# SENSOR REDUCTION ON EMG-BASED HAND GESTURE CLASSIFICATION

*Giovanni Costinini[1], Giovanni Saggio[1], Lucia Quitadamo[1], Emanuele Gruppioni[2], Daniele Casali[1]*

[1]Dept. of Electronic Engineering, University of Rome Tor Vergata, Via del Politecnico 1, 00133 Rome, Italy,
e-mail costantini@uniroma2.it
[2] Centro Protesi INAIL, Budrio, Bologna

***Keywords: Neural networks, EMG, hand-gesture, classification, feature selection.***

This work concerns a system based on EMG sensors, signal conditioning circuitry, classification algorithm based on Artificial Neural Network, and virtual avatar representation, useful to identify hand movements within a set of five. This is to potentially make any trans-radial upper-limb amputee able to drive a virtual or real limb prosthetic hand. We focused on differences resulting with the adoption of a different number of sensors and therefore, by means of a very simple heuristic method, we compared different subsets of features, excluding the less significant sensors. We found optimal subsets of one, two, three, four and five sensors, demonstrating a decrease of the performance of only 0.8% when using five sensors, while with three sensors the accuracy can be as high as 81.7%. As shown in Fig. 1. In such a frame, an automatic system, able to analyze the hand gestures and classify their effectiveness, can be strategically adopted. In recent years, different systems was proposed to use surface EMG (sEMG) signal acquired on human forearms as input data to control a real prosthesis [1] or virtual device [2], either for interactive or clinical/rehabilitative [3] purposes. Most of the EMG-controlled device users are radial upper-limb amputees, i.e. amputation occurred below elbow. For these people, the replacement of missing arm functionalities could be a significant improvement to the quality of life. Moreover research showed that the visual-sensorial feedback provided by following the prosthetic or virtual hand movements can be useful to alleviate the phantom limb pain [4], an invalidating condition that affects between 50% and 80% of amputees [5].

In our system, after acquisition, raw EMG data were segmented using the overlapped windowing technique [6]: the windows length was fixed to 256ms, with 64ms of overlap between two successive. For every sensor we considered the following features:

- *Mean (M)*: represents the mean value of the EMG amplitude.
- *Root Mean Square (RMS)*: represents the mean power of the signal.
- *Willison Amplitude (WA)*: represents the number of counts for each change in the EMG signal amplitude that exceeds a predefined threshold, set to avoid background noise-induced counts. It is related to the level of muscle contraction.
- *Slope Sign Change (SSC)*: represents the number of times the slope of the EMG signal changes sign.
- *Simple Square Integral (SSI):* represents, similarly to Energy in continuous-time signal, the area under the curve of the squared signal.
- *Variance (V):* represents a statistical measure of how signal varies from its average value during the observation:
- *Waveform Length (WL)*: represents cumulative length of the EMG signal waveform. WL is a measure of EMG signal complexity.

For the classification, we implemented an Artificial Neural Network (ANN) with 10 neurons in the hidden layer and back-propagation training method. The number of neurons of the hidden layer was empirically determined in previous tests.

When using all sensors, a 5-fold cross-validation to measure the performance of every configuration gives a mean accuracy among all subjects of 88.8%, anyway there was a strong difference among subjects, being the standard deviation 7.2%. In order to determine what sensors are more important, we first repeated the whole test, with the cross-validation, excluding sensor 1, i.e. considering only the features based on sensors 2, 3, 4, 5, 6. Then we excluded sensor 2, and cross-validated the network using the features based on sensors 1, 3, 4, 5, 6. The same was repeated excluding, one at a time, all the sensors. We found that excluding sensor 1, the performance was almost the same as using all sensors. A similar concept was applied excluding sensor 1 together with every other, where we found if we want to use only 4 sensor, the best performance is reached by using sensors 2, 3, 5, 6, which means excluding sensor 1 and 4.

The same algorithm was applied until a single sensor remained. Results are shown in Fig. 1. As we can clearly see, a single sensor is not sufficient to have a good performance, but three or for sensor cold often be enough, depending on the available budget and required performance.

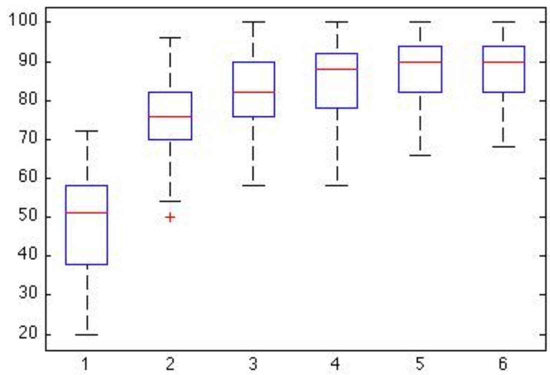


Fig. 1: Box-plot of the accuracy for every considered number of sensors.

## REFERENCES


[1] Matrone G.C., Cipriani C., Secco E.L., Magenes G., Carrozza M.C., (2010) "Principal components analysis based control of a multi-DoF underactuated prosthetic hand". *J Neuroeng Rehabil*, vol. 23, pp. 7-16.

[2] Li G., Schultz A.E., Kuiken T.A., (2010). "Quantifying pattern recognition- based myoelectric control of multifunctional transradial prostheses", *IEEE Trans Neural Syst Rehabil Eng*, vol. 18, no. 2, pp. 185-192.

[3] Scheme E. and Englehart K. (2011) "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use", *J Rehabil Res Dev*, vol. 48, no. 6, pp. 643-659.

[4] Castellini C., Gruppioni E., Davalli A., Sandini G., (2009). "Fine detection of grasp force and posture by amputees via surface electromyography", *J Physiol Paris*, vol. 103, no. 3-5, pp. 255-262.

[5] Flor H., (2002). "Phantom-limb pain: characteristics, causes, and treatment", *Lancet Neurol*, vol. 1, no. 3, pp. 182-189.

[6] Oskoei MA, Hu H, (2008). "Support vector machine-based classification scheme for myoelectric control applied to upper limb", *IEEE Trans Biomed Eng*, vol. 55, no. 8, pp. 1956-1965.