Galileo Bionic Hand: sEMG Activated Approaches for a Multifunction Upper-Limb Prosthetic

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***Abstract*—Surface electromyography (sEMG) commonly used in upper-limb prostheses requires expensive medical equipment to get accurate results, and even then only a few actions can be classified. We propose an sEMG activated embedded system based on Digital Signal Processing and Machine Learning, to interpret the user intention with the purpose of controlling a low-cost 3D printed hand prosthesis with multiple Degrees of Freedom (DOF). The system has three different operating modes with a user-friendly Human Machine Interface (HMI), in order to increase the amount of customized hand postures that can be performed by the user, providing functionalities that fit on their daily chores and allowing to use inexpensive surface mounted passive electrodes in order to keep a low cost approach. Inasmuch as sEMG activation allows the user to consciously perform the desired action, on the other hand a touchscreen enables the possibility to select different predefined actions and operating modes, as well as provide necessary visual feedback. Moreover, in another operating mode, a speech recognition module recognizes user speech in 3 different languages, allowing the user more sEMG activated postures. Finally, an operating mode based on Artificial Neural Networks (ANN) classifies 5 hand gestures that can be easily accomplished by below elbow amputees. The system was tested and obtained high accuracy and great responsiveness on the different modes of operation.**

Keywords. Upper-Limb Prostheses, Electromyography, Embedded Systems, Digital Signal Processing, Machine Learning, Artificial Neural Networks, Human Machine Interface.

I. Introduction

Galileo Bionic Hand is a low-cost 3D-printed prosthetic hand, which is planned to be released as a Do It Yourself kit (DIY), so that people with disabilities could contact local makers to help them to build the system. The prosthesis was designed to be easily built and repaired by anyone with no experience on prosthesis manufacturing anywhere in the world, ensuring its proper operation and removing the need to require expert support. Since, electromyography is a technique used to detect the activity of a group of muscles by measuring bio-potentials acquired by surface mounted electrodes, a controller based on this technique was implemented, allowing the user to consciously perform desired postures on the prosthesis. Although the complexity of the controller increases the cost of development and fabrication, we are focused to keep the price range below $500 and aiming at a DIY approach where the electronic components could be distributed as a kit which includes the system built on a printed circuit board (PCB), complementing the open source files of the 3D design and the materials to build the prosthesis.

Knowing the limitations of conventional steel hook prostheses and considering the elevated cost of a typical myoelectric prosthesis, like the beBionic3 [4], some low-cost open source projects have been released based on 3D printing technology. Global networks of volunteers, like e-Nable are designing and distributing free prosthetic hands for those in need, however, myoelectric prostheses are not available yet [9]. Moreover, companies like Handiii, who released the HACKberry, a simplified and open source version of its myoelectric prostheses do not offer a wide range of user actions [13].

A hybrid sEMG activated controller with multiple operating modes is proposed and described in Section II. This controller takes advantage of digital signal processing and machine learning techniques, in order to integrate different systems on a single embedded controller operated through a user-friendly HMI that perfectly adapts on the user lifestyle like a wearable device. This allows the performing of more and complex customized hand prosthetic actions, such as individual finger movements, different kinds of grasping and time based sequential actions.

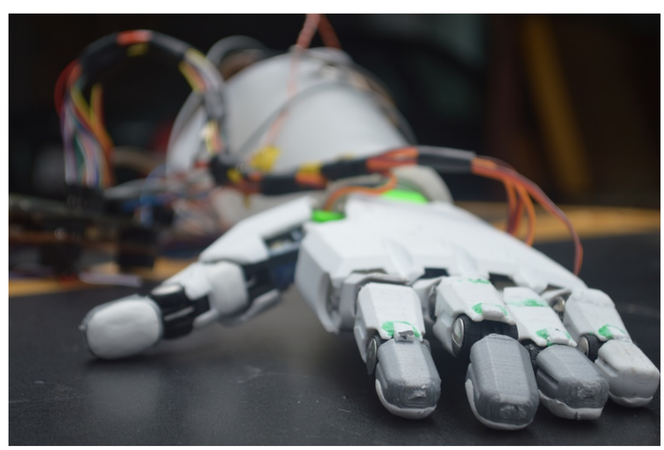

Fig. 1. Galileo Hand, 3D printed bionic version.

II. System Architecture

The system is based on low cost and high performance microcontroller unit (MCU) based on the ARM Cortex-M4 architecture, with signal processing capabilities, ideal for the type of tasks required to develop a high-efficiency, responsiveness and user-friendly controller. The block diagram proposed in Fig. 2 shows a flexible controller based on low-cost components, intended to be released as a DIY kit with the capability of providing customized hand postures that best suit the user's lifestyle.

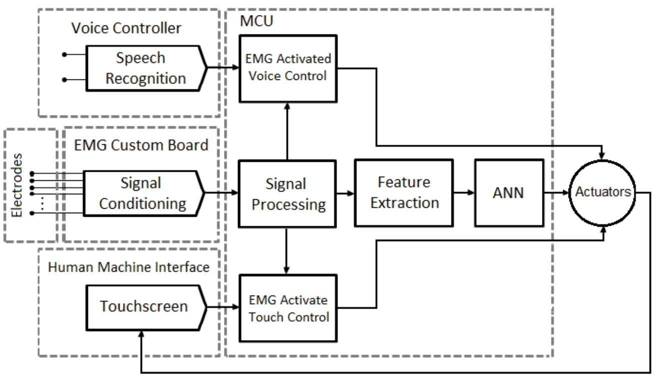

Fig. 2. The system block diagram showing the different operating modes.

A. HMI and Operating Modes

The controller has a user-friendly HMI with three operating modes to improve functionality and increase the number of customized hand postures. A QVGA TFT-LCD touchscreen is used, allowing to select between the different functionalities of the controller by pressing buttons directly on the touchscreen, beside the possibility to provide visual feedback to the user as shown on Fig. 3.

1) Hybrid sEMG-Activated Touch Controller: This approach allows to consciously activate predefined postures through a hybrid sEMG-touch interface. A Finite State Machine (FSM) is implemented, allowing the user to consciously activate and deactivate desired actions, by detecting sEMG signals on the muscles involved in the intended hand gestures. The user has to select the desired posture by pressing a button directly on the touchscreen and then perform it through sEMG activation by detecting contraction on flexor muscles of the forearm. Contractions on forearm extensor muscles releases the posture and allows the return to the default or rest posture.

2) Hybrid sEMG-Activated Voice Controller: This approach allows to consciously activate predefined postures through a hybrid sEMG-voice interface based on the Easy VR speech recognition module that communicates with the MCU through a UART interface. The user has the possibility to select between three predefined languages by pressing buttons directly on the display. Twenty six predefined voice commands and up to twenty eight customized voice commands are available, considerably increasing the number of postures that the user can perform [8]. To select the desired action the user has to press a push button and say a command before a 3 seconds timeout. If the voice command is recognized, a visual feedback will be displayed. Finally the user has to activate and deactivate the actions by sEMG signal detection, as described in the sEMG-Activated Touch Controller section.

3) sEMG Pattern Recognition: This operating mode takes advantage of machine learning algorithms, allowing the system to learn and classify five hand gestures produced by below elbow amputees. Useful information about the classification is displayed such as the prediction and the real valued confidence score for each class. Furthermore, by pressing a button on the touchscreen, the user has the choice between Off-line Learning (i.e. training) that collects sEMG features, in order to train the algorithm to properly classify the predefined gestures from a set of muscle contractions, and On-line Classification (i.e. usage) to let the system predict which hand action is intended from muscular activity.

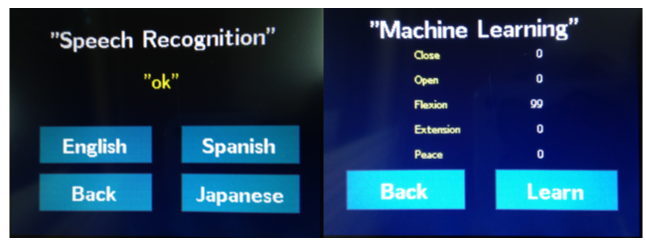

Fig. 3. Human machine interface for sEMG-Activated voice controller and machine learning controller.

B. sEMG Signal Acquisition

Two bipolar channels with standard surface mounted Ag/AgCl electrodes with wet conductive gels are placed on palmaris longus and extensor digitorum muscles, focusing only on below elbow disarticulation, as shown on Fig. 4. These electrodes have been well-characterized and most of its properties are well understood, except for some properties as drifting and low-frequency noise. Nevertheless, with proper preparation of the skin, the sEMG signal is excellent [12], [22]. These signals are differential with zero mean and an amplitude varying from $\pm 25\ uV\ to\ \pm 10\ mV$. The bandwidth is $30\ to\ 2000\ Hz$, depending on the dimension and the depth of the muscles contracting underneath the electrodes. These parameters are affected by power line noise and ground potential variability. The electrodes are placed on the skin surface and are connected to the input of a precision instrumentation differential amplifier based on Texas Instruments (TI) INA122, then its output is passed through an active low pass filter (LPF) based on TI OPA335 in order to sense the action bio-potentials of the muscular fibers with an output signal span in the range of $0\ to\ 3.3\ V$ and a bandwidth between $0\ to\ 500\ Hz$. The circuit is built-in on a custom PCB with 2 electromyography channels and a bias voltage reference output ($1.25\ V$); furthermore, it is compatible with TI Launchpad Development Ecosystem, which is ideal for the single ended input of a microcontroller in addition to contributing to low cost development kits [18], [20].

C. sEMG Signal Processing

With the exception of a few cases, the major power of surface EMG signals is accounted for by harmonics up to $400 - 500\ Hz$ and most of the remaining signal power is contributed by electrode and equipment noise [10].
The EMG signals are collected using the on-chip 12-bit ADC of the TI TM4C12x microcontrollers with a 1000 kHz sample rate considering Nyquist sampling theory, and then are processed in order to get more accurate results on event detection and pattern classification.

Fig. 4. Surface Mounted Electrodes Location.

1) sEMG Signal Detection: A precise detection of discrete events in sEMG is an important issue in the analysis of the motor system of the hand, a single-threshold method is used for detecting the On and Off timing of the muscles, comparing the Root Mean Square (RMS) value of the rectified signals with thresholds whose values depend on the mean power of the background noise of each channel [5], [17]. After removing the offset measured from the bias voltage reference, 100 samples are rectified to finally calculate the RMS value to detect the intended hand action used to trigger the transitions of the FSM that controls each operating mode.

2) Filtering: In order to eliminate the interference caused by AC frequency $(50 - 60\ Hz)$ of the mains power line. A window-based Finite Impulse Response (FIR) High-pass filter (HPF) which offers good performance at a very limited computational and memory cost was designed in Matlab software and implemented with the CMSIS-DSP software library for ARM Cortex-M processor based devices [6]. Once, an sEMG signal is detected, 500 samples per channel are collected and filtered, in order to condition the signal with a bandwidth between $(100 - 500\ Hz)$. Frequency and phase response are shown on Fig. 5.

D. Feature Extraction

The success of any pattern classification system depends almost entirely on the choice of features used to represent continuous time waveforms [2]. Taking into account that the time-domain features are preferred because of their low computational complexity [23] and knowing that sEMG signals are nonlinear and stochastic, once an sEMG signal is detected and filtered, six features per channel are extracted of time series analysis as proposed in [11], [12].

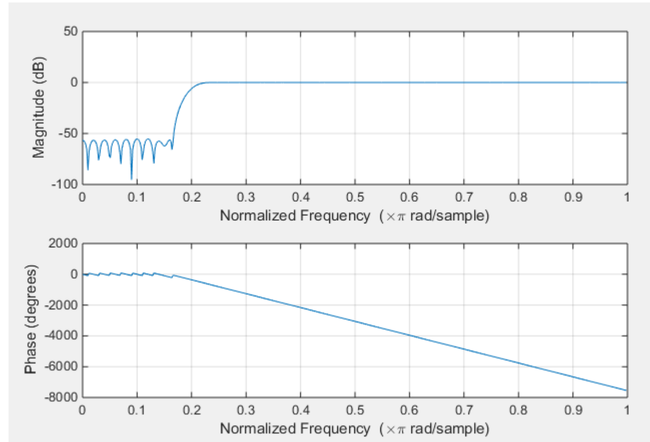

Fig. 5. Frequency and phase response of FIR high-pass filter.

1) Variance (σ^2): It is interpreted as a measure of the power density of the sEMG signal, and is given by

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

where x_n is the nth data sample of sEMG signal which has N data samples.

2) Waveform Length (WL): It is a cumulative variation in amplitude from sample to sample over the entire time period that can indicate the degree of variation about the sEMG signal. It is given by

$$WL = \sum_{n=1}^{N} |x_n - x_{n-1}| \tag{2}$$

3) Integral of EMG (I_{EMG}): This feature is an estimate of the summation of absolute values of sEMG signal. It is given by

$$I_{EMG} = \sum_{n=1}^{N} |x_n| \tag{3}$$

4) Zero Crossings (ZC): This feature counts the number of times that the signal crosses zero. This parameter is susceptible to noise, so a threshold method is implemented in order to reduce noise-induced zero crossing. It is given by

$$ZC = \sum_{n=1}^{N} [sgn(-x_n \times x_{n+1}) > 0 \wedge |x_n - x_{n+1}| \geq 0.06] \tag{4}$$

5) Slope Sign Changes (SSC): This feature counts the number of times that the slope of the signal changes of sign. The use of a threshold ensures that only significant changes are counted in order to reduce noise induced in slope sign changes. It is given by

$$SSC = \sum_{n=1}^{N} [(x_n - x_{n-1}) \times ((x_n - x_{n+1}) \geq 0.06] \tag{5}$$

6) Willison Amplitude (W_{AMP})*:* This parameter records the number of times that the signal change in amplitude exceeded a predefined threshold value set above noise level. It is an indicator of firing motor unit muscle potential and therefore it can indicate the muscle contraction level. It is given by

$$W_{AMP} = \sum_{n=1}^{N} f(|x_n - x_{n+1}|), \tag{6}$$

where,

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

E. Classification

ANN is a mathematical model that is inspired by the way the biological nervous system process information, This classifier has been devised as a Multilayer Feedforward Neural Network, with an input layer with 12 nodes, one hidden layer with 30 nodes and an output layer with 5 nodes. The inputs are the features extracted for each sEMG channel and whose outputs are the real valued confidence scores, where the index of largest value represents a class label between zero and four (5 classes). This architecture was chosen considering that an ANN with one hidden layer is a universal approximator, considering that its number of neurons in the hidden layer should be as small as possible to simplify the computation and to reduce the risk of overfitting [16], [21]. The implementation of the classification system is divided into two stages:

1) Off-line Learning: This stage allows the user to collect features between a set of five predefined hand gestures, which must be selected by pressing a button on the touchscreen, allowing the system to present sets of features with its corresponding class output. Fifty sets of features triggered by the muscle contraction of predefined hand gestures are collected by sending the data to a personal computer (PC) through a UART interface, which itself must be stored as a comma-separated values (CSV) file, in order to train the ANN in Matlab [2], [14]. The scaled conjugate gradient backpropagation method for fast supervised learning is used to train the ANN because it's more effective than the standard backpropagation method [15]. The dataset was divided in 70% for training, 15% for validation and 15% for testing [16]. Finally, readable, compact, and fast C code for use on an ARM Cortex-M processor is generated in order to implement the ANN on the embedded system [19].

2) On-line Classification: This stage allows the user to trigger predefined motions from a set of muscle contractions to let the system predict which hand gesture is intended from muscular activity. During system operation, the features extracted from sEMG signals are presented as inputs to the trained ANN, where the outputs are scanned in order to choose the largest value of the real valued confidence scores. If this value is above a specified threshold, the prosthetic hand function corresponding to this output class is selected and performed [2].

F. Simulation and testing

To facilitate collaboration between people and institutions working on this project, and later to train potential users without having to share an available mounted prosthetic, a simulation of the prosthetic (Fig. 6) was developed using the V-REP robotic simulation framework. The simulation is kinematically equivalent to the real prosthetic hand. Its modularity allows to plug the simulation instead of the real prosthesis to the human machine interface transparently, allowing the use of the same control hardware as the real prosthetic hand. Moreover, the 3D printed prosthesis is also used in order to test the entire system. Its fifteen DOF allow the user to experiment with a real prosthetic hand that provides a dexterous control, important for the performance of the most common tasks in modern life, specially with the thumb's rotation mechanism needed for properly performance of different kinds of grips such as fine pinch gripping and tripod grasping [1].

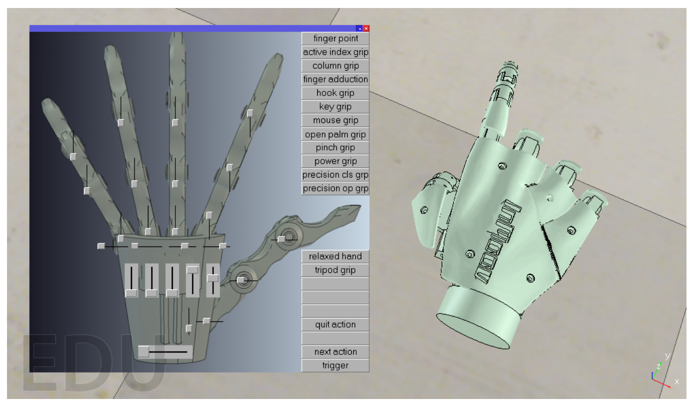

Fig. 6. Hand Prosthesis Simulation on V-REP from Coppelia Robotics.

III. Results

The interaction between subject and the integration of systems was tested successfully. Elected postures were tested twenty times for each operating mode. The correct rate for the sEMG activated controllers are shown on Table I. Remarkably, on the sEMG activated voice controller, the test results shown in Table II are satisfactory for three different languages (English, Spanish and Japanese). Furthermore, the correct rate for pattern recognition mode is shown in Table III.

Table I. Rates for each hybrid sEMG activated controllers.

Mode	Intended gesture	Hand posture	Rate
Touch controller	Flexion/extension	Power Grip	100%
	Flexion/extension	Pointing	100%
	Flexion/extension	Rock gesture	100%
	Flexion/extension	Pinch grip	100%
Voice controller	Flexion/extension	No. 0 gesture	100%
	Flexion/extension	No. 1 gesture	100%
	Flexion/extension	No. 2 gesture	100%
	Flexion/extension	No. 3 gesture	100%
	Flexion/extension	No. 4 gesture	100%

Table II. Correct rates of speech recognition.

Module	Command	Spanish	English	Japanese
Speech recogn.	One	100%	100%	100%
	Two	100%	100%	100%
	Three	100%	100%	100%
	Four	100%	100%	95%
	Five	100%	100%	100%
	Six	100%	100%	100%
	Seven	100%	100%	100%
	Eight	100%	100%	90%
	Nine	100%	90%	90%
	Total	100%	98.89%	86.11%

Table III. Correct rates of sEMG patter recognition.

Mode	Intended gesture	Hand posture	Rate
Pattern recogn.	Close	Power Grip	85%
	Open	Opening	80%
	Flexion	Pointing	75%
	Extension	Pinch grip	90%
	Peace	Lateral grip	100%
		Total	86%

IV. Conclusions and Future Work

It is shown that this integration of systems has advantages over traditional systems because of its user-friendly HMI that brings the possibility of increasing the amount of customized hand postures that can be performed, and allowing the utilization of low cost components in order to keep the price range below $500. Since sEMG activation allows the user to consciously perform the desired actions, the sEMG pattern recognition mode is the most natural way to let the system triggers predefine hand postures. However, its accuracy rate is below the other modes, and only a few hand gestures can classified. That reason supports that the hybrid sEMG voice controller is a great solution to let the system trigger a wide variety of predefined hand gestures with perfect accuracy, as long as the subject uses their native language. Moreover, if the environment is auditorily noisy, the hybrid sEMG touch controller also allows a trigger mechanism operating under any circumstance with perfect accuracy. The work described has not yet been tested on below elbow amputees. We are currently working on improving towards a better sEMG signal acquisition system with more channels, and improving the performance of the system, implementing the entire system on an ARM Cortex-M7 platform, in order to increase the accuracy rate of the pattern recognition operating mode and allowing for new useful HMI interfaces. Finally, we have to start the testing stages with disabled patients to get useful feedback in order to improve the entire system [3].

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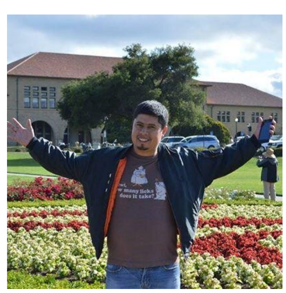

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Dr. Eric Rohmer, is a French robotic researcher at the Campinas State University (Brazil) since 2011. He co-founded the Brazilian Institute of Neuroscience and Neurotechnology (BRAINN). He is involved in the development of the V-REP robot simulation framework with Coppelia Robotics. He was appointed at the Tohoku University in Japan (2009-2011), as a lead researcher on the development of Quince rescue robot, the first Japanese robot used in the crippled Fukushima reactor. He was a research fellow at the Tohoku University's Space Robotics lab (2005 - 2009), working on rescue and space exploration robotics. He developed there a dynamic engin based telerobotic platform and a novel transformable hybrid wheel-limbs exploration hexapod. He received his Ph.D degree in Information Sciences from the Tohoku University (2005), a Master degrees, a B.Sc and a Polytechnic diploma in engineering in France. He was a mechanical engineer in Luxembourg, until 2001. Dr. Rohmer current research focus includes mobile robotics platforms and human robot interaction. He is especially interested in assistive robotics solutions to provide mobility to people with sever disabilities. In parallel, he is collaborating on the development of novel type of control for low-cost 3D printed prosthetic hands, for emergent countries, with the Galileo University in Guatemala.