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Conference Paper · July 2015

DOI: 10.1109/NER.2015.7146702

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In Proceedings of the IEEE EMBC Neural Engineering Conference (NER '15), Chicago (2015)

Evaluation of Regression Methods for the Continuous Decoding of Finger Movement from Surface EMG and Accelerometry

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***Abstract*— The reconstruction of finger movement activity from surface electromyography (sEMG) has been proposed for the proportional and simultaneous myoelectric control of multiple degrees-of-freedom (DOFs). In this paper, we propose a framework for assessing decoding performance on novel movements, that is movements not included in the training dataset. We then use our proposed framework to compare the performance of linear and kernel ridge regression for the reconstruction of finger movement from sEMG and accelerometry. Our findings provide evidence that, although the performance of the non-linear method is superior for movements seen by the decoder during the training phase, the performance of the two algorithms is comparable when generalizing to novel movements.**

I. INTRODUCTION

Classification methods have been extensively used for decoding movement intention from surface electromyography (sEMG) signals with high accuracy [1, 2]. Nevertheless, one severe limitation of classification methods for myoelectric control is that they are restricted to a finite, predetermined set of modules (e.g. grasp types). One way of achieving more natural and dexterous myoelectric control is by employing proportional and simultaneous control of a large number of degrees-of-freedom (DOFs) of the prosthetic device [3, 4].

Previous work on proportional myoelectric control was mainly focused on wrist kinematics decoding [5, 6]. Recently, a small number of studies have addressed the challenge of decoding finger movement by using sEMG. Notably, Smith et al. [7] estimated joint angles of the metacarpophalangeal finger joints of a non-amputee subject, by using a multi-layer perceptron (MLP). Hioki and Kawasaki [8] used a time-delayed, recurrent neural network, to estimate finger joint angles also in a non-amputee subject. Finally, Ngeo et al. [9] used a muscle activation (MA) model to reconstruct finger kinematics from sEMG, and demonstrated that a non-parametric (Gaussian Process) regression method outperformed artificial neural network (ANN) regression.

A comparison of linear and non-linear regression methods was performed by Hahne et al. [6] for the proportional and simultaneous control of wrist kinematics, and it was found that when a non-linear feature was used, the differences in decoding performance were marginal. Ameri et al. [10] compared the real-time performance of an ANN and support vector regression (SVR) in 10 non-amputee and two amputee subjects, and found that SVR outperformed the ANN in terms of decoding wrist movement, and also substantially reduced processing times.

The use of regression methods offers the potential advantage of generalizing to novel movements, that is movements not included in the training dataset. This is particularly important for clinical applications, where exhaustive training that could cover all possible combinations of finger movements would be prohibitively expensive in terms of both time and effort. To this end, we propose a framework for assessing the quality of finger movement decoding for both within-, as well as across-movement generalization. In this paper, we evaluate our method on the NinaPro database [11–13], which is a publicly available dataset comprising movements during execution of isometric and isotonic hand configurations, as well as functional movements and grasping of common household objects. Reconstruction of finger movement is achieved with using both linear regression (LR) and kernel ridge regression (KRR), and the performance of the two algorithms is compared for within- and across-movement generalization.

II. METHODS

A. NinaPro database

The second iteration of the publicly available NinaPro database [13] was used in this paper. Briefly, 40 able-bodied subjects were instructed to perform six repetitions of various hand, wrist and functional and grasping movements, organized in three distinct sets of exercises (referred to as exercises B, C and D in [12]). In our study, we only used data from exercises 1 and 2, for which hand kinematics data were collected. For exercise 2, wrist movements were excluded from analyses, since the motion of the fingers during these movements was negligible. Muscle activity was recorded by using 12 wireless sEMG electrodes, each integrated with a 3-axis accelerometer. From this total number of 12 electrodes,

*A. Krasoulis is supported by grants EP/F500385/1 and BB/F529254/1 for the University of Edinburgh School of Informatics Doctoral Training Centre in Neuroinformatics and Computational Neuroscience (www.anc.ac.uk/dtc) from the UK Engineering and Physical Sciences Research Council (EPSRC), UK Biotechnology and Biological Sciences Research Council (BBSRC), and the UK Medical Research Council (MRC). S. Vijayakumar is supported by the Microsoft Research RAEng. Fellowship, EU FP7 Grant TOMSY and EPSRC EP/H1012338/1. The work of K. Nazarpour is supported by EPSRC EP/M025977/1.

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eight were equally spaced around the forearm, and the remaining four were targeted to specific muscles. Hand kinematics were simultaneously recorded by using a 22-DOF data glove, which returns values that are proportional to joint angles. The sampling rate was set to 2 kHz for myoelectric signals, and to 25 Hz for accelerometry and glove data. The synchronization of the three different streams was performed off-line by using high-resolution timestamps [13].

B. Signal preprocessing

Myoelectric signals were digitally band-pass filtered between 20 and 500 Hz by using 4$^{\text{th}}$ order Butterworth filters. Digital filtering was performed both forward and backward in time to avoid introducing phase delays. For feature extraction, a sliding window of 256 ms length was used, with an increment of 100 ms. From each sEMG channel, four time-domain (TD) features were extracted; the mean absolute value (MAV), waveform length (WL), log-variance (Log-Var) [6], and 4$^{\text{th}}$ order auto-regressive (AR) coefficients. For accelerometry and hand kinematics signals, the mean value (MV) feature was used, which computes the average value of the signal within the processing window. All features and kinematics signals were normalized in the range $[0, 1]$, and finally mean subtracted. Feature scaling and mean subtraction followed cross-validation (CV) (Section II-E), and were thus performed by using training data only.

The input dimensionality was (7 sEMG features + 3 acceleration signals) / channel $\times$ 12 channels = 120 input features, while the output dimensionality was defined by the number of recorded glove sensors. For decoding, a mapping $f\colon \mathbb{R}^{120} \rightarrow \mathbb{R}^{22}$ was learned by using LR and KRR, as explained in the next section.

C. Linear regression

Linear regression was performed by solving the linear system of equations (ridge regression):

$$\hat{B} = \left(X^T X + \lambda I\right)^{-1} X^T Y, \tag{1}$$

where X denotes the design matrix in which rows represent training samples and columns represent input features. The rows of the output matrix Y represent training samples, whereas the columns of Y represent target signals (i.e. data glove measurements). The parameter λ is a regularization constant.

D. Kernel ridge regression

Kernel ridge regression was performed by solving the system of equations:

$$\hat{A} = (K + \lambda I)^{-1} Y, \tag{2}$$

where K represents the Gram matrix, whose elements are inner products in the kernel feature space

$$k\left(x_i, x_j\right) = \langle \phi(x_i), \phi(x_j) \rangle. \tag{3}$$

In this study, the squared exponential kernel (also known as radial basis function or Gaussian kernel) was used, which is defined as follows:

$$k\left(x_i, x_j\right) = exp\left(-\frac{\left\|x_i - x_j\right\|_2^2}{2\sigma^2}\right), \tag{4}$$

where the hyper-parameter σ controls the width of the kernel.

E. Cross-validation

Subject-specific decoders were learned during training. The quality of reconstruction of finger movement was assessed in two distinct scenarios; within- and across-movement generalization. Hence, two different cross-validation (CV) procedures were designed; for *within-movement generalization*, decoders were trained by using five out of six repetitions of each movement, and subsequently tested on the left-out repetition. This yielded 6 folds for each subject. For *across-movement generalization*, decoders were trained on data from all except one movements, and subsequently tested on the left-out movement. Since the number of performed movements was different for the two sets of exercises [12], this procedure yielded 8 and 23 folds for exercises 1 and 2, respectively. In each case, across-fold averages were computed and reported for each subject.

For both LR and KRR, hyper-parameters were optimised via CV on a subset of 10 subjects, which was then discarded from subsequent analyses. Concretely for LR, the optimization of the regularization constant λ was performed via a log-linear search in the range $\{-4, -3, -2, -1, 0, 1, 2\}$. For KRR, a grid search was performed for the optimization of the hyper-parameters λ and σ. The log-range for σ was $\{0, 1, 2\}$. In both cases, the values of hyper-parameters which yielded the highest average performance were chosen, and used to report results on the test subject subset.

F. Decoding performance assessment

The quality of reconstruction was assessed by using the coefficient of determination (R^2) index which is defined as follows:

$$R^2 = \frac{\left(\sum_{j=1}^{M} \left(p_j - \bar{p}\right)\left(\hat{p_j} - \bar{\hat{p}}\right)\right)^2}{\sum_{j=1}^{M} \left(p_j - \bar{p}\right)^2 \sum_{j=1}^{M} \left(\hat{p_j} - \bar{\hat{p}}\right)^2}. \tag{5}$$

where p_j and $\hat{p_j}$ denote measured and reconstructed data glove values for the j^{th} sample of a CV-fold, and $\bar{p}$ and $\bar{\hat{p}}$ denote their respective expected values over all the samples of the fold $j = 1, \ldots, M$.

G. Chance level decoding performance

For chance level decoding performance assessment, LR was used and predictions were made for randomized input data matrices. Concretely, a random version of the design matrix was fed into the decoder, which did not correspond to the segment of hand kinematics data to be predicted. Chance level decoding performance was hence assessed on a plausible, rather than just some arbitrary input matrix.

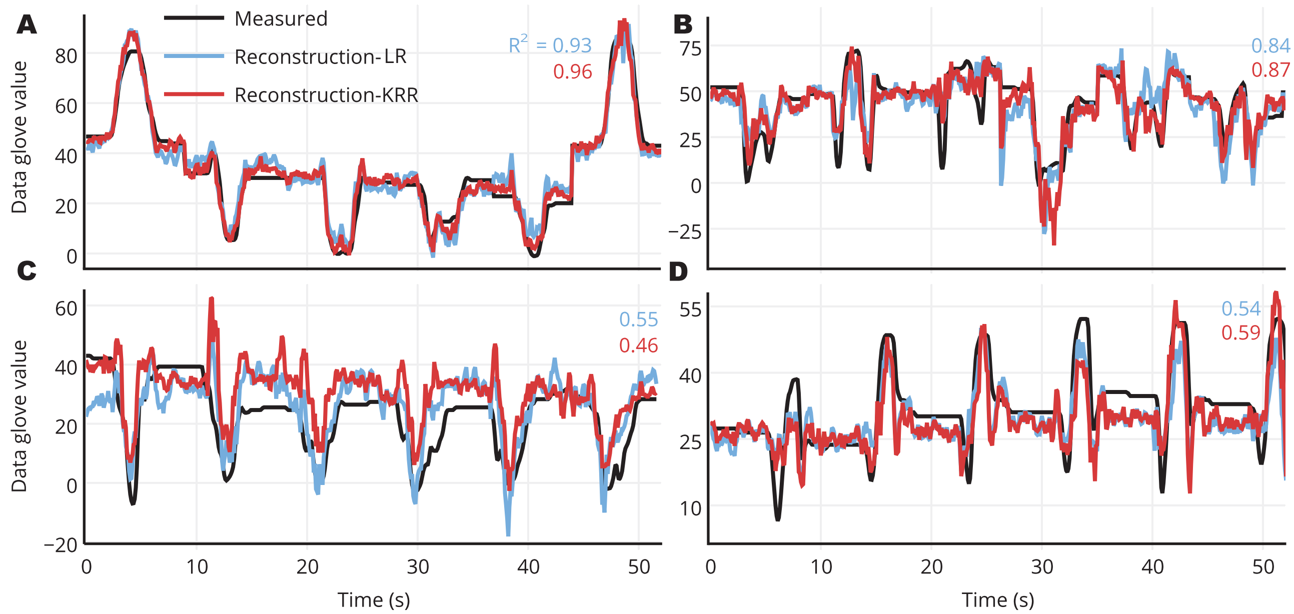

Fig. 1. Representative traces of finger movement reconstruction from surface electromyography (sEMG) and accelerometry. The measured activity of the closest to the index metacarpophalangeal joint glove sensor is plotted against the estimates with linear regression (LR) and kernel ridge regression (KRR). **(A)**, **(B)** Within-movement generalization for exercises 1 and 2. **(C)**, **(D)** Across-movement generalization for exercises 1 and 2.

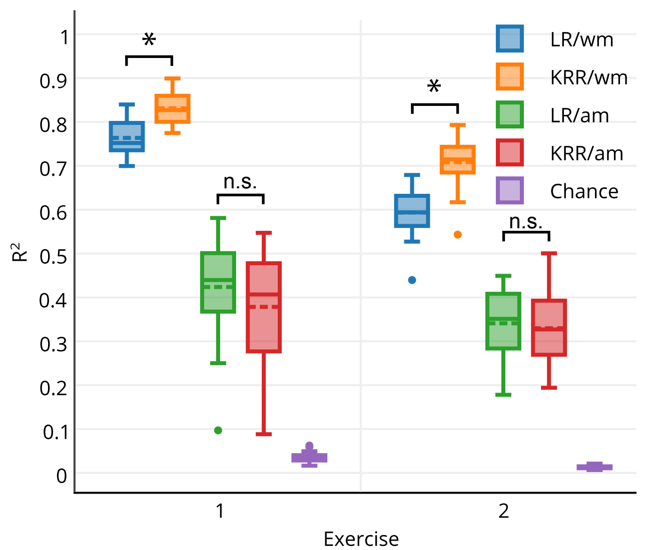

Fig. 2. Summary quartile plots of decoding performance (R^2). Straight lines, medians; dashed lines, means; solid boxes, interquartile ranges; whiskers, overall ranges of non-outlier data; circles indicate outliers. *LR*, linear regression, *KRR*; kernel ridge regression; *wm*, within-movement generalization; *am*, across-movement generalization. Results shown for 30 subjects and 22 glove sensors. Results averaged across cross-validation (CV) folds and glove sensors.

H. Statistical tests

A non-parametric analysis of variance (ANOVA) test, namely the Friedman test, was used to compare the performance of LR and KRR for within-, and across-movement generalization. Post-hoc pairwise comparisons were performed by using Wilcoxon rank sum tests and the Nemenyi correction for multiple comparisons. The significance level was set to $\alpha = 5 \times 10^{-2}$. Statistical tests were performed on across-fold computed averages for each subject, so that the sample independence assumption of the test was not violated.

III. RESULTS

The hyper-parameter values selected via CV (Section II-E) were $\lambda = 0.1$ for LR, and $\lambda = 10^{-4}$, $\sigma = 10$ for KRR. By using these parameter settings we were then able to reconstruct finger movement for 30 subjects. Representative traces of kinematics activity recorded with one of the data glove sensors are shown in Fig. 1 for the two exercises. Predictions with LR and KRR, both for within- (Fig. 1A,B), and across-movement (Fig. 1C,D) generalization are also shown in the same figure.

Summary decoding results for 22 DOFs and 30 subjects are presented in Fig. 2. As expected, a decrease in performance was observed for across-movement generalization. A Friedman test was performed to compare the decoding accuracy of LR and KRR. In all cases, decoding performance significantly outperformed chance level prediction (all p values smaller than 10^{-17}). For within-movement generalization, KRR significantly outperformed LR ($p < 10^{-3}$), and the improvement in performance was larger for the exercise 2. On the contrary, for across-movement generalization the performance of the two algorithms was comparable, with LR yielding marginally, however not significantly higher decoding accuracy. Finally, the performance of both algorithms was significantly higher in the case of within-movement generalization (both p-values smaller than 10^{-12}).

IV. DISCUSSION

In this paper, we used sEMG and accelerometry to achieve highly-accurate reconstruction of the movement of a large number of DOFs of the human hand. For within-movement generalization, the overall decoding performance was $R^2 = 0.70 \pm 0.04$ for LR, and $R^2 = 0.79 \pm 0.04$ for KRR, which is higher than $R^2 = 0.55$ reported by Smith et al. [7]. Comparison to other studies is more challenging, due to differences in electrode placement [8, 9].

The use of regression methods offers the potential advantage of generalizing to novel movements. To evaluate this hypothesis, we implemented a novel CV method and tested the performance of the decoding algorithms on movements not included in the training dataset. Although a decrease in decoding performance was observed (Fig. 2), finger trajectories were still tracked reasonably well (Fig. 1C,D).

A decoding accuracy comparison was performed for LR and KRR. Previous work has shown that the use of non-parametric methods, such as Gaussian Process regression, can improve decoding performance, especially in the case of limited availability of training data [9]. We argue, however, that any algorithmic comparison should be assessed on both within-, as well as across-movement generalization. In this study, we provide evidence that although a non-linear regression method can outperform linear regression during within-movement generalization, the performance of the two methods is comparable when generalizing to novel movements. From a clinical perspective, our results imply that the extra computational cost induced by the use of non-linear methods may not necessarily be associated with an increase in performance in real-life decoding situations.

For wrist movement reconstruction, Hahne et al. [6] found that when a non-linear sEMG feature was used, the performance of (generalized) LR and KRR was comparable, hence implying that any non-linearities in the mapping from sEMG to kinematics could be captured by the non-linear features. A direct comparison of their results to ours is not straightforward, since the notion of across-movement generalization cannot easily be transferred to the case of wrist movement decoding. Nevertheless, our findings reinforce the belief that under a given non-linear feature representation, the performance of LR and KRR is comparable.

Our study provides a benchmark for the reconstruction of finger movement from sEMG and accelerometry. Further verification of our results with amputee subjects and during online myoelectric control are required to evaluate the merit of our approach for clinical applications.

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