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Automatic Handwriting Recognition with a Minimal EMG Electrodes Setup: A Preliminary Investigation

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***Abstract*—Electromyographic (EMG)-based human-machine interfaces showed great potential in hand gesture recognition and recently they have been developed for realizing automatic recognition of handwritten characters or digits. Although smart sensors were commercialized for the forearm, the optimal electrode configuration for high accuracy with minimal channels remains debated. A total of six healthy subjects were asked to write a set of thirty common words of the english vocabulary while EMG signals from forearm and wrist were acquired to perform handwriting recognition using five state of the art feature sets and three pattern recognition models, i.e., K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM). Among the three classifiers the KNN outperformed both LDA and SVM showing a mean accuracy of 71.4% and 96.5 % respectively without and with majority voting post-processor when using combined forearm and wrist EMG information. On the other hand, using only wrist electrodes showed significantly performance drop in all classifiers with accuracy lower than 30.0%. Hence, combining forearm and wrist EMG data is crucial for accurate handwriting recognition with sparse electrode configurations, and limiting the sensing area to the wrist alone may not be sufficient for complex myoelectric decoding tasks. Further research is needed to explore alternative feature sets to improve performance with limited electrode setups.**

***Index Terms*—EMG, handwriting, pattern recognition, electrodes setup,**

I. Introduction

The use of electromyographic (EMG) signals is assuming a central role in the development of new and intelligent interfaces between humans and machines [1], [2]. Many wearable armbands, i.e., Myoarmband (Thalmic), Gforce+ (OYMotion), are now consolidated technologies that are guiding the development of EMG-driven interfaces for controlling interaction with computers or prosthesis [3], [4]. Such sensors offer a reliable ground for the application of signal processing tools and features extraction methods that guarantee the use of pattern recognition techniques capable of decoding the volition of hand movement from EMG patterns, eventually translating those patterns into actions implemented by software or machines [1].

To confirm the potential of the aforementioned architectures, recent literature highlights the possibility to recognize gestures among large sets of hand movements, i.e. more than 40 movements, with accurate performance [5], [6]. This offers the possibility to use a variety of hand movements in virtual and augmented reality, with more engagement by the subjects during the motor tasks they have to perform in the new scenario [7], [8]. For example, in the field of motor rehabilitation, the use of EMG for clinical evaluation is dominant. However, EMG can also be integrated in smarter rehabilitative frameworks by including automatic hand gesture and writing recognition systems [8], [9]. The advent of virtual reality combined with EMG sensors can open up opportunities to manipulate the learning environment, leading to a more immersive learning experience that has the potential to enhance the patient's neuroplasticity [10]. In this field, recent studies argue about the possibility to challenge the typical EMG-based pattern recognition models which employ well acknowledged hand gestures, by modeling the recognition of complex motor functions as the handwriting of letters or digits [1], [11]. In addition, in order to develop the above mentioned smart interfaces, researchers posed the attention to the role of forearm and wrist for EMG data recording [1]–[3]. In [3] wrist appeared more promising than forearm electrodes location commonly employed with armbands. However, using data recorded only from the wrist seems to be not reliable in recognition of handwritten digits [1], whereas a combination of data recorded from wrist and forearm showed best classification results [1]. Although literature seems to indicate the use of more dense EMG setup involving both forearm and wrist electrodes placement [1], no detailed assessments were carried out in large class of handwriting tasks, i.e. recognition

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of handwritten words. Indeed, in [1] a myoelectric pattern recognition problem with 10 classes, i.e., recognized classes from 0 to 9 was encountered using sparse electrode setup.

The aim of this study is to investigate possible minimal EMG setups for the development of myoelectric based architectures of handwriting recognition using electrodes located on the forearm and wrist. For this reason, in the present work the problem of automatic recognition among the 30 most used words in the English dictionary was taken into account using state of the art EMG-based pattern recognition schemes by comparing data recruited from wrist and forearm. This was done to see how consolidated pattern recognition pipelines perform in a hard classification task that involve the decoding of neuromuscular information related to complex hand motor tasks, in order to highlight if, in this bottleneck technological condition, the use of conjugate information from wrist and forearm allow the realization of reliable myoelectric human-machine interfaces.

II. Materials and Methods

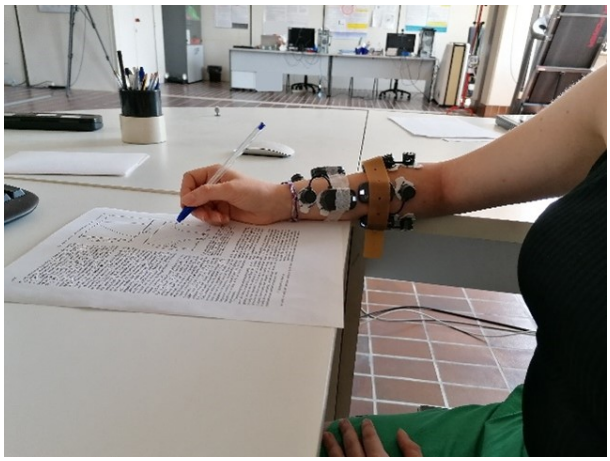
A. Experimental Protocol

The study recruited a total of six healthy subjects, consisting of three females and three males, aged between 25 and 40. Each subject received information about the experimental procedure and provided written consent to participate, following the guidelines set by the Declaration of Helsinki. To ensure consistency, all participants were fitted with six surface EMG electrodes, which operated synchronously at a sampling frequency of 1000 Hz using the FREEEMG system from BTS Bioengineering. The same expert operator placed the electrodes on the forearm and wrist of each subject to avoid effects related with inter-operator variability. Specifically, the first four electrodes were positioned on the extensor digitorum, flexor carpi ulnaris, flexor carpi radialis, and brachioradialis muscles [1]. The remaining two electrodes, were placed on the distal end of the flexor carpi radialis and on the extensor digiti minimi, respectively (Fig. 1).

The reason of using only two electrodes in the wrist was guided by two main reasons: firstly, the use of 4 electrodes on the wrist seemed to not consistently improve the classification performance in handwriting recognition of the ten digits if compared with two-electrode configurations [1]. Secondly, enlarging the number of probes on the wrist increased the users discomfort hampering the correct execution of the tasks. Thus a refined configuration as the one here employed ensured both extensive arm coverage (Fig. 1(a)), and participant's comfort during the execution of writing tasks (Fig. 1(b)). To further confirm the latter aspect, all subjects were asked about their comfort state before the beginning of each trial.

The experiment consisted in writing the 30 most commonly used words in the English dictionary according with the lines suggested by Oxford (http://oxforddictionaries.com) and reported in Table I. Each participant wrote with a pen on a paper in cursive a repetition of 10 times the same word, with a pause of 5 seconds between two repetitions. After completion of a sequence, subjects were asked to take a break for at least two minute to ensure comfort, and than starting a new sequence of repetitions for another word. The EMG data were saved in separated files, each one containing data relative to a specific word. The word writing order was attributed according to the specific class label (see Table I).

(a)



(b)

Fig. 1. Figure shows the EMG channels covering of forearm and wrist following the indications provided by [1], [3]. Panel 1(a) showed the electrodes placement for a subject with the use of straps to fix the positioning of the electrodes. Panel 1(b) showed the same subject while performing the handwriting task.

TABLE I
THE TABLE DISPLAYS THE 10 NOUNS, ADJECTIVES, AND VERBS RECORDED DURING THE EXPERIMENT. EACH WORD IS ASSOCIATED WITH A CLASS NUMBER FOR THE MYOELECTRIC PATTERN RECOGNITION PROBLEM.

Nouns		**Adjectives**		**Verbs**	
word	class	word	class	word	class
time	1	good	11	be	21
pearson	2	new	12	have	22
year	3	first	13	do	23
way	4	last	14	say	24
day	5	log	15	get	25
thing	6	great	16	make	26
man	7	little	17	go	27
world	8	own	18	know	28
life	9	other	19	take	29
hand	10	old	20	see	30

B. Data Preprocessing and Machine Learning Models

The raw data were filtered between 35 Hz and 450 Hz by means of a second order Butterworth band-pass filter with zero phase. Then, data segmentation was used to extract muscle activity epochs with respect to rest periods [12], [13] (Fig.2). After the segmentation, 5 Feature sets commonly used in myoelectric control, i.e., *Hudgins*, *Du*, *Phinyomark1*, *Phinyomark2*, and *TDAR* were computed for all the channels and for each active epoch available by using a sliding window of 150 ms with an overlap of 75 ms [6], [14]–[17].

At this stage, feature sets of the same type can be aggregated by changing the number of channels that one wants to include, eventually resulting in feature sets with dimension depending on the number of channels as indicated in [1]. For example *Hudgins* set expresses data points in a space of dimension equal to 4 feature $\times$ n$^\circ$ of channels. It deserves to be noticed that this does not alter the number of samples extracted for each subject, but it affects the dimension of the space the information is represented. Thus, here on, the same name of the feature set is used independently by the number of channels included, which will be indicated when needed in order to specify the role that the aggregated channels may have in obtaining more accurate pattern recognition models.

C. Pattern Recognition Experiments

In this study, two pattern recognition experiments were conducted. The initial experiment aimed to determine the most suitable machine learning model from a selection of state-of-the-art architectures used in myoelectric control. This model would be used for a challenging 30-class handwriting recognition problem. To achieve this, support vector machine (SVM), linear discriminant analysis (LDA), and K-nearest Neighbours (KNN) were utilized to train intra-subject models [1], [6], [16], [18]. Each model was trained using all the features contained in the feature sets previously mentioned avoiding redundancy in the aggregation step and in three different conditions, i.e., using all, only the forearm and only the wrist EMG channels, respectively. For each subject, data were randomly split 70%-30% for training/validation and testing respectively by keeping balanced the two sets. The training/validation step with hyper-parameter optimization was pursued through five-fold cross validation approach to prevent large biasing of in the models. Thus, the validated models were tested over the remaining 30% of the unseen data. The mean classification accuracy among subjects for the same family of model was computed either with and without majority voting post-processor (MV) applied [14], [18]. The best model was selected following the criterion for which the accuracy was the highest and MV provided actual boost of the performance [18].

In the second experiment, the best machine learning model selected from the first experiment was trained using all the five feature sets, in three different conditions, i.e., using, respectively, all, only the forearm and only the wrist channels. Mean accuracy among subjects for each type of feature set was used as a metric to proper assess the role of electrodes location without possible bias factors introduced by the feature extraction pipeline.

III. RESULTS

Figure 3 shows the first results of the first experiment in which the superior performance of the KNN is depicted. Indeed, the mean accuracy obtained in testing among the feature sets is 71.4% without post processing of the decision signal and reaches values of 96.5% when MV is introduced. On the other hand SVM showed mean accuracy value of 64.1% and 82.7% respectively with and without MV, whereas the LDA showed in both cases values of 36.9% and 51.3% respectively with and without MV making these models not suitable for further analysis.

Based on the results obtained in the first experiment, the KNN was selected as model for the second experiment (see section II-C. The results of such experiment are shown in Fig.4.

The top-performing feature sets were *TDAR* and *Phinyomark 1*, with average accuracy rates of 74.6% and 73.4%, respectively. In contrast, the least effective was *Hudgins*, which achieved an average accuracy of 61.0%. It is important to note that these results represent the classifier outputs only, without the involvement of a post-processor. In terms of electrode configuration, there was a noticeable decrease in accuracy when transitioning from using all channels to focusing on the forearm and wrist (refer to Fig. 4). Specifically, in the case of *Phinyomark 1*, the accuracy dropped to a maximum of 29.1% with wrist electrodes, while for forearm electrodes, the accuracy consistently remained below 59.0%, as seen with the *TDAR* feature set.

IV. DISCUSSION

The study highlights that only specific configurations of EMG electrodes and pattern recognition models guarantee good results among subjects. However, the identification of a technology that involves a minimal and generalizing setup, i.e. two electrodes on the wrist, further requires investigation. Indeed, the two experiments carried out through the study

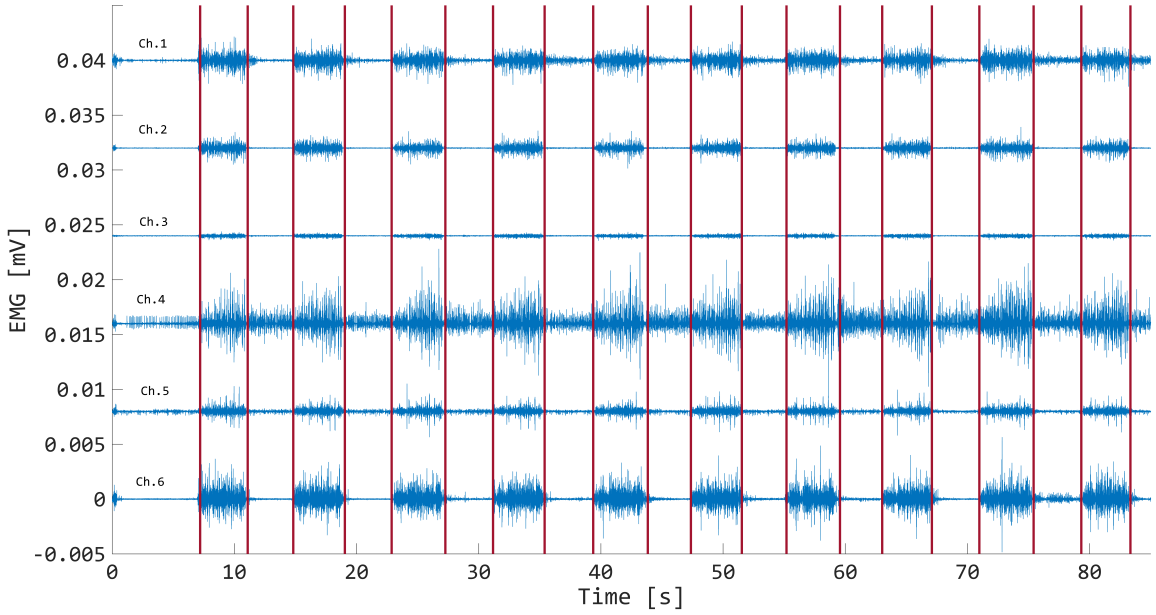


Fig. 2. Figure shows an example of data segmentation for the 10 repetitions of the word ”time” performed by subject 3. All signals in figure were z-score normalized for better visualizing them. Channels are reported from top to bottom starting from forearm to wrist in the order proposed in section II-A.

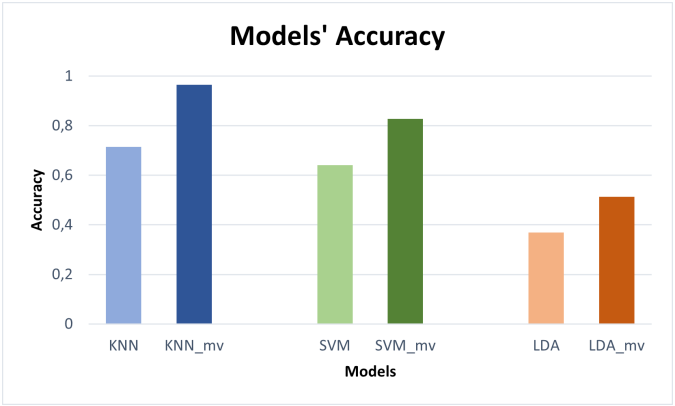


Fig. 3. Bar plot of the mean accuracy for KNN, SVM, and LDA, before and after the application of MV.

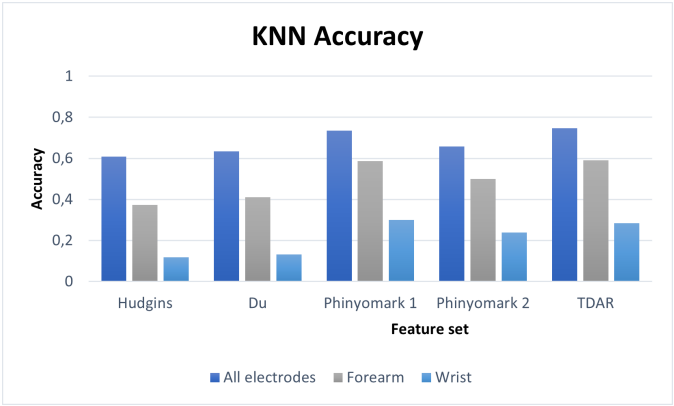


Fig. 4. Bar plot of the mean accuracy for the KNN and for all the five feature sets considered. Dark blue bars expresses the performance considering all the channels, grey bar refers to the performance obtained using the forearm electrodes while the light blue bars refer to wrist electrodes configuration.

suggested that handwriting recognition represents a challenging task when faced through EMG data since results showed average good performance only when KNN and MV was applied. However, the use of EMG as sensing technology can be particularly useful in developing human-machine interfaces, as highlighted in [1], [6]. Indeed, neuromuscular information acquired through EMG is strictly related with the human intent of motion and thus can have predictive power that can be exploit from machine to better frame the experience of interaction. Regarding the first experiment, typical pattern recognition models used for myoelectric control, i.e. SVM and LDA, showed performance not consistent with hand gesture recognition, where accuracy greater than 90% are nowadays confirmed by many studies [2], [3], [6]. On the other hand, the KNN showed acceptable performance for applicability in a real scenario, this can be attributed to the non-parametric approach of the KNN model which can also reveal that handwriting is mapped through complex pattern that hardly fit with hypothesis the grounds LDA or SVM. Confirmation of this point can be found in [1], [11], where SVM with quadratic kernel or deep learning methods were employed.

Hence, this supports the use of non-parametric pattern recognition approaches as KNN when sparse electrode setup are used to model complex hand motor task. Indeed, it deserves to be noticed that only 6 electrodes are employed

for the study, whereas armband generally has from 8 to 16 EMG channels upon which compute features and run standard machine learning models as LDA or SVM [3], [19]. Under this perspective, one may wonder whether a reduction of EMG probes can be a good methodological choice. However, it deserves to be noticed that previous studies dealing with hand-gesture recognition for prosthetic control showed good models using only two or four electrodes located in the forearm with the use of KNN [20], [21], proofing the advantage of working with minimally cumbersome setups. Moreover, using only few channels located close to the wrist can be beneficial if one would prototype the wristband or incorporate EMG patches within a smartwatch. Thus, the first experiment promoted the use of specific family of machine learning models, i.e. KNN, also when the problem involve a large set of fine movements of the hand, i.e. identifying among 30 handwritten words, supporting that not all the standard pipelines available in myoelectric control are valid when the problem increase in complexity.

The second experiment confirmed the findings from a previous study on handwritten digit recognition as reported in [12]. It was observed that utilizing only a pair of EMG channels located in the wrist, for each feature set, was inadequate in generating effective classification models, resulting in consistently poor accuracy levels below 30% (refer to Fig. 4). Similarly, when examining models developed using forearm muscles, they outperformed those based on wrist muscles. However, they were not applicable in practical scenarios due to their persistently low accuracy. This contrasts with the outcomes presented in [12], where models utilizing EMG signals from the same forearm muscles demonstrated good classification accuracy. However, it is important to highlight that the current study encountered a more difficult task, i.e., distinguishing between 30 handwritten words. This was done to emphasize the limitations of the setup proposed in [1]. Consequently, the overall performance decreased compared to that reported in [12], suggesting that such drop in accuracy may be attributed to the challenges in generalizing across the 30 movements considered in this study with respect to the 10 previously employed [12]. It deserves to be noticed that, differently from the first experiment, MV was not applied in the pipeline of experiment two. This was done to better emphasize the role of the EMG channels location that may be potentially masked by MV or other post processors [18].

Although the scenario was adequately selected to reach a bottleneck, the second experiment gave important information regarding the use of fuse information from wrist and forearm. Indeed, the performance increased when the forearm and wrist electrodes were used together. This suggests that limiting the EMG sensing capabilities only at the wrist requires future research [12], and on the contrary, acquiring data from the forearm is a more ready technological solution in order to develop handwriting or hand gesture recognition models able to decode a widest set of words. However, possible solutions designed to improve the performance of the wrist-based pattern recognition architectures warrants to be investigated in future studies. Indeed, one possibility is to adopt specific processing pipelines in which all the features are aggregated, and feature selection or reduction schemes are exploited. Moreover, different features that account for time-frequency signal description can be included [22], [23]. Indeed, as a limitation of the study, the feature-sets employed encompasses features in the time and frequency domain without extracting features from wavelet filter-bank decomposition. However the last mentioned approach can be promising to capture fine characteristics of the motor task also when there is no large number of channels from which retrieve information [22].

V. Conclusion

Findings of the study highlight the limitations of current minimal EMG, i.e., 2 wrist EMG electrodes, for developing automatic handwriting recognition. On the other, increasing the number of EMG channels up to 6 and combining forearm and wrist data offers promising results. Further research is needed to refine minimal wrist-based solutions. Future studies may explore time-frequency domain feature sets to potentially improve recognition accuracy with limited electrodes. Overall, this work contributes to the development of more efficient and user-friendly EMG interfaces for human-machine interaction.

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