Improved Pattern Recognition Control of Hannes

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***Abstract*— Poly-articulated, myoelectric hand prostheses reproduce complex multi-degree of freedom movements to effectively assist amputees in the execution of daily life activities. In this scenario, we tested Linear Discriminant Analysis (LDA) classifier, gold standard, in comparison with Non-Linear Logistic Regression (NLR) to decode opening/closure of the hand and flexion/extension of the wrist from EMG recordings of arm muscles, collected from healthy subjects and amputees. We aimed at minimizing the number of EMG electrodes (6 maximum) by optimizing both classifiers in terms of the F1Score. We then compared the performances of the classifiers. We found that the NLR algorithm achieved the best results with 5 EMG electrodes. The optimized algorithms were then tested on four amputees by controlling the Hannes system.**

Keywords—pattern recognition, prosthetic hand, human like

I. Introduction

Poly-articulated myoelectric hand prostheses are characterized by a high number of degrees of freedom (DoF). A crucial feature for their functionality and usability is their controllability. Indeed, low usage intuitiveness, often due to the poor ergonomics of the control system [1], lies among the main causes for prosthesis abandonment.

To promote a natural usage of a multi-DoF prosthetic hand in daily life scenario, here we propose an ergonomic decoder that is characterized by high accuracy, it does not rely on additional sources of input and it does not require the rearrangement of the natural contraction schemes. We also aimed at reducing the number of EMG sensors. We tested and optimized Linear Discriminant Analysis (LDA), gold standard in EMG pattern recognition application, and Non-Linear Logistic Regression (NLR) to decode hand and wrist movements, from up to 6 EMG electrodes, and to online control the Hannes system [2]. The performances improvement was observed not only on healthy subject data, but also on upper limb amputees when Hannes movements (rest, hand opening/closing – HOC) and wrist (flexion/extension - WFE) [3] were controlled.

II. Material and Methods

A. Subjects and Experimental Protocol

We recruited 10 able-bodied, right-handed subjects (6 males, age 36 ± 9 years) and 4 trans-radial amputated subjects

Six commercial EMG electrodes (13E200 AC, Ottobock) were embedded into a custom-made elastic brace placed around forearm or stump to collect electrical activity from 6 relevant muscle groups involved in grasping and wrist's flexion/extension movements (Figure 1 B).

We asked subjects to sequentially perform HOC and WFE 10 times (Figure 1 A). We also collected 16 repetitions of hand at rest (duration 2s, sampling frequency 1kHz).

B. Training and testing of the classifiers model

The analysed classifiers first underwent a calibration

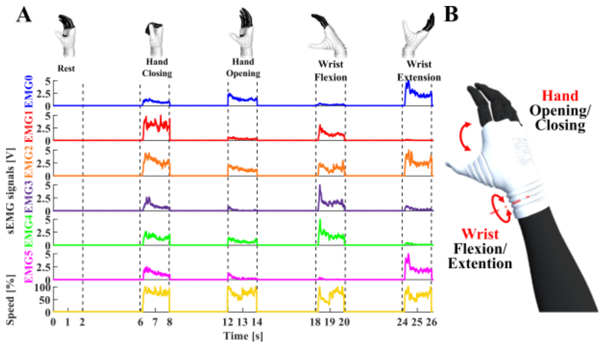

Figure 1. Surface EMG activities related to the single joint movement. **A**: EMG signals and Hannes system speed during different hand and wrist movements. **B**: available DoFs of the Hannes system.

procedure to estimate the best set of internal parameters for further on-line use, as detailed in [3]. For the LDA algorithm, we split the dataset into a training set (70% of the data) and test set (30% of the data). For the NLR algorithm, we first down-sampled the data from 1kHz to 40Hz, obtaining a training group (4% of the data) and a test set (96% of the data). The training group was in turn divided into a training set (2.4% of the data for off-line tuning of the internal parameters), validation set (0.8% of the data for tuning the hyperparameters to prevent overfitting), and threshold optimization set (0.8% of the data for tuning the likelihood threshold for the abstention criteria [4]). During validation, we tested the F1Score, calculated on the test set, with respect to the number of EMG electrodes. This analysis was used to estimate the minimum number of electrodes. Then, we compared algorithms performance, evaluated in terms of F1Score and abstention (% of non-assigned movements). The best configuration of classifiers was then used for testing the algorithms on amputees' dataset.

Finally, we used the resulting best algorithm, already calibrated, for on-line decoding of hand motions and control the Hannes system with sampling frequency set to 300Hz.

Statistical analysis was performed with the Wilcoxon-Signed-Rank test using a Bonferroni correction [5].

C. Hannes System

The Hannes prosthetic system 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

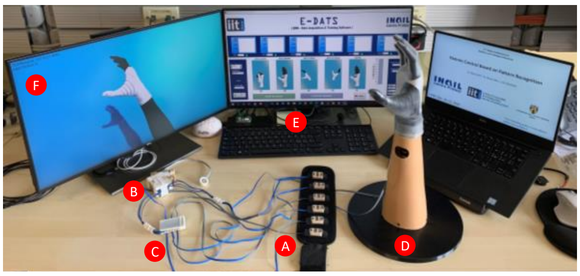

Figure 2. Experimental Setup. **A**: EMG electrodes, **B**: power supply, **C**: EMG processing board, **D**: Hannes system, **E**: E-DATS software, **F**: Hannes system in a non-immersive virtual-reality on Unity.

WFE, and (v) a battery pack (Figure 2). The EMG processing unit ("EMG-Master") acquires the analog sensor output and synthesizes the control signals for each active joint. The movements of the hand and wrist are proportional to the RMS of the six EMG signals, normalized in the range 0 to 100%.

III. Results

A. *Effect of EMG electrodes number on performance*

We first established the minimum number of EMG electrodes needed to maximize performance of algorithms, expressed as the non-statistical difference between the distributions of F1Score obtained from the test set (Figure 4).

For the NLR, we found that a configuration of five electrodes was enough to reach the same performance as with six electrodes. For LDA algorithms, the full configuration with 6 EMG sensors saturated its performance.

B. *Comparison of algorithms performances*

Figure 3 summarizes the performance scores in terms of F1Score and abstention obtained by the algorithms in their optimized configurations (i.e. with the optimized number of electrodes and hyperparameters).

With respect to F1Score (Figure 3 A) NLR always obtained the highest value. Although NLR has no statistical difference with LDA (gold standard). However, NLR also obtained highest percentage of abstention (Figure 3 B).

C. *Algorithms evaluation on the amputees' dataset*

We tested the classifiers on four trans-radial amputees, using an optimized configuration, as obtained from the analysis of the healthy dataset. TABLE I shows the values of F1Score, classification, and abstention obtained from patients. Scores of the amputees matched those obtained by healthy subjects: NLR obtained the highest F1Scores, classification, and abstention score.

IV. Discussion and Conclusion

We tested two pattern recognition algorithms to decode hand movements and we identified NRL is the one producing the best performances. Indeed, our results demonstrate that NLR is the only algorithm which reached the highest classification performance with five EMG electrodes. This is crucial for amputees whose residual arm is proximal, the smaller the number of electrodes, the smaller the possibility of undermining the socket robustness as well as the stability and costs of the entire prosthetic system.

When comparing classifiers in their optimized form, we found that, also in this case, the NLR outperform LDA in term of F1Score. NLR also obtained a greater number of abstentions. However, this apparent weakness is counterbalanced by the high classification frequency set.

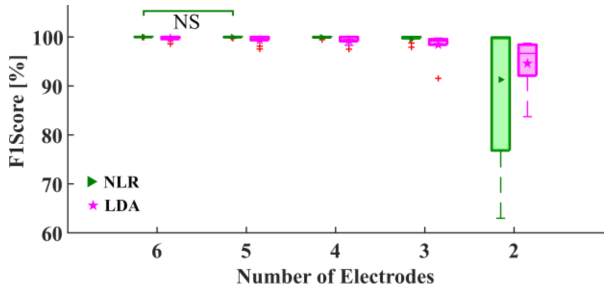

Figure 4. F1Score obtained by the classifiers using different number of electrodes. For NLR the value of D is fixed to 7. NS: not significant.

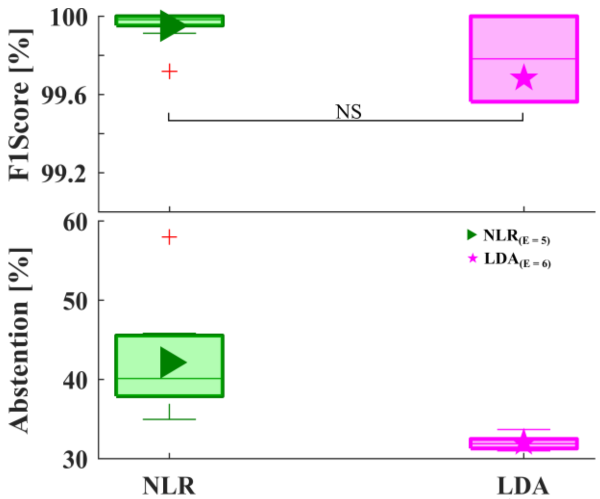

Figure 3. Algorithm comparison. **A**: F1Score. **B**: Fraction of abstention. NS: not significant.

We confirmed these results with upper limb trans-radial amputees, who were able to successfully control the Hannes system by activating the residual muscles of the stump in a natural way. Clearly, we need to extend the study to a wider population of amputees and we also need to confirm these promising results with clinical trials. However, as verbally described by the amputees, NLR algorithm allows them to reliably translate real-time movement intentions into actions.

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TABLE I: Classifiers performance scores obtained by amputees (P). In bold are reported the best scores according to each indicator.

P.	Algorithm	EMG [#]	Classification [%]	F1Score [%]	Abstention [%]
1	NLR	**5**	**99.9**	**99.8**	62.3
	LDA	6	99.8	**99.8**	**35.5**
2	NLR	**5**	**98.4**	90.0	62.7
	LDA	6	96.2	**96.1**	**32.5**
3	NLR	**5**	**100**	**100**	57.2
	LDA	6	98.4	98.4	**32.6**
4	NLR	**5**	**97.6**	**97.6**	85.1
	LDA	6	91.6	91.6	**32.0**