Brazilian Journal of Instrumentation and Control
REVISTA BRASILEIRA DE INSTRUMENTAÇÃO E CONTROLE

Self-adaptive Method for sEMG Movement Classification Based on Continuous Optimal Electrode Assortment

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***Abstract*—Surface electromyography (sEMG) analysis is becoming increasingly popular in a broad variety of applications. Despite satisfactory classification rates are frequently obtained through supervised machine learning (ML) algorithms, there are some issues mostly related to the data acquisition which are not properly addressed in current studies. In this paper we present a method capable of mitigate the noise in the sEMG acquisition caused mainly by loose or misplaced non-invasive electrodes. To address this issue we propose a stage of pre-processing capable of being adapted on a variety of classifiers. The proposed method is capable of identify this two anomalies in the signal and provide the data to retrain the classifier, discarding the problematic channels. Once the method is retrained using only the most relevant channels it is possible to increase the accuracy rate of the ML method. The method was tested on a database containing five able-bodied subjects and four amputee subjects of both sexes. The average classification accuracy for the adaptive input selection method was 83,96 ± 6,5% for the able-bodied subjects and 61,15 ± 7,7% for the amputees subjects against 72,06 ± 8,0% in able-bodied subjects and 39,77 ± 10,6% for the amputees subjects considering the non-adaptive approach. Both systems make use of the proposed method to classify 9 distinguish upper-limb movements with different degrees of freedom.**

***Index Terms*—electrode assortment, upper-limb signal, neural network, auto-adaptive methods, surface electromyography**

Research supported by CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior) and CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico).

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I. Introduction

In recent years, there has been an increased interest in using Machine Learning (ML) to process biological data such as sEMG [1]. Typically, a sEMG signal movement classification consists on a pattern recognition / classification algorithm, which includes several popular methods such as LDA [2, 3], Artificial Neural Networks (ANN) [4, 5], Fuzzy Logic [6, 7], Neuro Fuzzy [8], Genetic Algorithms, Support Vector Machines [9], Bayesian Networks [10-12] and Logistic Regression [13]. There are also some approaches using Independent Component Analysis (ICA) [14] and Principal Component Analysis (PCA) [15, 16] focusing on dimensionality reduction and efficient computation, techniques focused on provide more efficiency to classification stage.

ANN is one of the most popular techniques among machine learning strategies and so it is on the classification of sEMG data. As example, Ahsan et al. [5] presented the detection of four hand motions using an ANN. Additionally, considering the advantages of Fuzzy Logic combined with the power of adaptation of an ANN, a Neuro-Fuzzy algorithm for myoelectric control has been proposed [1, 17] for the intelligent control of a prosthesis. Also, a hierarchical Neuro-Fuzzy [7] controller has been found to be adapting well on people who generate different muscle activity levels. Recently, there have been some attempts to apply Hidden Markov Models (HMM) [11] and the Gaussian Mixture Model (GMM) [12] to upper-limb movement classification using myoelectric signals. Moreover, Bayesian approaches have as characteristics being good at assimilate prior data and construct an adaptive process without concrete information [10].

Even though a several methods have been attempted so far, achieving a powerful algorithm is still quite challenging because sEMG signals are commonly affected by the environmental changes, movement performed and subjects

DOI: ISSN:2318-4531

[10]. Due to the sensitive nature, external noise sources and artifacts can influence sEMG signals, which frequently mislead the classification algorithm, resulting in poor classification accuracy. Most of the noise, artifacts and interference that may contaminate sEMG signals consist of electrode noise, motion artifacts, power line noise, ambient noise and inherent noise in electrical & electronic equipment [18, 19]. There are some works like [2, 19, 20] which respectively aim on classify and identify the destructive interference present in the sEMG signal. Indeed, the acquisition process is a critical stage that directly affects the posterior processing stages, undermining the classification process and accuracy of the system.

Accuracy is an important factor when developing a multifunction prosthesis controller. This factor can be improved by extracting more discriminant information from muscle signal, and adopting a classifier that is capable of exploiting this information [21].

In this scenario, two possible solutions are interesting to raise the accuracy level: I) to increase the number of sEMG channels that are used in data collection (which could increase the delay in the system due the quantity of information to process); II) to select the sEMG channels containing more significant data in order to promote a high-level training of the ML method.

Despite the use of a large number of sEMG channels presents itself as a possible solution to boost the accuracy, at the same time it represents a considerable increase of data processing, which in many cases may turn the embedded application of the system unfeasible. An attractive approach is to work with the most significant channels, in order to obtain a more-efficient classification, maintaining a continuous input selection of relevant data.

This work presents a solution which is capable of adapting itself based on environmental changes using only relevant channels to perform the ML supervised training in order to avoid information acquired by improper electrode positioning. The target interferences that the system proposes to mitigate are disconnected and misplaced electrodes. Based on these interferences, the system performs a continuous selection of the most proper electrode arrangements considering the signals that best describe the upper-limb movements [22]. The selection of the most proper channels is based on identification of brusque non-idealities in the input signal. Each time the set of inputs is update, a new training instance discarding the channels that present signals with characteristics of loose or misplaced electrodes is performed.

Two different groups of subjects took part in this study. To evaluate the results, the developed solution is compared with a neural network that does not discard any channel acquired. The methodology is detailed in the next section.

II. Materials and methods

In this section, the methods, equipment and conditions used in the acquisition and processing of the electromyography signals are explained. The Figure 1 represents a simplified block diagram of the auto-adaptive input selection method. The upper-limb myoelectric signals are acquired using commercial electromyography equipment and the assays performed as detailed below

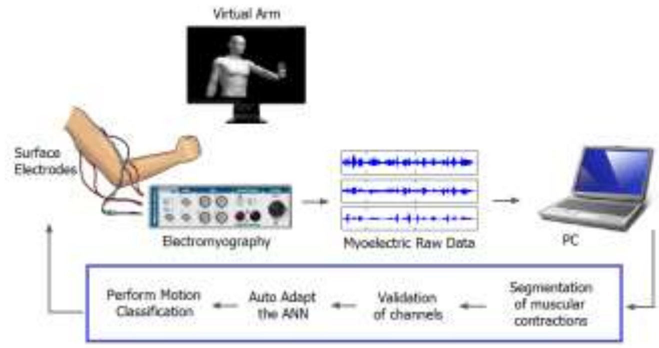

Fig. 1.Overall block diagram of the system.

A. Assays

The sEMG signals were acquired with 1 kHz sampling frequency while a random sequence of movements was shown in a LCD display to the subjects. The subjects were required to reproduce 18 movements, containing two repetitions of the 9 distinguish movements as naturally as possible, with no constrains in relation to time or force. The number of assays differs to each subject and the total of movements performed could be checked further on in Table 1.The movements are classified into two groups: simple motion (hand close, wrist extension, wrist flexion, forearm rotation and forearm flexion) and composed motion (forearm rotation/flexion, forearm rotation with hand closed, wrist flexion/extension, and forearm rotation with hand closed). All procedures performed in these studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

B. Subject Description and Electrode placement

Group 1 is composed by 5 able-bodied female and male subjects. The electrode positioning is muscle specific as illustrated on Figure 2a. The muscles used were biceps, flexor carpi ulnaris, flexor carpi radialis, extensor digitorum pronator teres, brachioradialis, palmar longus and extensor carpi ulnaris, respectfully acquired by sEMG channels from 1 to 8. For Group 1, six major sequences were performed.

Group 2 consists of 4 amputee subjects, female and male, with different upper-limb amputation degrees. For the data acquisition, 3 different major sequences of movements were considered. The electrodes were placed as presented in Figure 2b, in a random order and equally spaced, according to the amputation level of the subject.

C. Signal Segmentation and Feature Extraction

The segmentation of the acquired signal was based on the timing of the videos used for stimulus on the signal acquisition. For this analysis, three characteristics were acquired from the sEMG signal: RMS, Variance and the Kurtosis. These three features are among the most used involving sEMG signal

DOI: ISSN:2318-4531

processing. More detailing information about feature selection and its influence on accuracy rate could be obtained on [23] and [24].

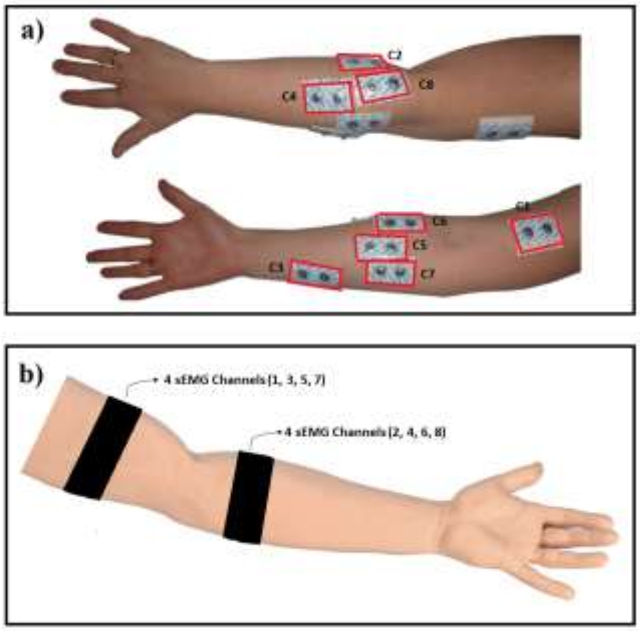

Fig. 2.Electrode positioning of: 2a) non-amputees subjects and 2b) amputees subjects.

D. *Motion Classification*

The sEMG classification was performed through ANN with a Multiple Layers Perceptron (MLP) topology. The MLP typically consists of an input layer, one or more hidden layers of highly interconnect computational nodes and one output layer. The input signal is propagated forward through all layers of the network. Moreover, multilayer networks can use several different learning techniques. For this solution, the learning technique selected is the back propagation algorithm. Therefore, was applied to the ANN an array of pre-determined entry and were analyzed the response of the network through the values of the output layer, which were compared with the desired response to compute the value of the error function (Supervised Training). In turn, the error signals were propagated back through layers of the network, against the direction of synaptic connections, adjusting the nodes weights, so that the actual output value of network approaches to the desired value in a statistical sense [8, 25].

The ANN dimension was determined empirically, based on previous tests with the dataset. The ANN developed has two dimensions of hidden layers with 50 and 25 neurons respectively, with inputs varying from 3 to 24, depending on the number of channels used, and with three characteristics of each channel mentioned previously (RMS, Variance and Kurtosis). Nine outputs are generated, representing the nine selected movements performed by the subject to be classified. The function used for the hidden layers of the network was a sigmoid function, and generates values with a range of -1 to 1.

E. *Auto-adaptive Method for Channel Selection*

The detection of loose and misplaced electrodes is especially useful to improve the overall performance of the recognition method in long-duration assays, were these two scenarios occurs more frequently. The proposed method returns a *Channel Status Map* that indicates the activation of each segment of signal, based on the Signal-Noise-Ratio (SNR) value. To generate the status of each channel, the RMS / SNR ratio value of each segmented is used to select which channels must be used as inputs of the ANN, creating a Signal Status Map through time (*Global Channel Status Map*). The thresholds used for the channel status definition were empirically defined based on the dataset. When a channel becomes inactive (*loose* or *misplaced electrode*), the channel is discarded. The adaptive method can also re-include the channel once that an inactive channel becomes active again.

Henceforth, it is possible to re-train the ANN using the *Channel Status Map* and historical data. All the re-training and identification is self-made, without any user interaction.

On an electromyography scope and acceptable SNR must present a moderate relation between the sEMG signal and the baseline noise or possible artifacts captured by the electrodes. Since the conditioning of sEMG signal implies a high amplification factor (usually more than 1000 times), simple noise interference could contaminate the sEMG signal at the point of turning it useless for our application, as presented on Figure 3. Figure 3 presents a situation of loose electrode, were white environmental noise is amplified at the point of overlap the muscle activity contribution, which is a typical scenario of very low SNR. Another scenario of low SNR may happen when the electrodes are not positioned on an appropriate section of the muscle, providing very low relevant signal, which confuses itself with the baseline noise and does not contribute with relevant information for the classification algorithm.

To test the proposed algorithm, assays with loose and misplaced electrodes were performed. In the assays, the disconnected electrodes presented a complete saturation of the signal, explained by the high-presence of noise captured by electrodes with low or null skin contact. Unlike the saturated output present in loose electrodes, a misplaced electrode, presents an insignificant signal level that reflects an inconvenient electrode positioning for the target movements since are no relevant influence of the chosen muscle.

Besides the assays for characterization, a validation assay was also performed in order to validate the proposed methodology. The validation assay consists of 3 sequences using electrode positioning presented on Figure 2b. During the assay, some electrodes were disconnected and then connected again with a pre-defined timetable. In the next sections, the methodology is explained based on the validation data.

F. *Identifying the Signal Relevance*

sEMG sensors are non-invasive, thus, a common issue when dealing with long-term assays is the decrease of electrode-skin contact over time. Therefore, it is important to consider the quality of the channels that are being acquired and eventually

DOI: ISSN:2318-4531

discard them. To identify all the loose electrodes (*LooseMap*) the proposed method addresses the constant noise over time and uses it as basis for the *threshold* definition. Once the RMS value of the segmented part of the signal is *4 times* higher than the historical calculation of the V_{RMS}, the signal is considered inactive. The channel is considered inactive since it is capturing a large amount of noise, saturating the signal and misleading the correct classification of the signal.

Misplaced electrodes are also a frequent problem in sEMG movement classification due to the change in electrode position over time, by several reasons, like sweat, excess movements and decrease in electrode-skin contact. In order to identify the misplaced channels (*MisplacedMap*), a method that defines a threshold based on the SNR is proposed. The SNR is calculated based on the RMS value during a moment of muscular relaxation and the RMS value of the current analysis window, to identify if the channel is providing any valid information during known muscular contractions (Figure 4). The algorithm takes into consideration the RMS value of the last 5 known muscular contractions (e.g. Seg 1… Seg 5) in order to decide if a channel is considered misplaced or not.

G. Global Channel Status Mapping

Based on *LooseMap*(*LM*) and *MisplacedMap*(*MM*), a combined *Global Channel Status Map* is created to identify each *Channel Status* according Equation (1). The process results in a map that represents which of the channels are active or not, for each segmented muscular contraction *(Seg)*; all this process of the *Global Channel Status Map* generation is presented on Figure 3. The map is stored along with the three characteristics extracted from each channel (*RMS*, *Variance* and *Kurtosis*) in the segmentation step to be used by the adaptive inputs selection methodology as detailed in the next section.

$$GlobalChannelStatus\ (Seg) = LM(Seg) \wedge MM(Seg) \quad (1)$$

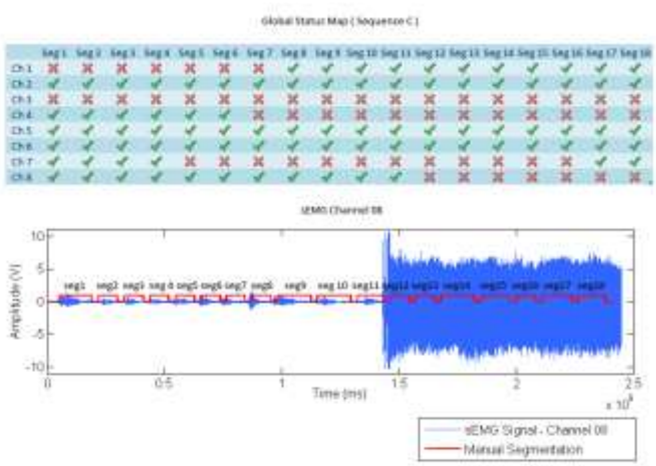

Fig. 3.Example of Global Status Map computed using the validation data (Sequence C) and corresponding sEMG data from Channel 08.

H. Adaptive Inputs Selection Methodology

The adaptive inputs selection consists on the constant checking of the channel status of last identified muscular contraction. Thus, is possible to confirm whether the channel statuses changed in anyway comparing with the channel status used for training the pattern recognition algorithm (*Training Status Map*). If a change is detected, the neural network is retrained using a different set of inputs, based on the actual *Channel Status Map*. The sets of inputs are selected considering the historical data (sEMG segmented signal), sorting the movements that have at least the same active channels, based on the *GlobalChannelStatusMap*, of the new training status map. This process assures that the trained ANN has only data containing significant information for the movement recognition. Figure 4 represents the flowchart of the referred methodology.

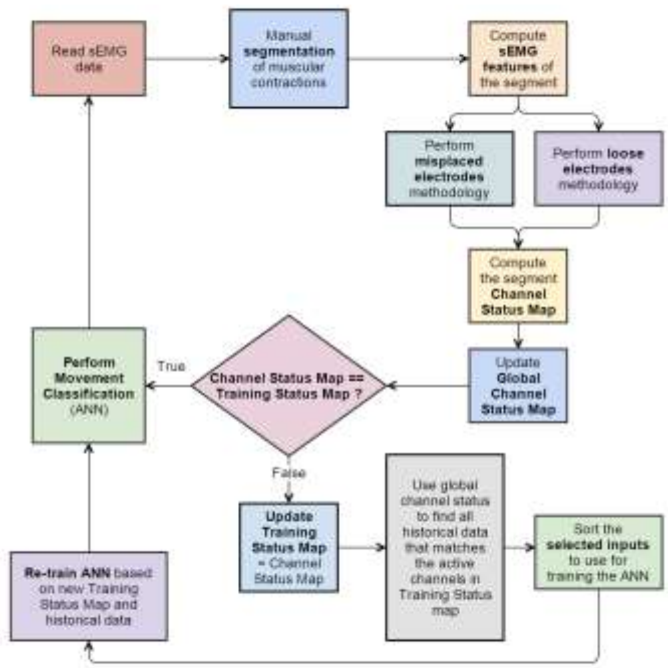

Fig. 4: Flowchart of the adaptive inputs selection methodology.

III. Results

In order to appraise the system, 50% of the acquired data was used to initially train the network (individually for each subject) while the remaining database was used to analyze the movements classification performance of the proposed method. The number of movement samples acquired for each subject differs from each other, due to the lack of time available, and is represented in Table I.

TABLE I. Number of movement samples for each subject

Subjects	AB 1	AB 2	AB 3	AB 4	AB 5	TR 1	TR 2	TR 3	TR 4
Samples	432	126	108	162	162	54	54	54	54

The results were computed in two different ways. First, the system was tested using all available data to classify the nine different movements for all subjects. Additionally, the network was trained and tested using the proposed intelligent algorithm

DOI: ISSN:2318-4531

for input selection. The comparison among the two methods is presented in the Table II.

The movements performed (M1 to M9) by each subject and its corresponding accuracy and the number of channels utilized are listed in the Table 2. Subjects AB 1 to AB 5 represents Group 1, the able-bodies subjects. Subjects TR 1 to TR 4 represents Group 2, the trans-radial amputee subjects.

The Table 2 presents the average accuracy for each subject. Analyzing the table it is possible to observe an increase in the average classification accuracy using the auto-adaptive method. It is also possible to notice a greater improvement for the amputee subjects in the movement classification comparing with the able-bodied subjects. A possible reason for this result is the fact that the amputee subjects trials were performed with random placement of electrodes. The random-placement of electrodes could lead to signals with low SNR providing poor-movement classification, which is optimized by the proposed technique.

TABLE II - CLASSIFICATION ACCURACY FOR BOTH INPUT SELECTION METHODS PERFORMED.

Subject	Method	Average Accuracy (%)	Channels Used
AB 1	**Adaptive**	**92.8%**	**6**
	Non-Adaptive	77.3%	8
AB 2	**Adaptive**	**80.2%**	**7**
	Non-Adaptive	75.3%	8
AB 3	**Adaptive**	**75.8%**	**6**
	Non-Adaptive	69.4%	8
AB 4	**Adaptive**	**84%**	**6**
	Non-Adaptive	79%	8
AB 5	**Adaptive**	**87%**	**6**
	Non-Adaptive	59.3%	8
TR 1	**Adaptive**	**70.4%**	**4**
	Non-Adaptive	48.1%	6
TR 2	**Adaptive**	**63%**	**3**
	Non-Adaptive	25.9%	8
TR 3	**Adaptive**	**51.9%**	**6**
	Non-Adaptive	37%	8
TR 4	**Adaptive**	**59.3%**	**4**
	Non-Adaptive	48.1%	8

Analyzing the results, it is possible to observe the improvement in the average accuracy for all subjects when using the adaptive input selection solution. An interesting point to highlight is the decrease in the amount of data (channels) used to classify the movements and the correlated increase in the overall accuracy of the method. For instance, the minor improvement scenario occurred in subject AB 2, in which only one channel was discarded, and an improvement of accuracy of 5% was achieved. The best case scenario occurred with the amputee subject TR 2, in which 5 channels were discarded and an overall accuracy of 63% was achieved, 37% higher comparing to the scenario with the use of all channels.

Another point often overlooked, is that even if the increase in accuracy is just slightly better, the processing of less data (channels) represents a gain in the system computational performance. This can lead to a system with better timing response, which is crucial for commercial use of intelligent prosthesis [3].

IV. DISCUSSION

The proposed adaptive method achieved the main objective of this paper, which was to identify non-idealities in the input signal and perform a retraining of the ANN, updating the list of sEMG channels. The channels that may mislead the ANN considering its low significance to the classifier training were discarded leaving only the channels with relevant information to the method.

From the analysis of the results, it can be shown that the proposed algorithm is a promising auto-adaptive solution. The technique still need further tests and refinements in order to maximize its main capacity which is boost the accuracy rate by using less and more relevant data. This solution appears to be particularly efficient on amputee subjects, who frequently have some problems with signal integrity. By performing training with these channels, it is possible to create a more accurate training instance for the movement recognition and even, by using fewer channels, achieve higher accuracy levels.

Considering the possibility of reduction the number of channels, the proposed method presents itself as a promising embedded-processing technique since it results in data reduction to be processed and the scenarios aimed in this paper are more likely to occur with prosthesis for continuous use.

It is import to remark that the present work also comprehends the classification of the amputee subjects, which presents a more defiant classification problem considering the electrode positioning restriction due to the lack and atrophy of muscles. In addition, it is important to highlight the quantity of movements classified for this work. In the related studies, the number of movements varies from 4 to 7 simple-movements (except [9] which performs the classification of 12 movements). In this study, nine movements were classified, including 4 composed-movements which are constituted by 2 simple-movements that are also classified by the proposed algorithm. The composed-movements correlation with the simple-movements classification increases the complexity of the movement discrimination of the classification method generated by the ANN that reflects a lower overall accuracy of the movement classification. Although, [14] presents a series of parameters, which may be observed in online classification, especially regarding to time metrics, this work evaluated only in terms of accuracy and the feasibility of implementation of the proposed technique with a well-established classifier. The future improvements will focus on effective online and embedded classification and the use of a more effective classifier (e.g. LDA) to evaluate the proposed technique in terms of accuracy and time.

V. CONCLUSION

The proposed method aims to improve the accuracy rate of classifiers used to identify movements based on sEMG signal processing. To do that, the method automatically chooses the most relevant inputs to train and test the classifier based on SNR

DOI: ISSN:2318-4531

of each sEMG channel, therefore, discarding channels that present brusque non-idealities of the signal. Once the classifier is trained and tested with more representative channels, the characterization of the movement is improved, so as the accuracy rate.

Although the simple pattern recognition method (ANN) used on this initial study, the proposed method must be capable to be put together with any supervised machine learning algorithm. The objective was to show the possibilities that the adaptive method can bring to improve the overall classification of the movements respecting the channel choice based on the superior contribution of each individual channel to the classifier. That would be an alternative technique to feature dimensionality reduction, with the advantage that it could be performed on-the-fly, soon as the data is read. The technique is especially interesting to use with amputee subjects, since they frequently present a deteriorated sEMG signal due the lack of musculature and proper physiotherapy.

In order to evaluate to potentiality of the proposed method, further studies including classifiers as SVM and Extreme Learning Machines (ELM) are recommended. SVM is well-known in this application, demonstrating good capacity of generalization using a reduced amount of data. An ELM analysis would be particularly useful given the capacity of ELM reach an optimal solution through the pseudo-inverse use. Thus, it expected that reduce the channels (model variables) makes easier to find an optimal value and reduce the uncertain of the approximation made by the Moore-Penrose pseudo-inverse when it is not possible to reach an exact solution. Moreover, the studies of ELM on sEMG signal classification are incipient, typically the use of ELM base technique with a well-known pre-processing algorithm such as PCA.

Finally, as a future work implementation, it would be interesting to perform long-time assays in order to evaluate the decrease in the accuracy through the time caused by the looseness and misplacement due to prolonged electrode use and compare the results with a proposed algorithm implementation. In addition, it would be of great interest to utilize other classification methods on an embedded system combined with the technique presented in this paper to evaluate with which technique a better improvement is likely to be obtained in terms of accuracy and time response.

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