Static protocol for multiclass SVM classification of hand grasping movements

Alina Krasnobrizha & Olivier Polit
Emmanuel Valot & Laurent Gallimard
LEME, UPL, Univ. Paris Nanterre
50 rue de Sevres
92410 Ville d'Avray
akrasnob@parisnanterre.fr

Nicolas Jouandeau
LIASD, UPL, Univ. Paris 8
2 rue de la Liberte
93526 Saint-Denis
n@up8.edu

***Abstract*—This work is dedicated to the analysis and identification of hand movements using the surface electromyography signals (sEMG) of the forearm muscles. We present the combination of multiclass SVM with sigmoid function and a single feature to identify hand grasping movement. Myo Armband sEMG sensors are used for data acquisitions and two different protocols are defined: static and dynamic ones. The sequences of binary grasping movement, open/close, and multi grasping ones, rest/open/closed, are studied. Entropy is used as a single feature of sEMG signals and classification is performed by using SVM multiclass algorithm with one single optimization processing. A comparison between different protocols (dynamic and static ones) is realized. Furthermore, a discussion is proposed about overlapped window size and window step to calculate entropy characteristics. Our solution for hand gesture classification simplifies the signal analysis, increases the multi-gesture separability and has a low computational cost.**

***Index Terms*—Robotic hand control system, Electromyography, Entropy, Multiclass Support Vector Machine**

I. Introduction

The present work is part of a larger project called ProMain about the development of a precision hand prosthesis [1], [2]. As 86 % of daily human hand activity is dedicated to grasp objects [3], the developed prototype deals with these kind of movements. ProMain robotic hand belongs to the new generation of hand prosthesis using soft robotic concept. It incorporates flexible interaction with environment and smart materials. Furthermore, we aim to design a patient friendly smart hand prosthesis.

A developed hand prosthesis control system consists of the following steps: i) acquisition of data regarding the muscles activation; ii) data windowing adapted to real-time analysis; iii) feature extraction; iv) gestures classification via Machine Learning algorithm; v) a robotic hand control in real-time for activation of the prosthesis.

sEMG sensor is a simple and attractive way to control hand prosthesis. The sEMG is a non invasive method to capture muscle activities. In this work we use a wearable device called MyoArmband^{TM} developed by Thalmic Labs [4]. The device is placed around the forearm near the elbow joint. The sensors are placed on skin regions immediately above the muscle tissue and it measures the superficial voltage during muscle contractions. Since the muscle activity is a superposition of individual contributions of muscles contractions, the collected sEMG signals represent an encoded information about the subject's movement intention [5].

Characteristics or *features* are extracted from sEMG signal recovering informations about movement intention. There are several features often used to analyse the sEMG signals in time and frequency domains, such as: mean absolute value (MAV), zero crossing (ZC), slope sign changes (SSL), waveform length (WL) and autoregressive coefficients (AR), entropy (H), wavelet transform coefficients (WT). The comparison between different features is studied in works [1], [6]–[9]. The entropy is the most adapted feature to characterize a dynamic movement and it improves the efficiency of gesture recognition in real-time applications [1], [10], [11].

Entropy comes from information theory as a measure of the complexity and randomness of a system [12]. This magnitude allows us to quantity the amount of information in a mathematical way. In case of guaranteed event, the entropy takes its minimum value since the information content is low. A less predictable system has a higher entropy. The entropy features have been successfully applied as a unique feature to sEMG analysis for the hand motion classification [1], [13]–[15]. In this work, features are extracted from sliding overlapped windows with predefined lengths to produce gesture classification in time. The sigmoid function is used as high-pass filter to decrease the noise in entropy.

Once features are extracted, Machine Learning algorithms are applied for gesture classification. Nowadays, Support Vector Machine (SVM) is one of most popular classifiers. It defines the optimal hyperplane in the feature space between distinguished classes of data. Originally, this approach has been designed for binary classification and was expanded for multi-classification. Commonly, the multiclass SVM is reduced to multiple independent binary classification problems such as one-vs-rest or one-vs-one. However, these algorithms do not capture the correlations between different classes. Instead, the multiclass SVM "all-together" deals with the minimisation of a single objective function. The Crammer-Singer formulation uses a generalized notion of the margin to multiclass problem [16]. Then, the dual quadratic optimisation problem is decomposed into multiple small optimisations problems to ensure a memory and time efficiency. Then, the reduced individual optimisation problem is solved. In this work, the reduced problem is solved by an exact and efficient method using Euclidian projections onto the positive simplex proposed by Blondel et al. [17].

In order to apply the SVM classification, the data are separated on the training and validation dataset. Initially, the model is fitted using the training dataset and then the fitted model is evaluated on the validation dataset. The robustness of classification model is estimated by the k-fold cross-validation. Thus, the data set is divided into k folds or groups. The first fold is the validation set and the remaining k-1 folds are the training set. This procedure is repeated k times, and the average of the classification error is obtained.

As the studied hand prosthesis are dedicated to grasp objects, we are limiting our attention on the Open/Close and Rest/Open/Close hand gestures classification. The supervised learning is sensitive to the data used as a training set and the wrong labeled data drives to the classification error. Moreover, Lorrain et al. [18] reported that transitions between various movements and the rest position influence the classification process and should be taken in consideration. To improve the gesture recognition by SVM, we propose a new data acquisition protocol which allows us to get perfectly labeled data and to avoid the transition zones. Furthermore, entropy is used as a unique feature to increase the rapidity of movement recognition. The influence of overlapped window parameters (window size, step increment) on the classification score is also discussed.

In the first section, we present the materials and data acquisition protocols. The second part deals with features extraction and gesture classification algorithm. The next section presents the result of training and validation of SVM classifier for grasp gestures and some conclusions are proposed in the last section.

II. Materials and data acquisition

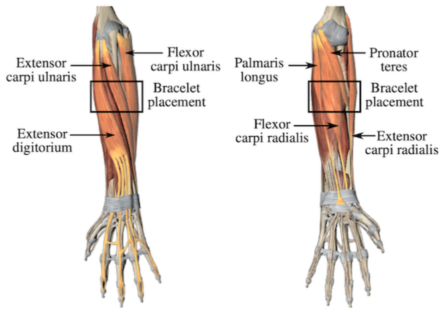
A. Equipement

In this work the wireless MyoArmband is used and 8 channels of 8-bit sEMG signal are recovered. The device is connecting to the computer via Bluetooth Low Energy (BLU) protocol and streams datas at 100 Hz sampling rate. The connection between the computer and the Thalmic Myo is made via a Python software MyoRaw.

B. Experimental Protocol

Three normally limbed right-hand subjects are involved in this study. MyoArmband is located around the forearm close to the elbow. To insure repeatability of the experiments, the MyoArmband sensors are placed in the same way for each subject. Therefore, sEMG sensors are labeled with IDs from 1 to 8 as shown in Fig. 1. The channel N°4 is placed in the prolongation of the middle finger followed by channel N°3 in clockwise and channel N°5 in counter clockwise directions. According to the location of the bracelet, the muscles directly linked with sEMG measurements are presented in Fig. 2.

Fig. 1: MyoArmband sEMG sensors labeling.



(a) Frontal muscles. (b) Posterior muscles.

Fig. 2: Muscles contribution according to MyoArmband placement.

During the experiment, each subject sits on a chair, with his elbow on the table, keeping an angle of approximately 90° at the elbow joint. Two types of data acquisitions are studied in this work named *"dynamic"* and *"static"* protocols.

During the *"dynamic"* protocol, a subject performs alternate hand gestures (open/close (OC) or rest/open/close (ROC)). Each subject realizes 6 tests which are saved in ascii files and the total duration of each file is 18s. Each OC test contains a sequence of 4 alternative movements with 2s per position while ROC test contains 3 gestures with 2s per position. A 3s pause is made between each test to avoid muscle fatigue. The respect of protocol instructions is required for correct data labeling and it is a crucial point for data training.

To avoid wrong data labeling due to delay during experiments, we propose a *"static"* protocol which consists of a single movement: open, close and rest position acquisition. According to static protocol, the subject keeps a static hand position (open, closed, rest) for 5s followed by 3s of rest. Each subject performs six acquisitions per gesture with a 5s duration. Then, a numerical algorithm is developed to create a virtual dynamic gesture by slicing the collected data by static protocol. The duration of movement and the movement sequences (OC, ROC, . . .) may be chosen arbitrary. It allows us to create numerically a various alternative movements with different gesture sequences and duration. It also guarantees a perfect data labeling.

An example sEMG data acquired with our dynamic protocol for one test of ROC gesture is presented in Fig. 3. In this figure, the 8 channels present different behaviour of muscle activity. During the rest hand position, all sensors receives small amount of informations and certain sensors, such as 4, 6 and 7 in this example, capture few information along the test. Sensor 1 has a clear pattern and access to protagonist muscles activity while sensors 2, 3 and 8 measure antagonist muscles activity. The sensor activation depends on the position of myo armband and may vary from user to user.

During data acquisition, protocol instructions are shown on the screen with sound notification at each transition. Then, the sEMG data are labeled in respect with protocol time sequences. In the Fig. 3, the clear grey zones correspond to the rest hand position, middle grey is an open hand and dark grey refers to the closed hand. We observe a delay in subject's movement compared to protocol time that leads to the wrong data labeling. The static protocol improves the data labeling and is discussed in the further section.

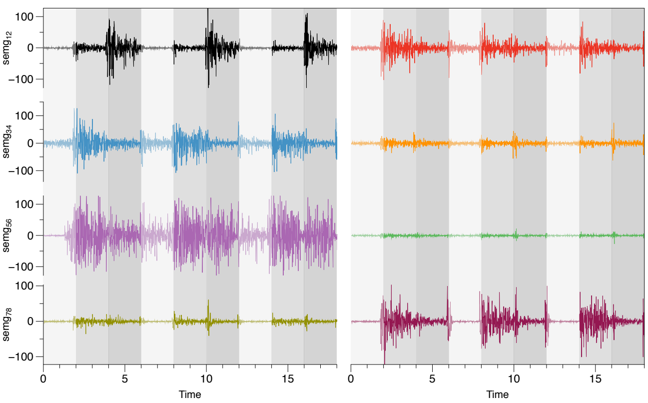


Fig. 3: sEMG signals during dynamic acquisition from 1 to 8, black, red, blue, orange, pink, green, swamp, purple

III. Feature Extraction and Gesture Classification

A. Entropy

In this work, the Shannon entropy is used to quantify how much information is present in a segment of the signal. In the case of MyoArmband, we have eight sEMG signals $(s_i)_{i=1,..,8}$ with W values. To detect the hand motion in time, we use a concept of *overlapped window* with N values ($N < W$) which is advanced in time with a certain *window step* n. The Shannon entropy is calculated for each *window* as follows:

$$H(s_i) = -\sum_{k=1}^{N_h} p_k \log_2 p_k, \quad i = 1,..,8 \tag{1}$$

MyoArmband bracelet employs a 8-bit analog to digital converter, and the output value is between $\{-127, 128\}$. A parameter *size of the histogram*, N_h, is introduced to define a number of possible classes to arrange the output signal. Then, the probabilities of occurrence p_k are defined as a ratio between a number of the absolute occurrence of signal values within one class $(N_k)_{k=1,..,N_h}$ and the total number of possible events N as follows:

$$p_k = \frac{N_k}{N}, \quad \text{for } k = 1, ..., N_h \tag{2}$$

It can be denoted that we have $\sum_{k=1}^{N_h} N_k = N$. Since we use a binary digits, the logarithm base is set to 2 in Eq. (1).

The entropy takes its maximum value when each class contains the same number of events leading to disordered system with $H = \log_2 N_h$. The maximum value of entropy increases with the number of classes or size of histogram. For a deterministic distribution, i.e. when one class contains all values, the entropy takes its minimum value $H = 0$.

As the data are obtained from experimental tests, noise can affect the data classification. To avoid this problem, a weighted function is added in entropy calculus. Since the sEMG signal is centered around zero, a sigmoid function is chosen as a high-pass filter and defined as follows :

$$\sigma(u) = \frac{1}{1 + e^{-\mu(u-\beta)}} \tag{3}$$

where $u \in [0, 1]$ is the input value, μ is the steepness of the curve and β is the Sigmoid's midpoint. In this work, we use μ = 20 and β = 0.15 in order to filter values below β.

Fig. 4 presents the comparison between dynamic (on the left) and static (on the right) protocols for ROC movements. The signal and entropy of the two most active sensors 1 and 3 are compared. The entropy is calculated for both signals with window size = 25 and step size = 10 and using sigmoid function. As it was mentioned above, the delay in dynamic protocol is found again while a static one shows a perfect agreement between labeling and movement.

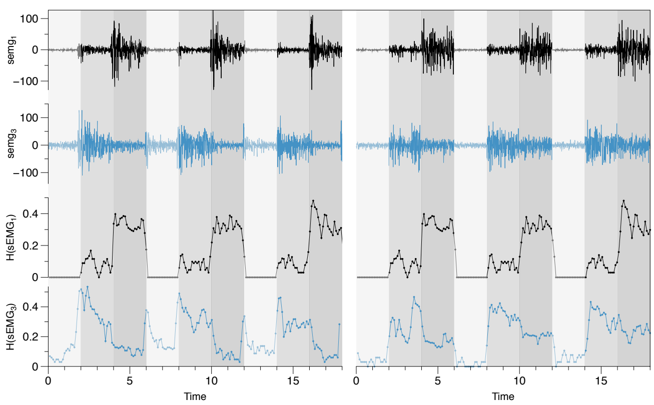


Fig. 4: Comparison between two sEMG signals and its entropy for dynamic (left) and static (right) protocols

B. SVM

Multiclass SVMs classifier is a decision function that maps each instance of input vector $\mathbf{x} \in \mathbf{R}^d$ to one of the k classes as follows:

$$\hat{\mathbf{y}} = \underset{m \in [k]}{\operatorname{argmax}} \, \mathbf{w}_m^T \mathbf{x} \tag{4}$$

where $\hat{\mathbf{y}}$ is the estimated class, $\mathbf{w}$ is a matrix (k, d) which defines a separating hyperplane and the dot product $\mathbf{w}_m^T\mathbf{x}$ is the projection of the training set $\mathbf{x}$ and also a score for the mth class. According to Eq. (4), the predicted label is the index of the row of matrix $\mathbf{w}$ with a highest score.

The values of $\mathbf{w}_m$ are the solutions of the following optimisation problem:

$$\min_{\mathbf{w},\xi} \frac{1}{2}\sum_{m=1}^{k} ||\mathbf{w}_m||^2 + C\sum_{i=1}^{N}\xi_i \tag{5}$$

$$\text{subject to:} \quad \forall i,m \quad \mathbf{w}_m^T x_i - \delta_{y_i,m} - \mathbf{w}_{y_i}^T x_i + 1 \leq \xi_i \tag{6}$$

where $C > 0$ is a regularization parameter. The dual problem to Eq. (5) is given in [16], [17] and for each α_j, jth row of matrix α, we have:

$$\max_{\alpha=[\alpha_{ij}]} -\frac{1}{2}\sum_{i=1}^{N} K(x_i, x_j)(\alpha_i \cdot \alpha_j) + C\sum_{i=1}^{N}\alpha_i \cdot \mathbb{1}_{y_i} \tag{7}$$

$$\text{subject to:} \quad \forall i \quad \alpha_i \leq \mathbb{1}_{y_i} \quad \text{and} \quad \alpha_i \cdot \mathbb{1} = 0 \tag{8}$$

where $K(\cdot,\cdot)$ is the kernel function and equal to one, and $\mathbb{1}_i$ is the vector whose components are all zero except for the i^{th} component while $\mathbb{1}$ is the vector whose components are all one. Then, the decision function Eq. (4) becomes:

$$\hat{\mathbf{y}}(\mathbf{x}) = \underset{m\in[k]}{\text{argmax}} \sum_i \alpha_{i,m} K(x, x_i) \tag{9}$$

IV. Training and validation

A. Cross validation using dynamic protocol

In this section, classification for OC and ROC hand gestures using the dynamic protocol described in Section II-B is proposed. The k-fold validation with $k = 3$ is used for each subject.

1) OC gesture: Firstly, we consider the classical OC hand gesture classification for three subjects. Since the window and step sizes influence the training score, a Particle Swarm Optimisation algorithm is used to identify the best couple of these parameters. Numerous optimisations figure out three couples of parameters which give a highest score with multiple occurrences. Therefore, window and step are set to $(40, 28)$, $(25, 10)$ and $(13, 5)$ and the histogram size is set to 11. Results are presented in Tab. I and show that training and validation scores are stable with an error limited within 10%, independently from subject and each window/step sizes.

2) ROC gesture: In this section we consider classification of ROC hand gesture. The entropy is calculated using the same pairs of window and step sizes as in the previous section. The cross-validation accuracy of multiclass SVM classification is presented in Tab. II. Obviously, the addition of rest hand position increases the classification error up to 20% compare to OC binary classification which is within 10%.

Fig. 5 shows the decision making process using SVM multiclass classification. We attribute label 0 to rest hand position, 1 to open hand and 2 to closed hand. The upper part of the graph shows the dot product used in Eq. (4) which corresponds to the projection of the training set on the axes of the three classes. The dot product with a highest value determines the winning class. The bottom part of Fig. 5 illustrates the classification score: red bullets signify that the movement classification is correct while the black bullets correspond to wrong detections. Obviously, some errors occur in the distinction of neutral and open hand positions especially in the beginning and the end of each movement. As reported in Section IV-A1, the open and close movements are separable because of antagonist muscles activity. Fig. 3 shows that the neutral hand position should have no muscle activity which is difficult to achieve during ”dynamic” data acquisition. Entropy features cannot capture the change of amplitude during muscle activity and the delay in the hand position changes lead to the wrong data labelling.

To avoid human error during data acquisition and to improve labeling of training dataset, we propose to use the static protocol.

TABLE I: k-fold validation for OC gestures using dynamic protocol as training and validation set

	Window	Step	Training score [%]	Testing score [%]
Subj 1	40	28	$94-98$	$95-98$
	25	10	$94-96$	$93-96$
	13	5	$91-93$	$90-94$
Subj 2	40	28	$92-97$	$91-97$
	25	10	$93-94$	$92-96$
	13	5	$92-94$	$91-95$
Subj 3	40	28	$90-94$	$88-94$
	25	10	$92-93$	$91-93$
	13	5	$91-92$	$90-92$

TABLE II: k-fold validation for ROC gestures using dynamic protocol as training and validation set

	Window	Step	Training score [%]	Testing score [%]
Subj 1	40	28	$88-90$	$89-92$
	25	10	$89-90$	$86-92$
	13	5	$87-90$	$85-92$
Subj 2	40	28	$77-86$	$76-90$
	25	10	$83-89$	$80-91$
	13	5	$84-88$	$82-91$
Subj 3	40	28	$80-87$	$80-93$
	25	10	$83-89$	$80-94$
	13	5	$83-88$	$79-90$

B. Gesture classification using static protocol

In this section we propose to improve the data for training step using the static protocol described in Section II-B. Each subject has performed three individual positions: O, C and R. Then, these data are numerically transformed in dynamic movement composed of two or three gestures (OC, ROC). The initial static data are sliced in packages of 200 samples corresponding to 2s similarly to the sequence of the dynamic protocol. The features are calculated for the same pairs of window/step sizes as in the case of dynamic protocol classification to compare both approaches.

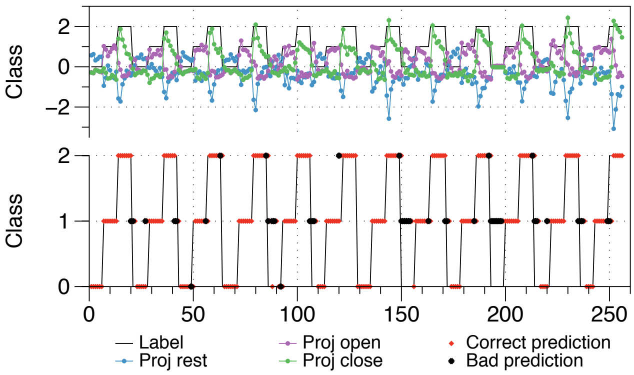


Fig. 5: Projection and prediction ROC movement using dynamic protocol

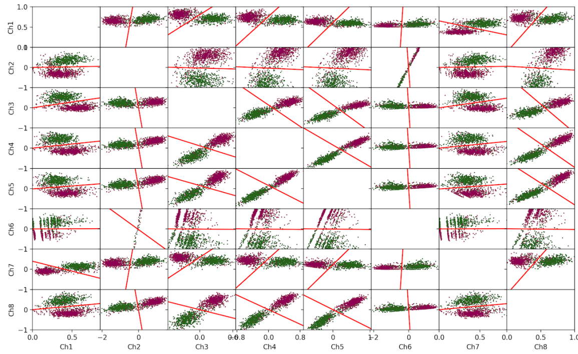


Fig. 6: Projection of the entropy of sEMG signal from OC dynamic protocol and hyperplane on the eight axes

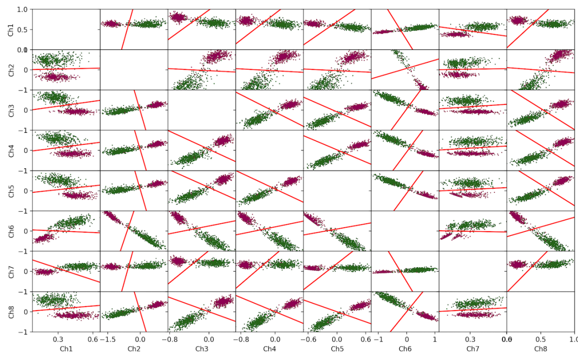


Fig. 7: Projection of the entropy of sEMG signal rebuild from OC static protocol and hyperplane on the eight axes

1) OC gesture: in this section we are interested in OC hand gesture classification using static protocol as training set. The training set is created numerically form the static protocol and contains 12 sequences of OC gestures with 2s per gesture. Then, the SVM classification is validated on the OC dynamic protocol. Tab. III presents the results and the classification error is within 10%, similarly to the dynamic classification score shown in Tab. I.

The projections of features and the separating hyperplanes for each pairs of sEMG channels are presented in Fig. 6 for dynamic OC protocol and Fig. 7 for static OC protocol. The red dots correspond to the open hand gesture and the green ones are associated to the close hand position. Obviously, there are some differences between the features and the separating hyperplanes and Fig. 7 shows that features projections in case of static protocol are more distinct and then easily separable. These results confirm the improvement in training dataset provided by static protocol.

TABLE III: Cross validation for OC gestures using static protocol for training and dynamic protocol as validation set

	Window	Step	Training score [%]	Testing score [%]
Subj 1	40	28	89	96
	25	10	94	95
	13	5	97	92
Subj 2	40	28	91	92
	25	10	95	92
	13	5	98	92
Subj 3	40	28	87	91
	25	10	93	92
	13	5	96	91

2) ROC gesture: in this section, the same procedure is proposed for multiclass ROC hand gesture classification. The training set is rebuilt numerically from the static protocol. The training test contains 12 ROC sequences with 2s per gesture. The validation set is dynamic data which represents 30% of training set. The classification accuracy is presented in Tab. IV. The training error is within 10% for all subjects except for the window/step 40x28.

Fig. 8 illustrates the classification result for the static training set. We still attribute label 0 to neutral hand position, 1 to open hand and 2 to closed hand. The upper part of the graph shows the dot product used in Eq. (4) which corresponds to the projection of the training set on the axes of three classes. The row of **w** with a highest dot product determines the number of winning class. The bottom part of Fig. 5 illustrates the classification score: red bullets indicate the correct movement classification and the black bullets correspond to the wrong detection.

This graph shows that the main error occurs at the end of each movement due to the use of overlapped window. Indeed, the decision point corresponds to the end of overlapped window and wrong decision is still possible in this transition phase. To decrease this error, derivative of the entropy can be used to detect the onset of the gesture. Furthermore, individual error can be removed using major vote, as used in [18], [19].

3) OC gesture testing using ROC classifier: this last section is dedicated to the verification of the multiclass static ROC classifier on OC dynamic protocol. The classification is validated on the OC dynamic protocol which contains 30% of

TABLE IV: Cross validation for ROC gestures using static protocol for training and dynamic protocol as validation set

	Window	Step	Training score [%]	Testing score [%]
Subj 1	40	28	90	94
	25	10	95	91
	13	5	97	90
Subj 2	40	28	81	84
	25	10	95	90
	13	5	97	91
Subj 3	40	28	86	82
	25	10	91	84
	13	5	95	77

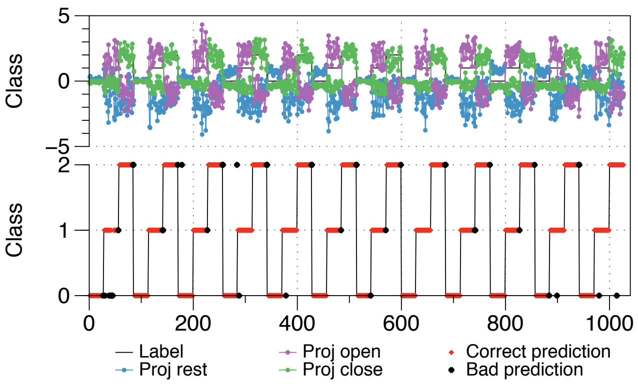


Fig. 8: Projection and prediction ROC movement using static protocol

training set. The testing score is presented in the Tab. V. The OC testing error is less then ROC testing error (see Tab. IV) because the main difficulties in classification is related to the separation of rest and open hand positions.

TABLE V: Cross validation of ROC classification based on static protocol using OC dynamic training set

	Window	Step	Testing score [%]
Subj 1	40	28	94
	25	10	91
	13	5	87
Subj 2	40	28	91
	25	10	93
	13	5	91
Subj 3	40	28	94
	25	10	90
	13	5	89

V. Conclusion

In this paper, SVM multiclass classification is proposed using classical k-fold cross validation of grasping hand gestures recognition. Open/Close and Rest/Open/Close combinations are proposed and compared using entropy as a single feature combined with sigmoid high-pass filter. Two different protocols are proposed to create the training dataset for the classifier. The dynamic protocol leads to wrong classification due to human error while the static protocol improves the obtained results. The influence of size and step of the window for entropy calculation has been studied and the results for training and test present an error around 10%.

The classification accuracy could be improved using majority vote which allows to avoid the error in the middle of hand position. Size and step windows have to be chosen with respect to acceptable delay for online classification and command of hand prosthesis.

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