A Hybrid sEMG Activated Human Computer Interface based on Inertial Measurement Unit

Julio Fajardo – werjevfh@galileo.edu, Alí Lemus – alilemus@galileo.edu
Alan Turing Research Laboratory, FISICC, Universidad Galileo

Introduction

The use of surface electromyography (sEMG) to control upper-limb prostheses requires expensive medical equipment to get accurate results. Biopotentials acquisition is affected by many factors, substantially by the limb position effect [2]. A hybrid sEMG activated embedded system combined with Inertial Measurement Units (IMU) is proposed in order to increase functionality and reduce costs of myoelectric controllers for multiple Degrees of Freedom (DOF) prostheses.

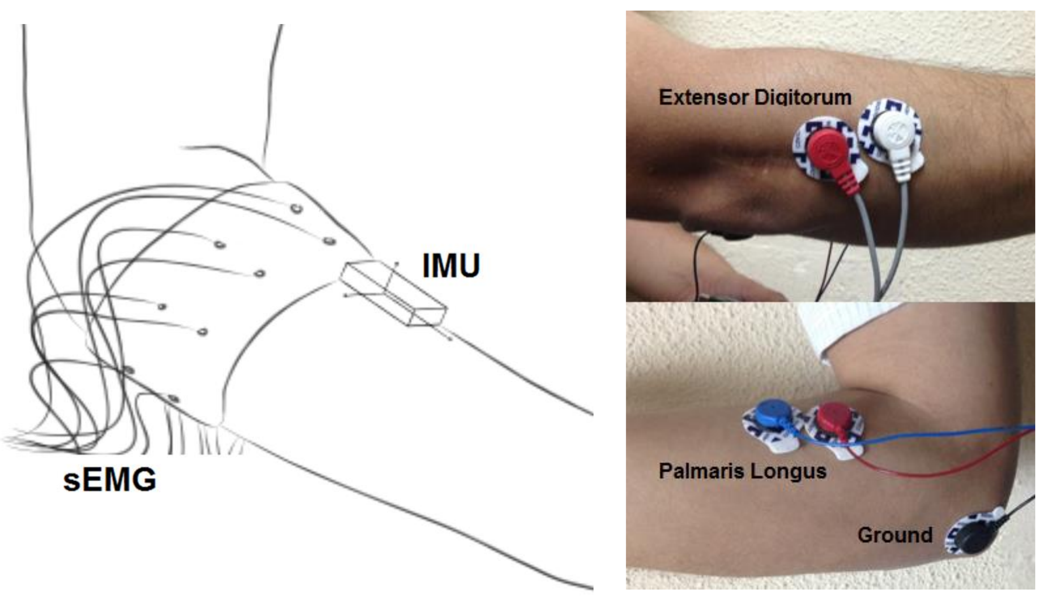


Fig.1. sEMG and IMU Human Computer Interface improvement.

Knowing the limitations of conventional prostheses and considering the elevated cost of a typical myoelectric prosthesis, some low-cost open source projects have been released and do not offer a wide range of user actions. A hybrid sEMG activated human computer interface based on inertial measurement units is proposed in order to increase the amount of postures that upper-limb bionic prostheses can perform..

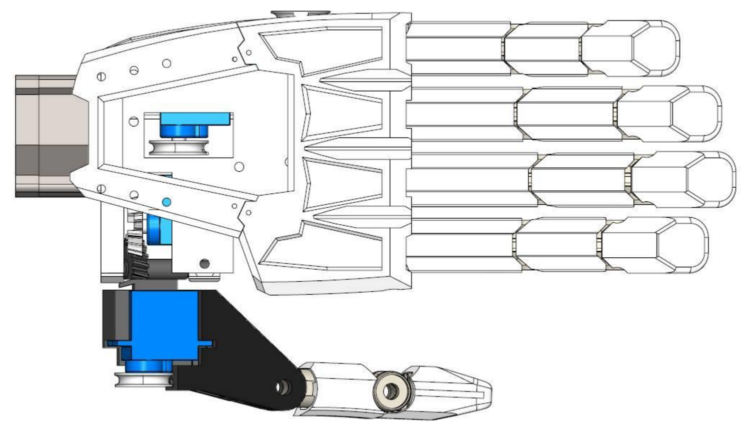


Fig.2. Galileo Bionic Hand. Open Source Project.

Methods

I. System Architecture

The block diagram proposed below shows a controller based on Digital Signal Processing and Machine Learning in order to interpret the user intention and perform predefined hand postures. The controller takes advantage of arm motion and position, not only for solving the limb position effect, but also taking advantage of arm motion in order to implement new ways of human computer interfaces for bionic upper-limb prosthetics.

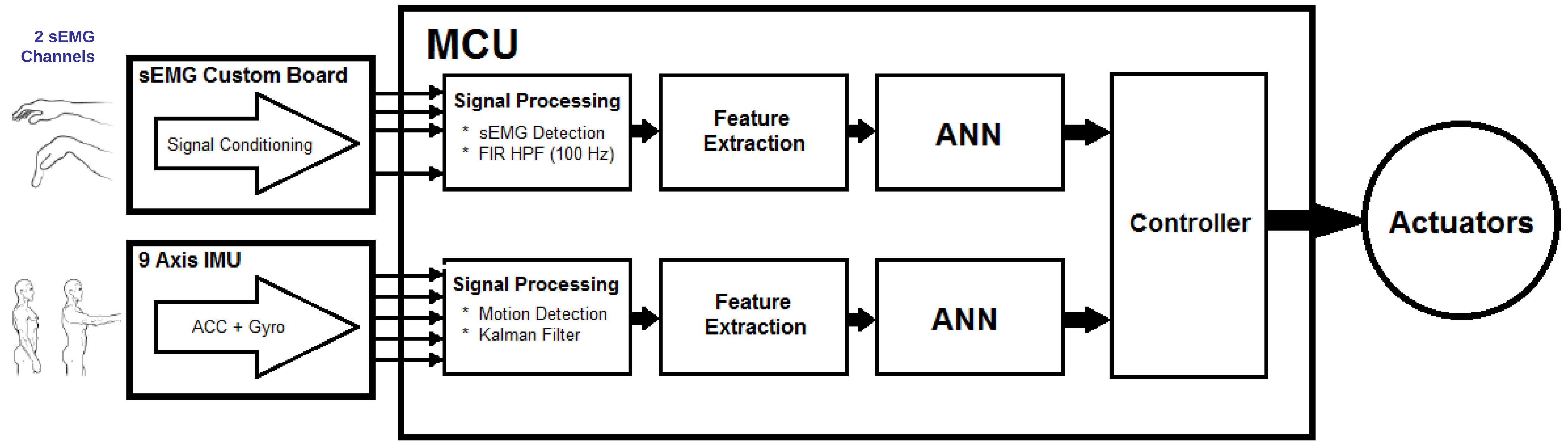


Fig.3. System Architecture, sEMG processing and IMU processing stage details.

II. Feature Extraction

The success of pattern classification systems depends on the choice of features [1]. The following time-domain features were selected for each classification stage.

sEMG Features
Ts = 1 ms 500 samples

$$\sigma^2 = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2$$

$$WL = \sum_{n=1}^{N} |x_n - x_{n-1}|$$

$$I_{EMG} = \sum_{n=1}^{N} |x_n|$$

$$ZC = \sum_{n=1}^{N} [sgn(-x_n \times x_{n+1}) > 0 \wedge |x_n - x_{n+1}| \geq 0.06]$$

$$SSC = \sum_{n=1}^{N} [(x_n - x_{n-1}) \times (x_n - x_{n+1}) \geq 0.06]$$

$$W_{AMP} = \sum_{n=1}^{N} f(|x_n - x_{n+1}|),$$

$$f(x) = \begin{cases} 1, & if\ x > 0.12 \\ 0, & otherwise \end{cases}$$

IMU Features
Ts = 10 ms 50 samples

Considering two sequences of measurements $X = (x_1, x_2, ..., x_n)$ of length n, $Y = (y_1, y_2, ..., y_m)$ of length m

$$DTW(X,Y) = d(n,m)$$

$$d(i,j) = ||x_i - y_j|| + min \begin{cases} d(i, j-1) \\ d(i-1, j) \\ d(i-1, j-1) \end{cases}$$

$$d(0,0) = 0, d(i,0) = d(0,j) = \infty$$

$$(i = 1, ..., n; j = 1, ..., m;)$$

- Acceleration (a_x, a_y, a_z)
- Angular Velocity $(\omega_x, \omega_y, \omega_z)$
- Euler Angles (α, β, γ)

Fig.4. Features extracted from time series analysis.

III. Classification

Multilayer Feedforward Neural Networks has been trained in order to select and trigger predefined gestures from a set of motions and muscle contractions.

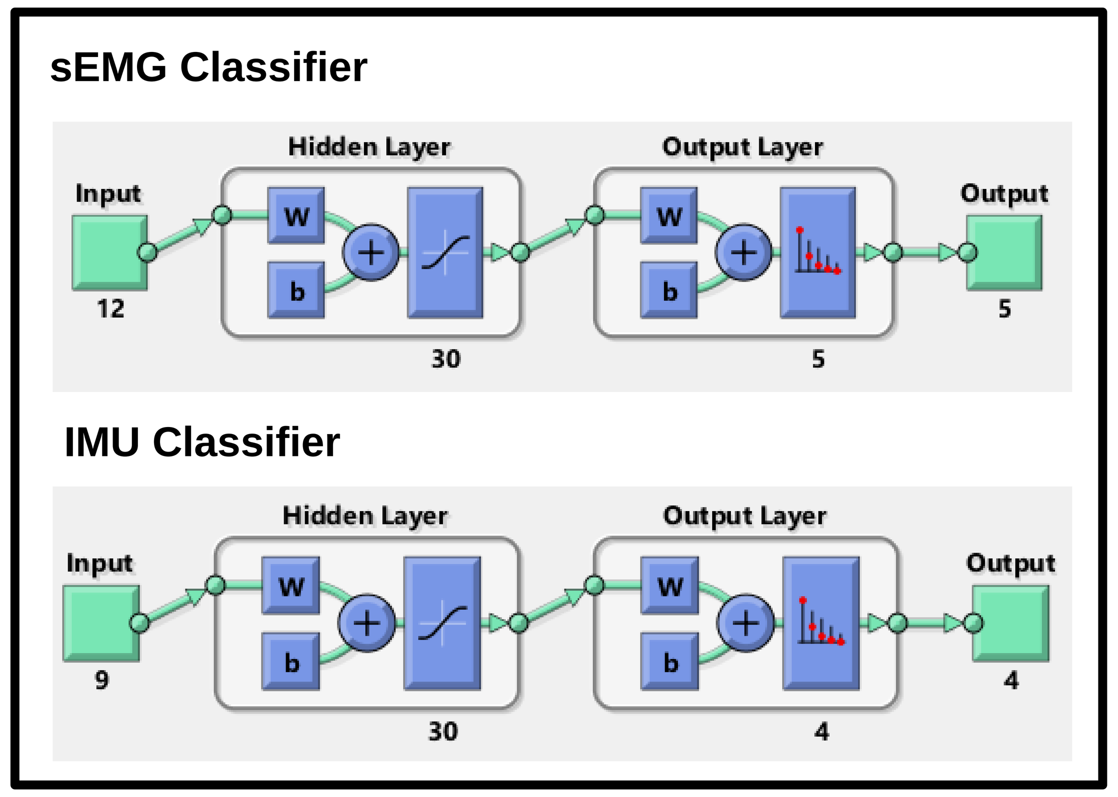
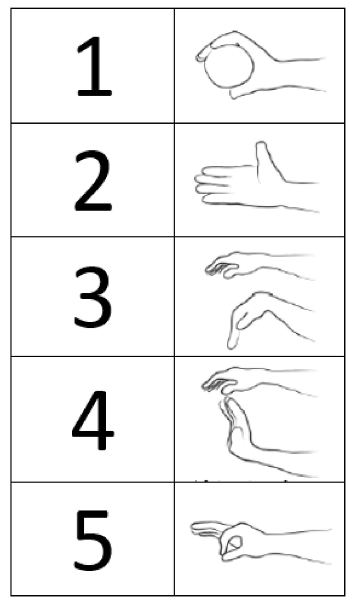


Fig.5. Feed Forward Neural Network Architecture

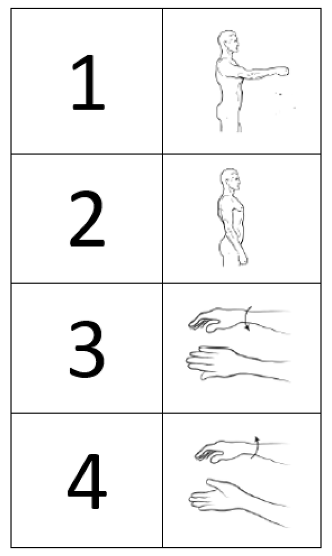
Results

The performance of the motion classifiers and pattern recognition classifier is shown below.



	1	2	3	4	5	
1	100 20.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	97 19.4%	0 0.0%	5 1.0%	0 0.0%	95.1% 4.9%
3	0 0.0%	0 0.0%	99 19.8%	0 0.0%	1 0.2%	99.0% 1.0%
4	0 0.0%	3 0.6%	0 0.0%	95 19.0%	0 0.0%	96.9% 3.1%
5	0 0.0%	0 0.0%	1 0.2%	0 0.0%	99 19.8%	99.0% 1.0%
	100% 0.0%	97.0% 3.0%	99.0% 1.0%	95.0% 5.0%	99.0% 1.0%	98.0% 2.0%

Fig.6. sEMG Pattern Recognition Confusion Matrix



	1	2	3	4	
1	50 25.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	50 25.0%	0 0.0%	0 0.0%	100% 0.0%
3	0 0.0%	0 0.0%	48 24.0%	2 1.0%	96.0% 4.0%
4	0 0.0%	0 0.0%	2 1.0%	48 24.0%	96.0% 4.0%
	100% 0.0%	100% 0.0%	96.0% 4.0%	96.0% 4.0%	98.0% 2.0%

Fig.7. IMU Motion Classifier Confusion Matrix

Conclusion

The results show that combination of sEMG and IMU as HCI, not only solves the Limb Position Effect, also improves the functionality of multi degree of freedom prostheses.

References

[1] H.P. Huang, C.Y. Chiang, *"DSP-based controller for multi-degree prosthetic hand"*, IEEE ICRA vol. 2, 2000.

[2] A. Fougner, E. Scheme, Adrian Chan, K. Englehart *"Resolving the Limb Position Effect in Myoelectric Pattern Recognition"*, IEEE NSRE vol. 19, 2011.