sEMG-based classification strategy of hand gestures for wearable robotics in clinical practice

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Abstract—**Every day more and more robotic aids enter the clinics to take part in the rehabilitative and assistive paths for patients with reduced mobility. Accompanying discharged patients with robotics-based remote rehabilitation and home assistance seems to be one of the most promising avenues to follow to increase the success rate of these practices and lighten the overall burden on national health systems. However, to get out of clinics effectively, robotics must become wearable and, therefore, based on the use of embedded low-power electronics, both for practicality and safety reasons. The point is further complicated when it comes to assisting or rehabilitating lost hand functionalities due to the small size and complex mobility of such a limb; moreover, ensuring the real-time execution of gesture classification algorithms for controlling these devices hence becomes a vital engineering challenge. A hand gesture classification solution, specifically designed for the implementation of embedded electronics, based on surface electromyography, and ensuring real-time action, will be presented in this paper.**

Index Terms—**Hand Exoskeleton, Wearable Robotics, sEMG**

I. Introduction

Robotic devices, in addition to the mechanical hardware, generally incorporate internal memory, communication channels, and an automatic control system to provide monitoring capabilities, as well as intuitive and safe utilization. These characteristics have made them particularly attractive to the clinical practice for which remote rehabilitation sessions or home assistance exploiting low-cost robotic devices can be indeed an effective solution to democratize services otherwise not accessible to everyone. Indeed, people with disabilities do not always have the opportunity to do rehabilitation in the clinic or can afford someone to assist them at home.

It is important to note that when moving from clinical to home, these devices shall guarantee some additional features such as: ensuring the greatest possible freedom of movement of the user while being worn for a long time and being easily and intuitively usable by people with reduced mobility.

In this article, the attention will be focused on a hand gesture classification strategy based on the analysis of electromyographic signals, which will be first introduced and then quantitatively analyzed. Such a procedure is in charge of providing the high-level command signals for a Hand Exoskeleton System developed by the Department of Industrial Engineering of the University of Florence (DIEF) [1].

II. Background

Control strategies for assistive or rehabilitative devices, as exoskeletons, shall be as intuitive as possible to best simulate a condition of pseudo-normality. When it comes to that, the literature suggests using techniques based on the recognition of the user's motor intentions and their subsequent reproduction using external devices, as HESs. The most accredited methods are based on the classification of surface ElectroMyoGraphic (sEMG) signals [2]. These signals, despite very convenient to use are particularly tricky to process, primarily because of their noisy nature. A compromise should be reached on the number of intentions discriminated against to simplify these approaches and make them runnable on low-power embedded electronics. For the proposed method, according to what reported in [3] the number of classifiable gestures has been limited to three, i.e., hand opening, closing, and resting.

In a previous pilot study [4], this technique has been implemented on a low-powered micro-controller to run at the operative frequency of 50 Hz (the same setup used in this work). Then, this strategy's performance has been qualitatively evaluated by enrolling a patient with Spinal Muscular Atrophy (SMA) and showed noteworthy results. Conversely, a quantitative analysis of the results, which may be used as a term of comparison with other classification techniques, does arise as the novel major contribution of the presented research work.

III. CLASSIFIER EVALUATION

The classification process exploited in this work involves the use of a particular algorithm, the so-called "Point-In-Polygon (PIP)", which allows for the classification of a general two-dimensional input. The PIP functionality relies on checking whether or not a point belongs to a specified polygonal area. In this case, its application primarily involves the sampling of a pair of sEMG signals collected in the form of an Integrated EMG (IEMG) value by two MyoWare™Muscle Sensors placed on the *extensor digitorum* and *flexor digitorum* muscle bands. These are the muscles naturally involved in the hand opening and closing movement.

A Pro Trinket (3 V, 12 MHz) has been used to read IEMG measurements at a frequency of 50 Hz. The pair of measurements is then considered as a point on a Cartesian plane (see Fig. 1) whose axes report the IEMG values coming from the above mentioned muscles — the axes range goes from 0 to 255 since the IEMG is collected as an 8-bit integer. A proper dataset has been collected to train, validate and test the classifier. A real patient suffering from SMA voluntarily enrolled in this study. He has been asked to reproduce for about 60 seconds the muscle contractions he would have liked to associate to each of the three possible exoskeleton's behaviors (hand opening, closing, and resting). This dataset has been labelled on the go by an operator (supervised learning), and has hence been split into the training set (equal to the 80% of the data), and the testing set (the remaining 20%).

The training of the PIP classifier consisted in the drawing, by external intervention, of the polygonal areas that circumscribed the IEMG samples corresponding to the hand opening and closing intention (see Fig. 1). The coordinates of the polygon vertices are then stored in the EEPROM memory of the Pro Trinket micro-controller which use them to real-time classify each new sEMG sample.
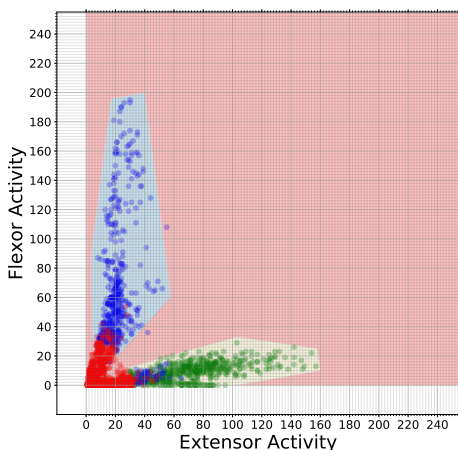

Fig. 1. The figure shows a sample of the acquired sEMG dataset, in particular the training and validation set is reported here; in green, blue and red, the opening, the closing and the resting samples respectively. Besides, the decision boundaries after the training and validation phase are shown.

Fig. 2. The confusion matrix of the proposed Point-in-Polygon-based classifier (Accuracy: 0.934, Precision: 0.932, Recall: 0.932).

IV. RESULTS AND CONCLUSIONS

From the confusion matrix shown in Fig. 2, it can be seen that the resulting metrics have achieved values ranging from 93.2% to 93.4%, confirming valuable performance.

Furthermore, the confusion matrix highlights a tiny number of misclassifications in which the movement that is opposite to the desired one is predicted (i.e., hand opening intentions classified as hand closing ones, and vice versa). This result is especially important since such errors can be annoying for the user and harmful both for the user and the device due to the sudden motion inversion.

This study has presented an analytical and quantitative analysis of the classification performance of a PIP-based sEMG classifier. In this research activity, the examined scenario concerned the classification of three possible hand gestures to accordingly control a wearable hand exoskeleton in assisting people with hand disabilities. The evaluation metrics outline the algorithm's correct functioning, and the qualitative analysis of the nature and structure of the decision boundaries shows remarkable robustness against motion artifacts disturbances.

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