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Impact of sEMG Time-series Segmentation Parameters on the Recognition of Hand Gestures

Carlos. E. Pontim, José. J. A. M. Júnior, Hygor V. P. Martins and Daniel P. Campos

Abstract **— Surface Electromyography (sEMG) have been widely researched signal for prosthesis control. This process is based on sEMG processing steps as segmentation, feature extraction, and classification, which recognizes these biosignals in gestures to be performed for prosthesis. Among these processes, segmentation is a fundamental step, however some variables are not explored, aiming to improve the classification performance. In this work, it was analyzed the influence of sEMG overlapping segmentation in pattern recognition for hand gestures used to control an upper-limp prosthesis. Data of six commonly used gestures were acquired by 8-channel commercial armband (Myo from Thalmic Labs) from 7 subjects in forearm. The evaluated segmentation parameters were window length, overlap fraction, and the full length of signal (truncation). Four time domain features were extracted: L-Scale, Maximum Fractal Length, Mean Value of Root Square, and Willison Amplitude. Linear Discriminant Analysis and K-Nearest Neighbor classifiers were used to recognized the gestures. Wilcoxon test was performed to evaluated significantly difference from results distribution ($p<0.05$). The best obtained results in classifier was achieved using the KNN classifier with the following specifications: window of 0.45s, overlapping fraction of 25%, and truncation of 100%, with 97.4% of accuracy. It was noted that increasing window length, the accuracy of classifiers also increase. The overlapping ratio presents some significant differences in the distribution, where smaller overlapping steps improves the accuracy. Regarding the truncation, the combination of start and last portion of the signal (not only the beginning) contain the useful information for pattern recognition.**

Index Terms **— sEMG, Machine Learning, Segmentation, Feature Extraction, Robotic Hand.**

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I. Introduction

PROSTHESIS are devices used to substitute specific members (in upper or lower limbs) of the human body. They have become useful either for the amputee population or for those who has a congenital deficiency [1]. Prosthesis supplies aesthetic needs. However, they are not restrained only in this function. In fact, their functionality is being further developed and improved [2]. Design, system control, and biofeedback in the prosthesis' state of art have been enhanced due to researches, incorporating physical characteristics and functionalities of an absent member.

Currently, there are two types of prosthesis: active and passive. Regarding the passive prostheses, they do not possess articulations nor mechanisms. Its objective is to reestablish the external aspect of the body (aesthetic). On the other hand, active prosthesis are user-controlled by different actuators, e.g.: electrical, hydraulic or pneumatic. These models incorporate both the aesthetic need with the actuation.

Concerning active models, the prosthesis based on myoelectric control have been widely researched and developed in both commercial and academic applications [3]. Electromyographic signals (EMG) are biopotentials generated by the activation of a motor unit that acts contracting a muscle. Thus, this signal are used to control robotic prosthesis due to their capacity to directly access muscle's physiological information [4], [5]. The control of myoelectric prosthesis are achieved through processing of the sEMG signals. This process is based on the segmentation, extraction of features, and classification steps from sEMG. To perform that stages, it is necessary the use of machine learning techniques [4], [6], [7]. The state-of-the-art methods of sEMG classification are based

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in seeking hand-crafted feature sets and segmentation parameters which lead to better accuracy rates and robustness [8], [9].

Among these stages, segmentation was the step that denotes some attention due to as composed by the identification of sEMG signal activation and its dividing in window segments [10]. Moreover the techniques of signal detection (as blind segmentation, double threshold onset method [10], and the use of inertial sensors[11], the parameters for window the signal are little explored. Parameters as window length (number of sEMG data points in a segment), overlapping rate (rate of overlap segments), and the total amount of signal (truncation) are essentials to guarantee data for the feature extraction and, therefore, for the classification. Its choice does not be arbitrary in data processing. Some guidelines are present in the literature, as the number of segments around 100 and 300 ms [12], [13] and fixed increment of overlap segments for classification around 25 and 100 ms [14], [15]. However, there is a need to verify the contribution of these parameters in the classification process.

This works aims the evaluation of the effect of EMG time-series signal segmentation parameters in the classification accuracy. Among these sEMG processing, segmentation is a fundamental step, however some variables aiming to improve the classification performance are fewer explored [11]. As the instances of the classifier are features extracted from a signal window, the length, the overlapping factor, and epoch of the signal used to train the classifier may affect its performance. This research has application in the development of myographic controlled robotic hands, whose focus is transradial amputees, in order to reestablish their functionalities.

This work is organized as follows: Section II presents the used Materials and the Methodology applied in this work for data processing; Section III exhibits and Section IV discuss the obtained results with the change of the segmentation parameters and their influence in classification process; and Section V presents the main considerations about the paper.

II. Materials and Methods

The data acquisition protocol used in this work was approved by Ethical Committee of Human Research of Federal University of Technology - Paraná (UTFPR) (CAEE 89638918.0.0000.5547). Figure 1 presents the main flow of the data processing. The sEMG signals were acquired from an armband device and were recorded for the data processing. After the acquisition, the signals were divided in segments. Parameters as window length, overlapping rate, and part of the signal (truncation) were changed on the signal. Each window was sent to feature extraction step and mathematical operations were made in the segments aiming to extract the its useful information. These attributes were sent into the classifiers as inputs, where the gestures were recognized. Concerning a prosthetic control, the classifier's output is responsible to send the movement that the prosthesis should be made, acting the circuits that drive the motors of the prosthesis.

The used acquisition device was the commercial armband Myo (Thalmic Labs). Myo has 8 sEMG channels (with 200

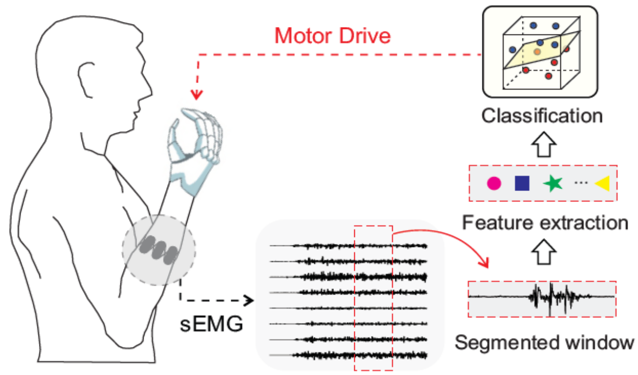

Fig. 1. Schematic of data processing flow. sEMG signals were acquired from forearm using 8-channel armband. The signals are segmented in overlapped windows. For each segment, features are extracted, changing the stochastic signal in useful information. The features are sent to the classifiers and from the recognized gesture, the motors in the prosthesis are actuated

samples/s and 8-bit resolution) and an inertial motion unity (3-axis accelerometer, gyroscope, and magnetometer). This device were chosen due to be ease of placement on the subjects and its wireless communication with a computer by Bluetooth. Thus, it did not need a physical connection by cables with the processor unity (computer), allowing the performance of dynamic gestures with more naturalness. Data from 7 health subjects were acquired: 7 males ranging 21 to 33 years, 1.7 to 1.87 m of height, and 71.4 to 130 kg of weight. Before each collection, hygiene and cleaning was performed on the device and on each forearm subject in the approximate region where the device would be positioned. In the protocol, the armband sensors were identified and positioned in posterior medial region, where the channel 3 of the armband was positioned on the extensor muscle, guarantee that the device have the same position for all the subjects.

The protocol for data acquisition was based on repeated execution for each pre-defined movement. Six gestures were chosen to this analyze: abduction of all fingers (FA), fingers flexed together in fist (FF), thumb up (TU), pointing index (PI), tip pinch grasp (PG), and tripod grasp (TG). This movements were chosen due to are commonly used during routine actions for a hand amputee person. These gestures were presented in Figure 2 with a sample from eight channels acquired from Myo armband. The gestures were executed repeatedly to subjects perform them more naturally throughout the acquisition.

Each movement was executed and sustained isometrically for 5 seconds and the subjects returned to relaxed state to guarantee that them have timely to perform and stabilize the required gesture, as well as relax completely after this execution. The gestures were performed with subjects seated in a straight chair with foots on the floor, legs apart, slight inclination of the trunk forward, keeping the spine aligned with the elbow resting on the thigh, and hand in a neutral position to prevent synergistic muscle activation.

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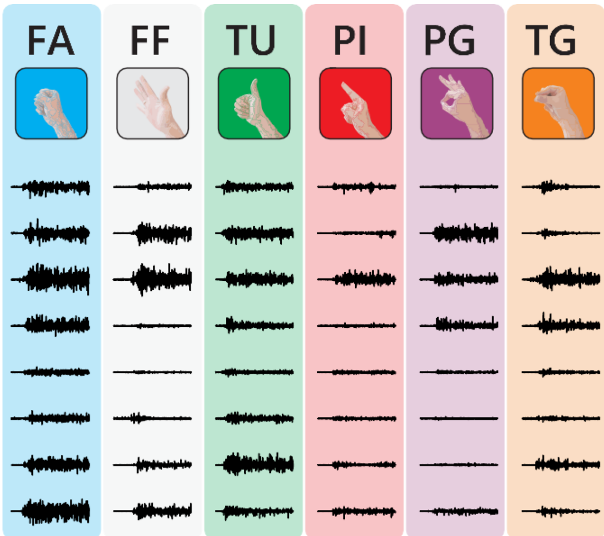

Fig. 2. Gestures acquired from subjects and a sample of ignal in each channel from Myo armband. The acquired gestures are: abduction of all fingers (FA), fingers flexed together in fist (FF), thumb up (TU), pointing index (PI), tip pinch grasp (PG), and tripod grasp (TG).

A. Segmentation

A slide window separates the signal periodically in fixed length segments with partial overlapping. In this work, the sEMG $\in \mathrm{R}^N$, being composed by a data sequence represented by $\boldsymbol{x} = [x_1, \dots, x_N]$, vector. This method, illustrated in the Figure 3, is a simple process that allows the operation for online EMG signal processing. The i-th segment is defined by:

$$\boldsymbol{s_i} = \{x_{(i-1)k}, \dots, x_{(i-1)k+W}\},$$

where W is the dimension of segment and k is the window step. The overlap fraction ϕ_o, which is the step size relative to the window size, can be calculated by $\phi_o = {}^{K}/_{W}$. This way $\phi_o = 1$ is a disruptive window, $\phi_o = 0.5$ is a half-step overlapping window and $\phi_o = 0.25$ is a quarter-step overlapping window. The number of steps to surpass a whole window (N_s) is equal to $N_s = \phi_o^{-1}$. The processing time will be proportional to the window size and inversely proportional to the overlap fraction. Thus, the processing time is proportional to a factor of $W/\phi_o = W.N_s = W^2/k$. This way, one seeks for the smaller window size as possible as its effect to the processing time if squarely proportional. Besides that, the whole segment was truncated. Knowing that each gesture was acquired from 5 s, it was analyzed the maximum segment for 2.5 s and 5 s after the identified threshold. This variable was named I_T (signal truncation) and was changed to 50 and 100%, 2.5 and 5 s, respectively.

Several methods have been employed, such as segmentation based on the onset detection [10], peak detection [16], sample entropy [17], time-frequency characteristics [18], and signal spectral changes [19]. The onset segmentation is a well-known technique for sEMG segmentation, however it requires the determination of a threshold, which is also a concern [20], [21]. The analysis were performed off-line, in other words, the signals were processed after the acquisition from raw data. However, the presented analysis enable the same process in online approach.

In this work, the following parameters were changing to evaluate the segmentation process: overlap rate (overlap fraction) of 0.25, 0.50, and 1, truncation of 50% and 100%, and window segment of 50 ms to 100 ms with step of 50 ms.

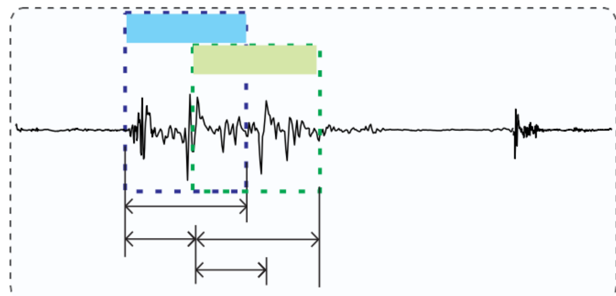

Fig. 3. Segmentation process applied in this work. After the detection the start of sEMG signal, the signal is separated in windows S_n with length W.

B. Feature Extraction and Classification

A robust sEMG classification depends on the correct feature selection, which may represent time and frequency characteristics [12]. Four features were chosen to extract the useful information from sEMG signal: L-Scale (LS), Maximum Fractal Length (MFL), Mean Value of the Square Root (MSR), and Willison amplitude (WAMP) [9].

The Maximum Fractal Length (MFL), is a method for measuring low-level muscle activation [22], [23]. It is expressed as:

$$MFL = log_{10}\left(\sqrt{\sum_{n=1}^{N-1}(x_{n+1} - x_n)^2}\right),$$

where, N is the total number of data points in the signal x (signal length).

The Willison Amplitude (WAMP) is defined by the number of times the amplitude difference between two consecutive points exceeds a given threshold. It is related to the muscular contraction level [24]. It can be calculated from:

$$WAMP = \sum_{n=1}^{N-1} f(|x_n - x_{n-1}|),$$

$$f(x) = \begin{cases} 1, & \text{if x} \geq \text{threshold} \\ 0, & otherside \end{cases}$$

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where the threshold was heuristically set as 10^{-2}.

LS is a feature based on L-moments which is less sensitive to outliers in the signal and biased estimation (if compared to other moments such as standard deviation). Commonly, the second moment (r=2) is used [9] and it can be defined as:

$$LS = r^{-1}\sum_{k=0}^{r-1}(-1)^k\binom{r-1}{k}EX_{r-k:r},$$

where, $X_{k:n}$ is the k^{th} order statistic of a random sample of size \$n\$, and \$E\$ is the expected value [25].

The total amount activity of sEMG can be calculated from the Mean Value of the Square Root (MSR), which is obtained by the averaged sum of every sample within the analysis window [26]:

$$MSR = \frac{1}{N}\sum_{n=1}^{N}\sqrt{x_n}.$$

These features do not depend of frequency-domain and are related with amplitude and signal complexity. Besides that, setting one feature set is useful to investigate the combination of segmentation parameters, since this feature set has presented robustness and high accuracy in classification systems.

Two classifiers were used to recognize the patters: Linear Discriminant Analysis (LDA) and K-Nearest Neighbors (KNN). These classifiers were chosen due to this simplicity and they are widely applied to signal sEMG classification. LDA is a classifier that uses the Fisher's discriminant to separate classes. LDA is a simple statistical approach and does not require any parameters adjustment. Also, it is computationally efficient for real-time operation and its classification performance for myographic signals [27]. KNN is a classifier based on distance between samples, and for this work, it was set for one-nearest neighbor. To classifiers analysis, k-fold cross validation was performed, with k being 10 folds.

To analyze the performance of classifiers and the alterations in segmentation process, a statistical analysis was performed aiming to find significant differences in distributions. It was used the Wilcoxon (Rank-sum) test to evaluated the null hypothesis with confidence interval of 0.05.

III. Results

The outcome results achieved using the KNN and LDA classifiers are shown in Figure 4 and Figure 5, respectively. The accuracy (hit-rate) of the classifiers are depicted in function of the window size for I_T of 50% and 100% and ϕ_o of 100%, 50% and 25% (or 1, 0.5, and 0.25) which are equivalent to disruptive, half-step overlapping and quarter-step overlapping segmentation. One may note that the accuracy increases with the segmentation window size. The overlapping factor improve the classification for KNN and for both approaches (KNN and LDA) using just the first portion (I_T = 50%) affects the accuracy.

The best result was achieved using KNN wih a window size of (W) of 450 ms, reaching 97.46±0.57%. However, KNN may present some issues for online operation, thus, as an alternative LDA can be used, where the best result was 78.39±1.69% with a window size of 750 ms.

LDA presented significant differences when using window sizes over 600 ms. Truncating data to 50% did not affect significantly the accuracy for windows above 550 ms. For KNN no significant difference was observed for windows above 200 ms considering overlapping of 25% (no truncation) at a significance level of 5% (p<0.05). Truncation lead to significant differences (exception to W = 1000 ms, 900 ms and 800 ms). Thus, KNN has not only performed better, but also performed similarly when using small segmentation windows, which may improve online operation. Moreover, using the first half of each signal did affect the accuracy for smaller windows. This way, the whole portion of the signal, and not only the beginning, contain useful information for pattern recognition.

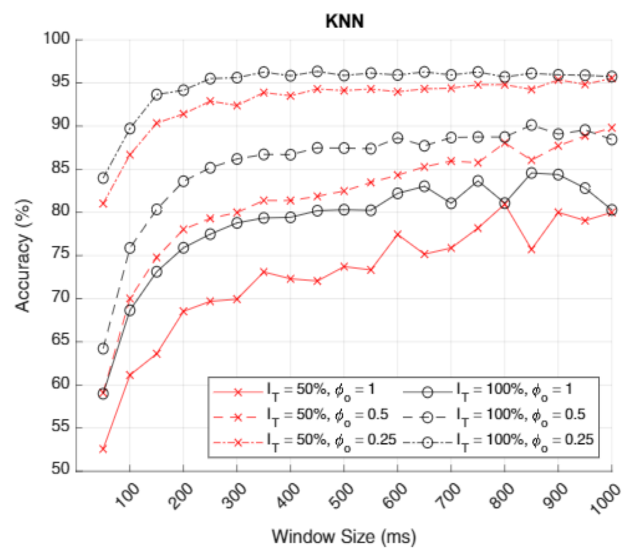

Fig. 4. Accuracy (hit-rate) of the KNN classifier in function of the window size for I_T of 50% and 100% and ϕ_o of 1, 0.5, and 0.25 (disruptive, half-step overlapping, and quarter-step overlapping).

The Figure 6 details the confusion matrix achieved using the best parameters (KNN with a window size of 450 ms and overlapping factor (ϕ_o) of 25\% and truncation (I_T) of 100%). The FF movement is the most distinct class (99.31%) and the major confusion occurs when the target is PI and TU.

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This behavior can be noted by the extraction of the evaluation metrics from the confusion matrix, presented in Table 1. All the classes presented precision and specificity higher than 98%. The differences between classes occurred in sensitivity parameter, which the class with highest precision also has the highest sensibility (the ability to identify true positives). The other classes presented values ranging 6%, and as this value was not accentuated for none other classes, it shows that the pattern recognition process did not privileged only one or two classes. On other words, as all the classes have similar values in these metrics, the segmentation parameters evaluated acting in all data set without privilege one class over than other.

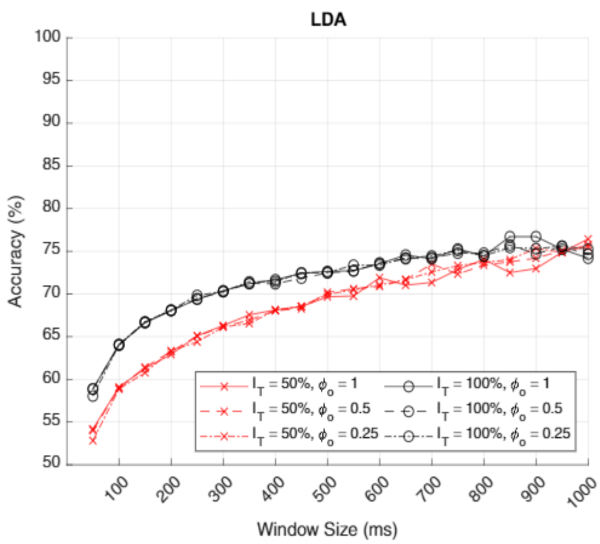

Fig. 5. Accuracy (hit-rate) of the LDA classifier in function of the window size for I_T of 50% and 100% and ϕ_o of 1, 0.5, and 0.25 (disruptive, half-step overlapping, and quarter-step overlapping).

IV. Discussion

Concerning the segmentation parameters, truncation also may reduce the number of instances during the training. This way, avoiding transitory signals could reduce the number of possible erroneous instances, but also will reduce the total number of the instances for the training step. The hypothesis is that is more important to have a wider variability of the instances features, including the transitory (in this case, the second half of the movement event), than to have cherry-picked epochs which is previously known to represent better the target event.

Following the aforementioned hypothesis, the overlapping has two functions. First as a data augmentation for the training, which could make the classifier more robust, as the number of instances increases proportional to a fraction of the overlapping factor. For example, if the step is half a window, the number of instances will double in relation to a disruptive segmentation. Regarding an on-line processing, the overlapping may help in post-processing techniques such as majority votes. This is

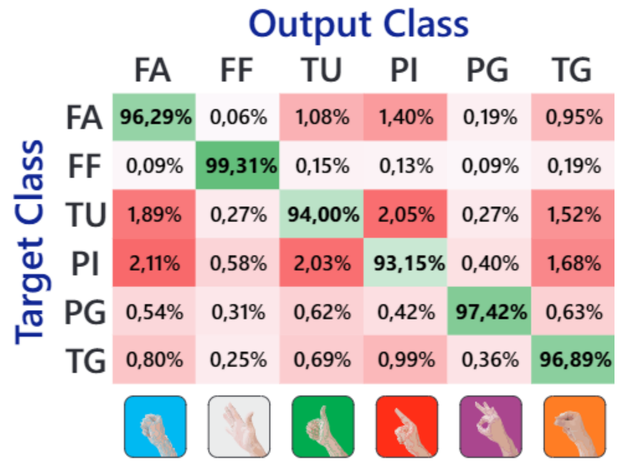

Fig. 6. Confusion matrix of the best result achieved using KNN with a window size of 450 ms and overlapping factor (φ_O) of 25% and truncation (I_T) of 100%.

because the overlapping creates redundancy within adjacent windows, and thus, those segments with anomalous signals will be averaged with adjacent overlapped windows. In other words, is like having a better resolution measure from the pattern recognition system.

A major drawback of reducing the windows step is increasing the processing cost. In order to process the overlapped signal on-line, fractions of the signal will need to be held in a buffer for processing. Moreover, a larger number of feature extraction and classification will be performed as the time step becomes smaller.

New hypothesis emerge from the results. Does the overlapping technique alone summed with post-processing techniques increase the classification accuracy, such as majority voting or Hidden Markov Models (HMM)? To test this possibility, the training process would have to be balanced in the number of instances, and the processing pipeline would have to consider the overlapping factor in the simulation of the on-line processing. In this case, the computational cost may represent a major factor in the analysis. Another issue is addressed to the contribution of the transitory events during the class. What is the accuracy divergence between a model that is trained using only the middle portion of the signal and a model that is trained to recognize transitory events? This question affects directly the interpretation of works that use one approach or another. Furthermore, is there a portion of the signal, which has more information about the movement than others? Finally, what is the better way to segment the signal to train a classifier? In this work, an overlapping approach was used, but even the segment window may affect the results. For example, picking random segments would lead to similar results? All those issues are each day more relevant considering the emerging wearable technologies and should be explored in future works.

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V. Conclusion

This paper evaluated the segmentation parameters effect in the myoelectric hand gestures classification accuracy. The best results was achieved using the KNN classifier. Increasing the segmentation window length, also, it increases the classification accuracy; however using a window greater than 200 ms has not affected significantly the performance. This way, it is recommended to use smaller segmentation windows to improve online operation. It was also observed that smaller overlapping ratios (25%) and using the whole signal (no truncation) is preferable to train the classifier.

Future works may test different feature sets and classifiers. Furthermore, the statistical analysis should be expanded, leave-one-out validation and comparing with other segmentation methods such as the onset based segmentation. In addition, the optimal number of instances and signal range to improve the classification and response time still an open problem. The evaluation of post-processing techniques, such as majority votes and Hidden Markov Models, could be added to future developments. Another hypothesis, which will be evaluated, is that dividing the motion into individual finger movements in a multi-label bank of binary classifiers should improve time and accuracy performance.

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Impacto de Parâmetros de Segmentação Temporal de sEMG no Reconhecimento de Gestos da Mão

Resumo — A eletromiografia de superfície (sEMG) tem sido um sinal amplamente pesquisado para o controle de próteses. Este processo é baseado nas etapas de processamento da sEMG como segmentação, extração de características e classificação, os quais reconhecem estes biossinais em gestos a serem realizados para próteses. Entre estes processos, a segmentação é uma etapa fundamental, porém algumas variáveis não são exploradas, com o objetivo de melhorar o desempenho da classificação. Neste trabalho, foi analisada a influência da sobreposição da segmentação sEMG no reconhecimento de padrões para gestos manuais usados para controlar uma prótese de limite superior. Os dados dos seis gestos heuristicamente usados foram adquiridos por uma braçadeira comercial de 8 canais (Myo da Thalmic Labs) de 7 voluntários no antebraço. Os parâmetros de segmentação avaliados foram o comprimento da janela, a fração de sobreposição e o comprimento total do sinal (truncamento). Foram extraídas quatro características de domínio de tempo: Escala L, comprimento máximo da fração, valor médio do quadrado da raiz, e amplitude de Willison. Para reconhecer os gestos, foram usados os classificadores: Análise de Discriminantes Lineares (LDA) e K-ésimo Vizinho mais Próximo (KNN). O teste Wilcoxon foi realizado para avaliar a diferença significativa da distribuição dos resultados ($p<0,05$). Os melhores resultados obtidos no classificador foram obtidos utilizando o classificador KNN com as seguintes especificações: janela de 0,45s, fração sobreposta de 25%, e truncagem de 100%, com 97,4% de precisão. Foi observado que o aumento do comprimento da janela, a precisão dos classificadores também aumenta. A relação de sobreposição apresenta algumas diferenças significativas na distribuição, onde etapas menores de sobreposição melhoram a precisão. Com relação ao truncamento, a combinação de início e última porção do sinal (não apenas o início) contém as informações úteis para o reconhecimento do padrão.

Palavras-chave— sEMG, Aprendizagem de Máquina, Segmentação, Extração de Características, Mão Robótica.

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