameter optimization of LS-SVM(2)

Fig. 5. Parameter optimization process of two independent LS-SVM

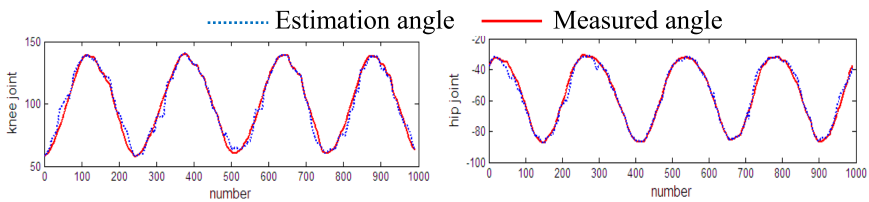
Table 1. Parameters of LS-SVM based regression model

Parameter	LS-SVM(1)	LS-SVM(2)
kernel parameter σ^2	6.197982	1.45296
penalty factor γ	187.2391	25.8838

In order to test performance of the trained LS-SVM regression model, two channels of sEMG data are sent into the model to estimate joint angle of the hip and the knee. Fig.6 shows good contact ratio between prediction and measured angle data. Root mean square error (RMSE) is calculated to quantitatively analyze performance:

$$RMSE = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}\left(\bar{\theta}_k - \theta_k\right)^2} \tag{11}$$

where $\bar{\theta}_k$ and θ_k is estimated and measured joint angle, N is test samples number .



(a)The knee joint angle estimation (b)The hip joint angle estimation

Fig. 6. sEMG based continuous joint angle estimation in treadmill exercise using LS-SVM

The outputs of estimation model based on LS-SVM are the hip joint angle and the knee joint angle. In experiment, the RMSE of prediction knee joint angle with the proposed model is 3.02° , and that of estimation hip joint angle is 2.09° .

3 Conclusions and Discussions

sEMG signal directly reflects human active motion intention, it is the best human-machine interface for active rehabilitation training of SCI, stroke or neurological injury patients. In this paper, we use LS-SVM to predict dynamic joint angle of the lower limb from sEMG signals. The input of the model derives from 7 Channels sEMG of lower limb muscles in treadmill exercise. Considering the data dimension of the input and correlation between sEMG and joint angle, sEMG of VR and VL after preprocess of de-noising, envelop calculation and filtering is selected for joint angle estimation. Finalized input of estimation model is a 20 dimensions processed sEMG and the output is two joint angles of the hip and the knee. Estimation model is constructed by 2 independent LS-SVM based regression model. Parameters of the established LS-SVM model are determined after the coarse and fine search. Statistics result of angle estimation using proposed method is represented with RMSE of prediction angle. That of the knee and the hip joint angle is 3.02° and 2.09°

respectively. This model based LS-SVM can successfully judge human motion intention and accurately estimate joint angle of the limb by using sEMG. It can provide new control strategy for rehabilitation robot or other motion assist devices.

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