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An Ensemble-based Regression Approach for Continuous Estimation of Wrist and Fingers Movements from Surface Electromyography

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Abstract— **Late development and evolution of high degree-of-freedom (DOF) robotic hands have seen great technological strides to enhance the quality of life for amputated people. A robust hand kinematic estimation mechanisms have shown promising results to control robotic hands that can mimic the human hand functions and perform daily life hand dexterous tasks. In this paper, we propose an ensemble-based regression approach for continuous estimation of wrist and fingers movements from surface Electromyography (sEMG) signals. The proposed approach extracts time-domain features from the sEMG signals, and uses Gradient Boosted Regression Tree (GBRT) ensembles to estimate the kinematics of the wrist and fingers. Furthermore, we propose two different performance evaluation procedures to demonstrate the efficacy of the approach in providing a feasible approach towards accurately estimating hand kinematics.**

I. Introduction

Today, many people are living with lost limbs and parts due to accidents, wars, and diseases. According to the National Center for Health Statistics [1], there are approximately two million people living with limb loss in the United States, with approximately 185 thousand new amputations occurring each year. Among those living with limb loss, the ratio of upper limb to lower limb amputation is one to four; with wrist and hand amputations are estimated to be 10% of the upper limb amputations, and trans-radial amputations accounts for 60% of the total wrist and hand amputations [2]. People with hand amputation may have several challenges and difficulties in their daily life, due to the lack of ability to perform primitive tasks that require dexterous control such as eating, drinking, writing, and using mobile phone.

Meanwhile, recent technological advancement and rapid leaps in wearable sensors and robotic hand assistive devices have shown promising results in building prosthetic hand to recover a significant part of hand functionality that has been lost. This in turns can greatly enhance the quality of life for amputated people. According to Merrill et al. [3], nearly 50% of the existing prosthesis is based on myoelectric control prosthesis (i.e., prosthesis that are controlled by surface electromyography). Surface electromyogram (sEMG) signals are often used in prosthesis controls and rehabilitation support applications that can reflect the motor intention of a user prior to the occurrence of the actual movements [4].

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Over the past two decades, pattern classification methods have been successfully utilized to decode finger movements from sEMG signals [5], [6]. However, such methods suffer from the limitation of restricting myoelectric control of predetermined and finite set of hand gestures and fingers movements, such as hand opening and closing. Recently, researchers have investigated control approaches that can achieve a natural and dexterous myoelectric control by applying regression methods to continuously estimate the joint kinematics of wrist and fingers. The advantage behind using regression methods over classification methods is the former method ability to generalize novel movements that are not captured in the training dataset. Such merit is highly significant for clinical applications, in which collecting training data that cover all the possible combinations of wrist and finger movements is prohibitively expensive in terms of time and strain.

In this paper, we propose an ensemble regression approach based on Gradient Boosted Regression Tree (GBRT) for continuous estimation of wrist and fingers movements from sEMG signals. The GBRT ensemble combines weak prediction models "decision trees" into a single strong predictor in an iterative fashion. This allows to reduce the prediction error compared to the error generated from the best individual prediction model [7], [8]. In order to validate the performance of the proposed approach, we have conducted extensive computer simulations using the publicly available NinaPro database [9], [10]. The NinaPro database comprises three types of movements: (1) basic movements of the fingers; (2) isometric, isotonic hand configurations and basic wrist movements; (3) grasping and functional movements. The remainder of this paper is organized as follows: in Section II, we provide an overview of existing work on continuous estimating wrist and finger movements from sEMG. Section III describes the proposed ensemble-based regression model and the evaluation procedure. Section IV presents the experimental results. We conclude with final comments in Section V.

II. Related Work

Literature reveals an increasing number of studies aimed at estimating hand/fingers movements. For example, Hioki and Kawasaki [11] propose a neural network based method for estimating the finger joint angles using sEMG signals. However, the work has focused on a limited number of hand movements such as fist with five fingers and grip with four

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fingers except thumb. Similarly, Jiang et al. [12], propose a multi-layer perceptron networks to estimate the joint angles of the hand wrist. The work has focused on three degrees of freedom (DoFs) of the wrist, namely the wrist flexion/extension, pronation/supination, and wrist radial/ulnar deviation. In addition, Ameri et al. [13], proposed a Support Vector Machine (SVM)-based methodology to analyze the sEMG signals associated with wrist flexion-extension, abduction-adduction and forearm pronation-supination. The proposed method outperforms the artificial neural network (ANN) based method in several performance metrics. However, the aforementioned work has broadly focused on wrist movements and not on the hand fingers per se. Furthermore, Ngeo et al. [14], utilize an sEMG-to-Muscle Activation model to provide an accurate estimation for multiple and simultaneous finger joint kinematics. Vogel et al. [15], explore training the amputees via building an Arm/hand/force association map using sEMG. The map is then used to predict new arm/hand movements. Smith et al. [16], propose a methodology on how to decode the sEMG signals associated with finger hand movements in order to predict the fingers' joints angels using artificial neural networks. Ngeo et al. [17] considered the fact that finger joints are highly correlated in order to improve finger joint estimation based on sEMG. The authors also compared the performance of Gaussian Process (GP) regression method with ANN, and found that GP model has achieved a better performance compared with ANN. Contrast to the above efforts, this work proposes an ensemble-based approach in order to continuously estimate wrist and fingers kinematics using sEMG signals.

III. Method

A. NinaPro database

NinaPro database has been acquired with the aim to form a worldwide benchmark dataset that allows researchers to study the relationship between sEMG and hand/arm kinematics, towards naturally control hand prosthetics for transradial amputees [9]. In this study, we use the first iteration of the NinaPro database, namely *database*1. The experimental procedures of the NinaPro database were approved by the Institutional Review Board. In this database, 27 intact subjects are instructed to perform 10 repetitions of 52 different movements by imitating a video. The 52 movements are organized in three different exercises. Exercise A consists of 12 basic movements of the fingers. Exercise B consists of eight isometric and isotonic hand configurations, and nine basic movements of the wrist. Exercise C consists of 23 grasping and functional movements that mimic daily-life activities. Muscular activities were measured using ten MyoBock (www.ottobck.com) active electrodes. Eight electrodes are placed around the forearm uniformly, while the remaining two electrodes were placed on the activity spots of the flexor/extensor digitorum superficialis. Hand kinematics are measured simultaneously using 22-sensors Cyberglove II (www.cyberglovessystems.com), which return values proportional to joint angles.

B. sEMG signal processing and feature extraction

The obtained sEMG signals have been amplified, bandpass-filtered, and Root-Mean-Squared (RMS) rectified. In order to extract the features, we utilize a sliding window of size $W = 256ms$ and overlap size of $O = 100ms$ over each sEMG channel. Then for each channel, we calculate three time-domain features at each window position. These features are: Mean Absolute Value (MAV), Variance (VAR), and sEMG Histogram (HIST) [18]. The MAV and VAR are calculated over the window W using (1) and (2), respectively:

$$\hat{x} = \frac{1}{W}\sum_{t=1}^{W}|x_t|, \tag{1}$$

$$\hat{y} = \frac{1}{W}\sum_{t=1}^{W}(x_t - \bar{x})^2, \tag{2}$$

where $\bar{x}$ is the mean of the sample values (x_t) over W. Finally, the HIST is calculated over the window W using (3)

$$\hat{z}_{1:B} = hist(x_{1:t}, B), \tag{3}$$

where *hist* is the histogram function, and B is the number of HIST bins, which is equal to 10. The dimensionality of the obtained features for each window position is equal to 120 features (12 features/channel). This implies that the input dimensionality for our ensemble-based regression model is a vector belong to $\mathbb{R}^{120}$, and the output dimensionality is defined to be the number of returned values from the Cyberglove that are proportional to joint angles. The next section describes the proposed model for realizing mapping functions that map features to joint angles.

C. GBRT ensemble-based regression approach

For the purpose of this work, we develop an ensemble-based approach that utilizes GBRT [19] in order to continuously estimate wrist and fingers kinematics. The proposed approach learns a vector of nonlinear mapping functions from the input to the output space, and can be described by

$$\begin{aligned}\mathbf{Z}(t) &= \mathbf{f}\big(\mathbf{X}(t)\big)\\ &= \big[f_1\big(\mathbf{X}(t)\big), \cdots, f_{22}\big(\mathbf{X}(t)\big)\big]^T,\end{aligned} \tag{4}$$

where $\mathbf{X}(t) \in \mathbb{R}^{120}$ and $\mathbf{Z}(t) \in \mathbb{R}^{22}$ are the extracted feature vector and the values returned from the Cyberglove when the sliding window is centered at time t, respectively. The vector of functions, $\mathbf{f}(\cdot)$, consists of a set of unknown nonlinear functions that estimate the angles proportional values obtained from the Cyberglove. Specifically, the function $f_i(\cdot)$ estimates the angle proportional value of the i^{th} sensor in the Cyberglove, where $i \in \{1, \cdots, 22\}$. Each function $f_i(\cdot)$ is realized by a GBRT ensemble that combines a set of M basis functions, called weak learners. GBRT uses decision trees of fixed size as a weak learners to model complex functions. Given a training set $\mathscr{D} = \{(\mathbf{X}_1, y_1), \cdots, (\mathbf{X}_k, y_k), \cdots, (\mathbf{X}_n, y_n)\}$, where $\mathbf{X}_k$ represents a feature vector, and y_k represents the correspondence target signal (i.e., Cyberglove measurement), GBRT ensemble attempts to find an approximation $\hat{f}_i(\cdot)$ for the function $f_i(\cdot)$ as a weighted sum of the base learners. The approximation $\hat{f}_i(\cdot)$ can be written as follows:

$$\hat{f}_i(\mathbf{X}) = \sum_{j=1}^{M} \psi_j \omega_j(\mathbf{X}), \tag{5}$$

Where $\mathbf{X} \in \mathscr{D}$, and $\omega_j(\cdot)$ is the j^{th} base function for $j \in \{1, \cdots, M\}$ and $i \in \{1, \cdots, 22\}$. In this study, the approximation $\hat{f}_i(\cdot)$ minimizes the average value of the least squares loss function L on the training data $\mathscr{D}$ using the steepest descent algorithm. More specifically, the approximation $\hat{f}_i(\cdot)$ is calculated in an iterative procedure of M stages. At each stage $m \in \{1, \cdots, M\}$, an approximation $\widehat{f_{i,m}}(\cdot)$ of the function $f_i(\cdot)$ is calculated using m weak learners as follows:

$$\widehat{f_{i,m}}(\mathbf{X}) = \widehat{f_{i,m-1}}(\mathbf{X}) + \psi_m \sum_{k=1}^{n} \nabla_{\hat{f}_i} L\big(y_i, \widehat{f_{i,m-1}}(\mathbf{X_k})\big), \tag{6}$$

where $\widehat{f_{i,m-1}}(\cdot)$ represents the current approximation of $f_i(\cdot)$ using $m-1$ weak learners. $\nabla_{\hat{f}_i}$ represents the gradient of the loss function L evaluated at $\widehat{f_{i,m-1}}(\mathbf{X_k})$. ψ_m represents the optimum step length and can be computed as follows:

$$\psi_m = \arg\min_{\psi} \sum_{k=1}^{n} L\Big(y_i, \widehat{f_{i,m-1}}(\mathbf{X_k}) - \psi \frac{\partial L(y_i, \widehat{f_{i,m-1}}(\mathbf{X_k}))}{\partial \widehat{f_{i,m-1}}(\mathbf{X_k})}\Big), \tag{7}$$

At stage M, an approximation $\widehat{f_{i,M}}(\cdot) \equiv \hat{f}_i(\cdot)$ for the function $f_i(\cdot)$ is obtained by applying (6) and using M weak learners.

D. Evaluation procedure of the regression model

In order to evaluate the proposed regression model in estimating the wrist and fingers kinematics, we have developed two different subject-specific cross-validation (CV) procedures, Leave One Movement Repetition Out (LOMRO)-CV and Leave One Movement Out (LOMO)-CV. In the LOMRO-CV, the regression model was trained using nine out of ten movement repetitions, and subsequently tested on left movement repetition. For the LOMO-CV, the regression model is trained using 51 movements out of the 52 movements in the NinaPro database, and subsequently tested on left movement.

For the purpose of measuring the quality of the regression model, we have used the coefficient of determination (R^2) index. The R^2 index is computed for each function approximation $\hat{f}_i(\cdot)$ as follows:

$$R^2 = \left(1 - \frac{\sum_{k=1}^{n}(y_k - \hat{f}_i(\mathbf{X_k}))^2}{\sum_{k=1}^{n}(y_k - \frac{1}{n}\sum_{k=1}^{n} y_i)^2}\right) \tag{8}$$

IV. Results

In order to determine the parameters of the GBRT ensembles, we have performed grid-based search along two directions. In the first direction, we varied the number of weak learners M in the ensemble, while in the second direction we varied the depth of the decision trees in the ensemble. Then, the best ensemble model is selected such that its parameters minimize the mean-squared error (MSE) between the predicted values of the Cyberglove data and its measured values. The grid search is performed using a subset of 12 randomly selected subjects, which was then discarded from subsequent analysis. The best parameters were found to be $M = 190$ and the depth of the decision trees was selected to be five. We evaluate the regression accuracy of the proposed GBRT ensemble model using the two different CV procedures described in Section III-D. For the LOMRO-CV, the regression accuracy in estimating the data value of the 22 Cyberglove sensors (we denote these sensors as $\{\theta_1, \cdots, \theta_{22}\}$) for 15 different subjects are shown in Table I. The first row represents the average R^2 index in estimating the Cyberglove sensors data for the 12 movements in exercise A. The second row represents the average R^2 index in estimating the Cyberglove sensors data for the 17 movements in exercise B. And, the third row represents the average R^2 index in estimating the Cyberglove sensors data for the 23 movements in exercise C. The results are expressed in terms of the average R^2 index for the movements in each exercise over 15 subjects. Using LOMRO-CV, the obtained overall average R^2 index for the GBRT ensemble model in estimating the Cyberglove sensors data was (0.8).

Furthermore, we evaluated the accuracy of the proposed approach in generalizing to a new movement that was not part of the training set using the LOMO-CV procedure. The regression accuracy in estimating the data value of the 22 Cyberglove sensors for 15 different subjects are shown in Table II. The results are expressed in terms of the average R^2 index for the movements in each exercise over 15 subjects. Using LOMO-CV, the obtained overall average R^2 index for the GBRT ensemble model in estimating the Cyberglove sensors data was (0.6). The results show that the overall average performance of the regression model has decreased from $R^2 = 0.8$ to $R^2 = 0.6$, when tested using LOMO-CV. This reduction in the performance is attributed to LOMO-CV, in which the GBRT ensemble model being tested using novel movements. Figure 1 provides two representative traces of the index finger flexion movement in exercise A. Figure 1a shows the Cyberglove measured data along with the estimated values of the sensor at location six (θ_6) in the Cyberglove using the GBRT ensemble model and LOMRO-CV. The sensor at location six (θ_6) in the Cyberglove represents the index finger distal joint [9]. Similarly, Fig. 1b shows the Cyberglove measured data along with the estimated values of the sensor at location six (θ_6) in the Cyberglove during LOMO-CV. The results illustrate the efficacy of our proposed ensemble-based regression approach for learning and estimating wrist and fingers movements.

V. Conclusions and Future Work

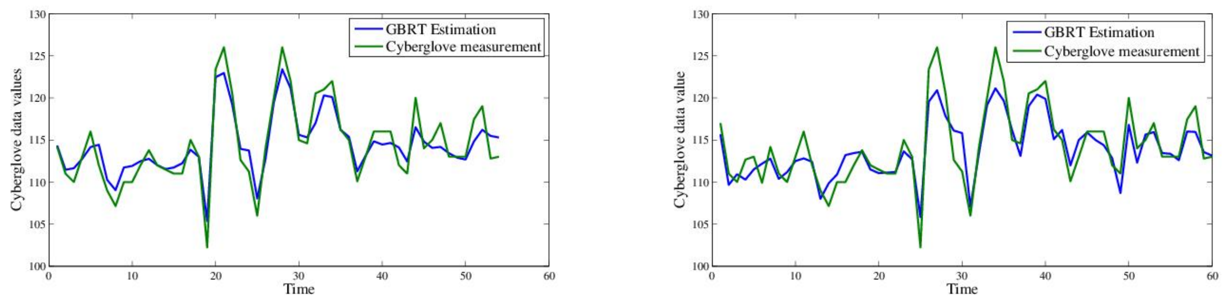
In this paper, we propose a novel approach for continuous estimation of wrist and fingers kinematics based on GBRT ensemble, using sEMG signals obtained from the NinaPro dataset. The experimental results have shown to be promising, with an average regression accuracy measured using the R^2 index of (0.8) using LOMRO-CV, and an average

TABLE I: Evaluation results of the GBRT ensemble model using the LOMRO-CV.

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	θ_{11}	θ_{12}	θ_{13}	θ_{14}	θ_{15}	θ_{16}	θ_17	θ_{18}	θ_{19}	θ_{20}	θ_{21}	θ_{22}
Exc. A	0.77	0.70	0.73	0.73	0.73	0.66	0.71	0.68	0.64	0.73	0.75	0.70	0.70	0.69	0.73	0.59	0.72	0.73	0.75	0.81	0.68	0.72
Exc. B	0.83	0.76	0.80	0.82	0.84	0.84	0.83	0.85	0.85	0.84	0.87	0.86	0.87	0.83	0.87	0.86	0.86	0.84	0.81	0.78	0.87	0.84
Exc. C	0.82	0.80	0.81	0.83	0.86	0.81	0.80	0.85	0.82	0.82	0.87	0.87	0.85	0.82	0.87	0.87	0.82	0.82	0.87	0.82	0.86	0.87

TABLE II: Evaluation results of the GBRT ensemble model using the LOMO-CV.

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8	θ_9	θ_{10}	θ_{11}	θ_{12}	θ_{13}	θ_{14}	θ_{15}	θ_{16}	θ_17	θ_{18}	θ_{19}	θ_{20}	θ_{21}	θ_{22}
Exc. A	0.28	0.36	0.51	0.47	0.72	0.67	0.65	0.64	0.82	0.64	0.44	0.73	0.77	0.70	0.70	0.80	0.78	0.66	0.87	0.54	0.74	0.70
Exc. B	0.65	0.50	0.73	0.50	0.73	0.72	0.71	0.70	0.75	0.69	0.49	0.65	0.59	0.63	0.43	0.65	0.73	0.69	0.42	0.53	0.55	0.48
Exc. C	0.59	0.62	0.76	0.60	0.49	0.37	0.39	0.60	0.48	0.44	0.45	0.46	0.57	0.57	0.42	0.50	0.74	0.58	0.57	0.69	0.64	0.50



(a) The estimation of the index finger distal joint using LOMRO-CV.

(b) The estimation of the index finger distal joint using LOMO-CV.

Fig. 1: Representative estimation results taken from index finger flexion movement in exercise A.

regression accuracy of (0.6) using LOMO-CV. For future work, we plan to apply further verifications to the proposed regression model including testing with amputated subjects. In addition, we plan to extend our evaluation procedure to include cross subject evaluation, and to measure the generalization of the GBRT ensemble model.

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