Team: Jacob Kennedy & Connor Maynes 03/02/2018

References - CNN ( convolutional neural network )

1. [Geng, Weidong](https://search.proquest.com/indexinglinkhandler/sng/au/Geng,+Weidong/$N?accountid=108)[Author Information](https://search.proquest.com/docview/1899337750?pq-origsite=summon#resolverCitation_preview_0); [Du, Yu](https://search.proquest.com/indexinglinkhandler/sng/au/Du,+Yu/$N?accountid=108); [Jin, Wenguang](https://search.proquest.com/indexinglinkhandler/sng/au/Jin,+Wenguang/$N?accountid=108); [Wei, Wentao](https://search.proquest.com/indexinglinkhandler/sng/au/Wei,+Wentao/$N?accountid=108); [Hu, Yu](https://search.proquest.com/indexinglinkhandler/sng/au/Hu,+Yu/$N?accountid=108); et al. [Scientific Reports (Nature Publisher Group)](https://search.proquest.com/pubidlinkhandler/sng/pubtitle/Scientific+Reports+$28Nature+Publisher+Group$29/$N/2041939/PagePdf/1899337750/fulltextPDF/722CCC9E4D1E4AFFPQ/1?accountid=108); London [Vol. 6,](https://search.proquest.com/indexingvolumeissuelinkhandler/2041939/Scientific+Reports+$28Nature+Publisher+Group$29/02016Y11Y01$23Nov+2016$3b++Vol.+6/6/$B?accountid=108)  (Nov 2016): 36571.

This article covers the use of CNN for classifying hand gestures for ASL from EMG signals, similar to our goal.

2. Sengur A., Gedikpinar M., Akbulut Y., Deniz E., Bajaj V., Guo Y. (2018) DeepEMGNet: An Application for Efficient Discrimination of ALS and Normal EMG Signals. In: Březina T., Jabłoński R. (eds) Mechatronics 2017. MECHATRONICS 2017. Advances in Intelligent Systems and Computing, vol 644. Springer, Cham

This article covers the use of CNN on EMG time-series data using several different architectures for the CNN.

3. Atzori M, Cognolato M, Muller H. Deep Learning with Convolutional Neural Networks Applied to Electromyography Data: A Resource for the Classification of Movements for Prosthetic Hands. FRONTIERS IN NEUROROBOTICS. 2016;10:9.

Simple CNN created and then various preprocessing and postprocessing techniques are attempted on the EMG data for 50 different hand gestures.

4. Cote Allard U, Nougarou F, Fall CL, Giguere P, Gosselin C, Laviolette F, et al. A convolutional neural network for robotic arm guidance using sEMG based frequency-features. IEEE; 2016.

Several different CNN architectures are attempted for classifying 7 different hand gestures

5. Pizzolato S, Tagliapietra L, Cognolato M, Reggiani M, Muller H, Atzori M. Comparison of six electromyography acquisition setups on hand movement classification tasks. PLOS ONE. 2017;12(10):e0186132.

Different electrode setups are attempted to collect the best possible data for use in classification. Several classification methods attempted.

6. Cote-Allard U, Fall CL, Campeau-Lecours A, Gosselin C, Laviolette F, Gosselin B. Transfer learning for sEMG hand gestures recognition using convolutional neural networks. IEEE; 2017.

Interpolation used to reduce the amount of data required for the CNN to learn. Looks at a way to reduce the training time of a network

7. Moslem B, Diab MO, Khalil M, Marque C. Classification of multichannel uterine EMG signals by using unsupervised competitive learning. ; 2011.

Different CNN structures for handling multichannel data are explored.

8. Rami N. Khushaba, Ali H. Al-Timemy, Ahmed Al-Ani, Adel Al-Jumaily, "A Framework of Temporal-Spatial Descriptors-Based Feature Extraction for Improved Myoelectric Pattern Recognition", Neural Systems and Rehabilitation Engineering IEEE Transactions on, vol. 25, pp. 1821-1831, 2017, ISSN 1534-4320.

Predicting what a user is going to do next, so that classification is more fluid and allows for more gestures than just the ones trained on.

9. Wei, W., Wong, Y., Du, Y., Hu, Y., Kankanhalli, M., & Geng, W. (2017). A multi-stream convolutional neural network for sEMG-based gesture recognition in muscle-computer interface. Pattern Recognition Letters.

Another approach to filling in the blanks when trying to classify actions, so that motion of robotic arm being controleld is fluid.

10. Kim, D., Kim, D. H., & Kwak, K. C. (2017). Classification of K-Pop Dance Movements Based on Skeleton Information Obtained by a Kinect Sensor. Sensors, 17(6), 1261.

Classification of body motions using EMG data, which could yield some insights into feature extraction and classification for hand gestures

11. Xia, P., Hu, J., & Peng, Y. (2017). EMG‐Based Estimation of Limb Movement Using Deep Learning With Recurrent Convolutional Neural Networks. Artificial organs.

Another approach to classification. Combines CNN and RNN to solve the problem of classification.

12. Du, Y., Wong, Y., Jin, W., Wei, W., Hu, Y., Kankanhalli, M., & Geng, W. (2017, August). Semi-supervised learning for surface EMG-based gesture recognition. In Proceedings of the 26th International Joint Conference on Artificial Intelligence(pp. 1624-1630). AAAI Press.

Plainly explains all steps involved in their CNN classification of EMG signals. Could help with understanding of CNN and feature extraction.

References - SVM ( support vector machine )

1. Alkan, A., & Günay, M. (2012). Identification of EMG signals using discriminant analysis and SVM classifier. Expert Systems with Applications, 39(1), 44-47.

Approach to classification of EMG data using SVM. Provides a good basis for future research.

2. Yoshikawa, M., Mikawa, M., & Tanaka, K. (2006, October). Real-time hand motion estimation using EMG signals with support vector machines. In SICE-ICASE, 2006. International Joint Conference (pp. 593-598). IEEE.

Real-time classification using SVM is explained and tested. Our goal is to get our deliverable working in real time, so this would help us understand how to deal with real-time calculations efficiently. Cepstrum coefficients feature used.

3. Rekhi, N. S., Arora, A. S., Singh, S., & Singh, D. (2009, June). Multi-class SVM classification of surface EMG signal for upper limb function. In Bioinformatics and Biomedical Engineering, 2009. ICBBE 2009. 3rd International Conference on (pp. 1-4). IEEE.

Feature extraction uses wavelet packet transform and singular value decomposition.

4. Bitzer, S., & Van Der Smagt, P. (2006, May). Learning EMG control of a robotic hand: towards active prostheses. In Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on (pp. 2819-2823). IEEE.

Covers classification of four fingers on the hand and their classification. Looks into ways of dealing with gray-area movement between classes.

5. Phinyomark, A., Quaine, F., Charbonnier, S., Serviere, C., Tarpin-Bernard, F., & Laurillau, Y. (2013). EMG feature evaluation for improving myoelectric pattern recognition robustness. Expert Systems with applications, 40(12), 4832-4840.

Looks at fifty different features that can be extracted from an EMG signal and tries to find the most valuable ones - the most robust ones - for long-term use of a robotic arm that uses neural networks.

6. Benatti, S., Milosevic, B., Casamassima, F., Schonle, P., Bunjaku, P., Fateh, S., ... & Benini, L. (2014, October). EMG-based hand gesture recognition with flexible analog front end. In Biomedical Circuits and Systems Conference (BioCAS), 2014 IEEE (pp. 57-60). IEEE.

Comparison of different classification techniques, would could increase understanding of SVM and tools that work well with this.

7. Savur, C., & Sahin, F. (2015, December). Real-time american sign language recognition system using surface emg signal. In Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on (pp. 497-502). IEEE.

ASL, EMG and SVM, which is very similar to what we are trying to do in our project. This should give us a big jump on how to use SVM for this type of problem.

8. Yousefi, J., & Hamilton-Wright, A. (2014). Characterizing EMG data using machine-learning tools. Computers in biology and medicine, 51, 1-13.

Combination of PSO and SVM for classification of gestures. This is a slightly different approach from pure SVM.

9. Chen, X., & Wang, Z. J. (2013). Pattern recognition of number gestures based on a wireless surface EMG system. Biomedical Signal Processing and Control, 8(2), 184-192.

Different feature extraction techniques are identified and combined together along with the combination of several different classification techniques, among which is SVM. Combining SVM with another technique could yield a far more accurate classification scheme than SVM could alone.

10. Stango, A., Negro, F., & Farina, D. (2015). Spatial correlation of high density EMG signals provides features robust to electrode number and shift in pattern recognition for myocontrol. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 23(2), 189-198.

Attempts to use a feature called a variogram in combination with SVM, along with high density EMG signals to try to classify different motions. The HD EMG signal collection and SVM combination may or may not be a direction we want to take in our project.

11. Riillo, F., Quitadamo, L. R., Cavrini, F., Gruppioni, E., Pinto, C. A., Pastò, N. C., ... & Saggio, G. (2014). Optimization of EMG-based hand gesture recognition: Supervised vs. unsupervised data preprocessing on healthy subjects and transradial amputees. Biomedical Signal Processing and Control, 14, 117-125.

Comparison of SVM against several alternatives, could help us to avoid any pitfalls of using a particular method as they will likely emerge after comparing to other classification methods.

12. Phinyomark, A., Quaine, F., Charbonnier, S., Serviere, C., Tarpin-Bernard, F., & Laurillau, Y. (2014). Feature extraction of the first difference of EMG time series for EMG pattern recognition. Computer methods and programs in biomedicine, 117(2), 247-256.

Highlights some of the pitfalls of SVM when applied to EMG and in general. Could help us avoid the same problems when creating a robust SVM that - ideally - does not need to be recurrently trained so that performance does not degrade as is apparently the usual case.

13. Kamali, T., Boostani, R., & Parsaei, H. (2014). A multi-classifier approach to MUAP classification for diagnosis of neuromuscular disorders. IEEE transactions on neural systems and rehabilitation engineering, 22(1), 191-200.

Special SVM structure(s) explored, which could help us in creating a more sophisticated SVM more capable of capturing nuanced hand gestures.

14. Xu, X., Zhang, Y., Luo, Y., & Chen, D. (2013). Robust bio-signal based control of an intelligent wheelchair. Robotics, 2(4), 187-197.

Incremental SVM is explored for the purposes of classifying EMG signals for wheelchair users. The SVM design could prove invaluable for development of a more sophisticated SVM in our project.

15. S. Bitzer, P. Smagt, "Learning EMG control of a robotic hand: Towards active prostheses", Proc. IEEE Int. Conf. Robot. Autom., pp. 2819-2823, 2006-May.

Real-time EMG control of a robotic hand with SVM that provides yet another SVM design that we might use or integrate with other designs.

16. Matsubara, T., & Morimoto, J. (2013). Bilinear modeling of EMG signals to extract user-independent features for multiuser myoelectric interface. IEEE Transactions on Biomedical Engineering, 60(8), 2205-2213.

SVM on EMG signals, but with a focus on ensuring that the SVM is not overtrained and can be used by virtually any person without a significant loss / change in functionality.

References - FFT ( fast fourier transform )

1. Ngeo, J. G., Tamei, T., & Shibata, T. (2014). Continuous and simultaneous estimation of finger kinematics using inputs from an EMG-to-muscle activation model. *Journal of neuroengineering and rehabilitation*, *11*(1), 122.

This is exactly what we are trying to do. They are trying to classify finger movements, using FFT for feature extraction which then bleeds into classification.

2. Tidwell, R., Akumalla, S., Karlaputi, S., Akl, R., Kavi, K., & Struble, D. (2013, July). Evaluating the feasibility of EMG and bend sensors for classifying hand gestures. In *Proceedings of the International Conference on Multimedia and Human Computer Interaction* (Vol. 63, pp. 1-8).

FFT and Cepstrum for classifying 10 different hand gestures and over 10 other gestures. Evaluation of various feature extraction methods against one another.

3. Zhai X, Jelfs B, Chan RHM, Tin C. Short latency hand movement classification based on surface EMG spectrogram with PCA. IEEE; 2016.

Generated a spectrogram using FFT and from this feature extraction, they classified the data. Numerous features dependent on FFT are explored.

4. Cannan J, Hu H. Automatic user identification by using forearm biometrics. IEEE; 2013.

Uses FFT in combination with a few other feature extraction tools over a large number of subjects, which would yield valuable cross-validation information for our project.

5. Oliver, A. S., Maheswari, N., & Samraj, A. (2014). Stable and critical gesture recognition in children and pregnant women by SVM classification with FFT features of signals from wearable attires. *Research Journal of Applied Sciences, Engineering and Technology*, *7*(23), 4917-4926.

FFT is used for feature extraction in combination with a SVM. While SVM’s are not a topic of study for us, FFT analysis is valuable. They are trying to use FFT for classifying hand gestures, which is just what we are trying to do.

6. Jang, E. H., Park, B. J., Kim, S. H., Chung, M. A., Eum, Y., & Sohn, J. H. Emotion Classification Based on Bio-Signals Using Machine Learning Algorithms.

Use of FFT among other feature extraction techniques to analyze EEG signals. While this is not the same biosignal, the paper could yield useful insights into how to best use FFT. I do not expect signification deviation in how to use FFT, based on different biosignals.

7. Funabashi, T., Ito, M., Ito, S. I., & Fukumi, M. (2015, May). On-line recognition of finger motions using wrist EMG and simple-PCA. In *Control Conference (ASCC), 2015 10th Asian* (pp. 1-5). IEEE.

FFT used for feature extraction on finger motions, which is pretty similar to our project. The results are also compared to what they would be if machine learning was used and this is one our topics of study.

8. Salim, A. J., RAMLEE, R. H., & GUAN, D. (2013). *Physiological using FGPA in health monitoring system*(Doctoral dissertation).

Detailed exploration of different feature extraction techniques for biosignals ( EMG ), which are compared and extensively analyzed for a proposed commercial application.

9. Sadikoglu, F., Kavalcioglu, C., & Dagman, B. (2017). Electromyogram (EMG) signal detection, classification of EMG signals and diagnosis of neuropathy muscle disease. *Procedia Computer Science*, *120*, 422-429.

Another detailed exploration of different signal processing techniques when working with EMG signals. Should give us a good start on what FFT is and how to use it.

10. Shimei, E. The Creation and Use of an EMG.

FFT is used for preliminary analysis of biosignals to gain further insight into what avenues of feature extraction to next explore. Could teach us how to interpret FFT information that we extract.

References - IDM( inverse difference moment ) [ VERY LITTLE AVAILABLE RESEARCH ]

1. Latif-Amet, A., Ertüzün, A., & Erçil, A. (2000). An efficient method for texture defect detection: sub-band domain co-occurrence matrices. *Image and Vision computing*, *18*(6-7), 543-553.

Explores the use of IDM ( inverse difference moment ) for image processing. While this is not directly related to biosignals, it should provide a starting point to better acquaint us with the method.

2. Mohamed, M. M., & Hassan, M. A. Studying the Effect of HIV/AIDS on Human Brain Using MRI.

IDM explained and explored for use on EEG signals from an MRI machine. This is on biosignals, albeit a different one from the one under study, but it should provide a good basis of knowledge.

3. Mao, Q., Sun, Y., Hou, J., Yu, L., Liu, Y., Liu, C., & Xu, N. (2016). Relationships of Image Texture Properties with Chewing Activity and Mechanical Properties during Mastication of Bread. *International Journal of Food Engineering*, *12*(4), 311-321.

Combination of EMG signals gathered from someone chewing and IDM feature extraction are both topics of study for this project. We are studying hand and arm gestures, but the approach in either case is probably pretty similar.