Towards Low-Dimensionsal Proportional Myoelectric Control

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Abstract— One way of enhancing the dexterity of powered myoelectric prostheses is via proportional and simultaneous control of multiple degrees-of-freedom (DOFs). Recently, it has been demonstrated that the reconstruction of finger movement is feasible by using features of the surface electromyogram (sEMG) signal. In such paradigms, the number of predictors and target variables is usually large, and strong correlations are present in both the input and output domains. Synergistic patterns in the sEMG space have been previously exploited to facilitate kinematics decoding. In this work, we propose a framework for simultaneous input-output dimensionality reduction based on the generalized eigenvalue problem formulation of multiple linear regression (MLR). We demonstrate that the proposed methodology outperforms simultaneous input-output dimensionality reduction based on principal component analysis (PCA), while the prediction accuracy of the full rank regression (FRR) method can be achieved by using only a few relevant dimensions.

I. INTRODUCTION

Upper-limb powered myoelectric prostheses aim at partially restoring the motor functionality and appearance of a missing limb by using surface electromyogram (sEMG) signals from the residual arm. Deployment of simultaneous and proportional control strategies for multiple degrees-of-freedom (DOFs) remains one of the major challenges for next-generation prosthetic systems [1].

Proportional control is exhibited by a prosthetic device when both input and output control signals are continuous variables [2]. Recently, many research studies have demonstrated the ability of reconstructing both wrist [3], [4], as well as finger movement trajectories [5]–[7], by using features of the sEMG signal.

It has been well-known in the motor control community that synergistic patterns can be observed in both muscle activations [8], [9], as well as hand postures [10], [11]. Intrinsic and abstract muscle synergies have been widely used for myoelectric control in the recent years [12]. In general, muscle synergies are extracted by using an unsupervised learning method and subsequently used to predict kinematic variables. For instance, Jiang et al. [3] used a muscle synergy model based on non-negative matrix factorization (NMF) to decode wrist kinematics during real-time experiments with amputee subjects.

On the other hand, synergistic postural patterns have also been used to reduce the dimensionality of the target variable, with the hope of reducing the computational burden and/or increasing prediction robustness. For instance, Vinjamuri et al. [13] extracted temporal velocity synergies of 10 metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints from 5 able-bodied subjects, and used them to build a bank of Gaussian filters which were subsequently used to control a virtual hand by using electrocorticography (ECoG) signals from an epileptic patient. Other studies have used both linear (i.e. principal component analysis (PCA)), as well as non-linear (i.e. unsupervised kernel regression, Gaussian process latent variable model), to reduce the dimensionality of the output signal for controlling robotic [14], prosthetic [15] and virtual hands [16], [17].

Decoding finger movement from sEMG signals usually involves dealing with high-dimensional signals in both the input and output domains. Nevertheless, simultaneous input-output dimensionality reduction has received less attention. Artemiadis and Kyriakopoulos [18] used a framework based on low-dimensional embeddings to control a robotic arm with sEMG signals. The dimensionality of both spaces was reduced from three to two, by using PCA. Hoffmann et al. [19] reviewed linear dimensionality reduction methods in the context of locally-weighted regression and found that top performance was achieved by methods that optimize the correlation between input and output projections, such as reduced rank regression (RRR) and partial least squares (PLS).

In the current study, we address the problem of simultaneous input-output dimensionality reduction in the context of decoding finger movement from sEMG and accelerometry (Acc). We adopt a generalized eigenvalue problem formulation of the multiple linear regression (MLR) model, which is closely related to RRR. The proposed methodology is shown to outperform simultaneous input-output PCA-based dimensionality reduction on a benchmark dataset.

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II. METHODS

A. NinaPro database

In this work, we used the second iteration of the publicly available Ninapro database [20], which comprises recordings from 40 able-bodied subjects during two exercises; isometric hand configurations (Exercise 1), and functional movements and grasping of common household objects (Exericse 2). Muscular activity was recorded using 12 state-of-the-art sEMG sensors enhanced with 3-axis accelerometers, and hand kinematics activity was recorded with a 22-sensor data glove. The sampling rate was set to 2 kHz for sEMG data, and to 25 Hz for Acc and glove data.

B. Signal preprocessing and feature extraction

Myoelectric signals were digitally band-pass filtered in the range [20, 500] Hz by using 4th order bidirectional Butterworth filters. Four sEMG filters were extracted from each channel, namely the mean absolute value (MAV), waveform length (WL), 4th order auto-regressive (AR) coefficients and log-variance (Log-Var). Feature extraction was performed by using 32-ms binning windows with 7-ms overlap ($\approx 22\%$). Accelerometry and glove data were also binned to match sEMG features. Following cross-validation (CV) split (Section II-C), all data were normalized in the range [0, 1], and finally mean subtracted.

C. Cross-validation

Paricipants performed six repetitions of each movement. The training set consisted of five out of six repetitions of all movements, and the decoding performance was evaluated on the left-out repetition.

D. Dimensionality reduction

The proposed methodology for simultaneous input-output dimensionality reduction is based on the generalized eigenproblem formulation of MLR. Let $\mathbf{X} \in \mathbb{R}^{n \times d}$ denote the design matrix where n and d are the number of observations and input dimensions respectively, and $\mathbf{Y} \in \mathbb{R}^{n \times p}$ denote the target matrix, where p is the output dimensionality. We denote $\mathbf{C_{xx}}$ the input covariance matrix, and $\mathbf{C_{xy}}$ the input-output covariance matrix. By definition, $\mathbf{C_{xy}} = \mathbf{C_{yx}^{\top}}$. It can be proved [21] that the MLR problem can be stated as follows:

$$\mathbf{A}\mathbf{v} = \lambda \mathbf{B}\mathbf{v}, \tag{1}$$

where

$$\mathbf{A} = \begin{pmatrix} \mathbf{0} & \mathbf{C_{xy}} \\ \mathbf{C_{yx}} & \mathbf{0} \end{pmatrix}, \mathbf{B} = \begin{pmatrix} \mathbf{C_{xx}} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}. \tag{2}$$

$\mathbf{A}$ and $\mathbf{B}$ are both symmetric matrices, and $\mathbf{B}$ is also positive-definite, as a block diagonal matrix whose diagonal items are all positive-definite matrices, therefore all eigenvalues are guaranteed to be real. $\mathbf{A}$ has a special form, it is hollow symmetric, that is a symmetric matrix with zero diagonal elements, hence the eigenvalues of (1) come in $\pm$ pairs.

For simultaneous dimensionality reduction, we propose the following approach; first we solve the generalized eigenvalue problem described by (1) by using the Cholesky decomposition of $\mathbf{C_{xx}}$, and order the eigenvalues in descending order. The cumulative sum of the positive eigenvalues is then computed and the largest m eigenvalues are chosen, such that $\sum_{i=1}^{m} \lambda_i \geq 0.99 \sum_{i=1}^{k/2} \lambda_i$, where λ_i are the positive eigenvalues of (1), and $k = d + p$. The corresonding eigenvectors $\mathbf{w_1}, \ldots \mathbf{w_m}$ are then selected and organized in a matrix $\mathbf{W} = \begin{pmatrix} \mathbf{w_1}, \ldots, \mathbf{w_m} \end{pmatrix} \in \mathbb{R}^{(d+p) \times m}$.

The transformed low-rank input is then obtained by $\mathbf{X}' = \mathbf{X}\mathbf{W_x}$, where $\mathbf{W_x}$ denotes the $d \times m$ matrix whose rows consist of the first d rows of $\mathbf{W}$. Accordingly, the transformed low-rank output is given by $\mathbf{Y}' = \mathbf{Y}\mathbf{W_y}$, where $\mathbf{W_y}$ is the $p \times m$ matrix whose rows consist of the last p rows of $\mathbf{W}$.

E. Decoding

In our experiments, dimensionality reduction was followed by regressing the transformed low-rank output matrix $\mathbf{Y}'$ on $\mathbf{X}'$ by using a Wiener filter approach [22]. The length of the linear filters was set to 500 ms.

F. Performance assessment

The quality of finger movement reconstruction was assessed by using the coefficient of determination (R^2), which is defined as the squared correlation coefficient between the measured and reconstructed data glove signals:

$$R^2 = \frac{\left(\sum_{j=1}^{N} (p_j - \bar{p})(\hat{p}_j - \bar{\hat{p}}) \right)^2}{\sum_{j=1}^{N} (p_j - \bar{p})^2 \sum_{j=1}^{N} (\hat{p}_j - \bar{\hat{p}})^2}, \tag{3}$$

where p_j and $\hat{p}_j$ denote measured and reconstructed data glove values for the jth sample of a CV-fold, $\bar{p}$ and $\bar{\hat{p}}$ denote their respective expected values over all the samples of the fold $j = 1, \ldots, N$, and p_{max}, p_{min} denote maximum and minimum values respectively of the measured data glove signal within each fold.

III. RESULTS

The original dimensionality of the sEMG signal was 84 (12 channels $\times$ 7 features/channel), while for Acc and glove data the same figure was 36 and 22 respectively. The dimensionality of the full rank regression (FRR) problem is defined by the sum of the individual dimensionalities, hence in our case it was equal to 142. To validate our hypothesis that all three types of signals were highly-redundant, we initially estimated the intrinsic dimensionality of these signals by using PCA. The intrinsic dimensionality estimates for sEMG, Acc and glove data are visualized in Fig. 1, along with the joint space dimensionality estimate of all three variables. Intrinsic dimensionalities were estimated by applying PCA to the variable of interest (sEMG, Acc, glove data or a concatenated vector of all the above), and keeping the largest m eigenvalues, such that 99% of the variance of the original signal was retained in the transformed space, in other words
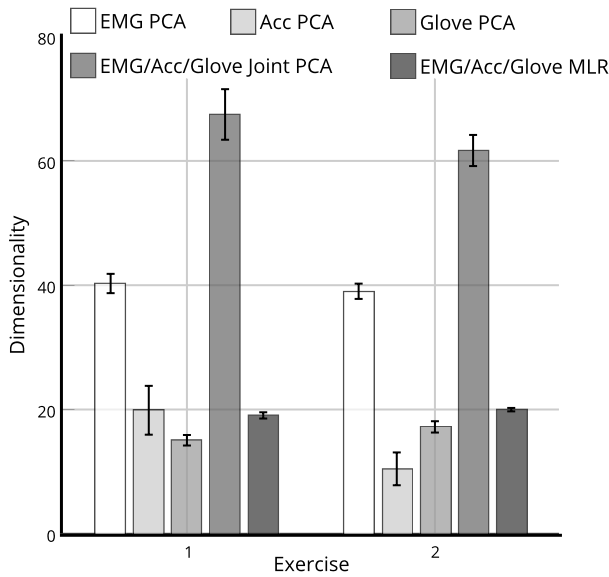
Fig. 1. Intrinsic dimensionality. The intrinsic dimensionality estimates for sEMG, Acc and glove data are presented. The joint dimensionality of all three variables is also shown by using PCA and MLR criteria (refer to main text for details). Error bars denote standard deviation across $n = 40$ subjects. Results averaged across CV folds.

$\sum_{i=1}^{m} \lambda_i \geq 0.99 \sum_{i=1}^{M} \lambda_i$, where λ_i are the eigenvalues of the covariance matrix, and M is the original dimensionality of the variable of interest.

The dimensionality of the three variables in an MLR sense (see Section II-D) is also shown in Fig. 1. It can be observed that the dimensionality of the regression problem (i.e. reconstructing glove data from sEMG and Acc) is considerably lower than the joint dimensionality of all three variables in a PCA sense. The results are presented separately for the two sets of exercises, however similar patterns can be observed in the two cases.

Next, we sought to evaluate the performance of the proposed methodology for low-rank regression and compare it to input-output PCA-based dimensionality reduction. We built finger movement decoders by varying the rank of the regression problem in the range $m = [1, 50]$ and used the performance of FRR as a benchmark. This analysis was repeated for the two sets of exercises, and the results are presented in Fig. 2.

Typical movement trajectories for the 2nd PIP joint are shown in Fig. 2a along with predictions with each of the three methods considered here; MLR, input-output PCA (denoted as "I/O PCA") and FRR. For MLR and I/O PCA, 19 projections were used both in the input and output domains. In Fig. 2b, the performance of the three methods is plotted against the number of selected dimensionality. It can be directly observed that the performance of the low-rank MLR method was superior to I/O PCA when the selected dimensionality was small. Low-rank MLR required on average 19 dimensions (i.e. projections) to achieve the performance level of the FRR method. On the other hand,

I/O PCA required on average 35 dimensions to achieve the same performance for Exercise 1, whereas for exercise 2 the decoding accuracy was inferior to FRR, even for $m = 50$.

IV. DISCUSSION

In this work, we propose the use of a low-rank regression approach based on the generalized eigenvalue problem formulation of MLR for the reconstruction (i.e. continuous decoding) of finger movement from sEMG and Acc signals. The proposed methodology is closely related to RRR. We evaluated the performance of the method on a benchmark myoelectric dataset, namely the Ninapro database [20], and compared its performance to FRR and input-output principal component regression (PCR).

The preliminary results reported in this paper suggest that the intrinsic dimensionality of the regression problem may be considerably smaller than both the dimensionality of the original problem, as well as the estimated joint input-output space intrinsic dimensionality estimated via PCA (Fig. 1). The experimental results further verified this assumption. On average, only 19 dimensions (out of the original 142) were required to account for 99% of the predictive power of sEMG and Acc for finger movement reconstruction (Fig. 2b). It is worth stressing that the proposed methodology does not induce the requirement for an extra layer of CV in order to select the optimal dimensionality, since this can be evaluated directly by using the approach introduced in Section II-D. Although in our experimental results we varied the number of selected dimensions to compare the performance of the three algorithms, our method correctly estimated in our preliminary analysis that the required dimensionality under an MLR criterion was indeed 19 on average (Fig. 1). It is also worth noting that this method performs dimensionality reduction in the input and output domains simultaneously, thus exploiting correlations in both spaces, whilst the objective function of the dimensionality reduction problem is the minimization of the target reconstruction squared error.

On the other hand, when PCA was employed for dimensionality reduction in the input and output domains individually, more dimensions were required to achieve the decoding performance enjoyed by FRR (Fig. 2b). This result was expected, since PCA-based dimensionality reduction in the input space is optimal with regards to the reconstruction of the variable itself, rather than its predictive power of another variable. Our results are in accordance with previous findings in the robotics literature [19].

This study is limited to off-line analysis with data from able-bodied subjects. Further verification of the proposed methodology with data collected from amputee subjects and during online myoelectric control is required, and currently seen as a future research direction.

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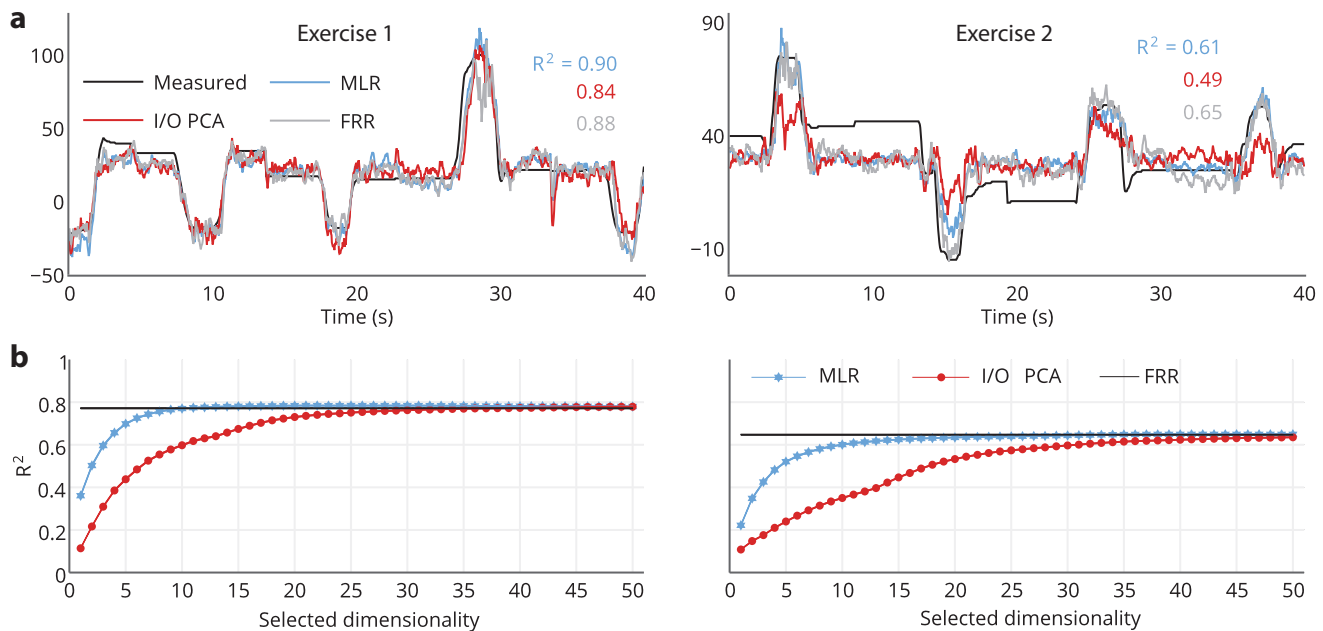
Fig. 2. Performance comparison of FRR, low-rank MLR and input-output PCA-based regression. **(a)** Typical movement trajectories for 2nd PIP joint are shown along with reconstructed activities with all three methods. For MLR and I/O PCA, 19 projections were used for the input and output variables. **(b)** The mean reconstruction accuracy of each method is plotted against the selected dimensionality. For FRR, a straight line is shown for comparison with other methods. Results averaged across data glove sensors, subjects and CV folds.

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