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Muscle Synergy-based Grasp Classification for Robotic Hand Prosthetics

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Abstract

The main goal of this study is analyzing whether muscle synergies based on surface electromyography (EMG) measurements could be used for hand posture classification in the context of robotic prosthetic control. Target grasps were selected according to usefulness in daily activities. Additionally, due to the feasibility constraints of robotic prosthetics, only 14 gestures (13 feasible grasps and 1 resting state) were analyzed. EMG signals of intact-limb subjects were decomposed into base and activation components for muscle activity evaluation. The results demonstrate that features based on muscle synergies derived from non-negative matrix factorization (NMF) outperform the ones derived from principal component analysis (PCA). Moreover, we also examine the robustness of these methods in the absence of electrodes (muscle importance) and show that NMF is able to provide sufficiently accurate results.

Keywords

EMG; Grasp classification; NMF; PCA; SVM; Muscle synergy; Prosthetic hand control

1. INTRODUCTION

Human-machine interface (HMI) can be defined as utilization of biological signals to control robotic devices and provide another channel for communication. Understanding of biological signals such as electromyogram (EMG), electroencephalogram (EEG) and increasing availability of signal acquisition devices give hope for many patients who suffer from partial or entire limb loss [15]. In this context, biological signal-based prosthetic limb control studies is of special interest.

EMG has shown promise as a powerful physiological signal for hand gesture classification both in research applications [6, 10] and commercially available prosthetics [1]. In addition, novel techniques and studies are available for more efficient utilization of these devices. For instance, [3] reveals that performance of both intact-limb and amputee people are quite satisfactory when their EMG signals collected only from six channels while they were performing individual finger movements.

There is no voluntary movement that can produced by only one muscle and all motor actions are controlled by a bunch of muscle groups which are activated simultaneously at different levels. Thus, one of the hypothesis on behavior of central nervous system (CNS) is that muscle synergies are instruments of CNS for controlling large number of muscles through small number of control signals [4]. In other words, it is possible to find another basis to represent EMG data of which elements are activated distinctively for performing different voluntary movements. Most of the synergy based approaches employ linearity assumption which means representation of EMG data by multiplication of base and activation matrices and decompose EMG data into its components by well-known techniques such as principal component analysis (PCA), independent component analysis (ICA) and probabilistic ICA (pICA) [11, 13].

The idea of matrix factorization under non-negativity constraints has been initially proposed in [9] to represent faces as additive combinations of different parts for face recognition studies. Non-negative matrix factorization (NMF) provides a low-rank representation of the data similarly for PCA and ICA; whereas, NMF inherently does not let subtractive components. Since all recorded muscular activations are positive-valued and NMF does not restrict the orthogonal representation of the data, it fits better to physiological structure of muscle than other decomposition techniques [2]. Lately, many muscle synergy-based EMG analysis studies are presented which mostly factorize the data by NMF. For example, in [2] it is shown that only 11 of 33 American Sign Language alphabet postures are enough to provide a synergy framework in order to predict the all postures with 90% accuracy. Moreover, 10 finger movements (5 simple and 5 complex) are classified by artificial neural network (ANN) where the NMF features extracted from 2 channel EMG data are utilized in [12].

In this study, we first investigate the effect of two primary myoelectric activity decomposition techniques on classification performances to discriminate 13 grasp types and a resting state: NMF and PCA. Only six bipolar channels are used in this study for classification and quite satisfactory accuracies are presented for the 14-class classification problem. Moreover, instead of focusing on individual finger movements, we aim to classify grasp types which can be more applicable in real world scenarios. Secondly, we provide an analysis about the behavior of these methods under missing channel/muscle scenarios. We demonstrate that muscle synergies extracted by NMF are better for representing the activation of different muscles even with less channels. Additionally, the results of this study claims that NMF provide better results for understanding the intention of patients with amputation because they are unable to provide EMG from most of the beneficial muscles.

The rest of the paper is organized as follows. In Sec. 2, subject properties, data collection, experimental setup, signal processing and classification techniques which are applied to the recorded data are presented in detail; whereas, the results are reported in Sec 3. The paper is concluded with aimed future work in Sec. 4.

2. METHODOLOGY

2.1 Data Acquisition and Experimental Setup

Experimental data were collected from 7 healthy (6 male, 1 female; mean age: 25.38 ± 1.92 years) and each subject participate in the experiment two times. Only 1 male subject was left-handed and only dominant hands were used for data collection. None of the subjects had any known motor or psychological disorders. Before the experiments, experimental procedure was explained to all participants and their informed consent were taken.

EMG data were collected using a g.USBamp biosignal amplifier from 6 bipolar electrodes and electrodes were located on extensor digitorum, flexor carpi ulnaris, flexor digitorum superficialis, extensor carpi ulnaris, brachioradialis and pronator teres muscle groups. The muscle locations were found by palpation when the subject contract the related muscle while performing a basic arm movements [cite book]. A schematic representation of electrodes are given in Figure 1. Electrodes were attached using double-sided disk shaped duct tapes and conductive gel is applied for decreasing skin resistance. The sampling rate of the EMG signals was 1200 Hz. A butterworth bandpass filter [10 – 500 Hz] of order 9 and a 60 Hz notch filter was applied during acquisition.

Subjects were seated a chair and the electrodes were connected to right arm while left arm is at rest. The dominant arm was supported from the elbow and the orientation of the arm was not restricted. Subjects were instructed to perform 13 different grasp gestures (i.e., large diameter, small diameter, medium wrap, ring, distal, tip pinch, precision disk, precision sphere, fixed hook, palmar, lateral, lateral tripod and writing tripod) and open palm position as the rest class. The human grasp is analyzed in [8] and grouped to 33 classes. Although a human hand can perform all these grasp types thanks to the high articulation of human body, the degrees of freedom of current robotic hands is not enough to perform all these movements. We have constrained the classification task to 14 classes by choosing grasps that can be useful to perform day to day tasks and that are feasible for our robotic hand prototype. Subjects performed and held each gesture for 6 times with each trial lasting for 8 seconds. Before a trial, an image illustrating the gesture was shown to subject. The subject was allowed to rest between trials. The order of gestures was randomized so that fatigue effect does not affect the classification results. Each subject performed two consecutive sessions.

2.2 Feature Extraction and Classification

The underlying assumption behind muscle synergies is that of co-activation of muscles (i.e. when performing a motor task), muscles are active jointly; moreover, motor tasks can be represented by a set of weights that modulate these muscle synergies. Let $w_k(n)$ be the k-th time varying control signal that corresponds to a particular hand posture.

$$\mathbf{w}(n) = \begin{pmatrix} w_1(n) \\ w_2(n) \\ \vdots \\ w_K(n) \end{pmatrix} \quad (1)$$

where K is the number of synergies that will be used. We define the muscle activation signals as $\mathbf{a}(n)$ for $1 \le m \le M$ muscles being targeted. Then, we can express $\mathbf{a}(n)$ as a linear combination of $\mathbf{w}_K(n)$'s with the coefficients set by the "synergy" matrix **S**:

$$\mathbf{a}(n) = \mathbf{S}\mathbf{w}(n) \quad (2)$$

with columns of S denoting the contribution of the corresponding synergy to all muscles. Notice that if we assume these matrices to be non-negative, then the synergy basis corresponds to a parts-based representation (no muscle inhibition possible) [14]. Given some measurements $0 \le n \le N - 1$, we would like to find and **S** and **W** such that:

$$\mathbf{A{=}SW} \quad (3)$$

$$= \begin{pmatrix} | & | & & | \\ \mathrm{s}_1 & \mathrm{s}_2 & \cdots & \mathrm{s}_K \\ | & | & & | \end{pmatrix} \begin{pmatrix} - & w_1(n) & - \\ - & w_2(n) & - \\ & \vdots & \\ - & w_K(n) & - \end{pmatrix} \quad (4)$$

assuming we can measure this muscle signal directly in a noiseless fashion. We can use EMG signals to measure muscle activations. Under constant-force, constant-angle, non-fatiguing contractions, EMG signals can be modelled with Gaussian distributions [7] and maximum likelihood estimates of the EMG amplitude (corresponding to muscle activation) is accomplished by root-mean-square (RMS). Moreover, mean-absolute-variation (MAV) is also very common processing technique due to its simpler analog hardware implementations and low computational requirements. Additionally, it is shown that MAV has slightly higher signal-to-noise-ratio than RMS. Then, we would like to find $\widehat{\mathbf{W}}$ and $\widehat{\mathbf{S}}$ that solve:

$$\begin{aligned} & \underset{W,S}{\mathit{minimize}} \quad \frac{1}{2}\left\| \tilde{A} - \mathbf{SW} \right\|_F^2 \\ & \text{subject to} \quad W \ge 0 \text{ and } S \ge 0 \end{aligned} \quad (5)$$

where the columns of $\tilde{A}$ correspond to $\mathbf{a}(n)$, the channel-wise muscle activation estimated from EMG. The non-negative contraints are needed to enforce the parts-based representation. This optimization problem can be solved using the multiplicative update algorithm from [9]. Since RMS isa better representation and MAV has better signal power than noise, this study investigates the both features and provides an comparison of two processors for the given problem on NMF. Additionally, we use PCA as a baseline for synergy extraction, relaxing the composition by parts assumption. Even though PCA does not enforce non-negativity constraints, it restricts the base functions to be orthogonal. In particular, synergy and activation matrices attained by PCA involve negative components that can model inhibitory behavior.

The recorded EMG data was transformed to bipolar measurements along the targeted muscles. Since the gestures were held during a trial, theoretically, contractions of all muscles were constant. In other words, the muscle synergy weights are assumed to be relatively clustered with small blocks of data tending to demonstrate similar characteristics. For this reason, MAV and RMS statistics were computed in 250 ms blocks with 100 ms spacing between blocks. The NMF algorithm inherently starts from a random initialization and provides the factorization minimizing the error function at each iteration. However, this may cause different factorizations due to the initialization and the optimization problem may stack at local minimum points. Thus, we first initialized the factorization matrices for 100 times, found the best initialization, and factorized the data based on this starting point. The columns of W, that correspond to hand postures in the synergy basis were used to train a SVM classifier with Gaussian kernel. We used 10 fold cross validation to assess the performance of the classifier. Since NMF is only applied on the training set, the corresponding synergy weight vector $\widehat{\mathbf{W}}$ for test data was found through non-negative least squares [5]:

$$\begin{aligned} &\underset{w}{\mathit{minimize}} \quad \frac{1}{2}\left\|\tilde{\mathbf{a}}-\mathbf{S}\mathbf{w}\right\|_2^2 \\ &\text{subject to} \quad w \geq 0 \end{aligned} \qquad (6)$$

where $\tilde{\mathbf{a}}$ is the estimate muscle activation amplitude from EMG in the test set and S is the learned synergy matrix. We compared classification results when 6, 5, and 4 synergies are used. Additionally, we explored the effect of removing individual muscles from classification and evaluated the robustness of the feature extraction methodologies.

3. RESULTS

Since selecting the number of synergies (K) as equal or less than the number of channels in NMF studies is very common, the NMF results are evaluated for 3 different sized synergy matrices by selecting the size of S as 6×6, 6×5 and 6×4. Because of the monotonically increasing structure of the performance values, smaller number of synergies are not included in this study. Two session performances of all subjects are evaluated separately and the averaged classification results of all subjects for different sized S matrices are given in Figure 2.

Despite the fact that classification results for all subjects are much higher than chance level for this 14-class problem, one can state that RMS features outperforms the MAV features for almost all of the subjects. Moreover, the results in Figure 2 demonstrates that if synergy size equals to the channel size, classification performances are quite satisfactory. However, the number of channels would be one of the most important reason for worse accuracies of low-rank synergy representations. Since our recordings do not target all the muscles in the forearm, the number of synergies must equal the number of channels. Sudden drop of classification performances with lower number of synergies supports this conclusion. Although the implementation of NMF with more channels would provide more concrete evidence, one can expect that even with more channels 6 synergies may represent the data well. Additionally, all subjects are able to perform the experiment with more than 90% accuracies for RMS feature with the exception of subject 3.

For PCA performance analysis, all possible number of components are evaluated. Maximum number of component size is 6 because of the number of channels and minimum is 2 (reducing data to a single dimension severely hurts performance). Similar to NMF, two different features are assessed as different classification problems and accuracies of all subjects are given in Figure 3.

Unlike NMF, the number of components in PCA does not affect the accuracies significantly. For most of the subjects, there is not considerable difference between 6 and 5 number of components. RMS features are able to provide better classification performances than MAV. Since the same pattern is also observed in NMF results, we can state that RMS features are more distinctive for our problem for almost all subjects. Although all subjects provide much higher classification accuracies than chance level, PCA results are not as high as NMF for any number of components.

This study also claims that NMF is a better approach for deficient electrode case. Because amputees may not provide all channels depending on their amputation level, we also examine the best decomposition technique under this circumstance. At each step, one bipolar electrode is eliminated and performances of all subjects are averaged for both MAV and RMS features in order to demonstrate missing electrode results. Figure 4 demonstrates the robustness of two algorithms to electrode extraction when maximum performance criteria is applied for synergy size selection.

From Figure 4, we claim that NMF is perceptibly more robust to the electrode elimination problem for both features without considering the electrode selection. Additionally, MAV and RMS features provide almost the same classification accuracies for PCA technique, whereas, RMS results with NMF are considerable better than MAV’s. Both algorithms are more sensitive to flexor digitorum superficialis and pronator teres muscle removal than the other channels. Since both muscles are located more proximally in the forearm, results of this study are beneficial and implementable for real world robotic prosthesis applications.

4. CONCLUSIONS

This study demonstrated that muscle synergy representation with NMF outperforms PCA in the task of classifying hand postures (14 grasps). The experimental data set was collected from 7 intact-limb subjects with 6 bipolar channels. We also showed that RMS is a more discriminative feature than MAV for our problem which implies that Gaussian distribution fits better to our model than Laplacian distribution [7]. Additionally, we investigate the problem of missing electrodes and evaluated the classification performance. Even though the contribution of two muscles (flexor digitorum superficialis and pronator teres) which are close to elbow are slightly higher to the classification accuracies, the experimental results indicate that NMF is more robust to missing electrodes. For future research, we plan to analyze the relationship between intersubject muscle synergies and extending the synergy decomposition to account for temporal dependencies.

ACKNOWLEDGEMENTS

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6. REFERENCES

[1]. Steeper RSL, BeBionic3. http://bebionic.com/. Accessed: 2017-03-21.

[2]. Ajiboye AB and Weir R. Muscle synergies as a predictive framework for the emg patterns of new hand postures. Journal of Neural Engineering, 6(3):036004, 2009. [PubMed: 19436081]

[3]. Al-Timemy AH, Bugmann G, Escudero J, and Outram N. Classification of finger movements for the dexterous hand prosthesis control with surface electromyography. IEEE J. Biomed. Health Inform, 17(3):608–618, 2013. [PubMed: 24592463]

[4]. Bizzi E, Cheung V, d'Avella A, Saltiel P, and Tresch M. Combining modules for movement. Brain Research Reviews, 57(1):125–133, 2008. [PubMed: 18029291]

[5]. Bro R and De Jong S. A fast non-negativity constrained least squares algorithm. Journal of Chemometrics, 11(5):393–401, 1997.

[6]. Cipriani C, Controzzi M, and Carrozza MC. The smarthand transradial prosthesis. JNER, 8(1):29, 2011. [PubMed: 21600048]

[7]. Clancy EA and Hogan N. Probability density of the surface electromyogram and its relation to amplitude detectors. IEEE Trans. Biomed. Eng, 46(6):730–739, 1999. [PubMed: 10356879]

[8]. Feix T, Romero J, Schmiedmayer H-B, Dollar AM, and Kragic D. The grasp taxonomy of human grasp types. IEEE Trans. HumanâĂ ŞMach. Syst, 46(1):66–77, 2016.

[9]. Lee DD and Seung HS. Learning the parts of objects by non-negative matrix factorization. Nature, 401(6755):788–791, 1999. [PubMed: 10548103]

[10]. Light C and Chappell P. Development of a lightweight and adaptable multiple-axis hand prosthesis. Medical Engineering & Physics, 22(10):679–684, 2000. [PubMed: 11334753]

[11]. Matrone GC, Cipriani C, Carrozza MC, and Magenes G. Real-time myoelectric control of a multi-fingered hand prosthesis using principal components analysis. JNER, 9(1):40, 2012. [PubMed: 22703711]

[12]. Naik GR and Nguyen HT. Nonnegative matrix factorization for the identification of emg finger movements: evaluation using matrix analysis. IEEE J. Biomed. Health Inform, 19(2):478–485, 2015. [PubMed: 25486650]

[13]. Rasool G, Iqbal K, Bouaynaya N, and White G. Real-time task discrimination for myoelectric control employing task-specific muscle synergies. IEEE Trans. Neural Syst. Rehabil. Eng, 24(1): 98–108, 2016. [PubMed: 25769166]

[14]. Ting LH and Chvatal SA. Decomposing muscle activity in motor tasks Motor Control Theories, Experiments and Applications. Oxf. Univ. Press, New York, pages 102v–138, 2010.

[15]. Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, and Vaughan TM. Brain–computer interfaces for communication and control. Clinical Neurophysiology, 113(6):767–791, 2002. [PubMed: 12048038]

CCS Concepts

•**Human-centered computing → HCI theory, concepts and models;** *Human computer interaction (HCI);* Empirical studies in HCI;

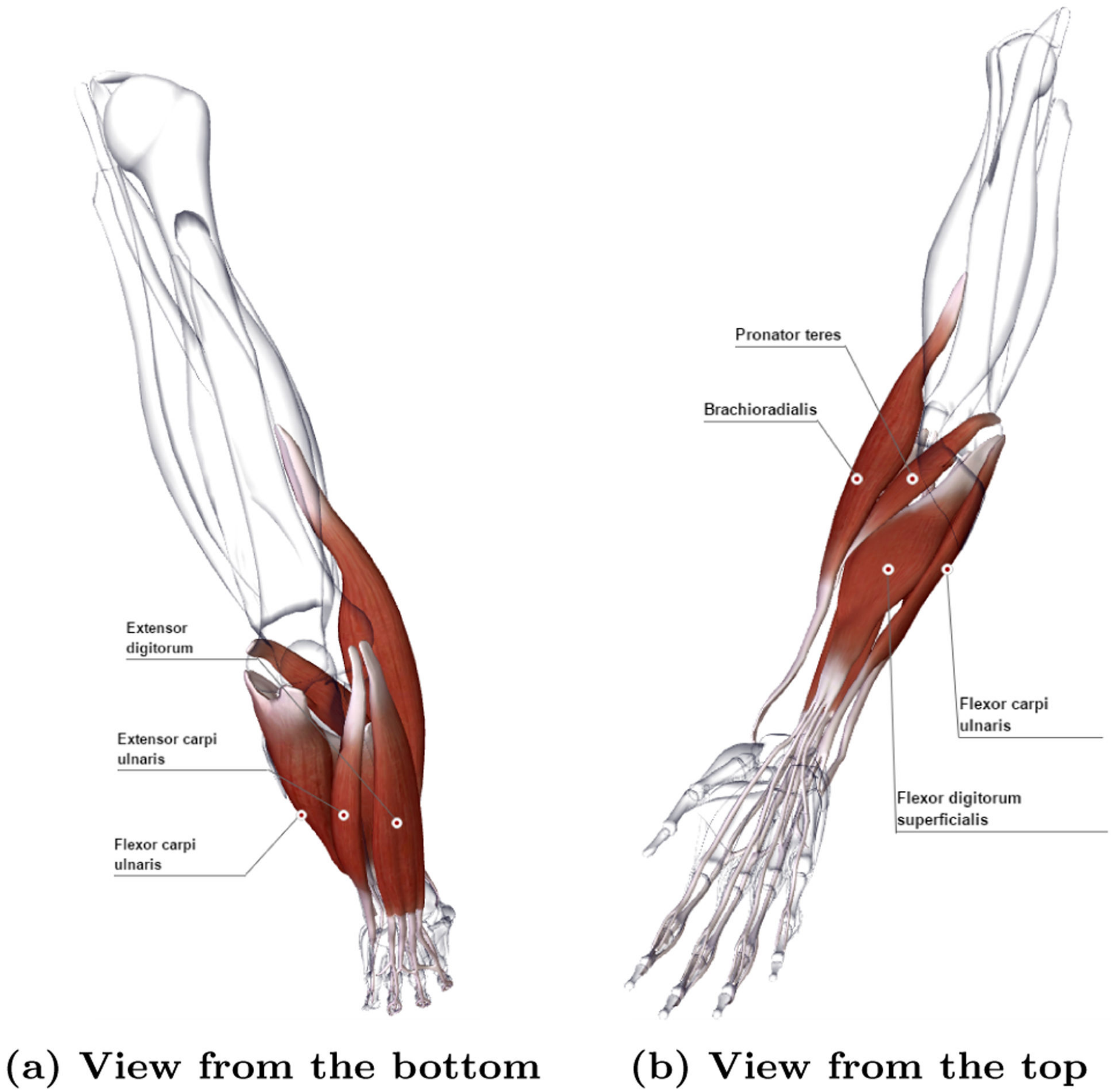


Figure 1:
Diagram of muscles targeted during experiment.

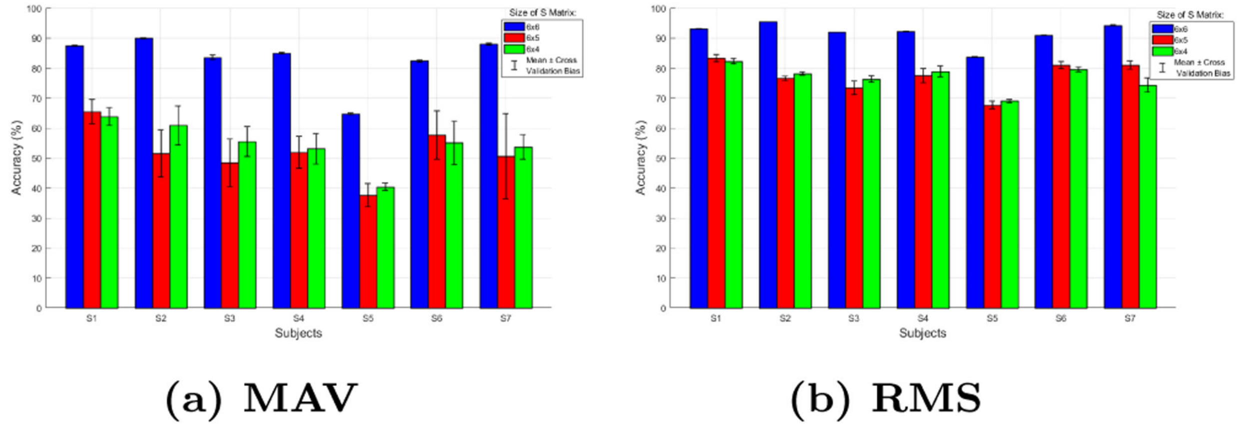
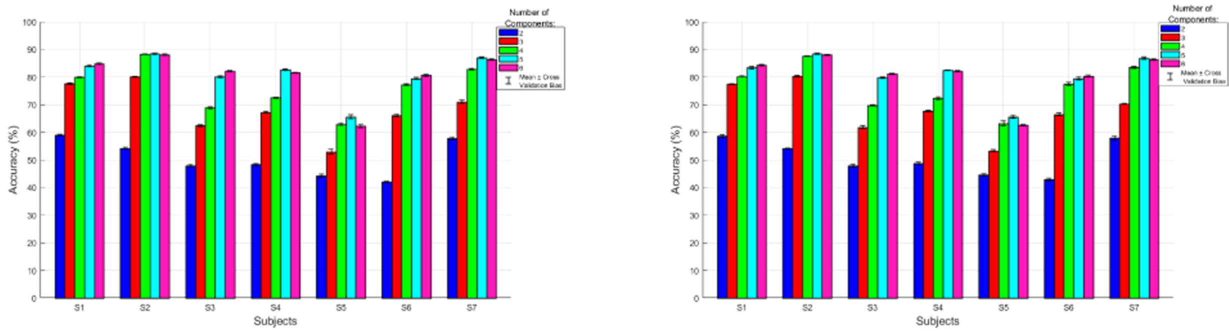


Figure 2:
NMF Results.



(a) MAV

(b) RMS

Figure 3:

PCA Results.

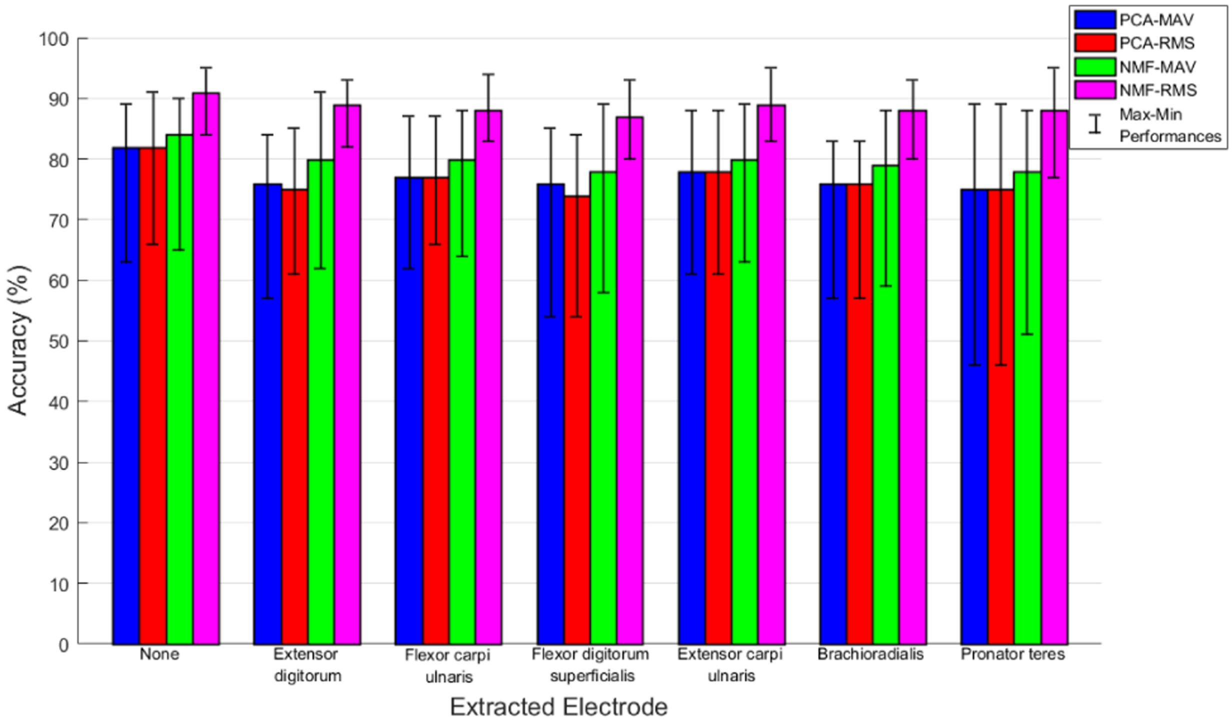


Figure 4:
Comparison of NMF and PCA Performances with Extracted Electrodes for MAV and RMS Features.