Identifying Hand Gestures through Myographic Signals via ANN

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Abstract

In this paper we develop a series of artificial neural networks (ANNs) for predicting hand gestures through nerve impulses detected by sensors placed on the forearms of a series of test subjects. We then compare these ANNs based on their accuracy, the time it takes to fit the models, and their overall complexity with the ultimate goal of determining the best model for use in the next generation of automated prosthetics. Dimension reduction techniques are also used in the modeling process with models fitted using a subset of the principal components compared to their higher dimension counterparts.

1 Introduction

In recent decades, advances in surface electromyographic signals (sEMG) recording systems have allowed researchers to determine the distinct groups of muscles involved in certain movements. [1], [2] Patterns found in these recordings have further enabled the classification of certain movements distinct movements, which have led to the development and use sEMG-based human-machine interfaces. Recent advances in sEMG analytics methods have encouraged the use of these type of muscular signals in human-machine interfaces used to control exoskeletons and protheses; however, challenges remain.[3] [4] [5]

These challenges are related the accuracy of motion recognition that different pattern classification methods can achieve, which tends to be highly variable. Although classification has mostly done via linear discriminant analysis (LDA), other methods that are commonly used in the field are support vector machines (SVMs) and Artificial Neural Networks (ANN). [6] [7] Overall, these methods have shown to have a high accuracy of simple body movements. However, given user movements are highly variable the accuracy greatly varies and can be suboptimal. Additionally, there is inherent noise of sEMG recording systems and user-specific anatomical characteristics that need to be considered. [8] In turn, these factors lead to downstream problems when attempting to convert these classifications into spatial directions (e.g. up, down, right, and left). Therefore, these challenges have greatly limited the deployment of human-machine interface systems for wider commercial use.

[1] **?**
[2] **?**
[3] Sergey Lobov & Makarov (2018)
[4] **?**
[5] **?**
[6] **?**
[7] **?**
[8] **?**

In this paper, we aim to address the former challenge of accuracy via ANN. Our goal is to design and implement a light-weight supervised learning model via a multi-layered neural network to accurately identify six distinct hand gestures from Lobov *et al* sEMG data. footnoteSergey Lobov & Makarov (2018) Our approach focuses on first determining the most relevant principal components from this multi-channeled dataset, and then assess the performance of multi-layered neural networks based on their accuracy vs computational time..

2 Methods

2.1 Workflow Overview

For this project our workflow was comprised of 4 main phases: preprocessing, dimension reduction via PCA, modeling, and performance comparison as shown in Figure 1 below.

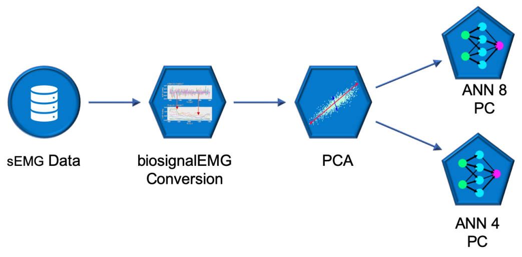
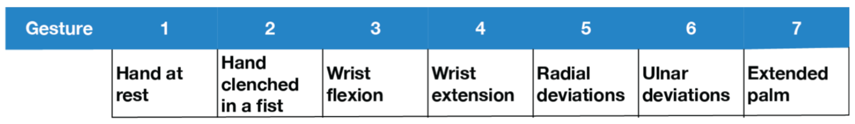


Figure 1: Schematic of overall workflow stages: preprocessing, PCA, modeling and performance comparison

2.2 sEMG Data

Raw sEMG signal data from 36 individuals was obtained online from Lobov et al [9]. Two series were recorded per individual, each comprised of signals obtained via 8 equally spaced sensors around the forearm (i.e. channels). For each series, subjects were asked to performed a set of 6 basic hand gestures. Each gesture was performed for 3 seconds with a 3 second pause in between. Gestures classification scheme is shown in Table 1.

Table 1. sEMG gesture classifications



Gesture	1	2	3	4	5	6	7
	Hand at rest	Hand clenched in a fist	Wrist flexion	Wrist extension	Radial deviations	Ulnar deviations	Extended palm

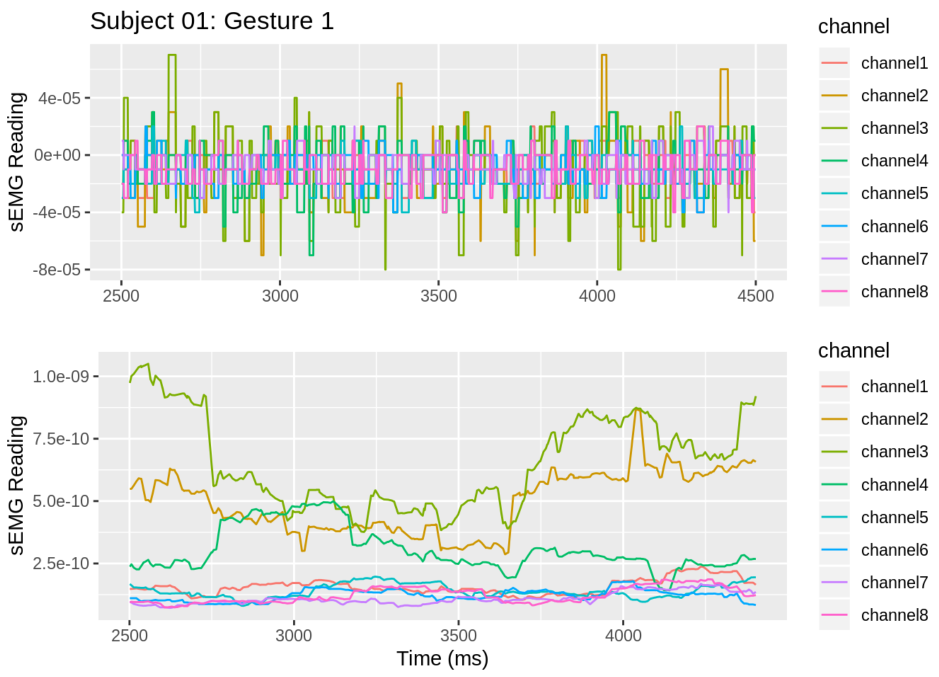
2.3 Preprocessing

We implemented a root means squared (RMS) envelope of 200 ms overlapping time windows at 100*ms* steps via the *biosignalEMG* R package[10] to remove some of the noise generated during sEMG signal collection. As shown in Figure 3 the pre-processing does help provide a means to generate clearer signals that show distinct patterns from each channel per gesture

[9]Ibid

[10]J.A. Guerrero (2018)

Figure 3: Schematic of overall workflow stages: preprocessing, PCA, modeling and performance comparison



Subsequently, the data was separated according to the gesture classifications (1-6) provided for each time step for further analysis.

2.4 Dimension Reduction

Dimension reduction for each gesture was done via a principal component analysis (PCA) of the 8 distinct channels used to record sEMG data in order to identify the most relevant channels for gesture classification and potentially reduce the training time of the neuronal network. We achieved this via the R *princomp* function that performs a spectral decomposition via singular value decomposition (1) of the gesture design matrix ($\mathbf{X}$)

$$\mathbf{X} = \mathbf{UDV}' \tag{1}$$

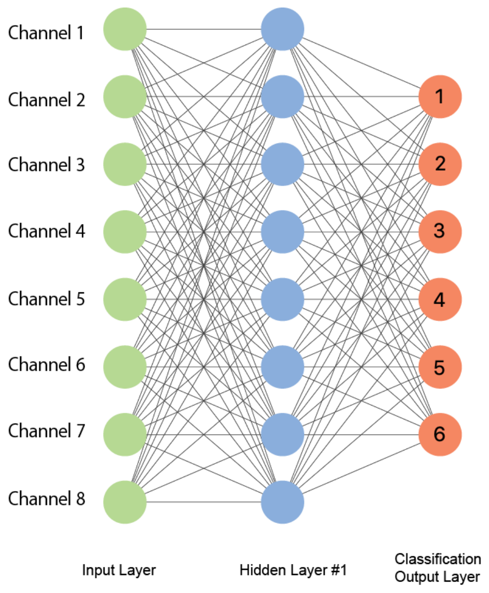
were U and V are the row and column space eigen vectors and D is a diagonal matrix with the eigen values.

2.5 Modeling

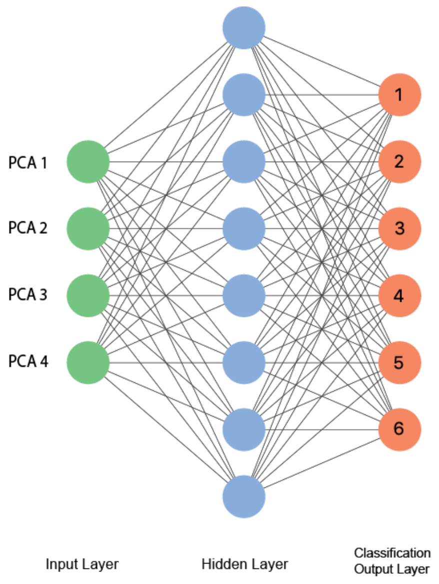
Before fitting an Artificial Neural Network (ANN) we "padded" the ends of each gesture's data matrix to ensure that the vectors passed into the models are of equal dimension. We then developed two ANN with one hidden layer, the first with all components and a second with channels subset selected during the dimension reduction stage (Figures 4a and 4b, respectively). Each of these has a single hidden layer with eight hidden nodes having linear activation. These eight nodes feed into six output nodes with a soft-max activation function. This model was inspired by Lobov et al's approach.[11]

The computation graphs for the ANN were generated via an R implementation of Keras[12], which relies on Google's TensorFlow engine for backpropogation. This allowed us to implement a flexible design framework so that we could add, edit, and remove layers from our models quickly and efficiently during our development process.
Afterward, five additional ANN were generated with an increasing number of hidden layers ($l = 1, ...5$) but only using the principal components as inputs. Figure 5 shows a schematic representation

[11] Sergey Lobov & Makarov (2018)
[12] Daniel Falbel (2019)



(a) Schematic of ANN with all 8 channels



(b) Schematic of ANN with 4 PC channels

Figure 4: Artificial Neuronal Net structures

of how each hidden layer was added following a similar process for inputs and outputs as for the initial ANNs.

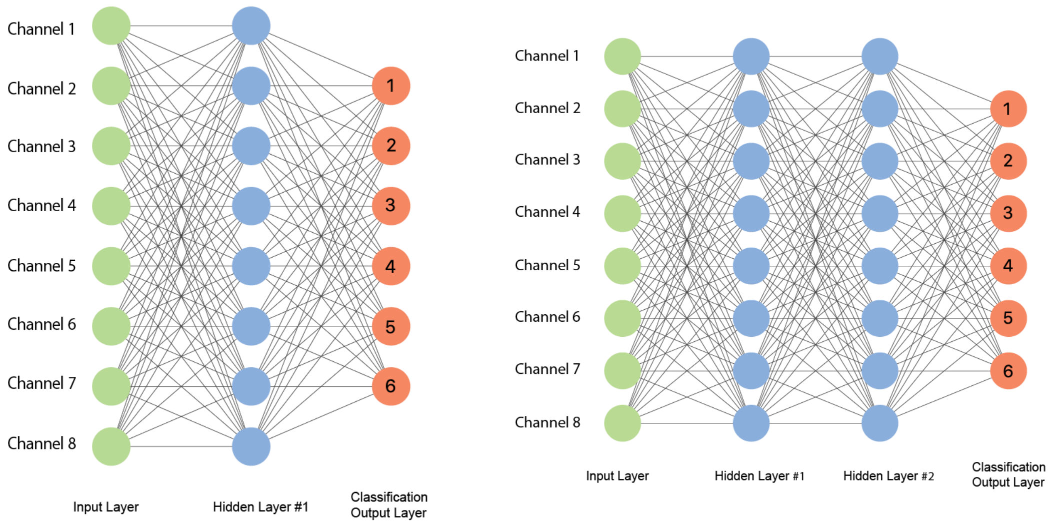


Figure 5: Increasing number of hidden layers in Artificial Neuronal Net structure

2.6 Performance Assessment

To assess the performance of each ANN, we used an k-fold cross validation strategy ($k = 5$) to split our data to generate a gesture-specific training and a testing sets. These were using the *caret* R package via random sampling. We then assessed the average classification accuracy of each ANN using a categorical cross entropy metric which measures the *Kullback-Leibler* (KL) divergence between the true distribution of the response variable and the distribution of the predictions. This was done for both the initial ANN previously mentioned and shown in Figures 4a and 4b, as well the subsequent ANN with increasing number of layers from Figure 5.
Additionally, our code was timed to assess the computational costs versus gains in accuracy as we increase the number of layers.

3 Results

3.1 Principal Component Analysis

Using the spectral decomposition we found that only 4 of the 8 principal components in our dataset contributed meaningfully to variance in our response. From figure 3, we can see that these 4 components account for approximately 80% of the variability we are seeking to model.
We might be interested in comparable results, or a decision rule which is applicable to different data sets. We introduce a relative measure κ which can be used for the PCA of data sets with any dimension. Let p be the number of dimensions of the original data set.

$$\kappa_i = \frac{proportional\ explained\ variance_i}{\frac{1}{p}} = proportional\ explained\ variance_i \times p$$

for $i = 1, ..., p$.

One can define a decision rule, which is dependent on a threshold δ: *Include* $PC_i \ \forall \ \kappa_i > \delta$

For our data set we choose $\delta := 0.6$.

Figure 6: PCA Screeplot and cumulutive variance plot

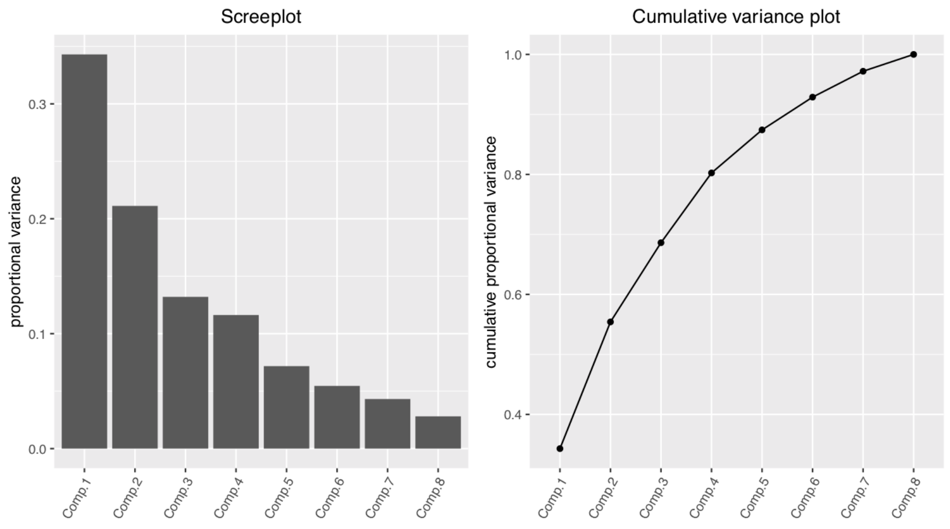


Table 1: PCA measures

	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7	Comp. 8
proportion of explained variance	0.343	0.211	0.132	0.116	0.072	0.055	0.043	0.028
cummulative explained variance	0.343	0.554	0.686	0.802	0.874	0.929	0.972	1
κ	2.744	1.689	1.056	0.930	0.574	0.437	0.345	0.225

By reducing the number of inputs from 8 smoothed signals to only 4 principle components, we were able to reduce overfitting in our model prior to utilizing any dropout layers. This reduction in overfitting decreased prediction accuracy in the validation data set only slightly see the *ANN Performance Comparison* section.

3.2 ANN Performance Comparison

First we compare the time and validation accuracy for 1 layer Neural Netwrok using 4 components and 8 components to get the taste of the advantage of using PCA.

Table 2: 4 Principal Components and 8 Principal Components Comparison

	4 Principal Components Analysis	8 Principal Components Analysis
Training Time System Time	$62.622s$	$78.302s$
Accuracy On Validation Dataset	0.775	0.809
Ratio of change in accuracy to change in time	~	0.002

Figure 7: 1 Layer NN with 4 Principal Components

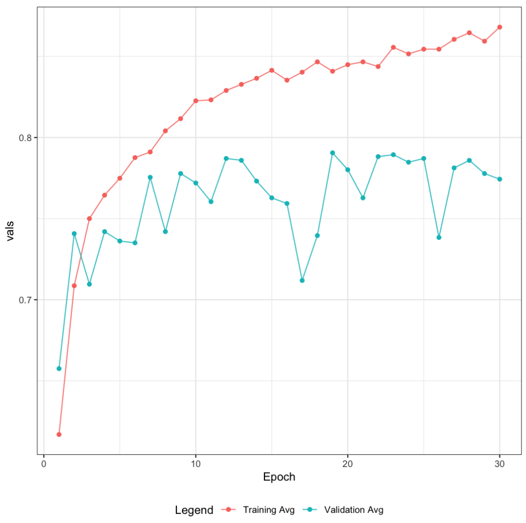
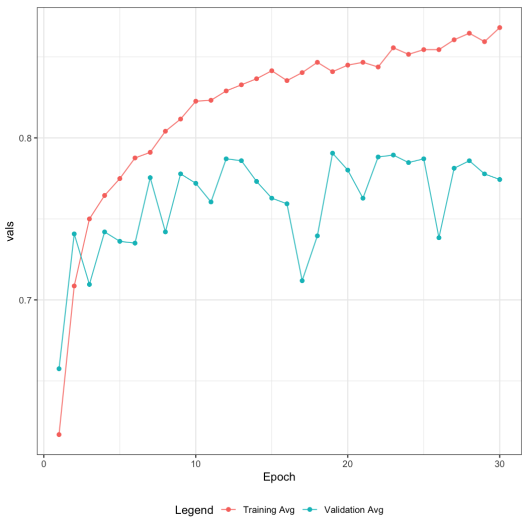


Figure 8: 1 Layer NN with 8 Principal Components



From the timing and accuracy table for 4PC and 8PC as well as two plots above, we can see that in one layer Neural Network, the training time using 4PC is much less than that using 8PC (or the whole information), which means that this data reduction helps decrease much computation intensity when training models. Besides, by comparing their classification accuracy on the validation dataset, using 4PC only sacrifice little on the performance of the model, the ratio of change in accuracy to change in time is only 0.002.

After balancing the gain and loss, we decide that training model with 4 PC is a better choice, because it's much less computational intense while maintain the most part of the information in the original data as well as high performance on the model. In fact, it is not necessary to presume such little more accuracy at the price of so much time and computation intensity.

Next we train our model using 4PC with different number of layers and results are as following:

Table 3: Timing and Accurary

	One Layer	Two Layers	Three Layers	Four Layers	Five Layers
Training Time System Time	$55.267s$	$77.497s$	$90.501s$	$110.841s$	$122.357s$
Accuracy On Validation Dataset	0.750	0.735	0.715	0.720	0.655
Ratio of change in accuracy to change in time	~	-0.0006	-0.015	0.002	-0.005

Figure 9: One Layer Accuracy

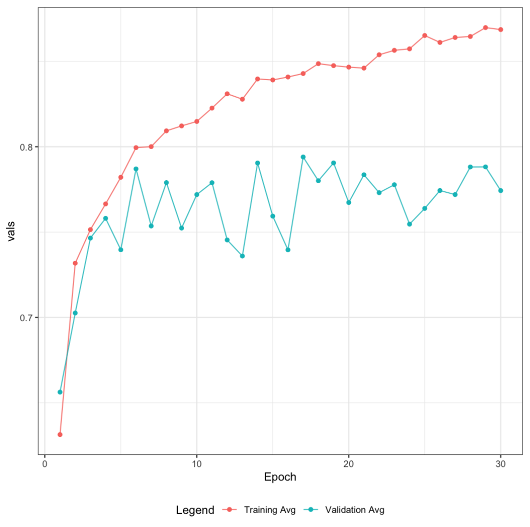
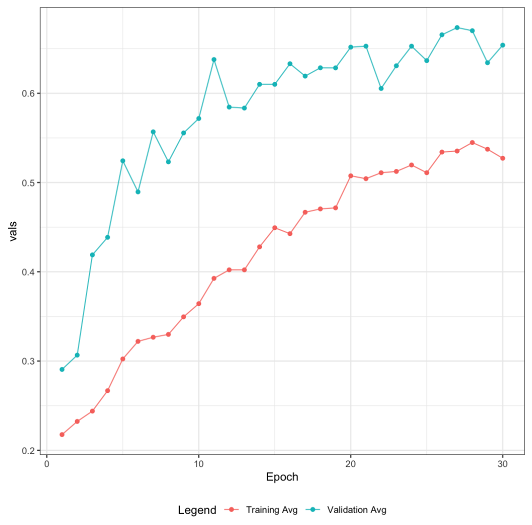


Figure 10: Five Layers Accuracy



From the timing and accuracy table for every number of layers (layer) and two plots above, we can see that the most time-wasting method is 5 layers ANN, which will take about 122s on the training, while the fastest method is 1 layer ANN, which only takes about 55s on the same training dataset. This result is not surprising because as we add more layers, the computation intensity increases at the same time.
Now considering the classification accuracy, it turns out that one layer Neural Network has the highest accuracy on validation dataset and the performance doesn't improve when adding more layers but become worse sometimes.
Another thing that is worth to point out is that when doing validation, the accuracy on the validation dataset exceeds that on the training set and this kind of thing doesn't always happen. It is partly because of the characteristic of our dataset. Since it highly depends on time sequence, the training dataset and validation dataset are highly correlated and we may have underfitting on the training set.

4 Conclusion

Through the analysis and modeling procedures described above, we have shown that it is possible to predict gestures using using artificial neural networks trained on sEMG signals data. Although increasing the number of dense hidden layers in the network did not result in greater predictive power, we were able to reduce the computational cost of fitting the ANN using a conceptually simple spectral decomposition for dimension reduction.

This result is important because it not only serves to validate some of the results of the original research performed by Lobov *et al* but it also demonstrates that they could have achieved similar accuracy with a less complex model through some standard dimension reduction techniques. Furthermore, our work shows that the next generation of prosthetics and exoskeletons can be equipped with sensors to record sEMG signals and pre-trained ANNs that are capable of responding to the user's nervous impulses in an intelligent, automated manner. However, the user-specific anatomy will remain as a current limitation to the accuracy of ANN implemented. Furthermore, we believe that the results presented here can be improved upon through further experimentation into recurrent neural network models and more specialized hardware to this task.

References

Daniel Falbel, e. a. (2019). Package ‘keras’ [Computer software manual].

J.A. Guerrero, J. M.-D. (2018). Package ‘biosignalemg’ [Computer software manual].

Sergey Lobov, I. K. V. K., Nadia Krilova, & Makarov, V. A. (2018). Latent factors limiting the performance of semg-interfaces. *Sensors*, *18*(1122).