Segmentation of electromyography signals for pattern recognition

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***Abstract*—The use of gestures as interface between humans and robots to facilitate communication between them is a long-sought goal. Although many gesture solutions have been presented, none of them cope entirely with wrong gesture recognition. This study proposes a novel electromyography (EMG) prototype sensor to capture gestures and also algorithms and procedures to discriminate data containing valid gestures (segmentation). Gestures are recognized using convolutional neural network (CNN) model. The proposed solution presented high recognition accuracy overcoming other similar studies in literature. Test results demonstrated that the proposed solution presents high performance and suggested its use in industrial environment.**

***Index Terms*—Pattern recognition; Electromyography; Industrial Robotics; Industry 4.0**

I. Introduction

A great ambition of Industry 4.0 is to reach more production in less time with less human effort. On the same time, operators perform deeper industrial process supervision to obtain better product quality with less waste. A key factor to attain efficient supervision is associated to the communication/interaction between operators and machines [1]. The interaction must provide the following characteristics: practical, high availability, fast, efficient and intuitive. From the different types of interaction, human-gestures are ones that aggregate the requirements previously highlighted [2]. Upper-limb gestures seem to be suitable for industrial purposes because operators can perform many different gestures with high repeatability and controlled stroke movement.

A few devices can be used to capture upper-limb human gestures such as vision systems and wearable sensors. Surface electromyography (sEMG) sensors gather the advantages of wearable sensors and on the same time is a non-intrusive sensor, ergonomic, easy to use, hassle-free and can operate without interruptions for long working periods. To use a sEMG sensor, the user simply puts it over the human skin in a muscle region of interest.

A sEMG signal, which is non-stationary, represents the sum of subcutaneous motor action potentials generated through muscular contraction. Artificial intelligence can then be leveraged as the bridge between sEMG signals and an industrial collaborative robot. A feasible solution must be able to identify what is a valid gesture (gestures belonging to a training dataset), what is an invalid gesture (gestures not belonging to the training dataset) and what is a no-gesture (rest). This is the way to achieve a solution that presents the robustness and reliability necessary to arouse the interest of the industry.

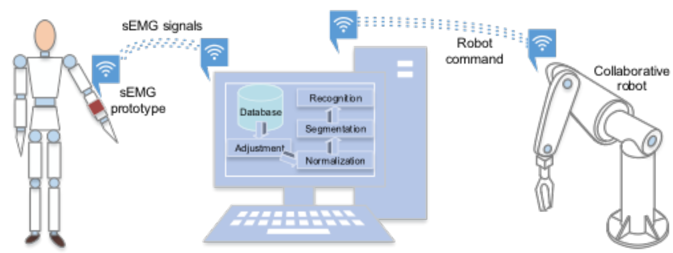

Fig. 1: System architecture.

In pattern recognition, segmentation consists in data processing to identify if there is any valid pattern on a data-stream. When a segmentation process labels a data-stream as containing a valid pattern, a deeper analysis/processing must be carried out with this data-stream to identify which pattern is in the data-stream. This one is called recognition process. Many studies have been carried out in pattern recognition, but the majority of them do not separate the segmentation process from the recognition process [3]–[5]. Despite all these studies, no optimum solution has been achieved, a solution that can conveniently identify all the three types of gestures mentioned above. As such, the main contribution of this study is to present a novel segmentation scheme to select the sEMG signal that contain useful information (human gestures) and send it to a pattern classifier (for sEMG-based gesture recognition purposes). The user's gestures are captured by sEMG sensors and transmitted via Wireless to a personal computer which analyzes the data and subsequently sends commands to a collaborative robot. A schematic representation of the used architecture is displayed in Fig. 1.

This paper is organized as follows: section II presents a survey of pattern recognition studies for industrial purposes whose process of data segmentation is approached. Section III describes the hardware components used to capture human gestures. This section also details the algorithms and all the steps used to recognize gestures. Section IV presents procedures followed by users, who carried out tests, and implementation. Finally, section V displays results, highlights outcome testing and accuracy analysis the experimental setup, while section VI concludes the paper.

II. Literature Review

The problem of novelty detection is important in order to improve robustness of pattern recognition systems. Even if a given system presents a relatively high accuracy in the classification of predetermined (trained) classes, it is still likely to miss-classify novel classes as one of the trained classes. This is a seldom addressed failure mode that could lead to unexpected results and potentially endanger users and their environment.

Liu and Huang propose the use of an ensemble of one-class (OVA) SVDD classifiers that demonstrates a high level of generalization [6]. If a new sample does not fall into any of the SVDD hyper-spheres, it is considered an outlier, a novelty. Else, it is considered a targeted pattern and can be further processed. However, this ensemble does not replace a multi-class classifier because the SVDD hyper-spheres may intersect. In this case, the same pattern is classified as multiple classes, so an extra step must be taken to determine the final classification output.

A different solution using modified boosted Random Forests (MCLPBoost) was studied to solve the problem of novelty detection [7]. The effect of arm movements on sEMG pattern recognition for hand and wrist motions was studied in [8]. Results showed that arm movements significantly impact classification performance when the classifier is trained in one arm condition and tested in another.

A method to accurately divide continuous data-streams into dynamic and static blocks was suggested by [9]. Segmentation, the name given to this method, proposes to identify when a gesture starts and ends. This study reported reduction of the number of wrongly classified gestures. If a segmentation process is not properly defined, the beginning of a gesture is assumed too late ignoring important parts (data frames) from the gesture, over-segmentation (excessive segmentation). In order to overcome this issue, Simão et al. proposed the use of a genetic algorithm to optimize a segmentation method [10]. This method demonstrated reduction of over-segmentation error to acceptable values.

The process of data segmentation is many times despised in gestures recognition. Segmentation is treated as a classification issue and not isolated from the broader purpose [3]–[5], [11], [12]. Segmentation is more challenge when sEMG data are used to represent a gesture. This kind of data/signal is not clearly stable being difficult to set boundaries even for human limbs in relaxed states. sEMG technology is more sensitive to involuntary movements than other technologies [13], [14].

III. Methodology and equipment

A. Hardware

A novel prototype device based on sEMG and inertial measurement unit (IMU) developed by Technaid S.L. was used in this study. The prototype is constituted by two bracelets, one of them is composed of an 8-channel sEMG, dry-electrode, and the other one is composed by a 6-channel sEMG. A variable number of 9-axis IMUs can integrate this prototype. In this study no IMU data are used.

The great advantage of the prototype is its non-intrusive nature, as the dry-electrodes allow users to simply put it over human-skin without any preparation. Unlike, gel-based electrodes require the shaving and washing of the skin to obtain optimal contact between the user's skin and electrodes. However, dry electrodes, such as the ones employed in this prototype, are less accurate and robust to motion artifact than gel-based ones [15].

A personal computer with a NVIDIA GeForce GTX 1080 Ti GPU and an Intel(R) Core(TM) i7-8700k CPU was used to carry out all signal acquisition and processing stages of this study. A collaborative KUKA iiwa robot was used in experimental tests.

B. Signal processing (Dimensionality and Filtering)

When a data frame is collected by the prototype, twenty sEMG data objects, on average, are received from the prototype. In fact, the number of sEMG data objects can be different from frame to frame being required a data dimensionality adjustment. The approach proposed consists in excluding objects that exceed twenty objects, keeping the most recent twenty objects, or repeating the last object up to obtain twenty objects.

All sEMG signals were sampled at 1000 Hz and then filtered in order to decrease the captured noise, signal artifacts and power line interference. A notch filter of 50 Hz and a fourth-order Butterworth band-pass filter of 20-500 Hz were used, the same filtering approach suggested in two studies that reported good results [16], [17].

C. Sliding-window

A sliding-window method is used in this study. This method consists in grouping a given number of frames, the last ones acquired, and uses them in the processing stages presented in the next sections of this manuscript. sEMG signals are sectioned into 500 ms (500 frames) segments with variable increments which can range from 250 ms (250 frames, 50 % overlap) to 0 ms (no overlap). The size of the sliding-window was based on the time necessary to complete the longest gesture of an experiment detailed in section IV.

An array variable ***m_5***, which is detailed in section III-F2, consists in a binary variable of 20 elements (for this study) and each element contains the information relatively to 25 frames and all sEMG channels. If an element value is 1, its corresponding frames contain muscular activity, which indicates that those frames are part of a gesture. The last 10 components of ***m_5***, corresponding to the last 250 sEMG frames of a sample, are processed to find muscular activity that can be reused as taking part in a next/future sliding-window. Just one full sequence of muscular activity is accepted to be reused in a future sliding-window, but it cannot be connected to the first 10 components of ***m_5***. For example: if ***m_5*** = [0 1 1 1 1 1 1 1 0 0 0 0 0 0 0 1 1 1 0 0 0], the last six frame groups (the last 150 frames) will be used in the next/future sliding-window; if ***m_5*** = [0 1 1 1 1 1 1 0 0 0 1 1 1 1 1 1 1 1 0 0 0], none frame of the current frame will be used in the next/future sliding-window; if ***m_5*** = [0 1 1 1 1 1 1 0 0 0 0 0 0 0 0 1 1 1 0 1 1], the last two frame groups (the last 50 frames) will be used in the next/future sliding-window.

Recent studies suggest that the latency should be kept bellow 300 ms for real-time purposes [18]–[21]. Nevertheless, in applications that do not require real-time, latency can be larger and ranges widely depending on the purpose/application. The solution presented in this manuscript is not intended to be used for real-time applications. However, the procedure presented above can be adjusted to provide a latency lower than 300 ms to be used in real-time applications.

D. Normalization

Generally, sEMG signal is a very changeable signal that can be affected by different factors and presenting undesirable effects such as offset. Data normalization can provide to sEMG signal relational characteristic, improvement data integrity and reduction processing complexity. When normalization is used as part of a pattern recognition solution, normalization is pointed as yielding faster training times whilst allowing better generalization [4]. Data provided by each sEMG channel are normalized with mean 0 and standard deviation 1. In order to establish normalization parameters, in an initial acquisition step, when the prototype is turned on, a few sEMG frames are acquired. Notice that different and independent normalization parameters are established for each sEMG channel.

E. Feature extraction

Extraction of features from a sensor signal is a common procedure in pattern recognition. This step is particularly import to better represent/explicit a given pattern.

Feature extraction gains particular relevance in sEMG because such a signal is not intuitive to perceive, it usually presents low amplitude and is full of variability sources. Features allow easy differentiation between patterns while reducing the variance of examples within the same pattern. Features can be regrouped into different types, mainly: time, frequency and time-frequency domains [4], [18], [22], [23].

In this study the time domain features were used to carry out segmentation process, namely the variance feature.

F. Segmentation process

In order to decide if a data-stream contains a valid pattern (which belongs to a pattern library), two methods are suggested, namely an algorithm based on artificial intelligence k-nearest neighbors (k-NN), and a threshold-based algorithm.

1) k-nearest neighbor algorithm: This algorithm consists in using a pattern classification model that distinguishes two classes, valid pattern and invalid pattern. If a data-stream is classified as invalid pattern, no gesture is included in the data-stream, it is forgotten and consequently deleted. On the other hand, if the data-stream is classified as valid pattern, the data-stream is used again in another pattern classification model to identify which pattern is represented by that data-stream. This last pattern classification model is known as recognition process and will be presented in section III-G.

A method proposed to carry out the segmentation process consists of a k-NN classification model. In the construction of this classification model, the Euclidean distance method and 5 neighbors were used. As referred in section III-E, the features used as inputs to both segmentation algorithms were the variance of the sEMG signals.

2) Threshold-based algorithm: A threshold algorithm based on several thresholds and binarizations was developed to perform segmentation. The main steps of threshold algorithm are clarified bellow. The algorithm starts by acquiring 500 sEMG frames (***SEMG***) which are grouped in small sets with a given number of frames, defined by variable *num_f*, and the variance for each set is computed (line 2 in the algorithm Segmentation). Following a binarization of the feature variance (*Var*) by comparing it with a threshold array (***thre_arr***) which has defined a threshold value for each channel (line 3). A new data grouping is performed in line 7 through the algebraic sum of a given number of frames, defined by *num_f*, in turn the new data are binarized by comparing it with a zero's array (line 8). Data from different channels are grouped in line 10 and compared with a threshold value, *thre_num* in line 11, binarizing once again the sEMG data. One last data grouping are performed in line 12 resulting a single value which is compared with value 0 to check if the sEMG data contain a valid gesture or not (lines 14 to 17).

A genetic algorithm (GA) was used to establish ***thre_arr***, a threshold value for each sEMG channel. Some samples with muscular activity and without it were collected, their frames were grouped, with equivalent size (*num_sub_sets*) and order to variable ***m_5***, and labelled (***frame_set_label***) accordingly. From this stage resulted a number of sets *n_sets* properly labeled. Each frame group was used by the GA to minimize a cost function *err* (1). Although the ***frame_set_label*** and ***m_5*** variables are boolean variables, they are used by the cost function as algebraic variables assuming the value 0 or 1 when their elements are false or true respectively. The GA benefits from having its variables constrained. The lower limit is zero, and the upper limit can be the maximum values of the ground truth features. Furthermore, the GA used the segmentation algorithm presented above with the *thre_num* being defined by the user by a trial and error process.

$$err = \sum_{i=1}^{n\_sets} \sum_{j=1}^{num\_sub\_sets} |\boldsymbol{frame\_set\_label}\,(i,j) - \boldsymbol{m\_5}(j)| \quad (1)$$

G. Pattern recognition process

A recognition process must be executed to identify which gesture from a gesture library is represented by a sEMG signal. The classification model used in this study is based

Algorithm 1 Segmentation ($\boldsymbol{SEMG}$, num_f , $\boldsymbol{thre\_arr}$, $thre\_num$)

inputs :
sEMG data matrix $\boldsymbol{SEMG}$
number of frames in a set num_f
threshold array $\boldsymbol{thre\_arr}$
threshold value $thre\_num$
output :
flag to identify if the data contain a gesture $gesture\_flag$

for $i \leftarrow 1$ to length($\boldsymbol{SEMG}(num\_channels,:)) - num\_f$
  $Var(:) \leftarrow$ Variance($\boldsymbol{SEMG}(:,i{:}i+num\_f)$)
  $M\_1(:) \leftarrow Var(:) > \boldsymbol{thre\_arr}(:)$
end
$num\_sub\_sets \leftarrow$ length$(M_1(num_channels,:))/num_f$
for $i \leftarrow 1$ to num_sub_sets
  $M\_2\,(:,i) \leftarrow \sum_{j \leftarrow i}^{i+num\_f} M\_1(:,j)$
  $M\_3(:,i) \leftarrow M\_2\,(:,i) > [0]$
end
$\boldsymbol{m\_4}(:) \leftarrow \sum_{i \leftarrow 1}^{num\_channels} M\_3\,(i,:)$
$\boldsymbol{m\_5}\,(:) \leftarrow \boldsymbol{m\_4}\,(:) > [thre\_num]$
$m\_6 \leftarrow \sum_{i \leftarrow 1}^{num\_sub\_sets} \boldsymbol{m\_5}\,(i)$
if $m\_6 > 0$
  $gesture\_flag \leftarrow true$
else
  $gesture\_flag \leftarrow false$
end
return $gesture\_flag$

on Convolutional Neural Networks (CNN), a deep-learning method that extracts features from the sEMG signal directly and then uses these features to identify which gesture is contained on them (classification). The CNN used in this study is displayed on Fig. 2.

Owing to transitions between gestures (hand motion from one gesture to another) and, sometimes, while holding a gesture, one sample could be misclassified. This could restrict final implementations of the gesture recognition system. To avoid this issue and improve gesture recognition, the last five predictions are kept and a gesture is considered as it has been performed, if and only if, at least four of the five predictions are the same. Otherwise, without producing any result the oldest prediction is forgotten and a new one is considered altogether with the previous four. Whenever a gesture is recognized, all the predictions are forgotten. This procedure is just adopted in the robotic use-case described in section IV-C.

IV. Experiments

A. Users and acquisition conditions

Four healthy, able-bodied, right-handed users (three males and one female) aged 29.4 ± 4.3 years with body mass index 21.6 ± 1.8 kg/m2 participated in this study. They performed the gestures in four stages. On a first stage, 15 samples of a gesture class were collected with the user standing. The user rested for a short time between each collected sample. After that, on a second stage, the user seated in a chair performed the same gesture for more 15 times. The procedure was repeated again with the user standing in a third stage and sitting in a fourth stage. In total, 60 samples from each class were collected in each acquisition session having each user rested for 5 minutes between acquisitions of different classes. The user's right-arm, the one used to perform gestures, was randomly positioned in four different slopes 0º, 45º, 90º and 135º during gesture acquisition. Jochumsen proved that arm slope has strong influence in arm gesture recognition captured by sEMG [5]. This procedure was followed by each user once a day, for each class, during five uninterrupted days. Each user performed his/her gestures at different times of the day in order to capture different conditions the device is subjected and device behavior throughout the day which affects sEMG signal. The recording procedure was executed with the user holding each gesture during a non-fixed time, higher than the sliding-window size, and resting for a short time after each recording. Each sample was recorded only when a key was pressed on a keyboard, so there were no transition samples recorded that had to be discarded. Following this procedure, two datasets were produced one to train all classifier models and other one to test classifier models [24].

B. Classes/Gestures

Six hand/wrist gestures are considered in this study. The first five gestures are valid gestures: fist, finger spread, wave in, wave out and double tap, Fig. 3. The sixth gesture from the gesture library referred to as neutral is the natural posture of the hand of the user when no significant muscle activity is detected (rest). Whereas this gesture must be eliminated with the segmentation process (invalid pattern), it is also known by the recognition process in order to confer more robustness to the system (section III-G). There is a seventh gesture that composes the gesture library (non-gesture). This last class is a generical gesture that intends to represent all gestures that are possible to be performed by a user and are different from the six gestures previously mentioned. The idea of using a class to represent all unknown gestures was successful proposed to recognize gestures from upper-limb human body, captured by IMUs [25].

C. Robotic use-case

In order to prove that the prototype device is reliable for industrial use, a simple use-case was created. This use-case consists in a user performing one of the five valid gestures, and when it is recognized, a command is sent to a collaborative robot. In turn, the robot executes an industrial task, associated to that particular gesture, it can be a simple robot movement, open or close a gripper, turn a digital input on or off, or initialize a collaborative task whose robot moves by compliance between human hand contact and the robot itself [26], [27].

In this real scenario each valid gesture was performed by each user 20 times each one. On the other hand, the rest gesture and the non-gesture were performed unknown number of times. Anyway, when one of these gestures was recognized,

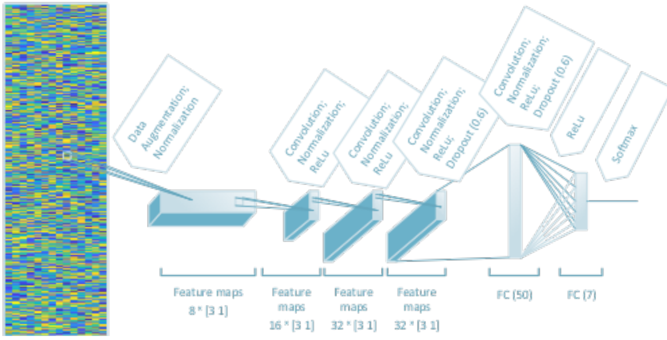

Fig. 2: CNN classification model used to gesture recognition.

Fig. 3: Six gestures: G1 – Fist; G2 – Finger spread; G3 – Wave in; G4 – Wave out; G5 – double tap; and G6 – Rest.

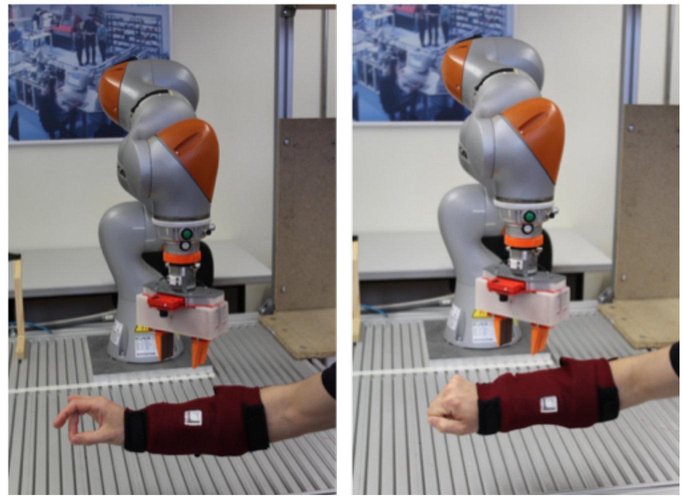

Fig. 4: Test scenario with collaborative robot and sEMG prototype.

it was registered. The test scenario is presented in Fig. 4 in which the collaborative robot and the sEMG prototype is highlighted.

V. Results and discussion

Two sub-datasets with 2400 gestures each were created from the two main datasets [24]. While one of the datasets is just used to train the k-NN algorithm, the other sub-dataset is used to test both algorithms used for the segmentation process. Each sub-dataset is composed by the 1200 samples of the gesture rest (invalid pattern) and from 1200 samples randomly extracted from the six other classes (valid pattern). The data are taken from the main dataset that satisfy training or testing purposes. Table I displays the results of both algorithms used for the segmentation process. Both algorithms present good performance, with the threshold algorithm outperforming with 97 % accuracy, while the k-NN algorithm presents 92 % accuracy.

All data from the two main datasets were used to train and test the recognition algorithm, depending on its purpose. The test results for the classifier used in the recognition process are displayed in Table II. The suggested recognition process was tested with the test dataset reaching a high overall classification accuracy of 99 %. The results presented in Table II represent the recognition of each gesture performed once. The second approach that just accepts a gesture as recognized when it was recognized 4 times in 5 recognition trials was just used in the online tests, i.e. the results presented in Fig. 5 and Table III.

The online tests carried out by interfacing with an industrial collaborative robot, in which the users performed 20 valid gestures of each gesture belonging to the library of gestures, resulted in the accuracies displayed in Fig. 5. The overall accuracy reached in these online tests was 95 %. This is a good result because it is in-line or is higher than the results displayed in recent similar studies [4], [5], [11]. Other good point presented by the proposed solution was the system capacity in reject/identify non-valid-gestures (classification of rest (G6) and non-gesture). Additionally, when a gesture performed by a user was wrongly recognized, it was not recognized as other valid gesture, as shown in Table III. This suggests the solution presents robustness and feasibility to be used in industrial scenarios.

Notice that the good performances achieved in the offline tests, which made use of data belonging to the testing dataset, was not reached by data captured and processed (recognized) online. Anyway, this kind of approach must be followed in order to compare with the results of other studies because all of them follow the same approach. The reason for the higher performance is because when the data are provided from a dataset, a data discrimination has already been done, and the database practically just contains useful information (effective data about gestures). For example, the transition between two gestures does not belong to the database. As a transition is more challenging to exclude from a pattern, as well as more challenging to classify as non-pattern (given the enormous number of non-patterns that can exist in relation to the ones belonging to the training dataset), the classifier work is facilitated when non-patterns are not tested or all data about a gesture is contained in a data-stream.

The achieved results proved the viability of the algorithms and procedures proposed in this study. The good robustness presented by the system can be attributed to the high channel density to overcome variance in signal quality; electrode placement; and electrode doffing and donning (the contact conditions between the electrodes and the skin could possibly change). Other issues that the proposed solution has to deal with are confounding factors including dynamic arm postures, force variations, limb posture, and control arm alterations.

TABLE I: CONFUSION MATRIX FOR SEGMENTATION PROCESS.

True class	Predicted class			
	Threshold algorithm		*k-NN algorithm*	
	Invalid pattern	***Valid pattern***	***Invalid gesture***	***Valid pattern***
Invalid pattern	1138	62	1087	113
Valid pattern	14	1186	76	1124

TABLE II: CONFUSION MATRIX FOR RECOGNITION PROCESS.

True class	Predicted class						
	G1	***G2***	***G3***	***G4***	***G5***	***G6***	***Non-gesture***
G1	1196	2					2
G2		1198	2				
G3		2	1198				
G4			2	1198			
G5					1198		2
G6						1159	24
Non-gesture	7	2	11	11	11		1158

VI. Conclusion

In order to overcome the challenges imposed by online sEMG-based gesture recognition, a novel procedure and an algorithm for data discrimination were proposed. In addition, a recognition algorithm based on CNN was also suggested. The combination of both algorithms demonstrated to be good outcomes from this study since the high recognition accuracy shown by the tests. A novel sEMG sensor prototype was used in this study, providing its benefits to the solution namely, high-density sensory capturing which cover a large muscular region and consequently more data about gestures. Seven classes of gestures were proposed, in which five classes represent five valid gestures, one class represents human inactivity (rest/invalid pattern), and one last class represents all gestures different from the previous mentioned six gestures (non-gestures).

The proposed segmentation process allows the identification and exclusion of many rest gestures (invalid patterns) and discrimination of frames, which ones contain muscular activity to be reused in a next gesture recognition trial. Thus, the segmentation process seems to provide high robustness to the solution. The frame discrimination provides gesture samples with all or almost all their data frames about a gesture to a recognition process, facilitating the subsequent gesture recognition.

A real scenario was used to test the solution having the results presented high recognition accuracy, about 95 %. This result overcomes similar studies from the literature and suggests the use of a solution like the one proposed could be in industrial use soon.

This study will proceed performing tests with larger gesture libraries and the data fusion with other sensors will be pondered.

TABLE III: CONFUSION MATRIX RESULT FROM AN ONLINE TEST PERFORMED BY ONE OF THE USERS.

True class	Predicted class						
	G1	***G2***	***G3***	***G4***	***G5***	***G6***	***Non-gesture***
G1	20						
G2		19					1
G3			20				
G4				18			2
G5					19		1
G6						243	
Non-gesture							6

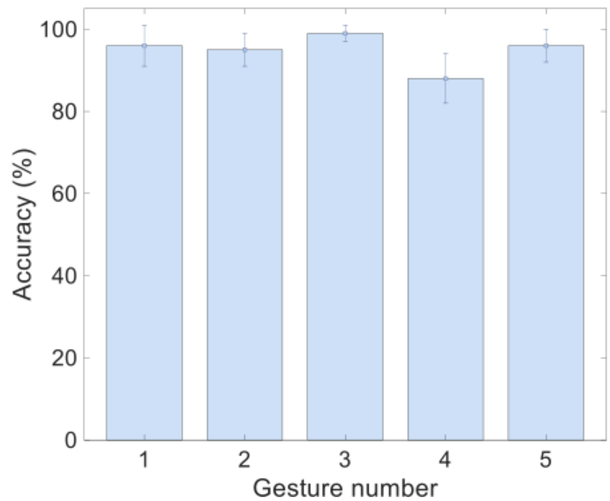

Fig. 5: Gesture recognition accuracy for the five valid gestures tested in online operation.

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