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

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I. INTRODUCTION

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 movement performed by a robotic platform. We think that intention of movement is a cognitive process used by human to accomplish an actual motion. Therefore this information is probably shared by many subjects. Several studies have been done about models built on a single subject. LLoyd[3] and Gerus[2] were able to estimate forces by tuning the model parameters to fit the motion of a particular person (subject-specific). On the other hand, executing a particular task intuitively leads to some constraints that could be extracted by looking to different interpretations of this task to obtain a subject-independent model. The aim of this paper is to extract a general model representing the cognitive process able to translate intention of movement to robot motion, in this initial phase limited to a single joint. We want to use the learned knowledge in order to do new movements by means of the data collected from a new person. The few attempts in literature [4] showed the possibility of creating a multiuser interface able to adapt to novel users. This paper evaluates the use of a widely spread learning technique like Gaussian Mixture Model (GMM)[1] trained through Surface Electromyography (sEMG) signals coming from human subjects to actuate the knee joint of humanoid robot. The goal is to create a general model based on data from different subjects, which can be used by every person without any train or with a very short one. The goodness of the model is evaluated by means of Goodness of Fit (GoF) by testing it on new, unseen data from a subject not in the training set. The whole procedure has been tested on a humanoid robot by remapping the human motion to the robotic platform in order to verify the proper execution of the original movement.

II. METHODOLOGY

The adopted procedure is very similar to the one used in our previous work on subject-specific models[5] in order to obtain comparable data. Three healthy subjects (S1-S3; age 30 $\pm$ 4; one female) were asked to naturally kick a ball from a sitting position. Electromyography (EMG) signals were acquired with an active 8-channel wireless EMG system at 1000 Hz to cover the principal muscular groups active during the kick task, namely *Rectus femoris* (Ch1), *Vastus lateralis* (Ch2), *Vastus medialis* (Ch3), *Tibialis anterior* (Ch4), *Gastrocnemius lateralis* (Ch5), *Gastrocnemius medialis* (Ch6), *Biceps femoris caput longus* (Ch7), *Peroneus longus* (Ch8). Synchronously, six infrared digital cameras recorded at 60 Hz the kinematic of the knee-joint angle from the position of 6 markers on the subject's leg. Each person repeated the movement about 70 times. EMG data has been processed by means of signal rectification and smoothing in order to highlight the muscular activation during the kick tasks. This method is widely exploited in literature to denoise EMG signals and extract useful information and features for classification purposes. The information extracted from EMG was used as input of a GMM to estimate its correlation with the knee bending angle α. The aim of GMM is to obtain the weighted sum of K Gaussian components which best approximates the input dataset representing the set of movements used for the training. The GMM has been trained through the Expectation-Maximization (EM) algorithm, resulting in a probability distribution of the train dataset later used to perform the regression of the knee angle by means of Gaussian Mixture Regression (GMR). This algorithm is able to retrieve a smooth generalized version of the signal encoded in the associated GMM. The number of components K has been set by using the Bayesian Information Criterion (BIC). The probability density function and a single data in input at the framework are described in Eq. 1.

$$p\left(\zeta_j\right) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}\left(\zeta_j; \mu_k, \Sigma_k\right), \quad \zeta_j = \{t, \xi, \alpha\} \in \mathbb{R}^D \qquad (1)$$

where π_k are priors probabilities; $\mathcal{N}\left(\zeta_j; \mu_k, \Sigma_k\right)$ are Gaussian distributions defined by μ_k and Σ_k, respectively mean vector and covariance matrix of the k-th distribution; $t \in \mathbb{R}$ is the time elapsed from the beginning of the trial; $\xi \in \mathbb{R}^C$ is the set of considered channels, $1 \leq C = |\xi| \leq 8$; $\alpha \in \mathbb{R}$ is the knee bending angle; $3 \leq D \leq 10$ is the dimensionality of the problem.

Finally, we exploited the Normalized Mean Square Error (NMSE) in order to evaluate the effectiveness of the GMM-based system:

$$\mathrm{GoF}_{NMSE}(t) = 1 - \left\| \frac{\alpha(t) - \hat{\alpha}(t)}{\alpha(t) - E[\alpha(t)]} \right\|^2 \qquad (2)$$

where t is the temporal instant from the beginning of the trial (ms); $\hat{\alpha}(t)$ is the estimated angle at the instant t; $\alpha(t)$ is the angle calculated through the motion capture at the instant t; $E[\alpha(t)]$ is the mean along the time of the angles given by the motion capture. By using this formula, the GoF costs vary between $-\infty$ (bad fit) to 1 (perfect fit).

III. RESULTS

GMMs have been trained with data from couple of subjects (S1+S2, S1+S3, S2+S3). For every couple, different sizes of training set have been considered (10, 30, 60, 120), half from the first subject and half from the second one. For the testing phase, we used 10 trials coming from the remaining subject in order to verify the generality of the model. The described procedure has been applied to all the collected EMG channels. Fig. 1 represents the GoF computed for the couple S1+S2 varying the EMG channel and the number of data used for training.

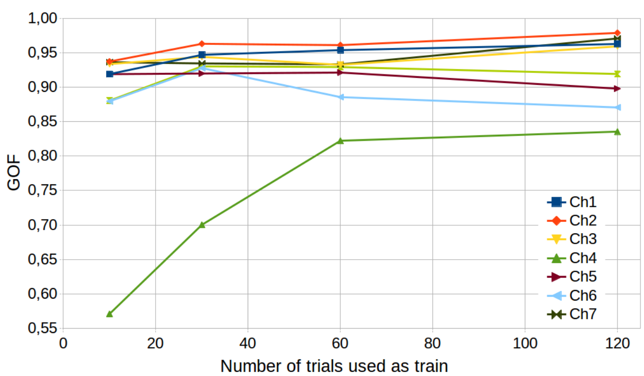

Figure 1. GoF values from every channel related to the number of trials used as train for subjects S1+S2

Results showed a good estimation even with few input data for almost all the channels. Increasing the cardinality of the training set we generally obtained similar or better performance with some exceptions. In fact, it was worth to use a number of trials varying between 30 and 60 in order to obtain more stable results during the testing phase, while using a greater number of trials raised significantly the time for model training without any apparent benefit in efficiency.

Tab. I compare the results between subject-specific and subject independent models regarding the most informative EMG channels. The subject-independent model for the subject Sn has been trained on all subjects except Sn and tested on Sn (n = 1, 2, 3), using a leave-one-out approach.

Subject	S1	S2	S3
Specific	0.9238	0.9700	0.9570
Independent	0.8887	0.9214	0.8733

Table I
GOF VALUES COMPARING RESULTS FROM SUBJECT-SPECIFIC AND SUBJECT-INDEPENDENT MODELS.

Looking at the whole set of results, they were generally quite similar, except for specific channels in some rare cases.

As regards the best EMG channels, generally Ch1, Ch2, Ch3 and Ch7 were the muscles bringing most information. In fact, the GoF for the EMG channels related to these muscles resulted between the most informative even in subject-specific models for all the three subjects. Moreover, the cited muscles are the principal actors of the considered movement from a biological point of view. Coherently, tests showed that the best trade off in terms of both stability and efficiency has been obtained using three out four of the already cited EMG channels (GoF = 0.9257 for Ch1+Ch2+Ch3 and GoF = 0.9409 for Ch1+Ch2+Ch7).

The whole procedure has been tested on a humanoid robot (Aldebaran NAO) by remapping the human motion to the robotic platform to verify the proper execution of the original movement. The robot could properly execute the movements of a person whose signals were not included in the model.

IV. CONCLUSIONS

In this paper, EMG signals from multiple subjects have been used to train a very general model based on GMM in order to actuate a humanoid robot through data coming from a new subject. Tests showed that the proposed learning framework produced results comparable with subject-specific models. Besides the good results, the dataset was composed by only 3 people. Since the population is so poor, bad performances of a subject could ruin the whole model. Therefore, we want to test other dataset composed by more subjects and apply the described method to a multiple joint motion. In fact, a bigger dataset could lead to even more general models. Furthermore, we plan to build a non stationary model that can be used online in order to control prosthesis or exoskeletons.

REFERENCES

[1] S. Calinon, F. Guenter, and A. Billard. On learning, representing, and generalizing a task in a humanoid robot. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 37(2):286–298, 2007.

[2] P. Gerus, M. Sartori, T. Besier, B. Fregly, S. Delp, S. Banks, M. Pandy, D. D'Lima, and D. Lloyd. Subject-specific knee joint geometry improves predictions of medial tibiofemoral contact forces. *Journal of biomechanics*, 46(16):2778–2786, 2013.

[3] D. Lloyd and T. Besier. An emg-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo. *Journal of biomechanics*, 36(6):765–776, 2003.

[4] T. Matsubara and J. Morimoto. Bilinear modeling of emg signals to extract user-independent features for multiuser myoelectric interface. *Biomedical Engineering, IEEE Transactions on*, 60(8):2205–2213, 2013.

[5] S. Michieletto, M. Antonello, L. Tonin, R. Bortoletto, F. Spolaor, E. Pagello, and E. Menegatti. GMM-based single-joint angle estimation using EMG signals. In *Proceedings of the 13th Conference on Intelligent Autonomous Systems (IAS-13)*, 2014.