Analysis of Robust Implementation of an EMG Pattern Recognition based Control

Simone Benatti[1], Elisabetta Farella[1,3], Emanuele Gruppioni[2] and Luca Benini[1,4]
[1]*DEI, University of Bologna, Bologna, Italy*
[2]*Centro protesi, INAIL, Vigorso di Budrio, Italy*
[3]*ICT Unit, Fondazione Bruno Kessler, Trento, Italy*
[4]*Integrated System Laboratory, ETHZ, Zurich, Switzerland*

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Abstract: Control of active hand prostheses is an open challenge. In fact, the advances in mechatronics made available prosthetic hands with multiple active degrees of freedom; however the predominant control strategies are still not natural for the user, enabling only few gestures, thus not exploiting the prosthesis potential. Pattern recognition and machine learning techniques can be of great help when applied to surface electromyography signals to offer a natural control based on the contraction of muscles corresponding to the real movements. The implementation of such approach for an active prosthetic system offers many challenges related to the reliability of data collected to train the classification algorithm. This paper focuses on these problems and propose an implementation suitable for an embedded system.

1 INTRODUCTION

Assistive technologies in the last years are boosting interesting research efforts to enhance quality of life. In fact, the availability of accurate sensing technologies at a relatively low price and the possibility to exploit the power of low-cost low-power and fast microcontrollers enable a whole new branch of applications, where wearable smart sensors and embedded systems can be used not only for monitoring but also for the implementation of sensor fusion techniques or complex machine learning algorithms and for provision of stimuli through actuation. An application field such as the control of prostheses can greatly benefit from this rapid technology evolution.

Recently, multi-finger active prostheses of the upper limb have appeared at commercial level (e.g. Touch Bionics i-Limb, RSL Steeper BeBionics 3, Otto Bocks SensorHand) enabling a larger set of gestures w.r.t. previous prostheses, therefore asking for an adequate strategy for their control. State of the art technologies for the feed-forward control of active hand prostheses are controlled via surface electromyography (EMG) in a way that forces the user to learn to associate contraction of what remains of the muscle to unrelated postures of the prosthesis, e.g., sequences of wrist flexion and extension correspond to various gestures. While at one side these techniques grant a good reliability and short activation time (within 30ms for the detection of the activity and less than 300ms for the classification), on the other side the control strategy is non-natural, requiring focus and a non-trivial learning curve for the user. It would be desirable instead to command the prosthesis movement by activating the muscle as to move the phantom limb.

Luckily, scientific literature recently proved that machine learning applied to EMG signals could be beneficial in prosthetics to bring the control towards more intuitive and natural strategies. In fact, convincing results have been shown both on healthy subjects (Englehart et al., 2001) and amputees (Castellini et al., 2009). This paper describes the preliminary analysis done in an on-going work towards a real-time embedded implementation of an EMG based control of an active hand prosthesis by use of machine learning techniques and in particular by use of a Support Vector Machine. Starting from the lesson learnt by literature, this work faces, as first step, the variability on classification results due to the changes in placements of the EMG sensors that occurs in real life. In fact, the wearer limb is subject day by day to physical differences due to swelling, fatigue, perspiration that can cause misplacements of the sensors w.r.t. the de-

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sired position. Furthermore the same gesture can be performed in various positions and orientation of the arm (along the body, lifted up, etc.). These changes affects the classification performance and must be addressed properly.

Starting from a data collection repeated in different days on 10 healthy subjects, this paper proposes the analysis of the reliability of the gesture recognition in an EMG signal controlled hand prosthesis. The analysis takes into account that our final target is an embedded implementation. The analysis is based on three main elements: (i) the selection of a correct signal acquisition chain, (ii) the analysis of the physiological best placement of the EMG sensors to grant a robust classification, and (iii) the analysis of the performance of the system through days, evaluating the difference of performance when the sensors are placed and removed in different sessions, as in the real use of the device for the classification of natural movements. The activation of the same gesture is considered in multiple combinations of the arm orientation and position to better study their influence on the classification performance and consequently improve the robustness of the classifier.

The paper is organized as follows. Section 2 illustrates background and related works,Section 3 introduces the architecture of the system used to get the EMG signals. Section 4 describes the tests made with the collected data. In section 5 we show the results and discuss the solution advantages. Finally in section 6 we draw the conclusions.

2 BACKGROUND AND RELATED WORKS

Three types of prostheses are widely available for people with upper limb amputations: passive, body powered, and electrically powered. Passive prostheses are often employed for cosmetic purposes and have limited functionality. Body-powered prostheses are used to restore basic tasks such as opening and closing a terminal device. These devices are often used because they are simple, robust, and relatively inexpensive. The user can actuate electrically powered or active prostheses but they are advantageous w.r.t. body-powered ones because they require less user effort, as movement is actuated with DC motors. They can be controlled through a variety of means such as force sensors, linear potentiometers, and EMG signals. Electrically powered prostheses restore some functionality to amputees, but control of these devices is typically limited to only one or two degrees of freedom.

As mentioned, however, recently, multi-finger active prostheses of the upper limb have appeared at commercial level (Bebionics, 2012, TouchBionics, 2013, Ottobock, 2009). These prostheses, driven by EMG sensors, can replicate most of the principal movements of the hand. To achieve robustness the movement of the active prostheses are typically driven by non-natural activation patterns, i.e. they decode mainly sequence of flexion and extension of the wrist (Castellini and Smaag, 2009). The most accurate EMG signal is taken directly on the spot near the muscular fibers by use of implantable sensing electrodes; however, they are invasive and pose safety issue, needing surgery. Our proposed application prefers surface EMG sensors. They suffer lack of performance, due to the noise of the skin surface and the crosstalk of near muscle. Nevertheless we can use improving signal methods (Reaz et al., 2006) for a machine learning approach.

In literature, machine learning algorithms chosen to extract muscular pattern and classify gestures vary from Linear Discriminant Analysis (LDA) classifier (Young et al., 2013) to Neural Network (Matsumura et a.l, 2002). Liarokapis and al. (2012) compare a set of classifiers for EMG signal and conclude that SVM (Boser et al., 1992) is the most accurate algorithm for pattern recognition with these kind of signals. Other works, like (Oskoei and Hu, 2008) and (Chen and Wang, 2013), made comparison for EMG pattern recognition and conclude that SVM gives the best result for these signals. The work of Englehart and al. (2001) studies how to enhance the performance of the SVM algorithm to reach the best accuracy of the classification, by optimizing the classification parameters and the feature extraction. These works give contributions in field of signal processing because they propose an optimized solution to a classification problem, but they do not keep in account the issues related to the use in daily life use, like for example the variation of classification accuracy during arm movements, or the sensor misplacing due to day by day application of the prosthesis.

Some papers show experiments with a high number of subjects and features to test the accuracy of their classification algorithm. These results reach accuracy ratio near 100% but they are not applicable in real scenarios, because they do not take into account the variability of the signal caused by the placement of the EMG sensors. The misplacement of the EMG electrodes among different sessions and the positions of the arm during the use of the prosthesis affect the classification performance. This work tries to address the problem analysing the best placement of four EMG sensors to maximize the recognition performance. Furthermore, we analyse the variability of training data along different days and caused by different positions of arm and forearm while performing the same gesture.

3 SYSTEM SETUP

3.1 EMG Signal Acquisition

The EMG signal measures the electrical activation of the muscular fibres. Muscle tissue conducts electrical potentials similar to the way nerves do and these electrical potentials are named muscle action potentials. When EMG electrodes are placed on the skin surface the signal is composed by all the action potential of the fibres underlying the electrode. The surface EMG sensors are made by two metal plates each one connected to the inputs of a differential amplifier that can sense the action potential of muscular cells.

The amplitude of this signal is 20mV (-10 to +10), with a bandwidth of 2000Hz. This kind of signals are also very noisy and difficult to manage. The main causes of this noise are the motion artefacts, the electrical equipment noise and the floating ground noise, because the body is not referred to a solid ground potential. To obtain information useful for the classification algorithms, it is required that sensors minimize the noise and provide significant quantitative pattern of muscular activation. For these reason we used, instead of classical differential sensors, the Ottobock 13E200 (Figure 1), a family of pre amplified sensors with single ended output (Ottobock, 2009). In Ottobock sensor the EMG signal is amplificated and integrated to reach an output span of 0 - 3.3V, ideal for the single ended stage of an embedded microcontroller ADC.

The bandwidth of the Ottobock sensor is 90-450Hz with a further notch filter for the 50Hz. This is because the sensors for the classification of the gestures do not need extensive frequency information but a clear low noise signal. The analog signals are acquired from an embedded board based on ARM CORTEX M4 microcontroller. The internal 16-bit ADC samples the data and an external Bluetooth interface sends it to a laptop. The embedded custom solution is preferable with respect to a data logger solution in this application because the final goal is to implement a complete embedded real time system. The board used for this application is shown in Figure 2. The data collected by the PC are managed in Matlab, for the signal processing and the pattern recognition.

Figure 1: Ottobock sensor.

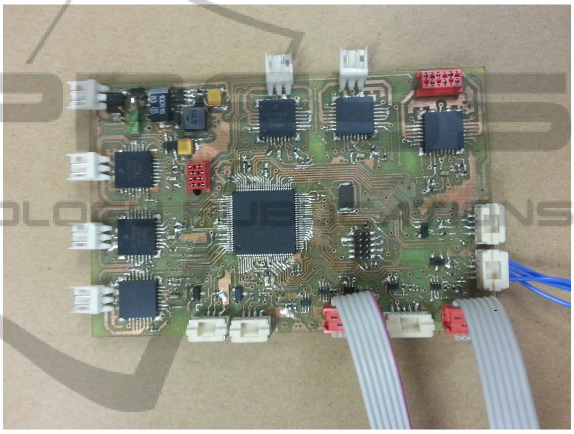

Figure 2: Embedded board.

3.2 Sensor Placement

The position of sensors is a critical task in using a limb prosthesis. Muscles in healthy subjects are placed in known position and it is possible to have little differences in the amplitude of the activation signal or in the position of EMG sensor. Amputees presents specific characteristics in muscular structure and difference of amplitude of activation signal if compared with healthy subjects and, for this reason, it is important to evaluate subject by subject the possibility for an amputee to use an active prosthesis. The positioning strategy is tested on healthy subject in this paper and the test on amputees is the goal of future works.

Our strategy started from a previous work of Castellini et al. (2009), that placed 5 sensors on an elastic strip, with an equal distance each others. The idea was to consider a sort of general pattern of the forearm muscle activation, without focusing attention on the anatomical structure of the arm. The risk of such approach is to lose the contribution of one or more sensors if misplaced. We propose an approach, based on a four sensors configuration, in two steps: a theoretical one that considers the muscles involved in hand movement and a practical one that verifies the good placement of the electrodes and the information given from all sensors.

The theoretical approach starts from the analysis of the muscular tissues of the limb. Signals have maximum quality where the muscle is wider, and the muscular fibres are spread. In the upper limb, the optimal zone is the proximal third. In the forearm, the muscles are divided in four groups, and the use of surface EMG sensors requires that muscle near the skin surface must be preferred for the classification. We can divide the forearm muscles in two groups: muscles in the internal part of the forearm (flexor radialis carpi, palmares longus, flexor carpi ulnaris, flexor superioris digitalis), involved in flexion movements, and muscles placed in the external part of the forearm (externsor comunis digitorum, extensor digiti minimi, externsor carpi ulnaris), involved mainly in extension movements.

Nevertheless, the theoretical selection of muscles is not sufficient, because in the practical case the electrode catches a zone of many muscular fibres, introducing noise and requiring to verify the usability and the integrity of the target signal. Forearm was divided in different zones considering the dimension of the selected Ottobock sensors. The zones are numbered with progression, starting from the flexor carpi radialis, with counter clockwise sequence. Sensors are placed on the muscle primarily involved in movement selected. The muscles are found with tactile analysis and the corresponding number is used to place the sensor on the elastic strip used in this experiment (Figure 3).

By placing sensors on the flexor carpi radialis, flexor carpi ulnaris, extensor digitorum communis and extensor carpi ulnaris we obtained a good differentiation in classification pattern. The assumption for a pattern recognition control system is that the set of signals and features describing a given state of muscular activation are different from one state of activation to another. Figure 4 shows the gesture of the hand and the corresponding activation pattern acquired by the four sensors. The amplitude of each of the four sensors is a clear discriminant among patterns, even if the presented solution is not intended as the best

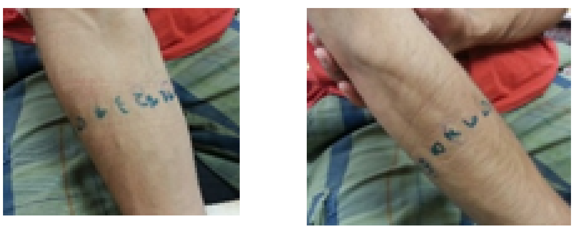

Figure 3: Muscle selection.

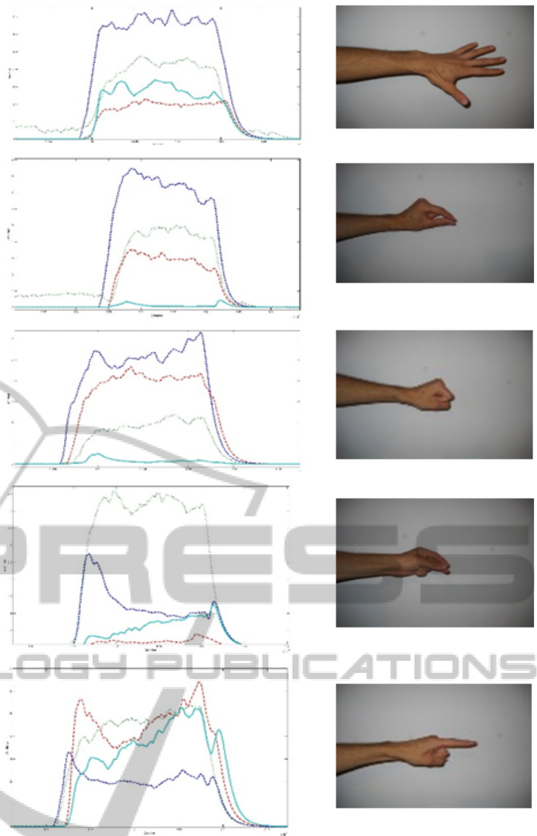

Figure 4: EMG amplified signal pattern for selected gestures.

placement, because the final target of this application is the use of the board on transradial amputees, and for these patients the placement strategy must be tuned subject by subject.

3.3 Classification of the Data

A pattern recognition algorithm classifies the different hand gestures. The control is considered a supervised classification problem. Training data are collected during the controlled training session and a set of labels are assigned to each pattern to train the classifier. SVM is a machine learning technique used for pattern recognition (Burges, 1998). SVM goal is to found the optimal separation hyperplane between two classes. Support vectors are samples of the training dataset used to build the separation hyperplane.

In the SVM algorithm, only the data of the training set are used to create the separation hyperplane and maximize distance between plane and datasets. Sometimes data are not linearly separable, and SVM algorithm can map the predictor on a higher dimension space, where it is possible to separate data. If the system becomes too complex and the calculation of the Euclidean distance between the point of the dataset and the separation hyperplane becomes too hard, SVM can introduce Kernel functions. These kind of functions operate in a feature space and calculate only the inner product between images of all pairs in the feature space instead of the Euclidean distance in a high dimensional space. This operation is computationally simple and allows using SVM with high dimensional classification problems. Initially the algorithm was developed only for a 2-class problem, but it is possible to expand it with a One Versus All approach. The implementation of the SVM algorithm used in this paper is taken from libSVM (libSVM, 2011) a freeware library implemented for Matlab and C, compiled by GCC and usable in embedded systems.

The EMG signals present differences from one acquisition to another. This behavior is due to many factors, clinical, electrical, and patient dependent. The not fully repeatable placement of the electrodes that can generate different traces and crosstalk, the different muscular contraction strength due to fatigue or repeated muscular activity, the variable conductivity of the skin surface, due to humidity, perspiration or other physiological and environmental condition, can induce significant changes in the shape of the activation pattern. Some training strategies can try to overcome this problem. In the work of Hargrove et al. (2008), authors used a sort of extended dataset method, based on particular high density EMG system. The dataset collected using these sensors can make more robust the training phase but it is difficult to use this system in a real application. Furthermore, it is not considered that the activation patterns can change in different days and for different position of the arm. For this reason, an important part of this work is a collection of a robust dataset of EMG signals.

3.4 Acquisition Protocol Description

The collection of the dataset follows an acquisition protocol described in this paragraph. Selected movements are the most common hand gesture used in daily life, to ensure a good quality of social reintegration. Gesture selected are shown in Figure 4 (closed hand, open hand 2-finger pinch, 3-finger pinch, point index).

The classification includes also the rest position of the hand, recorded between two subsequent gestures. There are 9 subjects involved in the dataset acquisition. Gestures are acquired in 10 sessions collected 1 for day in 10 days not necessarily consecutive.

The sequence of gestures is repeated and scrambled in four arm positions (Figure 5). Each acquisition session is divided in 4 steps, one for each position of the forearm. The collected sequence is composed by 10 repetitions of muscular contraction 3 second long. Between each contraction there are 3 seconds of rest. One file for each acquisition is captured. Subjects wear an elastic strip with the 4 EMG sensors.

Figure 5: Different arm position.

Sensors positions are tuned with a simple procedure described below. An arm as shown in Figure 6. The operator ideally traces a line on the axial direction of the forearm (Figure 6-left). Then the operator places Sensors 1 and 2 at 30mm respectively on the left and on the right side of the line at the proximal third of the forearm. The operation is repeated for sensors 3 and 4 with the arm flex in the position shown in Figure 6-right by considering the ideal line and placing sensor 3 and 4 at 30mm of distance symmetrically at the two sides of the line, at the proximal third of the forearm. Once the sensor are placed, a good positioning signals trace is acquired to avoid misplacement of the strip. The test is made with the gestures of hand open and closed,, which correspond to a non-zero signal for all the sensors.

To avoid that the subject learns the sequence of gestures and loses the naturalness in movements, the sequence are scrambled and each acquisition in a different arm position has a different pattern of gesture.

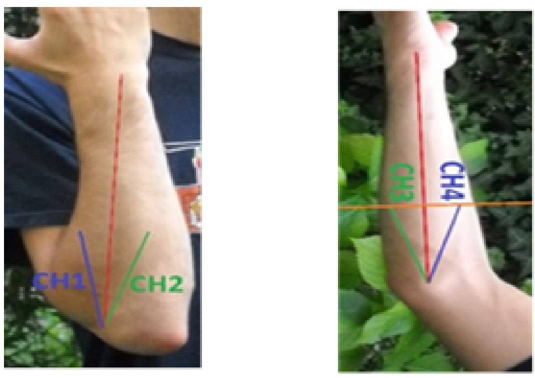

Figure 6: Sensor placement.

Table 1: Confusion matrix for single training session.

ACCURACY %		REST	PREC	OPEN	POWER	POINT
99,4	**REST**	77185	118	0	339	0
91,6	**PREC**	149	24992	0	1688	445
75,8	**OPEN**	125	416	10088	2689	0
95,7	**POWER**	186	162	6	14745	302
82,3	**POINT**	82	756	0	1820	12371

For the same reason, the positions of the arm are not always in the same sequence: for example in session 1 sequences are captured in distal position and in proximal position, in session 2 these sequence is inverted, and scrambled with different pattern of gesture in other sessions.

4 EXPERIMENTAL RESULTS

The implementation of a pattern recognition system in a real application for the gesture classification has three main issues: the correct placement of the EMG sensors, the variability of the activation pattern due to the various positions of the arm and the variation of muscular contraction among following acquisition sessions. The importance of this aspect is acknoledged in literature, where other works address specifically the problem of placement and the difference between surface and intramuscular sensors (Hargrove et al., 2007) and propose their placement schemes. The training of the SVM is a critical phase since the quality of the training and the resulting matrix strictly affects the fidelity of the recognition. In turn, the segmentation phase performed on data collected is therefore crucial to augment the quality of the training. However data preparation, thresholding and segmentation are subjective operations based on the knowledge of the signal and on experience (Milosevic et al., 2010).

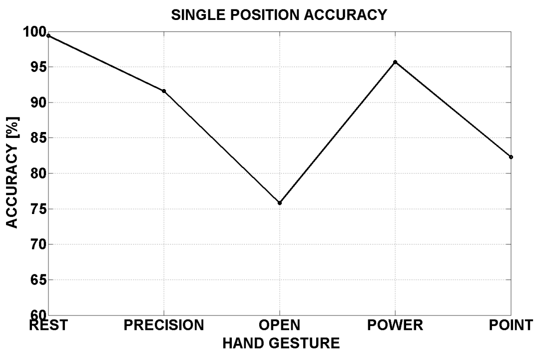

Figure 7: Accuracy for a single training session.

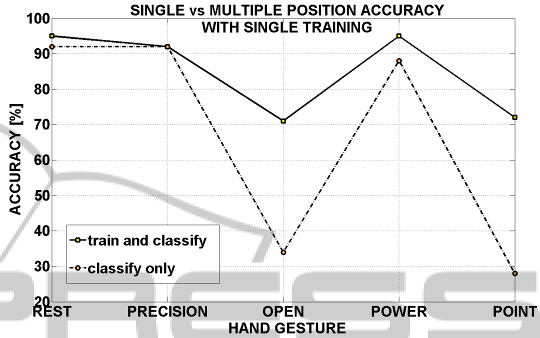

Figure 8: Difference of accuracy between classification in the position of the training and in other arm position.

4.1 Single Arm Position Classification

Our first purpose for the experiments is to verify the performance of the proposed placement scheme, to guarantee that a good classification is possible. For this application, we considered only the three fingers precision grip, because many commercial prosthetic systems, in the operating configuration, admit to choose between two or three finger precision grips. In the initial test, we considered only one session dataset (i.e. 10 gestures per position) per each patient. The training set is the 25% of the session dataset (i.e. 3 gestures per repetition) obtained with manual segmentation. The training stage is performed offline on MATLAB libSVM. After the creation of the model, the classification gives the mean accuracy for each gesture. We selected the proximal position of the arm because it is natural and tipically used in the EMG test on pattern recognition accuracy. The data presented are the result of the mean values of accuracy for all subject involved in the experiment. Confusion matrix (Table 1) shows that the rest position, the power grip and the precision grip are the gestures recognized with higher accuracy.

The open hand and the index point gestures are recognized with lower accuracy because it is more difficult for the subject to repeat them exactly. Average classification accuracy is between 75% and 99.4%, as shown in Figure 7. This data validates the positioning strategy proposed and the setup used in our approach, because results meet the performance declared in literature on this topic.

4.2 Different Arm Position Classification

The variability in arm position is another important issue, when an EMG classification system is proposed for upper limb prostheses. Scheme et al. (2010) and Fougner et al. (2011) start to analyse this problem and propose a solution based on the placement of two inertial sensors used to detect the exact position of the limb. The position of sensors is on the arm and forearm and the combination of their information is used to detect the arm position. This approach is interesting, however it presents some practical problems if integrated in user daily routine. The solution presented is not integrated; the EMG board and inertial sensors are on separate boards and need separate power supply and a communication infrastructure. Furthermore, the system requires frequent calibrations due to the misplacement of inertial nodes on the body.

In this section, we evaluate the performance improvements coming by the use of an additional training session, which combines samples of the patterns from the different arm positions without modifying the test setup. The use of an excessively large training sets in traditional machine learning approach is not recommended, because usually the number of support vectors created by the algorithm is too high to guarantee a strong classification and a computational charge suited for an embedded implementation.

In the case study, we identified the most common positions of the arm in which a grip action of the hand is required. Positions are shown in Figure 5. Initially a training session is performed for each patient only in the proximal position of the forearm and the classification performance is evaluated for the other limb position in the same acquisition session without further training.

Figure 8 plots the difference of accuracy in classification with arm positions not included in the training, showing the decreasing of performance compared with the classification in the position used for training. Even in this case the open hand and the point gestures suffer lack of performance. To verify the efficiency of the training made for the different positions of the arm, in Figure 9 the recognition accuracy obtained by the SVM classifier is shown when training on one position compared with the training in multiple positions. This strategy gives major benefits to the classification of the two gestures with major recognition errors because includes in the training set the gesture with more variability.

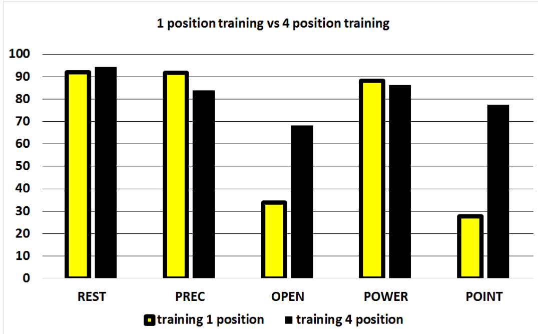

Figure 9: Single vs multiple position training.

4.3 Multisession Classification Performance

The activation patterns of EMG sensors is strongly dependent from the position and the orientation of the electrodes (Young et al., 2012). Small displacements of the sensors among the sessions can create big differences in the EMG traces and consequently reduce significantly the accuracy of the classification. The difference of classification performance in this paper considering the training made on a single session or on two different sessions. The work of Saponas et al. (2010) uses an 8 electrodes system and evaluates the performance of the system in 3 different sessions. The proposed system has 8 electrodes and the set of gestures chosen targets HCI applications, instead of our daily use grasping types. Neverthless the results of this work can confirm the decreasing trend of the performance caused by misplacement. The SVM in this experiment is trained by merging the support vectors determined in the previous tests and the vectors of an additional session.

With this procedure, it is possible to observe the behaviour of the recognition accuracy dependent from the two sessions. The first test uses the complete training session of the last paragraph to evaluate the accuracy of the classifier among the different sessions. The sequences of the movements are coded in the acquisition protocol and for each trace the different movements can be located. The prediction of the SVM algorithm is used on all the traces, and the mean value of accuracy are collected for each patient. The single training session cannot satisfy minimum requirements for reliability of classification. The differences of accuracy in the 5 gestures are shown in Figure 10.

The procedure to place the electrodes, described in session 2, is standardized and repeated for all subjects; however still little inconsistency in position of the electrodes can cause big differences in muscular activation pattern. To cope with this issue, we evalu-

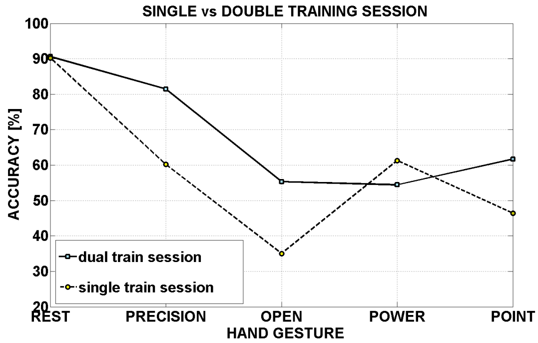

Figure 10: Single vs double training session.

ate the use of multi-stage training and compare the accuracy per arm positions in single versus double training session. The extended training merges two training sessions to create a unique training model. This kind of training method enhances the performance of the classification accuracy as shown in Figure 11.

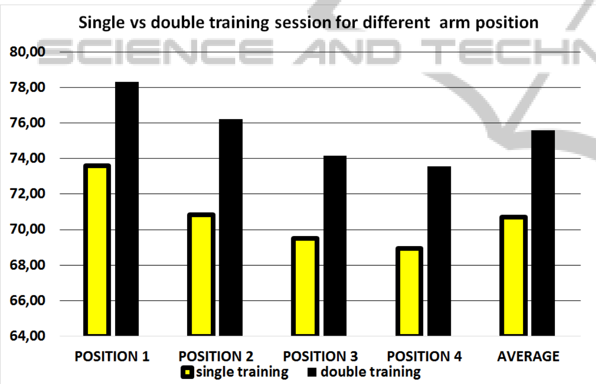

Figure 11: Single vs double training session in different positions.

5 DISCUSSION

The results of the experiment show that a robust classification for EMG signals cannot be achieved without considering the issues coming from the electrodes placement, which can present differences, even if slight, from one use to another and/or day by day. Furthermore, this work outlined the differences in classification accuracy, which occur for the same gesture performed in diverse positions of the arm (parallel to the ground, proximal to the body, lifted upwards, etc.). The idea behind this paper is that multiple sessions training is necessary for a realistic application and a SVM with light signal filtering can give good accuracy in recognition of activation of muscular patterns.

The proposed setup is ideal for an embedded implementation, because the hardware setup is simple and the signal processing is light weight, suitable on a microcontroller. The EMG signal is filtered and de-noised directly by the sensors, and the hardware signal conditioning allows to have well differentiated patterns even with a four sensors setup and small digital filtering.

The SVM training algorithm is quite heavy from the computational point of view and runs on a PC application offline, but it is possible to implement the classification on embedded platform maintaining response time compatible with the use of a prosthesis. The computational time of the prediction function is in the most part dependent from the number of Support Vectors present in the model. More support vectors indicates a complex model due to overlapping of different patterns. The choice of an appropriate training set and the tuning of the algorithm parameters can reduce the number of support vectors. Obviously the model becomes more complicated when multiple sessions and multiples arm positions are considered.

Figure 12 shows the number of support vectors in different cases of the experiment.

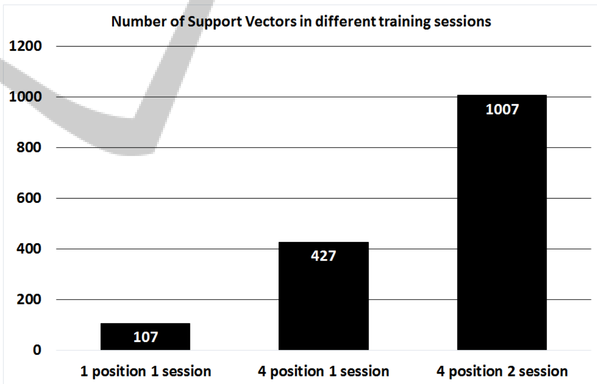

Figure 12: Suport vectors number in different testing conditions.

The platform used for the implementation of the SVM classification algorithm is an ARM Cortex M4, with 100MHz clock. The execution time of the classification routine is measured to understand if the usage of an embedded low cost platform can satisfy the specification of the system. The test is performed with different models, changing the kernel type and the number of the support vectors, to evaluate the tradeoff between complexity and response time of the algorithm.

Figure 13 and 14 shows the computation time obtained with FPU (Floating point unit) calculations. The response time allows to use the embedded platform to implement an active control of the prosthesis, with linear or RBF (Radial Basis Function) kernels. The number of support vectors can be reduced with

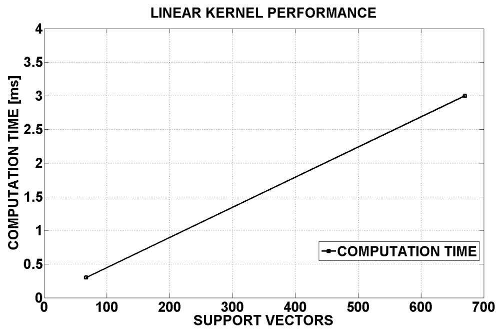

Figure 13: Linear kernel computation time.

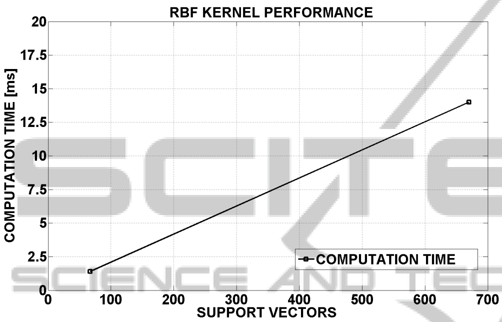

Figure 14: RBF kernel computation time.

an appropriate training sample selection and with the tuning of model made on the single subject. In this experiment we did not perform optimization of the parameters or differentiated selection of the samples in creating the training models. This choice is intended to show the starting point in implementing an embedded application and wants to contribute in evidencing and focusing on the problems and the issues that become critical in the implementation of this kind of devices.

6 CONCLUSIONS

In this analysis we found that the main challenge for the classification accuracy in a real application of an EMG interface is the acquisition interface, intended as the choice of the kind of sensor used and placement strategy. We proved that 4 sensors correctly placed and a light signal processing can give high classification accuracy, comparable with systems with more sensors and a signal processing with higher computational cost. It is not possible now to obtain good performance without considering the difference of classification in different arm positions and among multiple sessions, if EMG surface sensors, which can be removed, are used. The strategy of a double trining session, in different days, is compatible with the clinical scenario, because it is normal for a patient with an upper limb prosthesis to have periodical check-up of the prosthesis with technicians and doctors. Future works will test this methodology on subjects with transradial amputation of forearm, to optimize and standardize the placement methodology.

Another important challenge that we intend to achieve is the optimization of the parameter of the classification algorithm, which can speed up commutation time and enhance classification ratio, for example with a proper data thresholding and scaling and test with different kernels. The final goal is to investigate all the problem related to a real and reliable application and to come to an embedded implementation of the control interface.

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