

## Dimensionality Reduction in EMG-Based Estimation of Wrist Kinematics

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### ABSTRACT

Pattern recognition has shown remarkable success in decoding motor information from electromyogram (EMG) signals. To decrease the computational complexity in EMG pattern recognition, it may be useful to reduce the dimensionality of the model input. This paper investigates the effect of reducing the dimensionality of EMG features in a regression-based motion intent estimation model. Ten able-bodied subjects participated in this analytic study. EMG signals from the right forearm and angle of the left wrist in three degrees of freedom (DoF) were measured, concurrently. The TD features were extracted from eight EMG channels, resulting in a total of 32 features. Three dimensionality reduction methods including principal component analysis (PCA), non-negative matrix factorization (NNMF), and canonical correlation analysis (CCA) were applied to the EMG features. Reducing the dimension of the EMG features below a certain threshold degraded the performance of the EMG pattern recognition model. Otherwise, dimensionality reduction did not change the performance. These thresholds for the PCA, NNMF, and CCA methods were 25, 26, and 13, respectively. Based on the results, CCA substantially outperformed PCA and NNMF, as it allowed a significant reduction of the EMG features size, from 32 to 13, with no adverse impact on the performance.

**Citation:** Ameri A. Dimensionality Reduction in EMG-Based Estimation of Wrist Kinematics. *J Biomed Phys Eng.* 2020;10(5):669-674. doi: 10.31661/jbpe.v0i0.2004-1105.

### Keywords

Electromyography; Dimensionality Reduction; Pattern Recognition; Wrist; Principal Component Analysis

### Introduction

Pattern recognition has proven to be a highly efficient approach for decoding motor intent from electromyogram (EMG) signals. The decoded motor intention can then be used to control a prosthesis, robot, or computer interface [1]. The process of translating the estimated motor intent to control signals is referred to as myoelectric control. Because of the stochastic characteristics of EMG signals, it is not possible to derive motion intent at each instant, from the corresponding instantaneous EMG values [1]. As a solution, a series of features extracted from EMG segments are leveraged to decode the motor intent [2]. EMG segments between 100 ms and 250 ms have been shown to provide the highest performance [2].

EMG Pattern recognition models are twofold; classification [3, 4] and regression [5-7] models. In classification systems, the training target is discrete motions, whereas, in regression models, the target is continuous motions along one or more joint axes i.e. degrees of freedom (DoF). Regression models target can be limb kinematics such as the joint angles in each DoF [5].

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Received: 18 April 2020  
Accepted: 25 May 2020

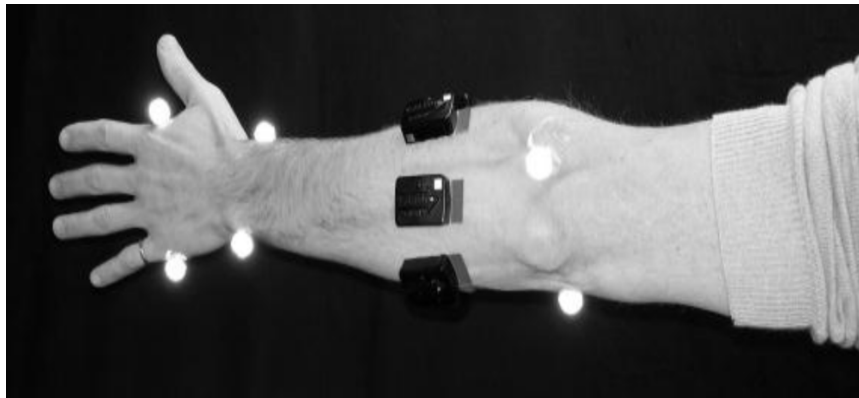
The most widely used EMG feature is a measure of the envelope of the signal such as mean absolute value (MAV), or root mean square (RMS). However, MAV or RMS alone is not sufficient for efficient EMG pattern recognition. To achieve higher performance, a series of other features are also extracted from EMG data. One of the most popular EMG feature sets is called the Time Domain (TD) set [8] and includes MAV, zero-crossings, waveform length, and slope sign changes. The TD set contains temporal and spectral characteristics of the EMG signals, and hence it can extract rich motor information from EMG data. Because several EMG channels are typically used in prostheses and computer interfaces, the total number of features is relatively high. Thus, dimensionality reduction may be leveraged to lower the number of model inputs and

hence decrease the complexity. In this work, three-dimensionality reduction techniques will be explored for EMG pattern recognition.

## Material and Methods

### Data Collection

Ten able-bodied individuals (ages: 24-39, all right-handed) took part in this analytic study. The experimental protocol was approved by the University ethics board. The subjects sat in a chair and their forearms were fixed to armrests with their palms facing inward in a resting position. Six reflective markers were placed on bony landmarks on the left upper limb as demonstrated in Figure 1. The position of the markers was recorded at 60 Hz by a Vicon 512 system with 8 infrared cameras. Eight EMG bipolar sensors (Delsys Inc.) were



**Figure 1:** Six reflective ball-shaped markers were placed on the left upper limb.

attached equally spaced around the right forearm, proximal to the elbow. The EMG signals were recorded at 1 kHz and were digitized by a 16 bit A/D converter. The Vicon and EMG systems were synchronized using a digital trigger.

The experiment involved dynamic wrist contractions in three DoFs of flexion-extension, abduction-adduction, and pronation-supination. The subjects were prompted to perform

motions with both left and right wrists in a mirrored fashion. Fourteen wrist motions including 6 single and 8 combined motions listed in Table 1 were elicited. Every trial lasted 24 s and comprised 4 repetition of the following cycle: 1 s of no-motion (resting position), 1 s of ramping up to a comfortable maximum motion angle in the corresponding DoF(s), 2 s of maintaining the maximum angle, 1 s of returning to no-motion, followed by 1 s of no-

**Table 1:** Fourteen trials corresponding to fourteen contractions listed below were conducted.

#	Contraction
1	Flexion
2	Extension
3	Abduction
4	Adduction
5	Pronation
6	Supination
7	Simultaneous Flexion and Pronation
8	Simultaneous Flexion and Supination
9	Simultaneous Extension and Pronation
10	Simultaneous Extension and Supination
11	Simultaneous Abduction and Pronation
12	Simultaneous Abduction and Supination
13	Simultaneous Adduction and Pronation
14	Simultaneous Adduction and Supination

motion.

### Data Processing

The wrist angle data at each of the three DoFs were calculated from the marker positions, and subsequently, were lowpass filtered at 1 Hz using a third-order Butterworth filter to match the frequency content of the wrist motion. The EMG data were bandpass filtered between 10-450 Hz by a third-order Butterworth filter. The EMG data were segmented into 200 ms windows with 50 ms increments. The TD feature set was extracted from EMG windows. For each segment, the average wrist angle at each DoF was set as the corresponding wrist angle. To map the EMG features to the wrist angle at each DoF, a separate multilayer perceptron (MLP) regressor was trained for every subject and DoF. A 4-fold cross-validation was employed where 3 repetitions in each trial

were included in the training set and the remaining repetition was included in the test set. The estimated angles by the MLPs were low-pass filtered at 1 Hz to match the spectral content of the measured angles. The coefficient of determination ( $R^2$ ) was employed to estimate the estimation accuracy of the MLP, at each DoF as in Eq 1.

$$R_k^2 = 1 - \frac{\sum_{t=0}^N (\widehat{f_k(t)} - f_k(t))^2}{\sum_{t=0}^N (f_k(t) - \overline{f_k(t)})^2} \quad (1)$$

Where  $\widehat{f_k(t)}$  and  $f_k(t)$  are the estimated and measured angle at  $k^{th}$  DoF, respectively.  $\overline{f_k(t)}$  is the mean of  $f_k(t)$  across all samples, and  $N$  is the total number of samples.  $R_k^2$  is the coefficient of determination for the  $k^{th}$  DoF. By averaging  $R_k^2$  across all three DoFs, the overall coefficient of determination ( $R^2$ ) is obtained.

A total of 32 features were extracted with 4 features from each of the 8 EMG channels. To reduce the complexity, three-dimensionality reduction methods were investigated to reduce the size of the features, including principal component analysis (PCA), non-negative matrix factorization (NNMF), and canonical correlation analysis (CCA).

#### A. PCA

PCA is a linear transformation that converts a set of possibly correlated variables to a set of uncorrelated variables called principal components. The principal components are sorted in order of decreasing variance. Hence, the first principal component has the largest variance and accounts for most of the variability in the data. The principal components (S) are computed as described in Eq 2.

$$S = W \times X \quad (2)$$

Where  $X$  is an  $m \times n$  data matrix ( $m$  is the number of features and  $n$  is the number of samples).  $W$  is an  $m \times m$  matrix that contains

the eigenvectors of the covariance matrix of the centered  $X$ . These eigenvectors are sorted in a descending order of the corresponding eigenvalues. For dimensionality reduction to size  $k$ , the first  $k$  rows of  $S$  is maintained.

### B. NNMF

NNMF is an algorithm that approximates a nonnegative matrix as the product of two non-negative matrices. Assuming  $X$  is an  $m \times n$  matrix of data, where  $m$  is the number of features and  $n$  is the number of samples, NNMF decomposes  $X$  into two nonnegative matrices of  $W$  and  $H$  (Eq 2), where the size of  $W$  is  $m \times k$ , and  $H$  is  $k \times n$ . For dimensionality reduction to size  $k$ ,  $k$  must be selected smaller than  $m$ .  $H$  is the reduced dimension matrix of data.

$$X \approx W \times H \quad (3)$$

### C. CCA

Similar to PCA, CCA decomposes a set of variables into an uncorrelated set of variables. However, the difference with PCA is that CCA decomposes data in a way that within each component (new feature), there is a maximum

temporal correlation between a sample and a linear combination of a neighboring (but not overlapping) region [9].

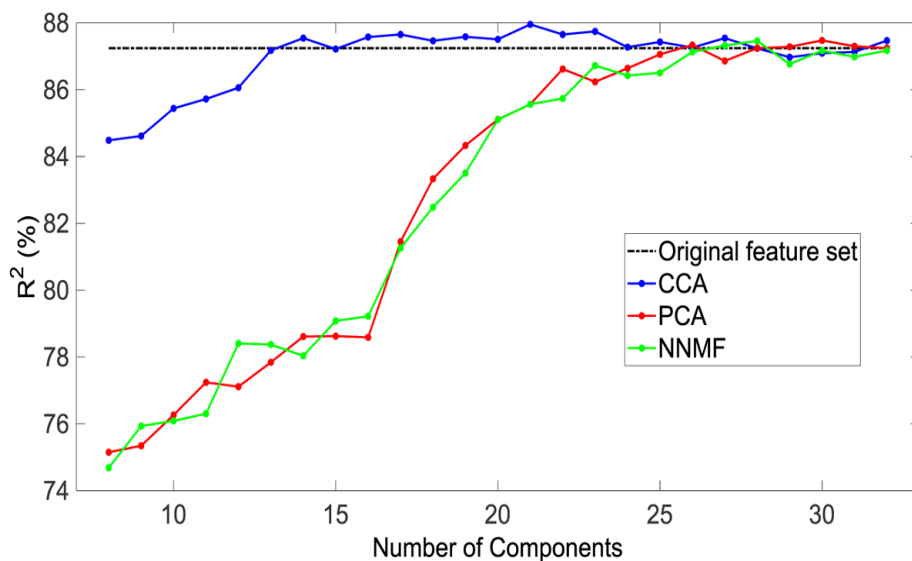
## Results

Figure 2 illustrates the overall wrist angle estimation accuracy ( $R^2$ ), for each dimensionality reduction method, averaged across all subjects, against the number of components (new features), i.e. the input size of the MLPs. Furthermore,  $R^2$  with original feature set (32 TD features) is plotted for comparison.

Paired samples t-tests indicated that in comparison with  $R^2$  of the original feature set, dimensionality reduction did not change ( $p > 0.05$ ) the  $R^2$  when the number of components was equal or greater than 25, 26, and 13, for PCA, NNMF, and CCA, respectively. Otherwise, dimensionality reduction resulted in a lower estimation accuracy ( $p < 0.05$ ) of the wrist angle.

## Discussion

This study investigated three dimensionality



**Figure 2:** The overall wrist angle estimation accuracy ( $R^2$ ) averaged across all subjects, are plotted against the reduced size, for each dimensionality reduction method. The performance without dimensionality reduction is also plotted for comparison.

reduction techniques to lower the dimensionality of the EMG feature set and hence reduce the complexity of the pattern recognition model. Dimensionality reduction projects features to a new feature space where the information within data can be described with fewer features. This can lower the computational cost of pattern recognition because reducing the input size decreases the complexity of the classification or regression model. Based on the results, with CCA, only 13 features were needed to achieve a performance similar to that of the original 32 features. This indicates the high efficiency of CCA in projecting features to a new optimal feature space. However, the PCA and NNMF feature projection was not as effective, as they required 25 and 26 features, respectively to describe the EMG information. Moreover, no performance improvement was observed using dimensionality reduction, which suggests that the MLPs did not suffer over fitting with the original feature set. The lower computational complexity of the MLPs, as a result of the CCA dimensionality reduction, can significantly reduce the estimation time of the MLPs which is important in real-time use such as in prosthetic control.

The effective estimation accuracy of the wrist angles from the EMG of the opposite forearm in this study supports the results of previous work [10] that found a high correlation between the left and right upper limbs during mirrored contractions. This approach is, therefore, suitable to train myoelectric prostheses for unilateral amputees by eliciting mirrored contractions of the phantom and intact limbs, where the position of the intact limb is used as the training target. Nevertheless, the disadvantage of this approach is that it cannot be used with bilateral amputees. In these cases, a visual training paradigm can be employed as described in [7].

## Conclusion

Three dimensionality reduction methods including PCA, NNMF, and CCA were investi-

gated for reducing the EMG features size for pattern recognition. The results revealed that CCA substantially outperformed PCA and NNMF in reducing the size of the feature set without affecting the pattern recognition performance. CCA efficiently projected the EMG features to a new space where the feature size reduced from 32 to 13 without losing motor information. Therefore, CCA allows for less computationally complex EMG pattern recognition models.

## Conflict of Interest

None

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