Unsupervised learning of myographic signals

Eduardo Coronado, Sebastian Knigge, Sam Voisin, Zheng Yuan

Motivation

Recent advances in surface electromyographic signal (sEMG) recordingsystems and analytics methods have encouraged the use of sEMGs in human-machine interfaces to control exoskeletons and protheses; however, challenges remain. Accurate classification of user movements is highly variable given the inherent noise of sEMG recording systems and per-user variability. In turn, this leads to problems downstream when attempting to convert these classifications into spatial directions (e.g. up, down, right, and left). Here, we aim to address the former challenge specifically. Our goal is to design and implement a light-weight unsupervised learning model via a multi-layered neural network to accurately identify six distinct hand gestures from sEMG data.

Data

Raw sEMG signal data from 36 individuals was obtained from Lobov *et al* (2018). 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

Methods

Workflow Overview

Our analysis workflow was comprised of 4 main phases: preprocessing, dimension reduction via PCA, modeling, and performance comparison as shown in Figure 1

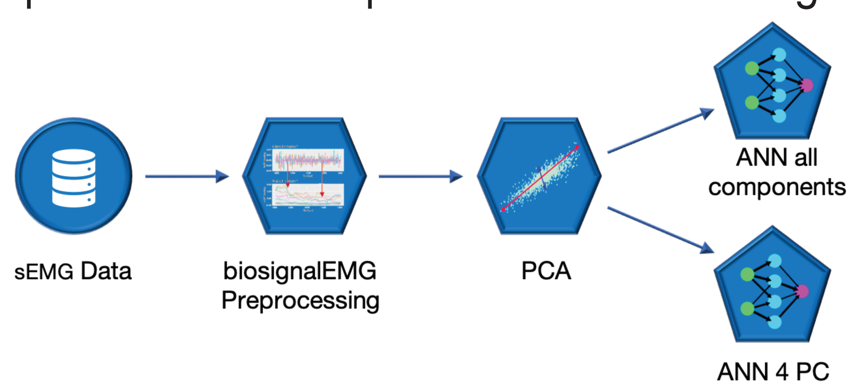

Figure 1. Schematic of overall workflow stages: preprocessing, PCA, modeling and performance comparison

Data Preprocessing

We implemented a root means squared (RMS) envelope of 200 ms overlapping time windows at 100 ms steps via the *biosignalEMG* R package to remove some of the noise generated during sEMG signal collection.

Dimension reduction

Dimension reduction was done via a principal component analysis (PCA) of the 8 distinct channels used to record sEMG data in order to reduce the training time of the neuronal network. We achieved this via the R princomp function that performs a spectral decomposition of the gesture design matrix.

Model

The final step of preprocessing requires adding "padding" to the end of each gesture's data matrix. This is done so that the vectors passed into the models are of the same dimension.We then developed two Artificial Neural Networks (ANN), one with all components and a second with a subset selected during the dimension reduction stage (Figure 2). 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* (2018) .

To create the computation graphs for the ANN we used the R implementation of Keras which uses TensorFlow for backpropogation. This allows us to add, edit, and remove layers from our models as needed during the development process. The flexibility of this modular design means we are able to prototype new models quickly.

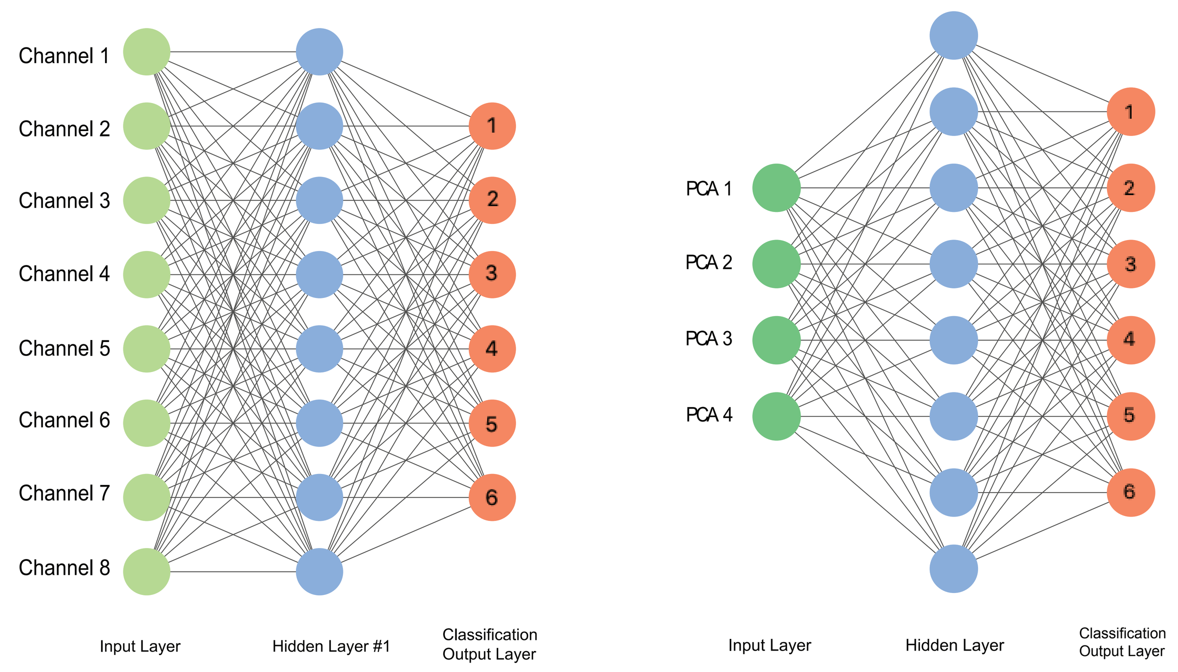

Figure 2. Schematic of input, hidden and classification layers of the two ANN with all components (left) and 4 PC (right)

Train/Test Sets and Performance

To assess the performance of each ANN, we used an 80-20 split our data to generate a gesture-specific training and a testing sets. These were done automatically in the Keras package via random sampling. We then assessed the classifcation accuracy of each ANN using a cross entropy metric measures the Kullback-Leibler (KL) divergence between the true positive distribution and true negative distributions.

Results

PCA Analysis

Our initial findings suggest that only 4 of the 8 channels best explain the sEMG variance we observe as seen in Figure 3. We see that components 1 throuh 4 explain approximately 80% of the variance.

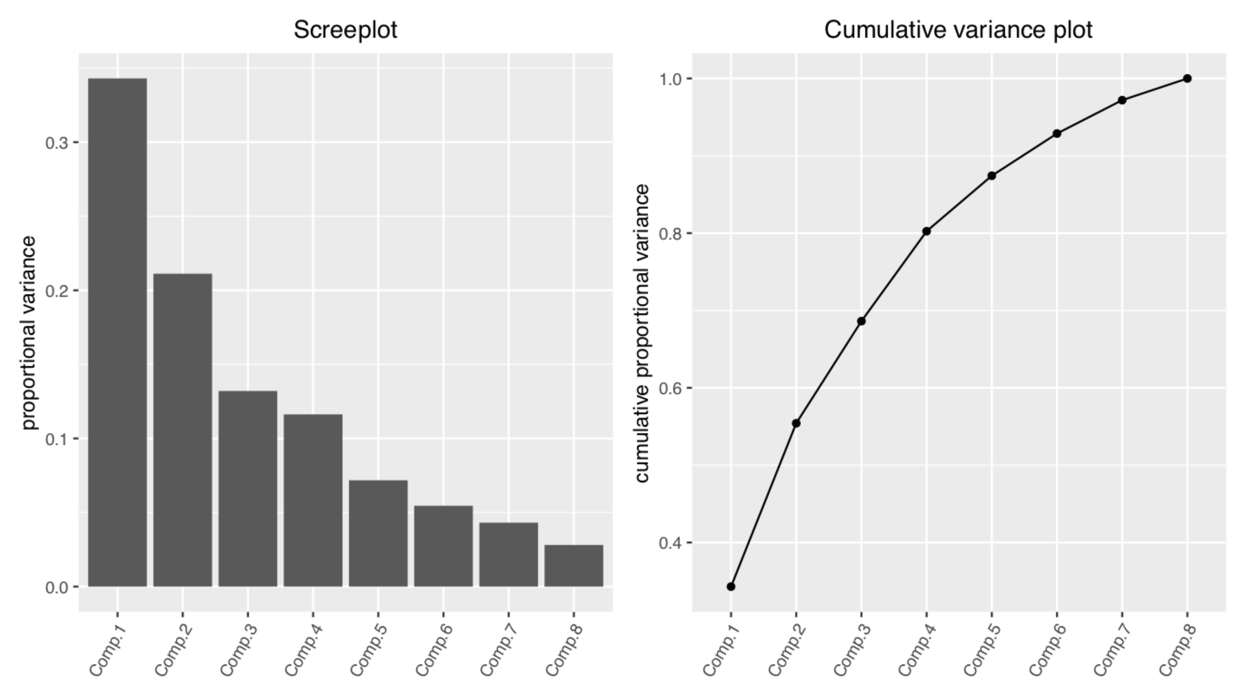

Figure 3. PCA Screeplot and cumulitive variance plot

ANN Performance Comparison

When comparing the performance of the ANN, one can observe that the difference in accuracy is marginal, compared to the reduction of information we achieved by PCA. While the accuracy ratio for the full information (8 components) tends to converge to an accuracy ratio of 0.75 over the epochs, the accuracy for the dimension reduced data (4 principal components) indicates stabilization towards a value of 0.70. In this modelling approach the cross entropy was minimized with a number of 30 epochs.

Figure 4 shows the accuracy ratio over the epochs for both a fit on the training data and a validation sample.

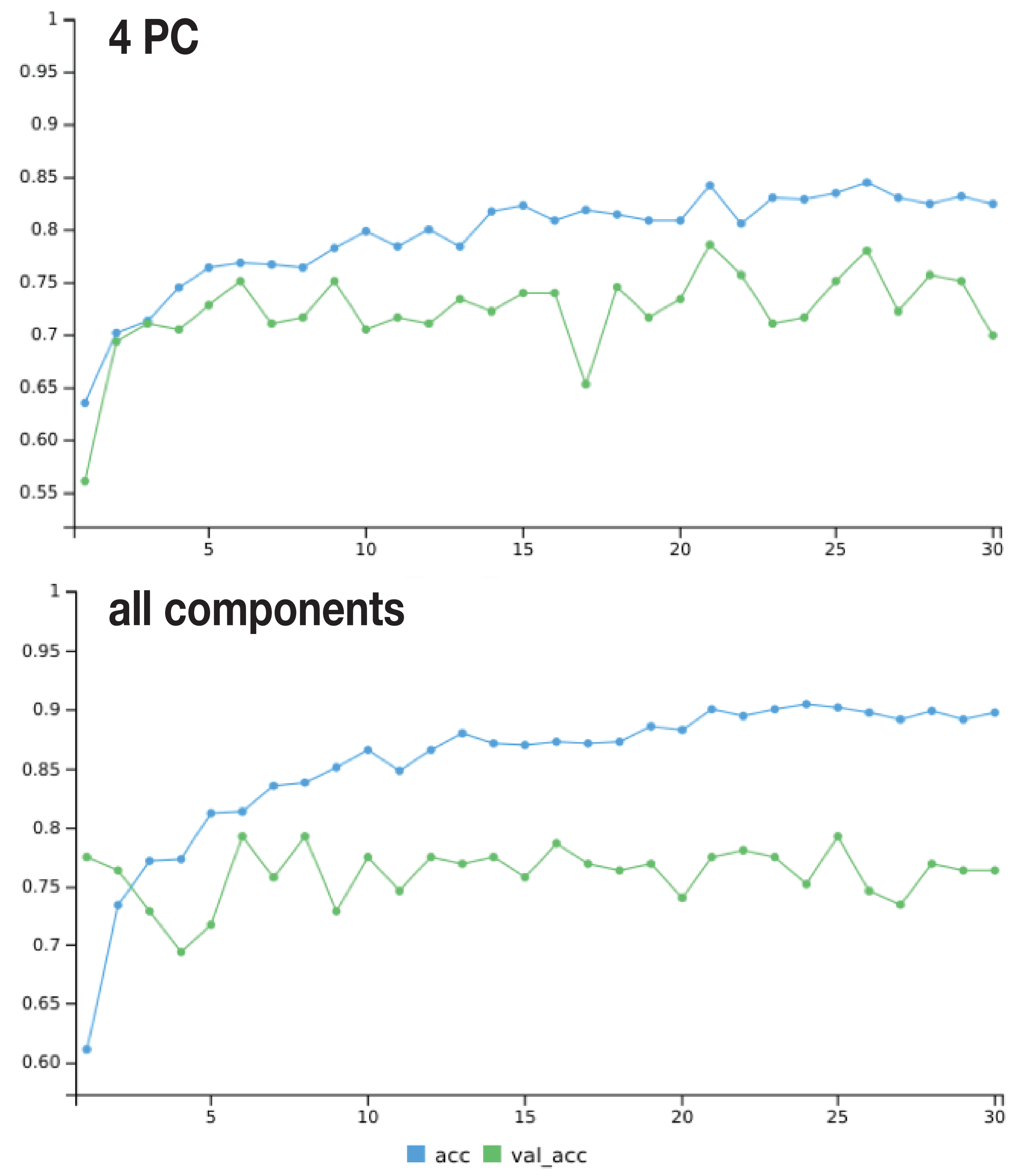

Figure 4. Accuracy ratio over epochs on training (blue) and testing (grean) data

Further Development

We believe that we can improve on this model with additional hidden layers to better approximate the function by which someone performing gestures will generate EMG data (Figure 5). To do this, we will start by adding an additional hidden layer that might also contain eight hidden units and linear activation. The output layer and soft-max activation would remain the same as our initial ANN.

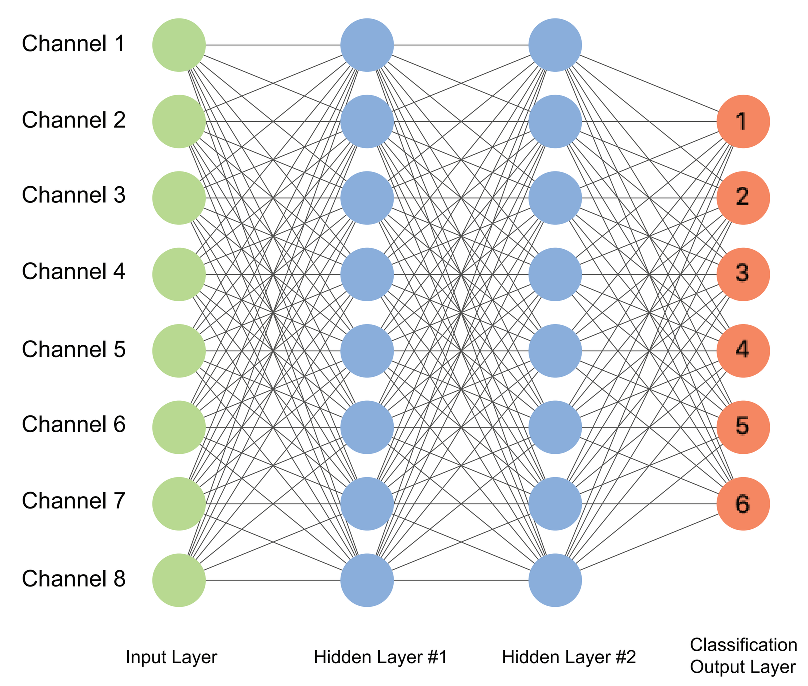

Figure 5. Schematic of 2-layer ANN that we expect would improve our performance.

Additionally, one from the plots in Figure 4 we can see that further experimentation on the number of epochs can be used used in the fitting process to avoid overfitting

References

- Daniel Falbel, e. a. Package 'keras'

- J.A. Guerrero, J. M.-D. Package 'biosignalEMG'.

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