EMG based Control of Transtibial Prosthesis

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Keywords: Transtibial Amputation, Active Control, Gait, EMG driven, Indirect BCI

Abstract: Amputation is defined as the loss of a limb. Transtibial amputation is the amputation below the knee. The purpose of this research is to develop an Electromyography (EMG) based control to mimic the three positions of an ankle. The EMG signals are extracted using eight channel Myo Armband on the tibialis muscles on eight subjects. These signals correspond to the two extreme positions of an ankle and a rest position. The features are extracted and K-Nearest Neighbour is used as a classifier to differentiate between the extreme positions with 98.75 % training classification accuracy. The classified signals are then used to control the prosthesis which mimics the ankle movement. This research can be applied to rehabilitate the ankle and help the people with lower limb amputations.

1 INTRODUCTION

A prosthesis is an artificial device that is developed to replace the function of a lost limb. There are two major types of limb prostheses: Upper-extremity prostheses and Lower-extremity prostheses. Upper-extremity prostheses include prostheses for trans-radial amputation, trans-humeral amputation, wrist dis-articulation, elbow dis-articulation and shoulder dis-articulation. Whereas, lower-extremity prosthesis includes prostheses for hip disarticulation, transfemoral amputation, knee disarticulation, transtibial amputation, ankle disarticulation and partial foot amputation.

Moreover, they can be divided into Active and Passive depending on the use of external power (Windrich *et al.*, 2016). The passive prosthesis does not contain any electronic or mechanical moving part. These prostheses are mostly used for cosmetic purposes and provide the basic functions like pushing, pulling and supporting (Maat *et al.*, 2018). An active prosthesis includes externally powered devices. They consist of sensors in contact with the skin, which pick up the signals from the skin and in turn control the devices/ actuators, which in turn controls the movement (Windrich *et al.*, 2016).

The intuitive control can be developed using different techniques like Surface Electromyography (sEMG) (Anil and Sreeletha, 2019), Ultrasound imaging(González and Castellini, 2013), electroencephalography (EEG) (Bright *et al.*, 2016), Force myography (FMG) (Cho *et al.*, 2016), Implantable Myoelectric Sensors (Pasquina *et al.*, 2015) and Targeted Muscle Reinnervation (TMR)(Cheesborough *et al.*, 2015). Out of these techniques sEMG, ultrasound imaging, EEG, FMG are non-invasive techniques whereas, Implantable Myoelectric sensor and TMR are invasive techniques(Turnip, Soetraprawata and Kusumandari, 2013).

The Myoelectric signals are produced due to variations in the state of muscle fibre. The variation in electric potential in the motor neurons is detected by the electrodes as an EMG signal. So greater the variation/contraction will be, greater the amplitude of the recorded voltage will be. The EMG signals can be detected either by intrusive/intramuscular or non-intrusive technique. The intrusive technique involves the use of needle EMG electrodes by inserting them into the muscle under examination. The advantage of this technique is that it reduces the muscle noise and thus produces more accurate results (Waris and Kamavuako, 2018). Whereas, the non- intrusive technique uses surface EMG electrodes which uses the surface-based detection technique for the EMG signal. This technique does involve more muscle noise but is preferred over the previous method as it does not involve any special formalities and procedure. Moreover, the latest research and technology has resulted in more sensitive sensors which can capture the signals from the skin much

Anis, A., Irshad, M., Hamza, S., Naseer, N., Nazeer, H. and Andrian, .
EMG based Control of Transtibial Prosthesis.
DOI: 10.5220/0009464200740081
In *Proceedings of the International Conference on Health Informatics and Medical Application Technology (ICHIMAT 2019)*, pages 74-81
ISBN: 978-989-758-460-2

very accurately without the need of inserting them (Del Vecchio *et al.*, 2017).

The aim of this research is to encounter all the issues faced due to passive prosthesis by developing a physical prototype of an ankle foot prosthetic active in nature to exhibit its benefits to a transtibial amputee. This includes development and implementation of methodology for EMG signal acquisition as well as classification and identification of intuitive signal for the lower limb prosthesis control. The prosthesis mimics the position of the ankle on the basis of the EMG signals that are classified using the KNN classifier.

The conducted research has various applications in the field of Robotics, Bio-medical Industry and Health sector. Such as, to help people with transtibial amputations to become independent and in defence sector to help the soldiers with amputations to return to normal life.

2 METHODOLOGY

The methodology of this project is divided into four major stages. The first step includes acquisition of data from the subjects. In the second step, the acquired data is then processed and different statistical features are extracted and fed to the classifier. The third step includes the training of classifier on the extracted features and the last step involves the testing of the classifier on the real-time data. The methodology of this process can be seen in the figure 1.

2.1 Data Acquisition

Myo Armband was utilized for the purpose of signal acquisition. It consists of eight EMG electrodes and and an in-built bluetooth for data transmission. The use of multiple channels improves the accuracy. It also comprises of accelerometer and a gyroscope. The transmitted signals can be captured via Myo SDK on MATLAB. The figure 2 shows Myo Armband sensor.

Figure 2: Myo Armband sensor.

It was worn by the subject just below the knee that continuously read the muscle data and sent it via the in-built Bluetooth to the laptop present right next to the subject in form of a vector. The laptop's Bluetooth received the incoming data and passed it to the MATLAB. Figure 3 and 4 shows position of sensor.

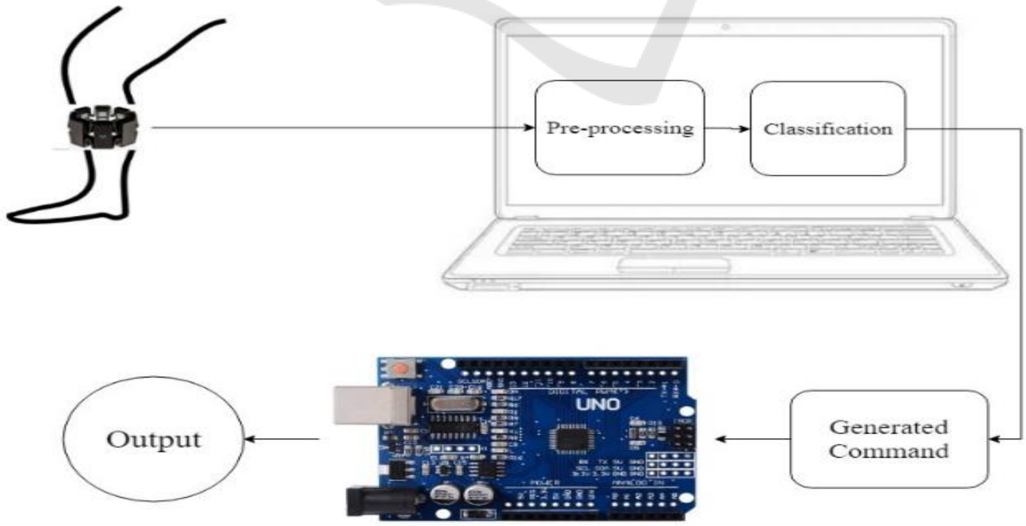

Figure 1: Experimental setup.

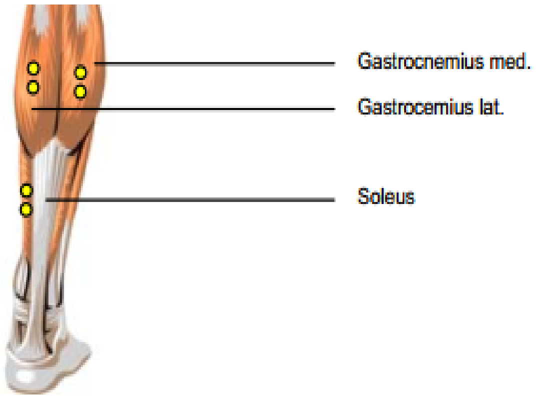

Figure 3: Location of electrodes on muscles (frontal view.)

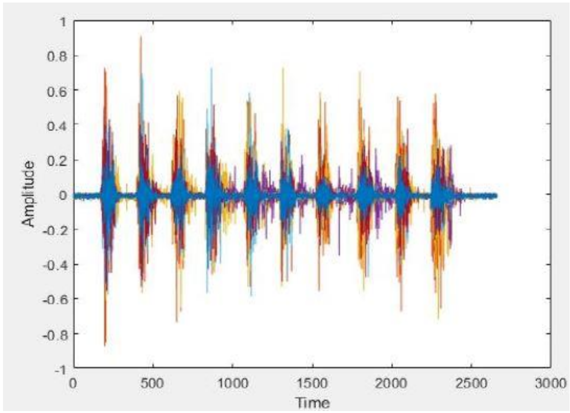

Figure 5: Un-filtered EMG signal.

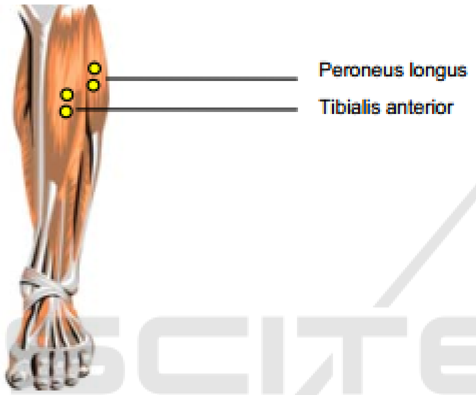

Figure 4: Location of electrodes on muscles (dorsal view).

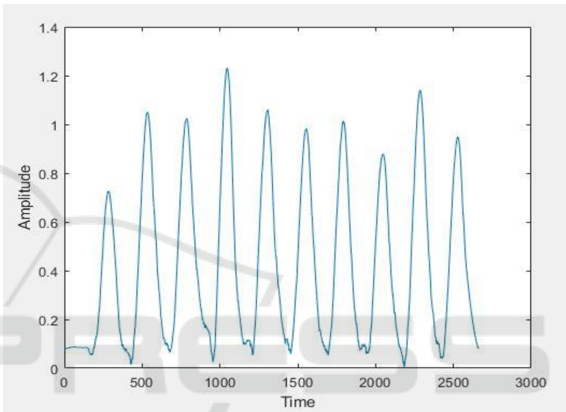

Figure 6: Filtered EMG signal.

The paradigm decided for this project is as follows:

- Number of classes(actions) = 2
- Number of subjects = 8
- Number of male subjects = 6
- Number of female subjects = 2
- Age group = 20-25 years
- Number of activities per subject per trial= 10
- Total time for each trial = 30s
- All subjects are healthy

2.2 Feature Extraction and Accuracy

The Myo Armband provides filtered signals so after receiving the data from Myo Armband, *Savitzky-Golay* filter was applied to smoothen the signal (Christov, Raikova and Angelova, 2018). Figure 5 shows un-filtered EMG signal whereas, Figure 6 shows filtered EMG signal.

After smoothing the signal, the features were extracted. The features help reducing the input data into less but useful data (Phinyomark, Khushaba and Scheme, 2018). They provide useful information about the signal; therefore, features need to be selected carefully. Different statistical features were extracted such as standard deviation, root mean square, mean absolute value, zero crossings, maxima and minima (Hong, Khan and Hong, 2018). The classifiers Linear discriminant analysis (LDA), Support Vector Machine (SVM) and k-nearest neighbours (KNN) were trained separately on each of the above feature. Maximum accuracy was achieved using Root Mean Square as a feature on KNN.

2.3 Real-time Classification and Application Interface

In this phase, the data is classified real-time on the trained classifier. It is also called Online classification. When the amplitude being calculated exceeds the threshold of 0.4, the wave is sent for feature extraction and then the features are fed to the classifier. The classifier then classifies the gesture into respective class and then, based on the output class, the prosthetic foot moves up or down. The process is shown in figure 7.

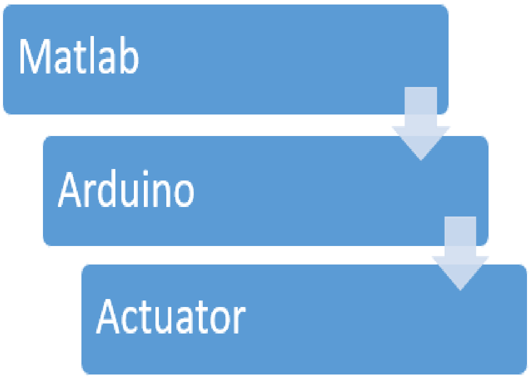

Figure 7: Application interface.

3 MODELING AND SIMULATION

3.1 Gesture

There are two gestures i.e. up and down. The rest position was distinguished on the basis of amplitude. If the calculated amplitude was greater than 0.4 then it meant gesture and its features were extracted and passed on to the classifier. Otherwise, it meant rest (Reaz, Hussain and Mohd-Yasin, 2006). The total number of classes is two as seen in Figure 8-10.

3.2 Data Collection

The Data was collected via Myo Armband which continuously sent the data wirelessly to the laptop at the sampling frequency of 200 Hz. The data was received in the form of a nx8 vector where 'n' depends on the duration of the activity and eight represents number of electrodes. It was then plotted and processed using MATLAB. The Figure 11- 14 shows the raw data obtained for rest, up and down gesture on each electrode as well as a combination of all the electrodes.

Figure 8: Rest position.

Figure 9: Up gesture.

Figure 10: Down gesture.

3.3 Classification

The classifier was used to differentiate between the two classes on the basis of input features(Qureshi *et al.*, 2016). A classifier was needed that could satisfy the following conditions: easy to understand, need only acceptably short calculation time and have a more than decent predictive power(Simbolon *et al.*, 2016). Three classification algorithms Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and K-Nearest neighbour (KNN) were trained, tested and validated.

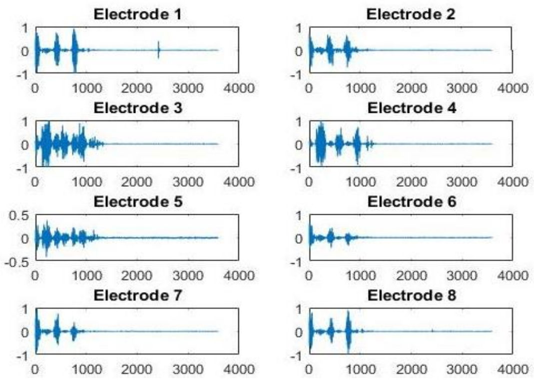

Figure 11: Raw EMG signal for rest.

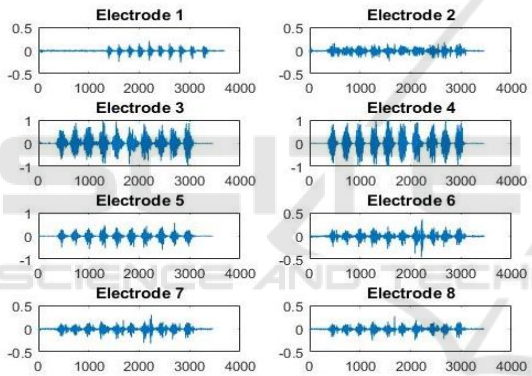

Figure 12: Raw EMG signal for up gesture.

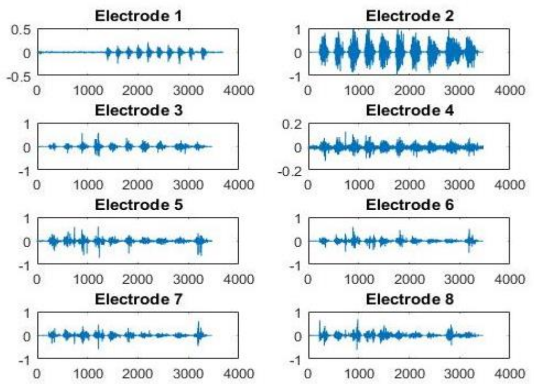

Figure 13: Raw EMG signal for down gesture.

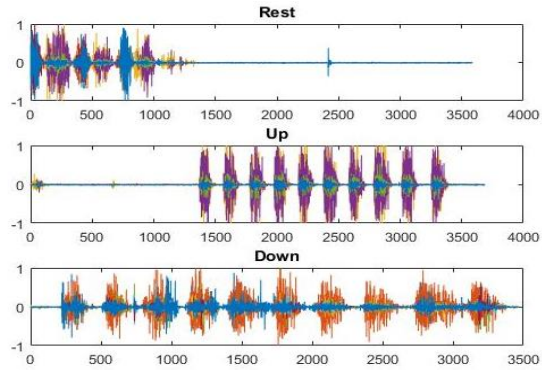

Figure 14: Raw signals for rest, up and down gesture.

In Support Vector Machine, each data item is plotted as a point in space where the dimension of the space depends on the number of features(Turnip *et al.*, 2016). The classification is then performed by finding the hyper-plane that separates the classes well. The new data is then plotted in the same space and the category is decided on the basis of the side of the gap where they fall(Alkan and Günay, 2012). An offline accuracy of 88.7% was achieved using SVM.

The LDA predicts the class of the set of data by calculating the probability for each class. The probability is estimated using the Bayes Theorem. The class with the highest probability is selected as the output class (Alam and Arefin, 2018).LDA is a general form of Fisher's linear discriminant, which is used in statistics and pattern recognition problems(Naseer *et al.*, 2016). An offline accuracy of 96.4%was achieved using LDA.

KNN is another method used for classification which makes use of the fact that the similar things exist in close proximity. The input data is assigned the class of majority of its closest neighbours. It is easy to implement and can be used for both the regression and classification problems. The advantages of this algorithm are that it doesn't need to make various assumptions and to build a separate model(Altın and Er, 2016). The only con is that it becomes slower as the number of examples increase(Khan *et al.*, 2018). An offline accuracy of 98.7% and an online accuracy of 90% was achieved. The KNN was chosen since it provided the highest classification accuracy and fast calculation time. The results can be seen in the Figure 15.

4 RESULTS

When the muscle is at rest then the calculated amplitude is less than 0.4 and no action is performed

Figure 15: Percentage accuracy versus features on three different classifiers.

at the output. So, if the foot is up then the prosthetic also stays up and if the foot is down then the prosthetic remains down at rest.

When the calculated amplitude is greater than 0.4 and a change in the muscle signals is detected, then the signal is sent for feature extraction and then to the classifier. Depending on the classification result, a command is generated.

The output command generated from the MATLAB is sent to the Arduino using Arduino hardware support package on MATLAB. On the basis of the classified signal the MATLAB generates the forward, backward or rest command to Arduino which controls the actuator integrated with it and moves the ankle up, down or keeps it in rest state.

In the Figure 16-18, one can observe the output of prosthetic foot against each of the gesture.

Figure 16: Rest position.

Figure 17: Up gesture.

Figure 18: Down gesture.

5 CONCLUSIONS AND FUTURE RECOMMENDATIONS

This paper presents an improved technique to control a transtibial prosthesis using EMG signals and machine learning algorithms.

The EMG signals were obtained using Myo Armband. Features such as root mean square were extracted and fed to the classifier and the classifiers were then trained, tested and validated on different features. It was found that using root mean square as a feature and KNN as a classifier gave maximum accuracy. An offline accuracy of 98.75% and an online accuracy of 90% was achieved(Anil and Sreeletha, 2019).

However, the prosthesis can be made more natural-like by mimicking the human gait that can be done by increasing the number of output classes on the basis of the angle of the ankle joint.

Moreover, the classifier performance can be improved by increasing the number of training data set. The combination of different features can also be implemented to increase the accuracy. The artificial neural networks or other deep learning techniques may be applied to improve the accuracy.

Although, the prime objective of controlling the prosthetic was achieved, closed loop control must be introduced for precise and robust control of the joint.

More work needs to be done to make the prosthesis portable by the introduction of single board computer like Beaglebone, Raspberry Pi and UDOO.

REFERENCES

Alam, M. S. and Arefin, A. S. (2018) ‘Real-Time Classification of Multi-Channel Forearm EMG to Recognize Hand Movements using Effective Feature Combination and LDA Classifier’, *Bangladesh Journal of Medical Physics*, 10(1), pp. 25–39. doi: 10.3329/bjmp.v10i1.39148.

Alkan, A. and Günay, M. (2012) ‘Identification of EMG signals using discriminant analysis and SVM classifier’, *Expert Systems with Applications*. Elsevier Ltd, 39(1), pp. 44–47. doi: 10.1016/j.eswa.2011.06.043.

Altın, C. and Er, O. (2016) ‘Comparison of Different Time and Frequency Domain Feature Extraction Methods on Elbow Gesture’s EMG’, *European Journal of Interdisciplinary Studies*, 5(1), p. 35. doi: 10.26417/ejis.v5i1.p35-44.

Anil, N. and Sreeletha, S. H. (2019) ‘EMG Based Gesture Recognition Using Machine Learning’, *Proceedings of the 2nd International Conference on Intelligent Computing and Control Systems, ICICCS 2018*. IEEE, (Iciccs), pp. 1560–1564. doi: 10.1109/ICCONS.2018.8662987.

Bright, D. *et al.* (2016) ‘EEG-based brain controlled prosthetic arm’, *Conference on Advances in Signal Processing, CASP 2016*, pp. 479–483. doi: 10.1109/CASP.2016.7746219.

Cheesborough, J. E. *et al.* (2015) ‘Targeted muscle reinnervation and advanced prosthetic arms’, *Seminars in Plastic Surgery*, 29(1), pp. 62–72. doi: 10.1055/s-0035-1544166.

Cho, E. *et al.* (2016) ‘Force myography to control robotic upper extremity prostheses: A feasibility study’, *Frontiers in Bioengineering and Biotechnology*, 4(MAR), pp. 1–12. doi: 10.3389/fbioe.2016.00018.

Christov, I., Raikova, R. and Angelova, S. (2018) ‘Separation of electrocardiographic from electromyographic signals using dynamic filtration’, *Medical Engineering and Physics*. Elsevier Ltd, 57, pp. 1–10. doi: 10.1016/j.medengphy.2018.04.007.

González, D. S. and Castellini, C. (2013) ‘A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees’, *Frontiers in Neurorobotics*, 7(OCT), pp. 1–11. doi: 10.3389/fnbot.2013.00017.

Hong, K. S., Khan, M. J. and Hong, M. J. (2018) ‘Feature Extraction and Classification Methods for Hybrid fNIRS-EEG Brain-Computer Interfaces’, *Frontiers in Human Neuroscience*, 12(June), pp. 1–25. doi: 10.3389/fnhum.2018.00246.

Khan, R. A. *et al.* (2018) ‘FNIRS-based Neurorobotic Interface for gait rehabilitation’, *Journal of NeuroEngineering and Rehabilitation*. Journal of NeuroEngineering and Rehabilitation, 15(1), pp. 1–17. doi: 10.1186/s12984-018-0346-2.

Maat, B. *et al.* (2018) ‘Passive prosthetic hands and tools: A literature review’, *Prosthetics and Orthotics International*, 42(1), pp. 66–74. doi: 10.1177/0309364617691622.

Naseer, N. *et al.* (2016) ‘Determining optimal feature-combination for LDA classification of functional near-infrared spectroscopy signals in brain-computer interface application’, *Frontiers in Human Neuroscience*, 10(MAY2016), pp. 1–10. doi: 10.3389/fnhum.2016.00237.

Pasquina, P. F. *et al.* (2015) ‘First-in-man demonstration of a fully implanted myoelectric sensors system to control an advanced electromechanical prosthetic hand’, *Journal of Neuroscience Methods*. Elsevier B.V., 244, pp. 85–93. doi: 10.1016/j.jneumeth.2014.07.016.

Phinyomark, A., Khushaba, R. N. and Scheme, E. (2018) ‘Feature extraction and selection for myoelectric control based on wearable EMG sensors’, *Sensors (Switzerland)*, 18(5), pp. 1–17. doi: 10.3390/s18051615.

Qureshi, N. K. *et al.* (2016) ‘Comparison of classification performance for fNIRS-BCI system’, *2016 2nd International Conference on Robotics and Artificial Intelligence, ICRAI 2016*, pp. 54–57. doi: 10.1109/ICRAI.2016.7791228.

Reaz, M. B. I., Hussain, M. S. and Mohd-Yasin, F. (2006) ‘Techniques of EMG signal analysis: Detection, processing, classification and applications’, *Biological Procedures Online*, 8(1), pp. 11–35. doi: 10.1251/bpo115.

Simbolon, A. I. *et al.* (2016) ‘An experiment of lie detection based EEG-P300 classified by SVM algorithm’, *Proceedings of the 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-*

Mechanical System, and Information Technology, ICACOMIT 2015, pp. 68–71. doi: 10.1109/ICACOMIT.2015.7440177.

Turnip, A. *et al.* (2016) 'EEG-based brain-controlled wheelchair with four different stimuli frequencies', *Internetworking Indonesia Journal*, 8(1), pp. 65–69.

Turnip, A., Soetraprawata, D. and Kusumandari, D. E. (2013) 'A Comparison of EEG Processing Methods to Improve the Performance of BCI', *International Journal of Signal Processing Systems*, 1(1), pp. 63–67. doi: 10.12720/ijsps.1.1.63-67.

Del Vecchio, A. *et al.* (2017) 'Associations between motor unit action potential parameters and surface EMG features', *Journal of Applied Physiology*, 123(4), pp. 835–843. doi: 10.1152/japplphysiol.00482.2017.

Waris, A. and Kamavuako, E. N. (2018) 'Effect of threshold values on the combination of EMG time domain features: Surface versus intramuscular EMG', *Biomedical Signal Processing and Control*. Elsevier Ltd, 45, pp. 267–273. doi: 10.1016/j.bspc.2018.05.036.

Windrich, M. *et al.* (2016) 'Active lower limb prosthetics: A systematic review of design issues and solutions', *BioMedical Engineering Online*. BioMed Central, 15(3), pp. 5–19. doi: 10.1186/s12938-016-0284-9.