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Application of multi-output support vector regression on EMGs to decode hand continuous movement trajectory

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Abstract. Applications of neural machine interfaces have received increased attention during the last decades. It is crucial to realize the continuous control of prosthetic devices based on biological signals. In order to deal with the highly nonlinear relationship between the Electromyography (EMG) signals and motion, this study presents a novel decoding approach which employs multi-output support vector regression (M-SVR). The proposed M-SVR is compared with other popular regression techniques and the experimental results demonstrate the effectiveness of M-SVR in hand continuous movement trajectory reconstruction.

Keywords: Electromyography (EMG), M-SVR, trajectory decoding, myoelectric control

1. Introduction

Neural machine interfaces (NMIs) have the potential to translate neural activity into control signals for the operation of prosthetic devices or computers, providing disabled people a better interaction with their surroundings. Most of the NMIs have focused on decoding the movement kinematics to reconstruct its trajectory [1]. Researchers have demonstrated that neural recordings in motor cortical areas and the posterior parietal cortex can provide plentiful signals to control the continuous movement of robotic arms [2-4] and computer cursors [5, 6]. Nevertheless, this signal source is practical for use in only a small number of patients due to its invasive nature [4]. Surface electromyography (EMG) contains rich information that can be used to control the prosthetic devices in a noninvasive manner. Previous studies have mainly focused on the realization of discrete myoelectric control with pattern recognition strategies, such as the classes of limb movement [7, 8] and the detection of grasp force and posture [9]. However, the number of classes is limited and the motion lacks smoothness [10]. It is an urgent task to decode hand movement trajectory from EMG to realize the continuous myoelectric control of prosthetic devices.

The main challenge in EMG-based continuous control is how to deal with the highly nonlinear

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relationship between the EMG signals and motion [11]. There have been some efforts devoted to mapping myoelectric activity to hand kinematic parameters, but the performance of the decoding algorithm remains limited. One approach is using recursive Bayesian estimation methods to predict the intended state from EMG signals, where the Kalman Filter (KF) has often been employed [12, 13]. Unfortunately, due to the linearity of the KF, it is restricted with regard to nonlinear problems. Another approach of decoding arm kinematic parameters is machine learning. Human hand movement trajectory has been reconstructed from EMG signals using an artificial neural network (ANN) [14], realizing single joint isometric motions only in the horizontal plane.

Support vector regression (SVR) has shown a better performance than other methods, because its computational complexity does not depend on the dimensionality of the input space and it can avoid multiple local extreme values [15]. Despite its potential advantages, the conventional formulation of SVR only have one-dimensional output, which cannot deal with multidimensional regression estimation problem such as hand movement trajectory decoding. The usual approach treats the different outputs separately in the multi-output case [16], which ignores the cross relations among output parameters and increases the algorithm complexity and computing time. To enhance the performance of traditional SVR, Pérez-Cruz, et al. [17] proposed a multi-dimensional regression tool named M-SVR, capable of obtaining better predictions than using a SVR for each dimension. M-SVR has become a powerful tool for multiple-output nonlinear channel estimation [18] and biophysical parameter evaluation from remote sensing images [19].

The aim of this study was to investigate an effective method for mapping EMG activity to motion. Considering the outstanding ability of M-SVR in dealing with multi-dimensional regression, we studied the applicability of M-SVR in the context of continuous movement trajectory decoding and compared it with other machine learning methods including SVR and ANN.

2. Materials and methods

2.1. Data acquisition

To validate the effectiveness of the proposed algorithm for decoding hand movement, we recorded EMG signals and hand kinematic parameters simultaneously. Two subjects voluntarily joined this study after being informed of the experimental purpose and procedure. They performed unconstrained 3-D right hand movements with variable speed in a wide range of hand workspace, while comfortably seated and constrained with lap and shoulder straps. Each movement lasted 10 seconds. After each movement session, the subject rested for 20 seconds with the hand resting on his lap. A total of 100 random movements were performed per subject, generating 200 results in total. EMG signals were recorded from the deltoid (anterior), deltoid (posterior), deltoid (middle), biceps brachii and triceps brachii. Hand movements were simultaneously tracked at 25 Hz using a data glove.

2.2. Features extraction

Generally, EMG signals are characterized by time domain or frequency domain features. As features in the frequency domain are mainly used to study motor unit recruitment and muscle fatigue [20], only time domain features are analyzed in this paper. To evaluate the performance of the decoding model, the combination of an autoregressive (AR) model coefficient and the root mean square (RMS) amplitude were prepared as a feature set. These features have been shown to be an effective signal representation of EMG signals [21].

Autoregressive (AR) model is a prediction model that characterizes EMG signals as a linear autoregressive time series. It is basically defined as:

$$x_k = \sum_{i=1}^{P} a_i x_{k-i} + e_k \tag{1}$$

where a_i is the autoregressive coefficients, P represents the order of the AR model, e_k is the residual white noise error term.

Root mean square (RMS) is one of the most popular features in the analysis of EMG signals. It is modeled as an amplitude modulated Gaussian random process which relates to constant force and non-fatiguing contraction. The RMS can be expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{2}$$

where x_i denotes the ith sample, N is the number of samples.

Based on the analysis above, a four-order AR model combined with RMS was used as a feature set for EMG decoding. The feature set was 26 dimensional vectors. We extracted the EMG features from a 160 ms analysis window, with the analysis window incremented by 40 ms.

2.3. M-SVR

To decode the hand movement from EMG signals, we established a support vector regression model. Considering the output kinematic parameters are multidimensional, the M-SVR was applied here. Generally, given a set of independent samples denoted as $\{(\mathrm{x}_i, \mathrm{y}_i)\}_{i=1}^{n}$, where x_i is input vector with dimensionality Q, y_i is observable output with dimensionality P. M-SVR solves the multi-dimensional regression estimation problem by finding the mapping between x_i and y_i. In our case, the input vector was the 26 dimensional EMG feature vector and the output vector was the 3 dimensional hand movement parameters. M-SVR is formulated as minimization of the following function:

$$L_P(W, b) = \frac{1}{2}\sum_{j=1}^{P}\left\|w^j\right\|^2 + C\sum_{i=1}^{n} L(u_i) \tag{3}$$

where

$$W = [w^1, \cdots, w^P]$$
$$b = [b^1, \cdots, b^P]^T$$
$$u_i = \|e_i\| = \sqrt{e_i^T e_i}$$
$$e_i^T = y_i^T - \varphi(x_i)^T W - b^T$$

The function $\varphi(\cdot)$ represents the nonlinear mapping from the primal space to high dimension feature space, C is a positive real regularized parameter which determines the trade-off between the regularization and the error reduction term. The ε-insensitive quadratic loss function $L(u)$ is defined as:

$$L(u) = \begin{cases} 0, & u < \varepsilon \\ u^2 - 2u\varepsilon + \varepsilon^2, & u \geq \varepsilon \end{cases} \tag{4}$$

As Eq. (1) cannot be solved straightforward, Sanchez-Fernandez, et al. [19] proposed an iterative reweighted least squares (IRWLS) procedure to obtain the desired solution. By using a first-order Taylor expansion of lost function $L(u)$, the objective of Eq. (1) will be approximated by the following equation [20]:

$$L'_P(W,b) = \frac{1}{2}\sum_{j=1}^{P}\left\|w^j\right\|^2 + \frac{1}{2}\sum_{i=1}^{n} a_i u_i^2 + CT \tag{5}$$

where

$$\mathrm{a_i} = \begin{cases} 0, & \mathrm{u_i^k} < \varepsilon \\ \frac{2C\left(\mathrm{u_i^k} - \varepsilon\right)}{\mathrm{u_i^k}}, & \mathrm{u_i^k} \geq \varepsilon \end{cases} \tag{6}$$

The constant term (*CT*) does not depend on W and b, the superscript k denotes the number of iterations. The best solution of minimization of Eq. (3) in feature space can be expressed as $\mathrm{w}^j = \sum_i \varphi(\mathrm{x}_i)\beta^j$, so the target of M-SVR is transformed into finding the best β and b. The IRWLS procedure can be summarized in the following steps.

1) Initialization: set $k = 0$, $\beta^k = 0$, $\mathrm{b}^k = 0$ and compute u_i^k and a_i.

2) Compute the solution β^s and b^s according to the following equation:

$$\begin{bmatrix} K + D_a^{-1} & 1 \\ a^T K & 1^T a \end{bmatrix} \begin{bmatrix} \beta^j \\ b^j \end{bmatrix} = \begin{bmatrix} y^j \\ a^T y^j \end{bmatrix}, \qquad j = 1, \cdots, P \tag{7}$$

where $\mathrm{a} = [a_1, \cdots, a_n]^T$, $(\mathrm{D}_a)_{i,j} = a_i \delta(i - j)$, and K is the kernel matrix. Define the corresponding descending direction:

$$P^k = \begin{bmatrix} w^s - w^k \\ \left(b^s - b^k\right)^T \end{bmatrix} \tag{8}$$

3) Use a backtracking algorithm to compute β^{k+1} and b^{k+1}, and further obtain u_i^{k+1} and a_i. Go back to Step 2 until convergence.

3. Results

To evaluate the performance of M-SVR on decoding hand movement trajectory, we examined and compared a series of regression techniques, including M-SVR model, SVR with Radial basic function (RBF) kernel and Dynamic Neural Network (DNN) with twenty hidden neurons. As described in Section 2.1, we performed 200 unconstrained movement trails in total. Here we took the first 150 trials as the training data to construct the decoding model. This was followed by the decoding of EMG signals to estimate the hand movement trajectory with the remaining testing part. All the results were smoothed by a Savitzky-Golay filter with the span of 0.1, because the motion of hand is smooth. The decoding experiments are implemented on a PC platform with Intel Core i5-3550 3.30 GHz CPU, 8 GB RAM, Windows 7 and Matlab development environment.

3.1. Evaluation criteria

This paper utilized two criteria to evaluate the accuracy of the estimated hand movement trajectory, including the correlation coefficient (CC) and the root-mean-square error (RMSE). The correlation coefficient represents essentially the similarity between the reconstructed and the actual trajectory. If the estimated and true trajectory matches perfectly, CC = 1. The root mean square error describes the deviation between the actual and the predicted values. We also studied the algorithm efficiency by comparing the computing time. The definitions of these criteria for decoding performance evaluation are described as:

$$CC = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i-y_i)^2}{n}} \tag{10}$$

where $\bar{x}$ and $\bar{y}$ denote the mean values of the observations x_i and the estimations y_i respectively and n is the sample size.

3.2. Assessment results

In this section, we compared the decoding performance of three regression methods. First, Figure 1 describes the x-, y-, and z-axes movement trajectory on 10-s testing data achieved by multi-output support vector regression (M-SVR), dynamic neural network (DNN) and support vector regression (SVR). The actual movement trajectory was compared with these three estimated trajectories. Second, Figure 2 shows Root-mean-square error (RMSE) values within the corresponding 10-s experiment interval. The RMSE of the reconstructed hand movement was calculated every one second for the 10-s testing data to analyze the variation trend of accuracy with the passage of time. Finally, the values of correlation coefficient (CC) and root-mean-square error (RMSE) for 40 testing trials with the M-SVR, DNN and SVR were computed respectively. We also calculated the total time of the 150 training trials and 40 testing trials. Table 1 shows the average values of CC, RMSE for 40 testing trials and total time for 200 training and testing trials using M-SVR, DNN and SVR, where CC_x, CC_y and CC_z is

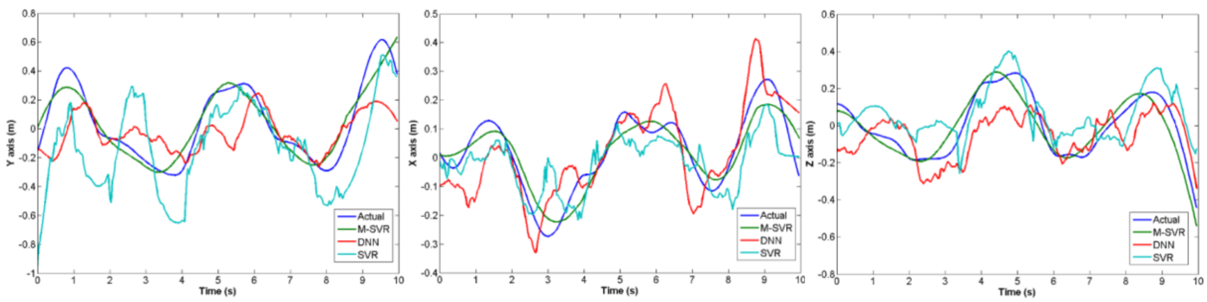

Fig. 1. Actual and estimated hand trajectory along the x-, y-, and z-axes for a 10-s period.

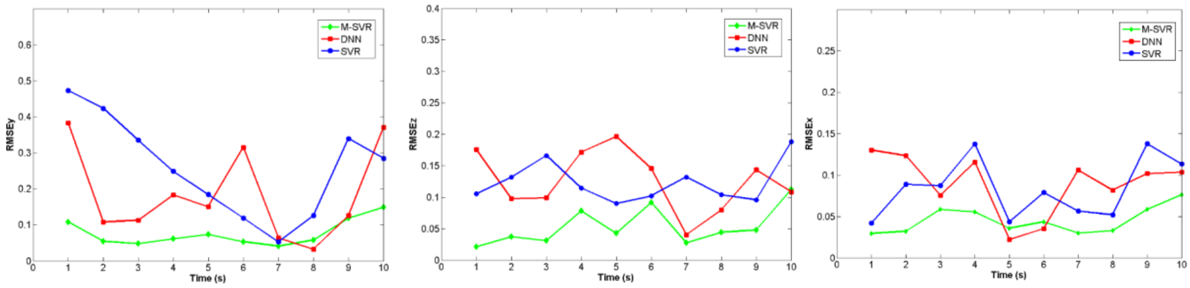

Fig. 2. Root-mean-square error (RMSE) values for the estimated hand position with respect to time using the three models.

Table 1

The average values of CC and RMSE for 40 testing trials and total time for 200 training and testing trials

Decoding model	CC_x	CC_y	CC_z	$RMSE_x$	$RMSE_y$	$RMSE_z$	Time (s)
M-SVR	0.9388	0.9505	0.9297	0.0478	0.0838	0.0607	8.0357
DNN	0.7892	0.6437	0.6444	0.0959	0.2202	0.1341	222.8571
SVR	0.7983	0.6831	0.7249	0.0906	0.2900	0.1266	17.57

the correlation coefficient along x-, y-, and z-axes, $RMSE_x$, $RMSE_y$ and $RMSE_z$ is the root-mean-square error along x-, y-, and z-axes.

4. Discussion

From Figure 1, we observed that M-SVR follows the dynamics more accurately and outperforms the other regression methods on estimating the hand trajectory. In contrast, both DNN and SVR predict the hand movement trajectory inaccurately. Specifically, DNN was easy to obtain partial optimal solutions and SVR was unsteady to decode the motion. Figure 2 shows the fluctuation of RMSE values with respect to time. As it can be seen, the RMSE values of M-SVR are less than the others for most of the time. The M-SVR model is able to estimate the user's motion robustly, while the other two models fluctuate with respect to time

Table 1 summarizes the decoding performance for all the training and testing trails. The average value of CC between M-SVR model and actual trajectory is close to 1, which means that the M-SVR model decodes hand movement from EMG robustly. Considering that the CC of M-SVR model is greater than other models and the RMSE value is less, M-SVR performs better than the other methods in accuracy on estimating hand motion. With regard to total time, DNN model requires a lot more training time than M-SVR and SVR. Furthermore, the M-SVR model only takes a small amount of run-time in comparison to the standard SVR approach, because M-SVR outputs the 3-axes movement parameters simultaneously while the standard SVR has to run three times to get these parameters. Thus M-SVR is the most efficient method.

From the above analysis of the results, it can be concluded that the M-SVR model is better than the DNN and SVR for all performance measures. It outperforms the other methods in both accuracy and efficiency and is a promising technique for trajectory decoding of EMG signals.

5. Conclusion

In this paper, M-SVR has been applied to decode hand continuous movement trajectory using EMG signals from the muscles of the upper limb. EMG signals from 5 muscles have been used to estimate the hand position during unconstrained motion in the 3-D space. The M-SVR turned out to be an accurate and efficient method and outperformed other popular algorithms. Different from traditional discrete myoelectric pattern recognition strategies, we realize the continuous trajectory decoding using only EMG signals. However, the method described in this paper is probably not directly usable for clinical application. The effectiveness of M-SVR for muscular-disorder people will be investigated in the future. Although this study focuses on the EMG signals decoding of normal people, it also has clinical implications. The realization of continuous trajectory decoding is an obligatory background for reconstructing movement function of disabled people.

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