Online Subject-Independent Modeling of sEMG Signals for the Motion of a Single Robot Joint

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***Abstract*— The interaction with robotic devices by means of physiological human signals has become of great interest in the last years because of the capability of catching human intention of movement and translate it in a coherent action performed by a robotic platform. Due to the complexity of EMG signals, several studies have been carried out about models built on a single subject (subject-specific). However, the execution of a certain task presents a common underlying behaviour, even if it is performed by different people. This common behaviour leads to some constraints that could be extracted by looking to different interpretations of the task, obtaining a subject-independent model. The few attempts in literature showed the possibility of creating a multiuser interface able to adapt to novel users (subject-independent). Nevertheless, the majority of the studies focused on classification problems, that are only able to determine the type of movement. We improved the state-of-the-art by introducing an online subject-independent framework able to compute the actual trajectory of the robot motion through a regression technique. The framework is based on a Gaussian Mixture Model (GMM) trained through Surface Electromyography (sEMG) signals coming from human subjects. Wavelet Transform has been used to elaborate the sEMG signal in real time. The goodness of the proposed framework has been tested with two different dataset involving various joints for both upper and lower limbs. The achieved results show that our framework could obtain high performances in both accuracy and computational time by reaching a statistically significant correlation (≥ 0.8). The whole procedure has been tested on two robots, a simulated hand and a humanoid, by remapping the human motion to the robotic platforms in order to verify the proper execution of the original movement.**

I. Introduction

Understanding the physiological bases of human and animal motion has received increasing attention from several points of view. During the last decades, a number of projects and experiments have been proposed to collect human intentions of movement in order to coherently actuate a robotic platform. This objective is crucial to achieve robust and intuitive Human-Machine Interfaces (HMI) able to control wearable devices like prostheses or exoskeletons. As an example, such interfaces will enable amputated and injured people to gain mobility and fasten rehabilitation processes.

Biomechanical and neurophysiological studies have shown that Electromyography (EMG) is one of the most effective methods to develop a proportional and simultaneous control of multiple Degrees of Freedom (DoFs) in orthotic and prosthetic devices. In particular, Surface Electromyography (sEMG) is able to measure electrical activity in response to a nerve stimulation of the muscle while maintaining the advantage of a simple and non-invasive technique. Several works have advanced the state-of-the-art by analyzing EMG structural features, reaching a classification accuracy up to 90%. Nevertheless, some problems are still open. Usually, the proposed techniques are centered on specific subjects and they often include too few people to obtain statistically relevant results. Moreover, the movement performed by the robotic device can be rarely modified by the user, since the emphasis is usually on recognizing high level motions, more than actuating the robot as aimed by the subject. Moving prostheses and exoskeletons is far from natural interaction, and users must undergo long and complicated procedures to be able to control these devices in their everyday life and perform the most simple activities. The usage of standard devices produced in series increases the need for adaptation coming from the human side, and up to now the learning activity is more related to the person than to the robot.

In this work, we aim to develop a subject-independent probabilistic framework based on Robot-Learning techniques in order to compute the motion trajectories of a standard robotic platform starting directly from human physiological data of several subjects, namely sEMG. Creating a subject-independent model enables to generalize the control procedure by extracting specific features of EMG signals coming from multiple individuals. Studies in this field are few and relatively recent. Orabona *et al* [1] proposed a way to provide patients with a pre-trained model, which will be subsequently refined and adapted to the specific subject to shorten the training phase. Castellini *et al* [2] performed a cross-subject analysis as additional study by comparing the performances of models built on single subjects when fed with data from different users. Gibson *et al* [3] presented a classification method based on optimized decision tree able to generalize across users without requiring an additional training phase, obtaining an accuracy of $79 \pm 6.6\%$. Matsubara *et al* [4] developed a multi-user interface which can classify different movements using a bilinear model, achieving an accuracy of 73%. Khushaba [5] described a method based on Canonical Correlation Analysis (CCA) capable of adapting to new users while maintaining good performances.

The majority of the studies in literature focus on classification problems which are only able to determine the type of movement, not the actual trajectories. The use of regression techniques allows a continuous and proportional control of robotic platforms. Krasoulis *et al* [6] proposed a regression technique for the continuous estimation of finger movements in a subject-specific framework. They proved that regression

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methods could generalize to novel movements, not included in the training dataset. According to our knowledge, the only attempts of mixing together subject-independent and regression techniques have been proposed by Tommasi *et al* [7]. Their aim was to shorten the training procedure starting from a similar known model by minimizing the Mean Square Error (MSE) of the features measured with respect to the ones already processed for a single individual or a combination of subjects. While the method proposed by Tommasi *et al* mainly aims at improving an already existing model, our goal is building a "ready-to-use" model able to guarantee good performances since the first trials of a new user. In a previous work [8], we based the system on a Gaussian Mixture Model (GMM)/Gaussian Mixture Regression (GMR) subject-independent framework, focusing on an offline procedure. On the contrary, in [9] we processed signals online using Wavelet Transform focusing on subject-specific framework. In this paper, we combined these two results, making our subject-independent framework able to process online signals through Wavelet Transform. EMG data are elaborated in order to obtain comparable information through different subjects. The computed information is used to train a GMM, resulting in a lightweight model with a reduced number of parameters to be kept, while GMR provides fast regression that perfectly matches the needs of online applications.

We test our system on two different datasets. The first one is the NinaPro [10] database, a publicly available collection of data coming from several intact and amputated subjects. In particular, we consider 2 upper limb movements repeated 6 times by 36 intact individuals (only right-handed) with the aim of validating processing and regression procedures by using a leave-one-out approach. The second dataset, also described in [9] and [11], involves only 3 subjects performing a kicking movement (lower limbs) with more than 60 repetitions. This dataset allows us to analyze the framework behavior when trained with novel information coming from a real user. Two standard robotic platforms are used as testing devices for the considered motions: a simulated robotic hand for upper limb tasks and a humanoid for lower limb movements. We aim to verify the robustness of the online procedure and to guarantee the generality of the developed interface to different kind of robots.

The remainder of the paper is structured as follows. Sec. II describes the feature extraction procedure from EMG signals, the algorithm for estimating the joints angles and the modelization technique. The two datasets used to test the probabilistic model are illustrated in Sec. III, while the experiments on different joint angles and subjects are presented in Sec. IV. The results of the study are also reported and discussed. Finally, Sec. V summarizes the achieved results while proposing some future extensions of this work.

II. Methodology

A. Signal analysis

A key contribution of this paper with respect to our previous work [8] is the online processing of the EMG data. In order to achieve this result, at each instant t, only a small window of the whole signal has to be considered. The idea is to look for a fast way to analyze the information in both time and frequency, and to compute a feature value able to highly characterize the small portion of EMG signal available. We used Wavelet Transform to extract significant information from the raw signal. Wavelet Transform [12] decomposes the signal into several kernel functions called wavelets. A base wavelet, called mother wavelet ($\psi(t)$), is scaled and translated by a scaling function to generate the set of M wavelets composing the original signal while providing multi-resolution analysis. Each wavelet is represented by a coefficient (γ_m). By looking at the good performances obtained for subject-specific cases in both accuracy and time [9], we selected the db2 mother wavelet from the Daubechies family for representing the input EMGs. Synthesizing the coefficients provided by Wavelet Transform to a single value representing the wavelet decomposition allows us to compare different signals. The synthesis function should guarantee a certain level of smoothness in order to avoid sudden changes from one instant to another and being fast enough to be computed online. Mean Average Value (MAV) (Eq. 1) represents a good candidate given the results achieved in [9].

$$\text{MAV} = \frac{1}{M} \sum_{m=1}^{M} |\gamma_m| \tag{1}$$

Nevertheless, data coming from Wavelet Analysis are still very jagged and they are not good enough to be used for a subject-independent modelization, since the great variability of the signal results in poor model performances. The Wavelet Transform of the EMG channels have been smoothed and normalized in order to obtain better and more robust models.

The smoothing function is based on a moving average filter. At the instant t, the average of S data points available within the windows is computed in order to smooth the data. This process is equivalent to lowpass filtering, with the response of the smoothing given by Eq. 2

$$\gamma_S(t) = \frac{1}{S+1} \sum_{s=1}^{S} \gamma(t-s) \tag{2}$$

Often the signals of a certain subject have different amplitude than the others, a normalization process has been introduced to regularize the EMG signals. The normalization phase has been executed offline for the training dataset by using the relative maximum within the processed trial. During the testing procedure, when no data were available on a subject, the mean of the maximums collected during the training has been used as normalization factor. Otherwise we used the mean of the maximums within the trials of the specific subject, with at least 10 attempts collected.

B. Gaussian mixture model and regression

The information processed from EMG has been used to train a Gaussian Mixture Model (GMM) to estimate a model able to predict the bending angle α of a specific joint during the movement. GMM approximates the input dataset by using a weighted sum of K Gaussian components which will represent the set of trials used as training. Naming n the number of trials used to train the system, and T the number of observations acquired during each trial, the total number of data samples is $N = nT$. For a specific subject h, a single data in input $\zeta_j^h, 1 \leq j \leq N$ at the framework is described in Eq. 3.

$$\begin{aligned} \zeta_j^h &= \{\xi^h(t), \alpha^h(t)\} \in \mathbb{R}^D \\ \xi^h(t) &= \{\xi_c^h(t)\}_{c=1}^C, \\ \alpha^h(t) &= \{\alpha_g^h(t)\}_{g=1}^G. \end{aligned} \tag{3}$$

with:

- $C = |\xi^h|$, number of EMG channels;
- $\xi_c^h(t) \in \mathbb{R}$, the value assumed from c^{th} EMG channel at the time instant t;
- $\xi^h(t) \in \mathbb{R}^C$, the set of values assumed from the considered channels at the time instant t;
- $G = |\alpha^h|$, number of joint bending angles;
- $\alpha_g^h(t) \in \mathbb{R}$, the value assumed from g^{th} joint bending angle at the time instant t;
- $\alpha^h(t) \in \mathbb{R}$, the set of values assumed from the considered joint bending angles at the time instant t;
- $D = C + G$, the dimensionality of the problem.

With respect to [8], there is no direct use of the time instant t in the data provided to train the model. We used data synchronization between different sensors as constraint for obtaining a good model. Therefore, there is no need of the whole signal in advance to enable the system working online.

The Expectation-Maximization (EM) algorithm [13] has been used to optimize the parameters of the GMM by maintaining a monotone increasing likelihood during the local search of the maximum on the data collected from H different subjects. This approach enables an autonomous extraction of the activity characteristic EMG signal while still maintaining an appropriate generalization. Finally, the resulting probability density function is computed:

$$p\left(\zeta_j^h\right) = \sum_{k=1}^{K} \pi_k \mathcal{N}\left(\zeta_j^h; \mu_k, \Sigma_k\right) \tag{4}$$

with π_k priors probabilities, and $\mathcal{N}\left(\zeta_j^h; \mu_k, \Sigma_k\right)$ Gaussian distribution defined by μ_k and Σ_k, respectively mean vector and covariance matrix of the k-th distribution. It is worth to notice that input data regards the subject h, while the model does not depend from a specific subject.

The number of components K has been selected by using the Bayesian Information Criterion (BIC) [14]. This criterion measures how well the model fits the data, while maintaining the model general by avoiding data overfitting.

The Gaussian Mixture Regression (GMR) provided a smooth generalized version of the signal starting from the GMM. The joint angle $\hat{\alpha}^h$ and its covariance are estimated from the EMG signals ξ^h known a priori respectively using Equation 5 and 6.

$$\hat{\alpha}^h = E\left[\alpha \left|\xi^h\right.\right] = \sum_{k=1}^{K} \beta_k^h \hat{\alpha}_k^h \tag{5}$$

$$\hat{\Sigma}_s^h = Cov\left[\alpha \left|\xi^h\right.\right] = \sum_{k=1}^{K} {\beta_k^h}^2 \hat{\Sigma}_{\alpha,k}^h \tag{6}$$

with:

- $\beta_k^h = \frac{\pi_k \mathcal{N}\left(\xi_c^h | \mu_{p,k}, \Sigma_{p,k}\right)}{\sum_{j=1}^{K} \mathcal{N}\left(\xi_c^h | \mu_{p,j}, \Sigma_{p,j}\right)}$, the weight of the k^{th} Gaussian component through the mixture;
- $\hat{\alpha}_k^h = E\left[\alpha_k \left|\xi^h\right.\right] = \mu_{\alpha,k} + \Sigma_{\alpha p,k} \Sigma_{p,k}^{-1} \{\xi^h - \mu_{p,k}\}$, the conditional expectation of α_k given $\{\xi^h\}$;
- $\hat{\Sigma}_{\alpha,k}^h = Cov\left[\alpha_k \left|\xi^h\right.\right] = \Sigma_{\alpha,k} + \Sigma_{\alpha p,k} \left(\Sigma_{p,k}\right)^{-1} \Sigma_{p\alpha,k}$, the conditional covariance of α_k given $\{\xi^h\}$.

assuming that the parameters (π_k, μ_k, Σ_k) defining the k^{th} Gaussian component are decomposed as follows:

$$\mu_k = \{\mu_{p,k}\, \mu_{\alpha,k}\} \qquad \Sigma_k = \begin{bmatrix} \Sigma_{p,k} & \Sigma_{p\alpha,k} \\ \Sigma_{\alpha p,k} & \Sigma_{\alpha,k} \end{bmatrix} \tag{7}$$

with μ_p and Σ_p respectively the mean and the covariance of the known a priori information. Thus, the generalized form of the motions $\hat{\zeta}^h = \left\{\xi^h, \hat{\alpha}^h\right\}$ required only weights, means and covariances of the Gaussian components calculated through the EM algorithm.

C. System effectiveness

Finally, we measured the performances of the model by using the correlation coefficient evaluated between the predicted bending angle $\hat{\alpha}^h$ and the real one α^h. The correlation coefficient $\rho_{\alpha^h, \hat{\alpha}^h}$ measures the statistical relationships between different signals and different subjects. The correlation coefficient (Eq. 8) is widely used [1] [7] as a measure of the degree of linear dependence between two variables, since it is based on common measures as covariance $Cov(\alpha^h, \hat{\alpha}^h)$ and standard deviations σ_α^h and $\sigma_{\hat{\alpha}}^h$ of the considered variables.

$$\rho_{\alpha,\hat{\alpha}} = \frac{Cov(\alpha^h, \hat{\alpha}^h)}{\sigma_\alpha^h \sigma_{\hat{\alpha}}^h} \tag{8}$$

The correlation coefficient can assume all the values between 1 and -1. The case of a perfect direct linear relationship (correlation) is represented by $\rho_{\alpha,\hat{\alpha}} = 1$, while $\rho_{\alpha,\hat{\alpha}} = -1$ corresponds to a perfect decreasing linear relationship (anticorrelation). The closer the coefficient is to either -1 or 1, the stronger the correlation between the variables. If the correlation coefficient approaches to zero the relationship between the variables decreases, when reaches zero the variables are independent.

III. Experimental Data

The effectiveness of our framework has been tested by using two datasets.

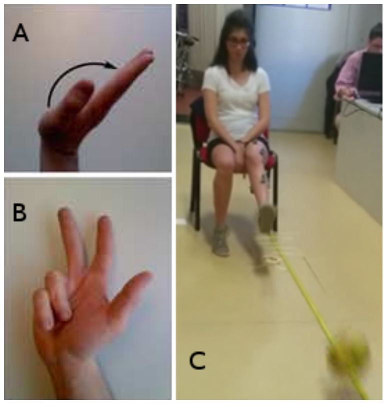

Fig. 1. Description of the movements analyzed in the paper: A) Wrist flexion; B) “Three posture”, C) Kick from a sitting position

A. NinaPro

The NinaPro [10] [15] (Non Invasive Adaptive Prosthetics) database is a robust and wide dataset, made with data collected from many different subjects, which perform several hand and wrist movements. The database enables the comparison of classification and regression performances obtained using various techniques by providing sEMG, hand/arm kinematics, dynamics and clinical parameters. The database contains data obtained from 40 intact subjects (28 males, 12 females; 36 right handed, 4 left handed; age 29.9 $\pm$ 3.9). Each subject performed 6 repetitions of 50 different movements. Because of time limitations, in our study we focused only on two motions (Fig. 1 (a,b)) and on right handed subjects, but the dataset offers the possibility to extend our experiments to different kind of movements including the flexion of the fingers, the grasping of different objects, and several other daily activities. Hand kinematics has been measured using a 22-sensor CyberGlove II (CyberGlove Systems LLC, www.cyberglovesystems.com) to provide joint-angle information at slightly less than 25 Hz. A 2-axis IS40 inclinometer with a range of 120° and a resolution of less than 0.15° (Fritz Kübler GmbH, www.kuebler.com) has been added to measure the wrist orientation with a frequency of 100 Hz. Muscular activity was measured using Delsys double-differential sEMG electrodes sampling signals at a rate of 2 kHz with a baseline noise of less than 750 nV RMS. These electrodes also integrate a 3-axes accelerometer sampled at 148 Hz. Eight electrodes were equally spaced around the forearm at the height of the radio-humeral joint; two electrodes were placed on the main activity spots of the *flexor digitorum superficialis* and of the *extensor digitorum superficialis*, two electrodes were also placed on the main activity spots of the *biceps brachii* and of the *triceps brachii*. An accurate timestamp has been associated to each data sample to properly synchronize the information collected.

B. Kicking Movement

This dataset [11] consists of three healthy individuals (S1 - S3; age 30 $\pm$ 4; one female). The subjects were asked to naturally kick a ball from a sitting position (Fig. 1 (c)). sEMG signals were acquired with an active 8-channel wireless EMG system at 1000 Hz. The electrodes were placed on the left leg of each subject in order to cover the principal muscular groups active during the kick task. The recorded muscles were: *Rectus femoris*, *Vastus lateralis*, *Vastus medialis*, *Tibialis anterior*, *Gastrocnemius lateralis*, *Gastrocnemius medialis*, *Biceps femoris caput longus*, *Peroneus longus*. Synchronously to the EMG signals, it has been recorded the kinematics of the left leg by means of an optoelectronic system. Six retro reflecting markers were placed on the subjects leg and six infrared digital cameras recorded the marker positions at 60 Hz during the whole recording session. The kinematic of the knee-joint angle was computed from the position of the markers placed on the leg at each time instant t. Each person repeated the same movement more than 60 times.

IV. Experimental Results

In order to obtain comparable results between the considered datasets we applied a series of standardizing approaches. A similar number of samples ($\simeq$ 2000) for trial has been considered by down-sampling the information available in the NinaPro database by a factor of ten. We looked at the most informative EMG channels by conducting a preparatory study. The study aimed to measure the engagement of each considered channel in the performed movement. By looking at the measure of engagement, we selected an equal number of channels for each motion. The db2 *mother wavelet* and MAV synthesis feature have been applied to the raw signal provided from every single channel. The resulting values have been associated to the corresponding bending angle along time. A model for each channel has been trained and GMR has been used to retrieve the estimated bending angle to be compared with a testing set. The three channels offering the best performances have been selected in order to obtain similar models. It is worth to notice that more channels could be considered for the NinaPro dataset, resulting in a more accurate estimation. Anyway, a subset of the significant channels have been selected to simplify the comparison with the models produced with the Kicking Movement dataset, for which only three channels provided significant correlation when considering information from available subjects.

A. NinaPro

The high number of subjects involved in this dataset is ideal to analyze the robustness of the proposed framework. Two different movements of upper limbs have been selected between the different movements contained in the dataset. In particular the wrist flexion (Movement 13) and the flexion of ring and little finger while extending others, namely “Three posture” (Movement 3), are analyzed. Both motions are quite simple and only some significant joints have been analyzed. The wrist has been considered for Movement 13, while for Movement 3 have been selected the motion of Interphalangeal Joints as well as Metacarpophalangeal Joints of Thumb, Index, Middle, and Ring, for a total of 8 joints.

The purpose of this choice is to focus on the model's independence from the subject more than on the complexity of the motion, while proving that our framework works on both single and multi-joints movements. The 3 most significant channels have been selected, according to the results coming from the preliminary study. The selected channels (3-5-7 for Movement 13, 2-3-7 for Movement 3) brought information from muscles around the forearm. A leave-one-out approach has been adopted by building the model on 35 right-handed subjects and tested on the remaining one. We obtained 36 models for each movement to be tested on the 6 repetitions of the testing subject. For each repetition we compared the estimated bending trajectory with the actual measured angles by computing the correlation coefficient. The mean and the standard deviation of the correlation coefficient have been estimated for each joint. Fig. 2 shows the correlation coefficient averaged between 6 trials of Movement 13 for all the subjects considered in the study. Fig. 3 regards Movement 3, the correlation coefficient has been averaged also on the joints, since many of them were involved in the movement.

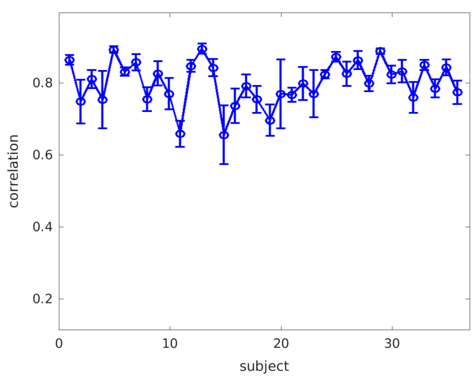

Fig. 2. Correlation and Standard Deviation for the model of a wrist flexion movement. The model was built on $n-i$ subjects and tested on the ith. For every subject the correlation is the mean on 6 trials.

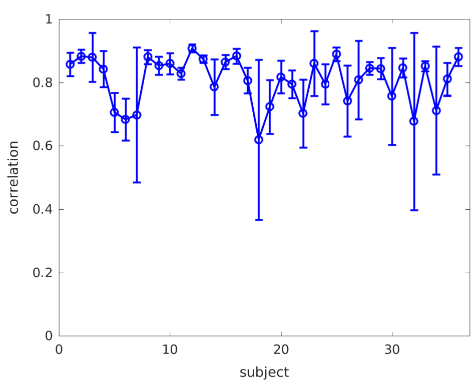

Fig. 3. Correlation and Standard Deviation for the model of the "Three posture". The model was built on $n-i$ subjects and tested on the ith. For every subject the correlation is the mean on 6 trials and 8 joints.

The generated motion has been successfully tested on a simulated hand by Shadow Robots Fig. 5 (a). The EMG signals were sent via software and estimated angle was computed to actuate the robot though TCP/IP protocol. The robot motion generated at 240 Hz was micro-interpolated from the simulated controller of the robot to match the actual rate of 1kHz. The results showed a good correlation resulting from the created GMM/GMR framework. Both the movements reached a statistically significant mean correlation coefficient ($\rho_{\alpha,\hat{\alpha}} \geq 0.8$), with good results for both single joint estimation ($\rho_{\alpha,\hat{\alpha}} = 0.8224$) for Movement 13 (Fig. 2), and multi-joints estimation ($\rho_{\alpha,\hat{\alpha}} = 0.8067$) for Movement 3 (Fig. 3). The performance reached for multi-joints motion was particularly good even if a bit lower than the single one, since the model has showed consistent results with similar correlation coefficients for all the considered joints.

B. *Kicking Movement*

In this dataset, the high number of repetitions of the same movement (about 60) performed by three subjects gave us the possibility to study the performances of the model adaptation to a novel person. The three most significant channels have been selected, according to the results coming from the preliminary study. The selected channels (1, 2 and 8) recorded the activity of the muscles *Rectus femoris*, *Vastus lateralis* and *Peroneus longus*. Again, a leave-one-out approach has been adopted by building the model on 30 trials coming from 2 subjects and tested on the remaining one. We obtained 3 models on the movement trained by using a total of 60 repetitions. For analyzing the progressive model adaptation, the data of every subject has been divided in block of 10 repetitions. In fact, 10 repetitions bring a valuable amount of information to the system, good enough to add a substantial contribution to the previous model. In the first part of the analysis, the different blocks of movements of a certain subject are used to test the model built on the other two subjects. This is represented in the Fig. 4 by the red lines. The blue line, instead, shows a model tested on the same data of the previous case, but using an updated model with the previous testing data added to the training set. In this way, the model is updated with the data from the third subject.

As the new data are added to the model, the results improved, giving generally better results with respect to the first part of the analysis. The model generally decreases its performances when the testing data shows more variability. Anyway, in a long term perspective the adaptation characteristics of the proposed framework could be a great resource for rehabilitation purposes. The generated motion has been successfully tested on a humanoid, namely a Aldebaran NAO Fig. 5 (B). The EMG signals were sent via software and estimated angle was computed to actuate the robot through TCP/IP protocol. Our software is able to send pose messages to robot at 240 Hz, although in practice the rate has been reduced to satisfy NAO bound of 50 Hz.

V. CONCLUSIONS

This paper proposed a method to online estimate joint angles starting from physiological data. Gaussian Mixture

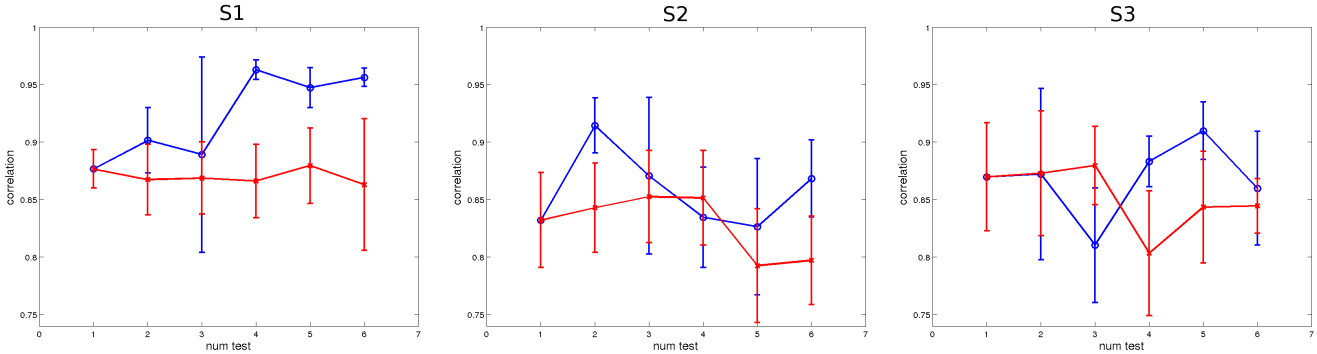

Fig. 4. Correlation and Standard Deviation for the model of a kicking movement. The red line represent the results of the model built on two subjects and tested on different data from the third subject, without updating the model. The blue line represent the results of the model tested on the same data than the previous case, but updating the model with the data of the third person.

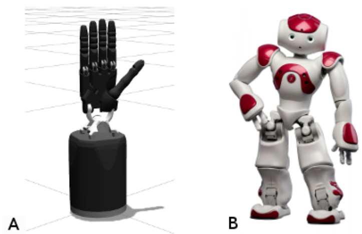

Fig. 5. Robots on which has been tested the framework: A) Simulated hand (Shadow Robot); B) Humanoid (Aldebaran NAO)

Models were built on sEMG signals from different dataset involving both upper and lower limbs. Joint angles related to new, unseen sEMG data have been estimated by means of Gaussian Mixture Regression. Wavelet Transform has been used to build the model in order to obtain an online framework. The key point was the capability of extracting features from the raw signals with no need to have all the information in advance.

The framework obtained significant results on new, unseen data, with great variability of subjects and few repetitions of the movements. It was able to estimate the motion of both single ($\rho_{\alpha,\hat{\alpha}} = 0.8224$) and multiple ($\rho_{\alpha,\hat{\alpha}} = 0.8067$) joints for different movements. Furthermore, we proved that is possible to improve a working model by adapting it to a relatively long series of data coming from a new subject. The results showed good trends for both low and high variability in the task execution. This is a very important feature for a model to be used in rehabilitation contexts, since it can evolve with the patient without any external intervention.

The estimated joint angles have been remapped to control online two kind of robots: a simulated hand for testing the upper limbs and a humanoid for testing the lower limbs.

As a further work, we plan to investigate the use of an online model generation method in order to easily update the model and enhance its adaptation capabilities. Moreover, we will extend our work by testing it with other and more complex movements.

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