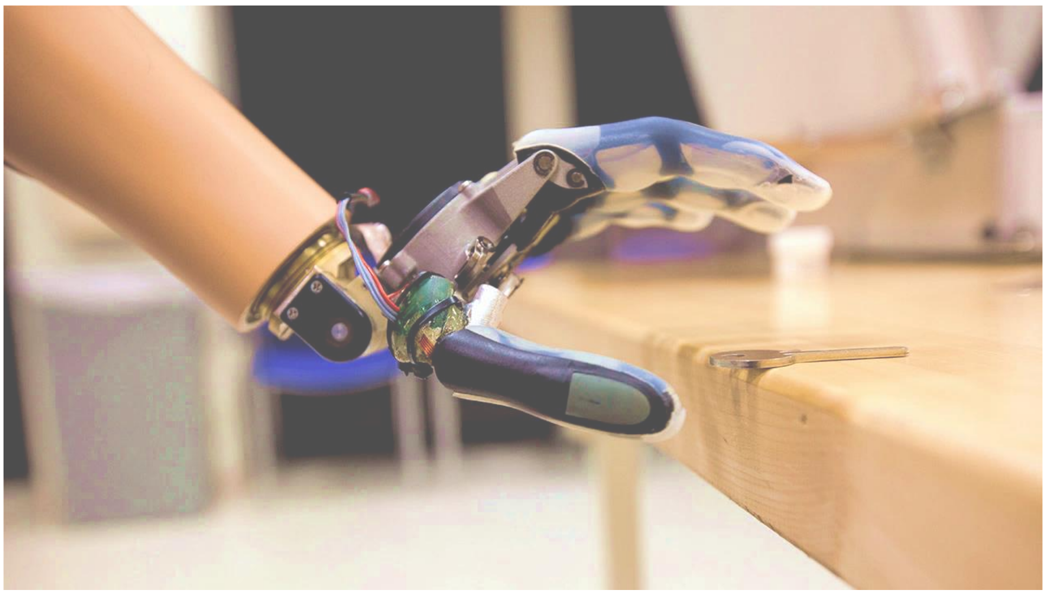
Koc University

ELEC-547 Biomedical Signal Processing



Group 16

Gesture Recognition for Prosthetic Hand Control

Enes Ulaş Dinçer

Feras Kiki

Recognizing hand motions and gestures using surface electromyography (sEMG) signals has gained significant attention in research and development due to its applications in human-computer interaction, assistive and rehabilitation devices, gaming, and so forth. Since human musculoskeletal dynamics are immensely intricate, processing sEMG signals to extract meaningful information is done via deep learning today. However, a plethora of methods has been suggested in the literature, not only for feature engineering but also for architectures and training procedures. This work aims to study the performance of the methods used in certain scenarios, methods, model architectures, and training procedures to achieve robust results.

Introduction:

Surface Electromyography (sEMG) is a technology used for evaluating and recording the electrical activity pro- duced by skeletal muscles without invading or puncturing the skin (Robertson et al., 2013). With sEMG sensors becoming more affordable and adequately precise in recent years, this technique has found its way into a broad range of applications, such as clinical diagnosis and therapy. Clinical studies using sEMG measurements typically concern muscle fatigue, motor neuron diseases (MND), neuro-pathic/myopathic conditions, and spinal cord injuries (Drost et al., 2006; Balbinot et al., 2022). Similarly, sEMG is used frequently in motor intention prediction (Bi et al., 2019) for therapeutic research purposes. Another example of an sEMG application involves the prediction of pose and/or joint angles in exoskeletons in the realm of assistive and rehabilitative robotics (Foroutannia et al., 2022). Research has also been conducted into creating more intelligent and more intuitive control of prosthetic robotic devices. Due in large part to advances in both human- computer interaction (HCI), human-robot interaction (HRI), and human-machine interface (HMI), gesture and motion recognition have become popular applications of sEMG techniques as well (Ghalyan et al., 2018; Taghizadeh et al., 2021). In the realm of physical human-robot interaction (pHRI), sEMG has been used for human intention recognition, typically followed by adaptive admittance/impedance control for minimizing human effort, or maximizing task efficiency (Sirintuna et al., 2020). Surface electromyography typically involves the placement of individual or densely-packed sets of monopolar or bipolar electrodes on human skin, on top of the center of a muscle. The sensor can measure the activation levels of the muscle. An example of individually placed bipolar sEMG sensors is the MyoWare Muscle Sensor AT-04-001 from Advancer Technologies Inc.® (Fig. 1).

Fig.1 (left) MyoWare EMG sensor, (right) Myo ArmBand

Examples of packed bipolar sEMG sensors include the Myo Gesture Control Armband from Thalmic Labs® (Fig. 1). Individual sensors such as the Myoware® must be attached to a pair of conductive patches closely placed on human skin at the center of the muscle, held firmly on the skin via an adhesive layer. They also typically include a third electrode which needs to be connected to a patch placed somewhere outside the muscle, where there is no activation, such as another tendon or bone. Densely packed sEMG sensors such as the Myo Armband® only contain a thick and large armband placed on the arm, forearm, legs, thighs, etc., on the circumfer- ence of which 6 or 8 bipolar sEMG sensors are placed close together. These sensors are more convenient to use than their counterparts because they do not need to be placed on patched adhering to human skin, nor do they need a third connection to a non-activated part of the limb. Most sEMG sensor outputs are voltage signals in the 0-10 Volt range. Due to the immense complexity and high-frequency outputs of the activations occurring in skeletal muscles, sEMG signals that are recorded from the sensors are not trivial to process or decompose. These raw signals contain multiple high-amplitude peaks across a wide range of frequencies and visually resemble audio signals. Even after preliminary amplification and band-pass filtering, extracting meaningful features from the processed signals is difficult, especially when trying to recognize motion/gesture, or when trying to estimate muscle force or human effort from sEMG signals. Therefore, modern approaches in (pre)processing sEMG signals often combine several signals processing, machine learning, and deep learning approaches (Bi et al., 2019; Foroutannia et al., 2022; Sirintuna et al., 2020; Xiong et al., 2021; Clarke et al., 2021). Due in part to its growing popularity in HCI, HRI, and gam- ing, and in part to the availability of a few proper datasets, we have selected motion/gesture recognition from sEMG signals as the application on which we would like to focus. Several studies (Du et al., 2017; Zia ur Rehman et al., 2018; C ˆot ́e-Allard et al., 2019; Chen et al., 2020; Ozdemir et al., 2020; Shanmuganathan et al., 2020; Yang & Liu, 2022) have attempted to use various deep learning methods to recognize motions/gestures of human arms and hands from sEMG sensors (more frequently using the densely-packed Myo Armbands) under different conditions. We will try to reproduce similar results to one of papers and understand how to apply the techniques used for motion/gesture recognition tasks.

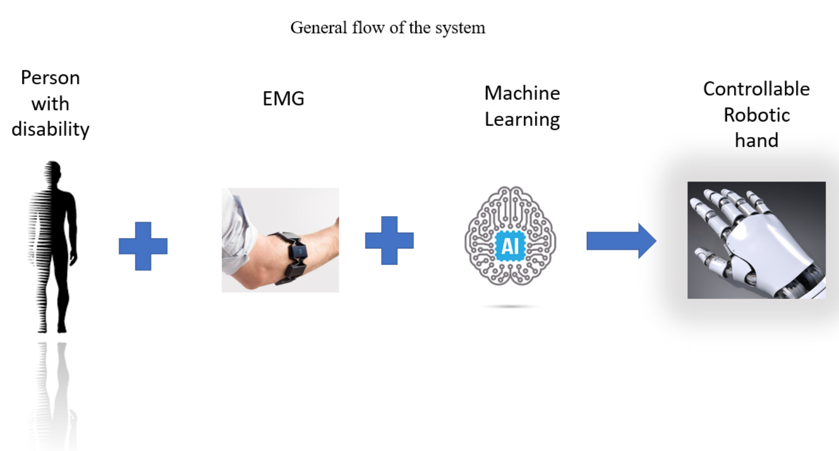


Fig.2 General flow of the gesture recognition system

A simple workflow of an EMG based robotic hand control system can be shown in the figure above. We will start with a person with severe hand injury or an amputee and detect the signal that is produced from his forearm. Granted, if the forearm muscles are not healthy, this system will be severely underperforming. After retrieving the EMG activation signal, we will be using a machine learning algorithm to map the input to meaningful input to the robotic hand. While the ultimate goal of such a system is to be able to map all muscle activations to the robot, we need to start with a simpler problem which is to map a specific small set of motions to distinct classes. Thus, we will try to classify EMG activation into a group of gestures.

Literature Review:

A review of the existing literature about motion/gesture recognition from sEMG tells how challenging it is to perform such a task online and potentially use it for instantaneous action in HCI/gaming, as well as adaptive control of prosthetic/rehabilitative devices, or robots, in pHRI scenar- ios, online (Xiong et al., 2021). Most papers studying hand motion/gesture recognition from sEMG have used deep learning, specifically various archi- tectures of recurrent neural networks (RNN), convolutional neural networks (CNN), or a combination of both. Ziaurrehman et al. (Zia ur Rehman et al., 2018) recorded sEMG data from Myo Armbands over multiple days with several subjects, then performed hand motion recognition using CNN from raw sEMG data (end-to-end approach). They then compared their results with other cases where the inputs were preprocessed using linear discriminant analysis (LDA) as well as stacked sparse autoencoders with features (SSAE-f) and raw samples (SSAE-r), and no CNN was used. They concluded that the raw-data-based CNN outperformed other approaches in relatively long-term comparisons such as between-day comparisons or leave-one-day-out scenarios. Chen et al. (Chen et al., 2020) also used CNN, even though with a much more compact architecture than is typically cho- sen, to detect hand gestures. They validated their findings on two main-stream hand gesture recognition datasets available online, and demonstrated acceptable results obtained with a much lighter architecture. Ozdemir et al. (Ozdemir et al., 2020) used only 4 individual bipolar sEMG sensors, which is more sparse than common, especially compared to the 8-channel Myo Armband, which they used to train a relatively deep CNN (a 50-layer ResNet architecture) to classify among 7 different hand gestures using data collected from 30 participants. They used the spectrogram images of sEMG data as inputs to the CNN. Shanmuganathan et al. (Shanmuganathan et al., 2020) used R-CNN (a combination of RNN and CNN) using wavelet-transformed sEMG signals coming from individual bipolar sEMG sensors to perform hand gesture recognition. They proved that preprocessing the inputs using a wavelet trans- form improved accuracy over regular feature extraction methods. Yang et al. (Yang & Liu, 2022) provided a few CNN-based AI frameworks for recognizing and decoding wrist move- ments in 3D Cartesian space. They used raw sEMG data as input to their CNN architectures and performed experiments related to prosthetic applications to validate their findings. Since collecting sEMG data requires arduous physical exper- imentation with multiple subjects, it is not always feasible to collect a dataset sufficiently large and statistically representative for performing the classification or regression task at hand. To this end, a few researchers have proposed transfer learning techniques in the form of model adaptation or domain adaptation to account for such deficiencies. Cote- Allard et al. (Cote-Allard et al., 2019) used transfer learning to perform hand gesture recognition using CNN, using raw and preprocessed data as input. They used a large dataset collected from multiple subjects using Myo armbands as the source domain, and a smaller dataset, taken from different subjects with Myo armbands placed differently, as the target domain. Du et al. (Du et al., 2017) proposed a deep- learning-based domain adaptation framework to enhance sEMG-based inter-session hand gesture recognition.

Approach:

In this study, we will investigate how to produce reliable motion/gesture recognition performance using machine learning and deep learning methods, as well as which preprocessing or training methods to select for more portable results. To this end, we will use open-access datasets produced by the previous researchers. Since the experiments in these datasets have been performed under a wide range of circumstances, over multiple sessions or days, with considerable variation in human subjects, sensor placement, gestures/motions chosen, time durations, etc., so they offer a great resource for this task.

While investigating the ap- proaches, we will try various (pre)processing and feature extraction procedures, and record their effects on model performance.

For validating the proposed models, methods, and heuristics, we will keep a few unforeseen experimental conditions from the data, for testing purposes. We will employ the proposed models on testing data, and report their performance metrics to validate the findings that have come about when investigating performances in the training data. In addition, proposed methods/heuristics may be evaluated on a slightly different dataset, containing data from a slightly different task, albeit still containing sEMG data.

Datasets:

EMG datasets are available for multiple studies and the data acquisition method may vary based on the chosen gestures, hardware, protocol, subject injury status, etc.

NinaPro:

Among the most comprehensive and well produced datasets for the chosen application is NinaPro dataset collection and to test any model final accuracy, this dataset is the best choice. The first and second NinaPro datasets included a total of 78 subjects divided to 67 intact subjects and 11 hand-amputated subjects (Trans radial amputees) and included both right arm and left arm data. The acquired data includes EMG using Otto Bock and Delsys systems (2 different types) and has Hand Kinematics data acquired using Cyberglove II. The 5th data set is a simpler dataset that was acquired from 10 healthy individuals using 2 MyoArmbands for the EMG and similar setup for the rest of the hardware.

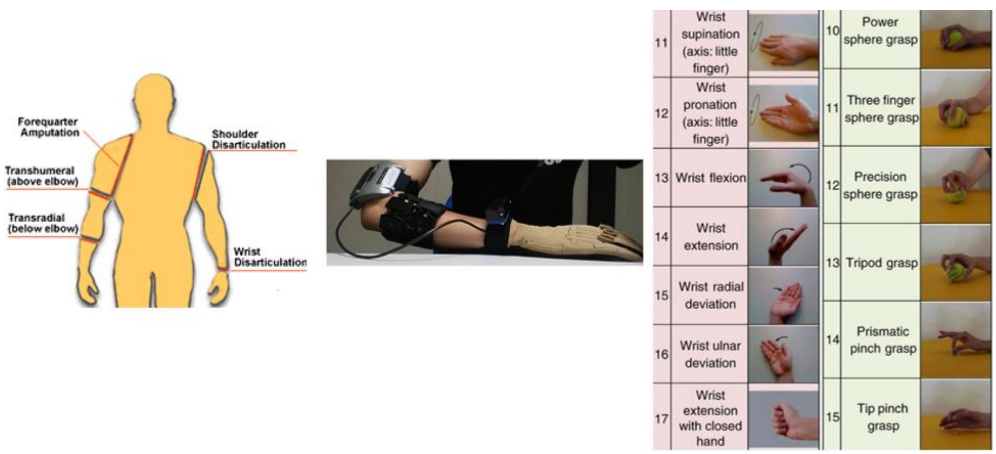


Fig.3 (left) Common types of arm amputation (middle) setup for 5th Ninapro, (right) example gestures from NinaPro

MyoArmBand Dataset:

Another simple dataset is the MyoArmBand dataset, which includes 6 gestures in addition to rest position. For our project, we decided to go with this dataset as an initial step and then expand the work finally to the NinaPro ones.

Fig.4 MyoArmBand dataset

Machine Learning:

KNN:

We performed classical machine learning on a portion of the NinaPro. We took 4 classes from the db5 dataset (gestures number 13, 14, 15, 16 from) and performed KNN classification on them. We used the EMG signal rectified without additional features. The accuracy we got before using moving average was not very high (accuracy= 43.49%) and the confusion matrix is shown below.

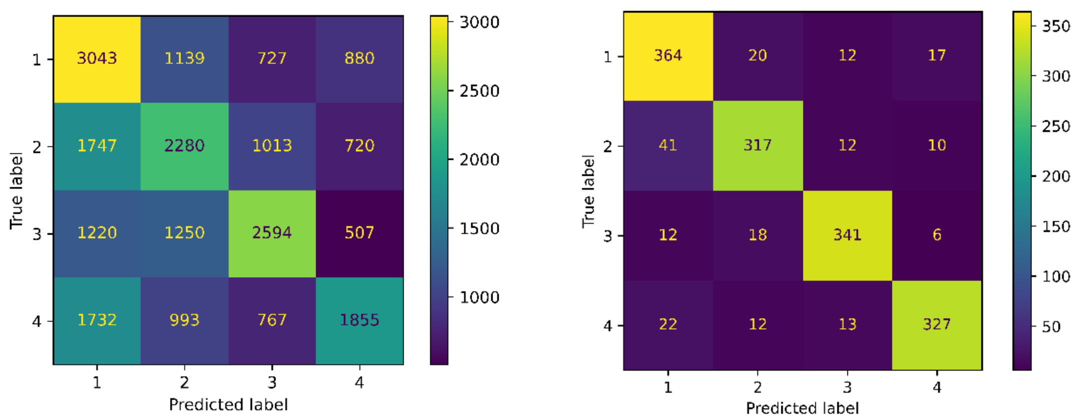


Fig.5 Confusion matrix: (left) before moving average, (right) with moving average

This shows that the model is not much capable of distinguishing between the classes and that the accuracy is a little better than random guess (25% accuracy expectation). However, after simply applying moving average with overlap, the accuracy increased significantly (accuracy = 87.37%) as is shown in the confusion matrix below.

While this accuracy is not bad, it can be improved by adding more features to the model. Still, it performed less than CNN as will be shown in the next section. This is not very surprising given that deep learning usually outperforms regular machine learning techniques.

CNN:

The deep learning approach is one that takes the input signal without doing feature engineering. Still, usual CNN models are based on images input so a common approach is to use spectrogram for each channel and feed them to the model then do classification as is shown in figure below. The approach for CNN was used following common literature approaches performed by Cote-Allard et al papers.

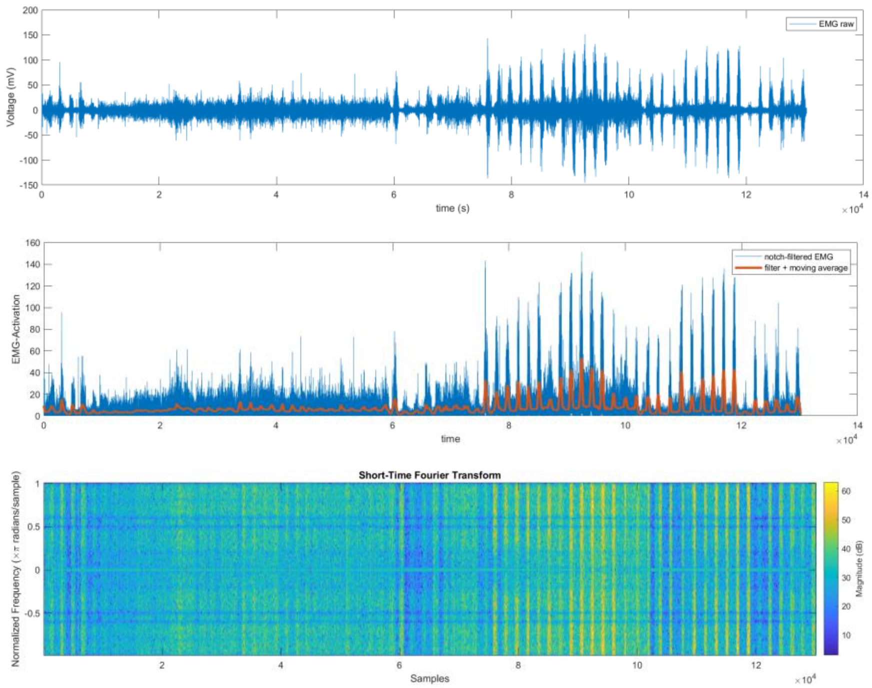


Fig.6 EMG and STFT Spectrogram preprocessing

The nonlinear activation chosen was Parameterized Exponential Linear Unit and for short PeLU (similar to Leaky ReLU but it has exponential term). Batch size chosen was 128, maximum pooling layers were used, and early stopping was applied. For the output layer, Softmax was used .

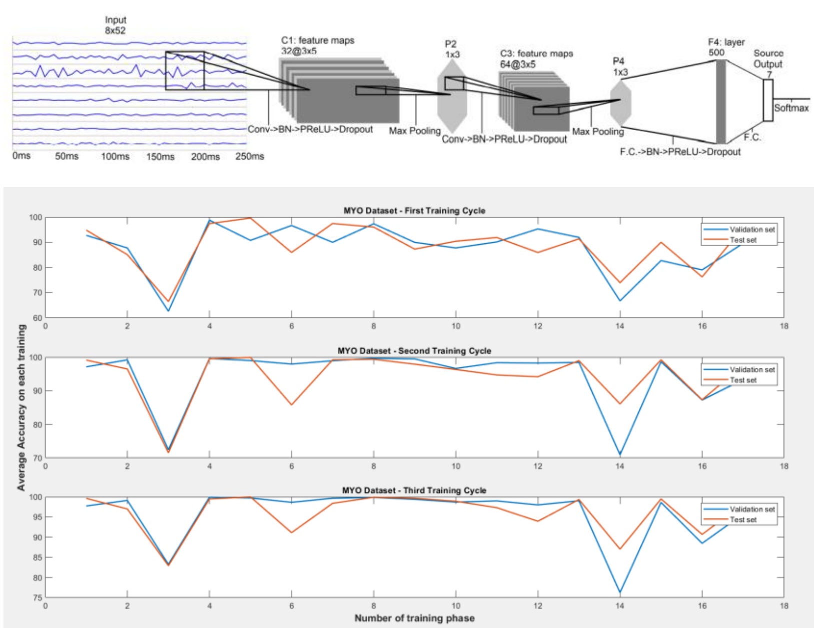


Fig.7 CNN accuracy results

As we can see from the figure, the accuracy was good overall reaching near 95%, which is a good indicator that the task can be performed well for a bigger dataset.

Future work:

A logical continuation of this work is use the models we have on a large scale and see the results on NinaPro full classes. Also, we need to check accuracy for injured people and see if the model can work optimally for the targeted people. We can also try other deep learning approaches, such as RNN LSTM and other combinations of CNN. Additionally, we can try to use wavelet transforms as they have been utilized extensively in the literature.

References:

Balbinot, G., Joner Wiest, M., Li, G., Pakosh, M., Ce- sar Furlan, J., Kalsi-Ryan, S., and Zariffa, J. The use of surface emg in neurorehabilitation following trau- matic spinal cord injury: A scoping review. Clini- cal Neurophysiology, 138:61–73, 2022. ISSN 1388- 2457. doi: https://doi.org/10.1016/j.clinph.2022.02.028. URL https://www.sciencedirect.com/science/article/pii/ S1388245722002103.

Bi, L., Feleke, A. G., and Guan, C. A review on emg-based motor intention prediction of continuous human upper limb motion for human-robot collaboration. Biomedical Signal Processing and Control, 51:113–127, 2019. ISSN 1746-8094. doi: https://doi.org/10.1016/j.bspc.2019.02. 011. URL https://www.sciencedirect.com/science/article/ pii/S1746809419300473.

Chen, L., Fu, J., Wu, Y., Li, H., and Zheng, B. Hand gesture recognition using compact cnn via surface electromyog- raphy signals. Sensors, 20(3), 2020. ISSN 1424-8220. doi: 10.3390/s20030672. URL https://www.mdpi.com/ 1424-8220/20/3/672.

Clarke, A. K., Atashzar, S. F., Vecchio, A. D., Barsakcioglu, D., Muceli, S., Bentley, P., Urh, F., Holobar, A., and Farina, D. Deep learning for robust decomposition of high-density surface emg signals. IEEE Transactions on Biomedical Engineering, 68(2):526–534, Feb 2021. ISSN 1558-2531. doi: 10.1109/TBME.2020.3006508.

Cote-Allard, U., Fall, C. L., Drouin, A., Campeau-Lecours, A., Gosselin, C., Glette, K., Laviolette, F., and Gosselin, B. Deep learning for electromyographic hand gesture signal classification using transfer learning. IEEE Trans- actions on Neural Systems and Rehabilitation Engineer- ing, 27(4):760–771, April 2019. ISSN 1558-0210. doi: 10.1109/TNSRE.2019.2896269.

Drost, G., Stegeman, D. F., van Engelen, B. G., and Zwarts, M. J. Clinical applications of high-density surface emg: A systematic review. Journal of Electromyogra- phy and Kinesiology, 16(6):586–602, 2006. ISSN 1050- 6411. doi: https://doi.org/10.1016/j.jelekin.2006.09.005. Project Proposal URL https://www.sciencedirect.com/science/article/pii/ S1050641106001209. Special Section (pp. 541–610): 2006 ISEK Congress.

Du, Y., Jin, W., Wei, W., Hu, Y., and Geng, W. Surface emg-based inter-session gesture recognition enhanced by deep domain adaptation. Sensors, 17(3), 2017. ISSN 1424-8220. doi: 10.3390/s17030458. URL https://www. mdpi.com/1424-8220/17/3/458.

Foroutannia, A., Akbarzadeh-T, M.-R., and Akbarzadeh, A. A deep learning strategy for emg-based joint position prediction in hip exoskeleton assistive robots. Biomedical Signal Processing and Control, 75:103557, 2022. ISSN 1746-8094. doi: https://doi.org/10.1016/j.bspc.2022. 103557. URL https://www.sciencedirect.com/science/ article/pii/S1746809422000799.

Ghalyan, I. F., Abouelenin, Z. M., and Kapila, V. Gaussian filtering of emg signals for improved hand gesture clas- sification. In 2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB), pp. 1–6, 2018. doi: 10.1109/SPMB.2018.8615596.

Jarrah, Y. A., Asogbon, M. G., Samuel, O. W., Wang, X., Zhu, M., Nsugbe, E., Chen, S., and Li, G. High-density surface emg signal quality enhancement via optimized filtering technique for amputees' motion intent character- ization towards intuitive prostheses control. Biomedical Signal Processing and Control, 74:103497, 2022. ISSN 1746-8094. doi: https://doi.org/10.1016/j.bspc.2022. 103497. URL https://www.sciencedirect.com/science/ article/pii/S1746809422000192.

Ozdemir, M. A., Kisa, D. H., Guren, O., Onan, A., and Akan, A. Emg based hand gesture recognition using deep learning. In 2020 Medical Technologies Congress (TIPTEKNO), pp. 1–4, Nov 2020. doi: 10. 1109/TIPTEKNO50054.2020.9299264. Pizzolato, S., Tagliapietra, L., Cognolato, M., Reggiani, M., M¨uller, H., and Atzori, M. Comparison of six elec- tromyography acquisition setups on hand movement clas- sification tasks. PLOS ONE, 12(10):1–17, 10 2017. doi: 10.1371/journal.pone.0186132. URL https://doi.org/10. 1371/journal.pone.0186132.

Robertson, D., Caldwell, G., Hamill, J., Kamen, G., and Whittlesey, S. Research Methods in Biomechanics. Hu- man Kinetics, 2013. ISBN 9781492581857. URL https: //books.google.com.tr/books?id= u56DwAAQBAJ. Shanmuganathan, V., Yesudhas, H. R., Khan, M. S., Khari, M., and Gandomi, A. H. R-cnn and wavelet feature extraction for hand gesture recognition with emg sig- nals.

Neural Computing and Applications, 32:16723– 16736, 11 2020. ISSN 14333058. doi: 10.1007/ S00521-020-05349-W/FIGURES/13. URL https://link. springer.com/article/10.1007/s00521-020-05349-w.

Sirintuna, D., Ozdamar, I., Aydin, Y., and Basdogan, C. De- tecting human motion intention during phri using artificial neural networks trained by emg signals. In 2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), pp. 1280–1287, 2020. doi: 10.1109/RO-MAN47096.2020.9223438.

Taghizadeh, Z., Rashidi, S., and Shalbaf, A. Finger move- ments classification based on fractional fourier trans- form coefficients extracted from surface emg signals. Biomedical Signal Processing and Control, 68:102573, 2021. ISSN 1746-8094. doi: https://doi.org/10.1016/j. bspc.2021.102573. URL https://www.sciencedirect.com/ science/article/pii/S1746809421001701.

Xiong, D., Zhang, D., Zhao, X., and Zhao, Y. Deep learning for emg-based human-machine interaction: A review. IEEE/CAA Journal of Automatica Sinica, 8(3):512–533, March 2021. ISSN 2329-9274. doi: 10.1109/JAS.2021. 1003865.

Yang, D. and Liu, H. An emg-based deep learning approach for multi-dof wrist movement decoding. IEEE Transac- tions on Industrial Electronics, 69(7):7099–7108, July 2022. ISSN 1557-9948. doi: 10.1109/TIE.2021.3097666.

Zia ur Rehman, M., Waris, A., Gilani, S. O., Jochumsen, M., Niazi, I. K., Jamil, M., Farina, D., and Kamavuako, E. N. Multiday emg-based classification of hand motions with deep learning techniques. Sensors, 18(8), 2018. ISSN 1424-8220. doi: 10.3390/s18082497. URL https: //www.mdpi.com/1424-8220/18/8/2497.