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Miniature EMG Sensors for Prosthetic Applications

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***Abstract*— Poly-articulated, myoelectric hand prostheses reproduce complex multi-degree of freedom movements. Typically, a pattern recognition algorithm translates the recorded electromyographic (EMG) activity into joint movements. Control algorithms may benefit by adding more EMG sensors, however, their mechanical integration within the socket strongly affects the physical robustness of the prosthetic system. Their typical size and rectangular shape are indeed non-optimal for the limited amount of space within the socket. To solve this issue, here we present and test custom-made sensors for decoding multi-joint hand movements from EMG recordings of arm muscles. The sensors have circular shape and smaller size with respect to their standard counterpart, thus allowing a higher number of channels for multi-DOF control strategies. In order to evaluate their performance for multi-joint decoding, we tested a Non-Linear Logistic Regression classifier on both healthy and amputated subjects. We optimized the classifier in terms of F1Score, depending on the number of EMG sensors, and in terms of Embedding Optimization Factor, depending on the polynomial complexity degree. We then compared performance with that of standard rectangular EMG sensors and found no significant difference. Our custom-made sensors achieved higher F1Score for all the patients. This result, coupled with more effective integration with the socket, suggests effective prosthetic applications for our sensors.**

I. INTRODUCTION

A crucial feature for the functionality and usability of a poly-articulated myoelectric hand prosthesis is its controllability. Indeed, poor controllability is one of the major causes of prosthetic system abandonment. Traditionally, myoelectric hand prosthesis control relies on the use of two electromyographic (EMG) sensors, respectively placed on flexor and extensor muscles. The muscle contraction was detected by EMG sensors, and the control policy regulates prosthesis velocity [1]. However, this solution does not allow simultaneous multi-DOF control and this prevents users from perceiving the prosthesis as a true substitute of the missing limb [2]. Recently, many groups focused on investigating solutions to improve the control of multi-DoF myoelectric hand prostheses [3-5]. One possible strategy consists in increasing the number of EMG sensors in order to provide the pattern recognition algorithm with more data for decoding hand posture [4]. However, one of the major drawbacks of current systems is that the gold standard Ottobock has a rectangular shape that badly adapts to the limited amount of space available within the socket, which also has unpredictable shape due to the residual limb. Moreover, the mechanical integration of EMG electrodes within the socket, strongly affects the physical robustness of the entire prosthetic system. This design is developed with an Inter Electrode Distance (IED) of 12 mm accordingly with the Nyquist theorem that suggests 8-10mm minimum [6]. To address these issues, we designed circular EMG sensors with a smaller design and a IED of 8 mm that is the minimum dimension for EMG application following the Nyquist theorem [6] and compared their performance versus the gold standard, while training a pattern recognition algorithm based on Non-Linear Regression (NLR) for decoding multi-joint hand posture. The NLR algorithm was chosen, instead of the gold standard Linear Discriminant Analysis, following on from the results showed on [7]. We tested both sensors on a group of healthy volunteers and on three trans-radial amputees using the Hannes hand [8] to understand the feasibility of this sensors on a prosthetic scenario.

II. MATERIAL AND METHODS

A. Subjects and Experimental Protocol

We recruited 10 right-handed able-bodied (6 males, age 36 ± 9 years) and 3 amputated subjects (mono-lateral, right trans-radial amputation of the dominant limb; all males; aged 72, 43 and 39, respectively). All subjects provided written informed consent. The study conformed to the standard of the Declaration of Helsinki and was approved by the ethical committees of Bologna-Imola (CP-PPRAS1/1-01).

Six standard EMG sensors (OTTOBOCK), and six custom-made (IIT) sensors (see section II.B) were used. Each set of sensors was embedded into a custom-made elastic brace placed around the forearm for collecting electrical activity from 6 relevant muscle groups involved in grasping and pronation/supination of the wrist (Figure 1 A). The muscles groups were: Extensor Carpi Radialis Longus Muscle (EMG0), Palmaris Longus Muscle and Flexor Carpi Ulnaris Muscle (EMG1), Extensor Digitorum Muscle (EMG2), Flexor Carpi Radialis Muscle (EMG3), Extensor Carpi Ulnaris Muscle (EMG4), and Brachio-Radial Muscle (EMG5). Subjects performed the experimental protocol

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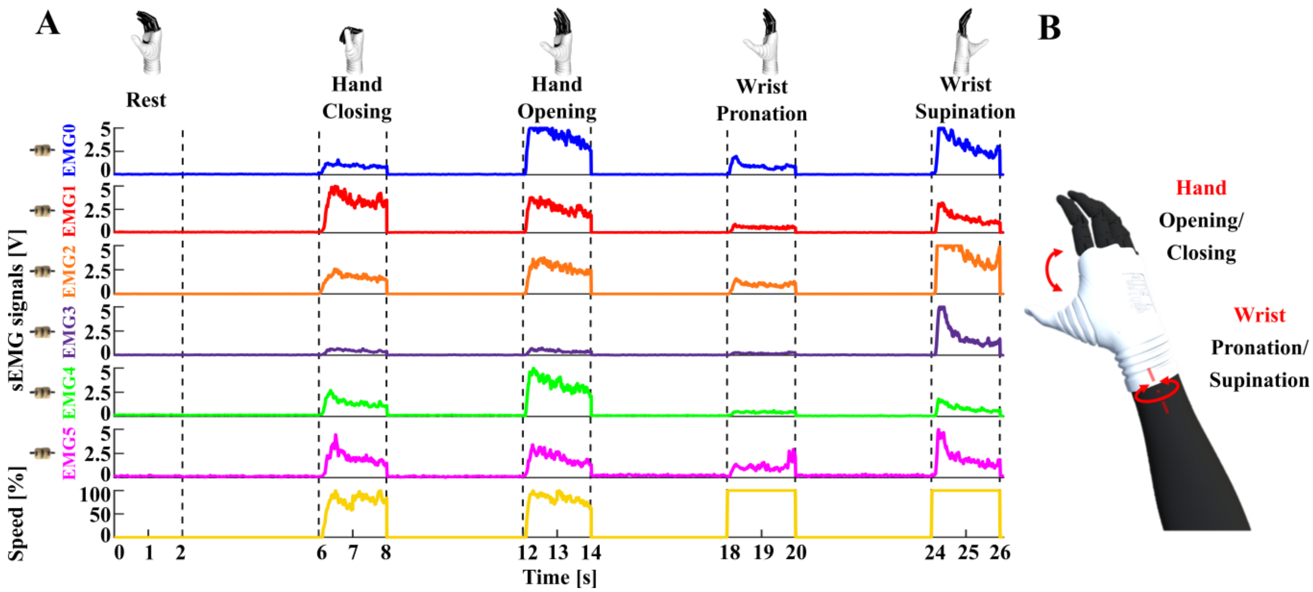

Figure 1. EMG activity associated to related joint movement. **A**: EMG activations and Hannes system speed during different hand and wrist movements. **B**: DoFs of the Hannes system.

twice: first with one set of EMG sensors (i.e. OTTOBOCK or IIT) and then with the other set. The order of EMG set placement was randomly assigned and 30 minutes of rest were allowed between sessions.

After sensors placement, subjects were positioned in front of a monitor displaying a virtual hand (VH) emulating the controlled prosthesis (see section II.C). We asked subjects to sequentially perform hand opening/closing and wrist pronation/supination for 10 times, then we collected 16 repetitions of resting state (duration 2 s, Fs 1 kHz).

B. EMG Sensors

In this study, two different set of EMG sensors were compared: the commercially available 13E200 MyoBock (OTTOBOCK, Figure 2 A) and the custom-made circular sensors (IIT) newly developed. IIT sensors were created to minimize the occupied surface of the internal lamination of the socket: this feature allows to fit a higher number of sensors around the residual limb, without compromising the mechanical strength of the prosthesis. Moreover, to facilitate the socket manufacturing process, we designed a custom PCB assembly composed by two boards fitting within a circular shape enclosure with a final diameter of 18 mm and a thickness of 9.5 mm, (Figure 2 B). According to the identified shape, three custom titanium electrodes were designed a connected directly to the lower side PCB via epoxy conductive glue. Consistently with the OTTOBOCK devices, the IIT sensor employs a bipolar configuration with differential sensing electrodes placed on the side with IED of 8 mm with a central reference electrode. The output amplified signal range is compatible with the 0 ÷ 5 V signal commonly needed by the standard prosthetic systems. The filtering stages consist in a cascade of a band-pass filter (from 90 to 450 Hz), a notch filter (to reject the mains common mode noise), and an envelope detector circuit with adjustable gain via a trimmer. Thanks to the input instrumentation amplifier configuration used in the very first stage, supplied by a very low noise voltage reference, a CMRR (Common Mode Rejection Ratio) of 100 dB was achieved. The output contacts can provide enveloped and raw EMG signal, both after the common mode rejection stage. Currently, on our pattern recognition application, the enveloped signal has been used: we are considering to use the raw EMG signal for further investigations.

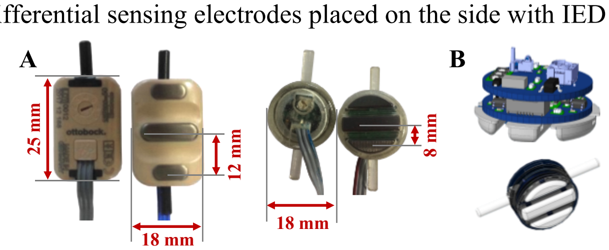

Figure 2. A: Ottobock (rectangular shape) and IIT (circular shape) sensors. B: Mock-app IIT sensor.

C. EMG Signal Processing

Regardless of the sensors used, all EMG signals were sampled (12bit resolution) by a custom EMG processing board based on an ARM Cortex M4 microcontroller, performing A/D conversion and then Bluetooth streaming of real-time data to a host PC.

NLR classifier (see section II.D) were then off-line trained using single samples of EMG signals recorded both during movement and rest. EMG signals were collected by a customized version of the EMG Data Acquisition & Training Software (EDATS), developed by Centro Protesi INAIL [7,

Figure 3. Experimental Setup. **A**: EMG processing board, power supply, sEMG armband, EDATS software, VH and Hannes system. **B**: VH control performed in Real-Time by a healthy subject. **C**: VH control performed in Real-Time by an amputee.

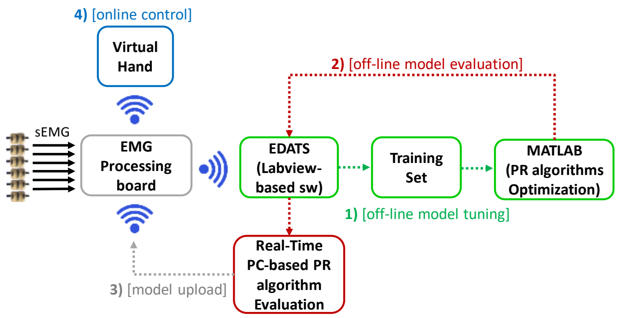

Figure 4. Experimental Setup block diagram.

9] (Figure 3 A), implemented in MATLAB (MathWorks).

Following NLR calibration, subjects were allowed to freely explore its control by performing any of the 4 movements, which were real-time decoded and replicated onto the VH, whose joint velocity was linearly dependent with EMGs RMS.

D. *Training, Optimizing and testing of the NLR model*

We used NLR classifier because in a previous study we found that it produces comparable or better results than the gold standard Linear Discriminant Analysis [7]. NLR is a supervised algorithm and thus needs a specific calibration procedure to estimate the best set of internal parameters for its further on-line use. The Dataset is acquired at a sample frequency of 1 kHz and divided into test set (TS), training set (TR) and validation set (VS). The TS was obtained after a down-sampling operation from 1 kHz to 40 Hz according with the optimal down-sampling found in [10]. The TR was composed by 70% of the remaining data, while the VS was finally composed by 30% of the remaining data.

Through a custom MATLAB API, the parameters of NLR were off-line tuned on the TR and validated on the VS to prevent overfitting (step 1 in Figure 4). It followed an evaluation phase in which the calibrated algorithm was used to on-line decode hand motion using a real-time PC based PR simulator (step 2 in Figure 4). The resulting outcomes were finally uploaded (step 3 in Figure 4) to the EMG processing board for the final on-line classification (step 4 in Figure 4), during which the user was able to freely control the VH or the Hannes prosthesis. For online use the NLR receives input data composed by a single sample of EMG array at 300 Hz, fast enough to detect variation of human movements and to guaranty the control loop execution.

We aimed at estimating the minimum number of EMG sensors able to provide top performance of the NLR algorithm, in terms of F1Score [11]. Further, we also considered the role of the degree (D) of complexity able to provide top performance in terms of Embedding Optimization factor (EOF), as in [7]. We also introduced a "truth index", based on Likelihood threshold [12]. The Likelihood maximizes the efficiency of algorithms: we set the threshold of likelihood around 70-80% in order to guarantee the classification of the voluntary movements only. Movements discarded from classification were considered as "abstentions" and did not produce any movement.

A comparison of NLR performance with different EMG sensors was evaluated in terms of classification (% of correctly decoded movements), F1Score, and abstention (% of non-assigned movements). The best NLR configuration (optimal number of sensors and degree of complexity) was then used for training the algorithm on the amputees' dataset, with both types of sensors. We assessed whether the obtained scores were comparable with those of the healthy population. Statistical analysis was performed with Wilcoxon signed rank test and Bonferroni correction for multiple comparisons [13].

E. *The Hannes system*

The *Hannes* hand prosthesis was jointly developed by INAIL and IIT. It allows to restore around 90% of motor capacity in trans-radial amputees [8].

The Hannes system (Figure 3 **A**) consists of: (i) a set of six EMG electrodes, (ii) a custom EMG processing unit, (iii) a myoelectric poly-articulated prosthetic hand, (iv) an active wrist pronation/supination (WPS), and (v) a battery pack. The EMG processing unit ("EMG-Master") acquires the analog sensor output and synthesizes the control signals for each active joint. The extent of the activation is proportional to the RMS of the six EMG signals, normalized in the range 0 to 100% for the hand control, while WPS is always controlled at the maximum velocity. The control signals are then sent to the respective motor control boards within the prosthetic system. Each motor driver is equipped with an on-board control loop to ensure the correct joint movement: closed loop speed control for the hand and open loop for WPS. The WPS consists in a standard motor-gearbox actuation and can provide 360° rotation. The description of the mechanical design of the Hannes prosthetic hand is provided in [8].

III. Results

A. *Effect of EMG sensors number on performance*

We first explored the minimum number of sensors required to achieve the saturation of performances, expressed as non-statistical difference between F1Score. Starting from the full configuration including 6 EMG sensors, we progressively reduced the number of EMG sensors by removing those placed on smaller muscles, according to the following order: EMG5, EMG2, EMG3, EMG4. We found that three OTTOBOCK sensors were enough to reach the same performance as with maximum number of sensors and that four IIT sensors reached the same performance as with maximum number of sensors (TABLE I and Figure 5).

B. *Effect of D parameter on performance*

We assessed performance in terms of EOF with different

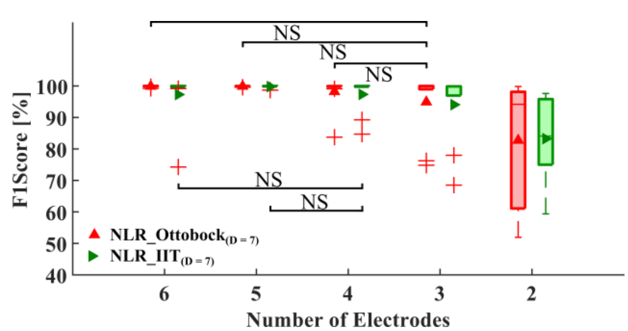

Figure 5. F1Score obtained for both sensors typology using different number of electrodes. The value of D is fixed to 7. NS: not significant.

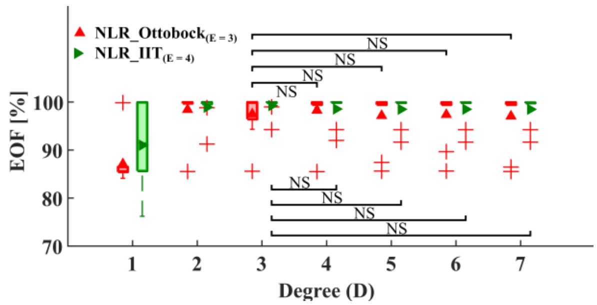

Figure 6. EOF obtained by NLR using different maximum value of parameter D and fixing number of electrodes to 3 for Ottobock sensors and 4 for IIT sensors, respectively. NS: not significant

values (from 1 to 7) of the parameter D, which regulates the maximum polynomial degree. As shown in Figure 6, we found that both for Ottobock and IIT sensors D = 3 maximized the performance

C. Sensors comparison

We compared F1Score obtained by both sensors' type through a Wilcoxon Signed-Rank test and found no statistical difference. TABLE I summarizes classification, F1Score, and abstention for both sensors type with the optimized number of sensors, as determined by the previous analysis. We observed no significant difference but IIT sensors led to more consistent results, as indicated by smaller standard deviation.

We also ran tests on three trans-radial amputees, using optimized number of sensors. TABLE II shows the values of classification, F1Score, and abstention obtained by amputees with both EMG sensors. Scores match those obtained by healthy subjects, with highest scores for IIT sensors.

IV. Discussion and Conclusion

We developed miniaturized circular EMG sensors for prosthetic applications and compared their performance in decoding hand movements using the NLR algorithm, with the commercially available gold standard. We performed tests on healthy subjects and found that IIT sensors led to similar or better performance. OTTOBOCK sensors reached highest classification performance with only three EMG sensors, while IIT sensors with four. However, IIT sensors are smaller and the overall areas occupied is 254 mm^2, while three OTTOBOCK sensors occupy a total of 486 mm^2. This is a clear advantage for prosthetics applications, because placing each sensor requires the opening of a hole in the socket. Therefore, the smaller the area occupied by sensors, the smaller the possibility of undermining socket robustness and system stability. This is crucial with proximal residual arm and reduced socket internal lamination. We also found that keeping a small degree of polynomial complexity (D = 3), maintained the same level of performance as with higher degrees in both Ottobock and IIT sensors. Therefore, the computational burden was still kept at a minimum.

Overall, we found that IIT sensors are promising for prosthetic applications, as indicated by upper limb amputees, who were able to move a VH by controlling residual muscles of the stump. More studies are needed to evaluate IIT sensors for prosthetic control in activities daily life and to validate them by testing frequency and time response.

TABLE I: NLR performances obtained for OTTOBOCK and IIT with different number of sensors on Healthy. In bold are indicated the number of sensors which saturated the F1Score.

Sensors	EMG (#)	Classification accuracy (%)	F1Score (%)	Abstention (%)
OTTOBOCK	2	98.2 ± 2.8	82.2 ± 12.3	82.4 ± 6.9
	3	**99.8 ± 0.2**	**94.1 ± 11.2**	**69.8 ± 9.6**
	4	99.9 ± 0.1	97.2 ± 5.6	60.7 ± 9.1
	5	99.9 ± 0.1	99.8 ± 0.4	60.0 ± 8.2
	6	99.9 ± 0.2	97.3 ± 8.1	55.1 ± 9.0
IIT	2	99.1 ± 0.8	82.7 ± 19.7	82.0 ± 7.8
	3	99.8 ± 0.2	95.0 ± 10.2	64.2 ± 8.4
	4	**99.9 ± 0.1**	**98.1 ± 5.0**	**57.2 ± 8.8**
	5	99.9 ± 0.1	99.9 ± 0.2	54.3 ± 8.1
	6	99.8 ± 0.2	99.9 ± 0.2	53.6 ± 7.8

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TABLE II: NLR performance scores obtained by amputees. In bold are reported the best scores according to each indicator (classification, F1Score, and abstention).

P.	Sensors	Classification accuracy (%)	F1Score (%)	Abstention (%)
1	OTTOBOCK	**99.8**	**98.4**	83.4
	IIT	99.4	89.6	**79.5**
2	OTTOBOCK	99.8	90.9	76.4
	IIT	**99.9**	**99.9**	**53.3**
3	OTTOBOCK	100	99.9	69.4
	IIT	**100**	**100**	**51.5**