A first approach to a taxonomy-based classification framework for hand grasps

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Abstract. Many solutions have been proposed to help amputated subject regain the lost functionality. In order to interact with the outer world and objects that populate it, it is crucial for these subjects to being able to perform essential grasps. In this paper we propose a preliminary solution for the online classification of 8 basics hand grasps by considering physiological signals, namely Surface Electromyography (sEMG), exploiting a quantitative taxonomy of the considered movement. The hierarchical organization of the taxonomy allows a decomposition of the classification phase between couples of movement groups. The idea is that the closest to the roots the more hard is the classification, but on the meantime the miss-classification error is less problematic, since the two movements will be close to each other. The proposed solution is subject-independent, which means that signals from many different subjects are considered by the probabilistic framework to modelize the input signals. The information has been modeled offline by using a Gaussian Mixture Model (GMM), and then testen online on a unseen subject, by using a Gaussian-based classification. In order to be able to process the signal online, an accurate preprocessing phase is needed, in particular, we apply the Wavelet Transform (Wavelet Transform) to the Electromyography (EMG) signal. Thanks to this approach we are able to develop a robust and general solution, which can adapt quickly to new subjects, with no need of long and draining training phase. In this preliminary study we were able to reach a mean accuracy of 76.5%, reaching up to 97.29% in the higher levels.

Keywords: Electromyography, Taxonomy, Grasps, Prosthesis

1 Introduction

New and innovative prosthesis devices can improve the life quality of amputated subjects, helping them to interact with the surrounding world. Indeed, everyday each of us use and grasp an high number of different objects with different shapes, dimensions and weight. The difference between the objects shape, weight, and deformability comport disparate ways of interacting with them by using different grasping approaches. The scientific community have selected a number of essential grasps, organizing them in taxonomies depending on several qualitative factors. Many different taxonomies have been proposed during the years, considering different aspects of hand motion. One of the most complete and detailed taxonomy has been proposed by Feix et al. in [6] by arranging together many different proposals. Their solution, called the GRASP taxonomy, organizes in a matrix 33 hand grasps, arranging the movements according to qualitative force parameters and fingers position. In this work we exploit a quantitative taxonomy of 8 hand grasps starting from Feix's one. The movements are arranged in a binary tree, where movements belonging to the same subtree have a common underlying behaviour. The considered taxonomy is based on quantitative parameters, i.e. it includes the information from the hand and fingers kinematics, and the muscular activation during the motion. In particular, the muscular activation and involvement is represented by the sEMG signals. These signals are also a commonly used for the control of prosthesis, we considered sEMG signals from the subjects with the goal of exploiting the physiological behaviour in order to emulate what happens in the human body. sEMG signals have the drawback of being non stationary, and very sensitive to the physical and physiological state of the subject. In particular, studies shown a sensibility for muscular fatigue, also stress and physical weariness [5]. These characteristics result in a great variability of the sEMG signals, even if they are collected from a single subject in a limited period of time. As a consequence, the traditional approach when using sEMG signals is to focus on the signals of a single subject, without mixing signals from several subjects. Nevertheless, despite the prevalence of subject-specific approaches, in literature there are some examples of subject-independent approaches. Castellini et al. [3] extend their previous works in two ways: they apply their technique to 10 healthy subjects and they test their results in a Daily-Life Activity condition. Matsubara and Morimoto [8] implement a bilinear model able to reach an accuracy of 73% classifying different movements in a multi-user interface.

Previous studies [10], [9] shown good results in the continuous online estimation of both upper and lower limbs movement, considering up to 40 different subjects. In our previous work we focused on subject-independent regression solutions for the continuous estimation of several joints for a fixed movement. In this paper we move to a subject-independent framework for the classification of hand grasps. The fusion of signals from several different subjects produces generally slightly worst performances, but has the vantage of obtaining a more robust and general model. Thanks to this generalization, a new subject can use the framework without the need of long training phases, or with no training phase at all. In fact, the obtained model has a so large variability, to let it embody a wide number of possible subjects behaviours. Furthermore, we used a freely available online dataset, the data was not registered ad-hoc for our intentions assuring general results, and the availability of the dataset makes the experiments comparable and reproducible.

In order to use the sEMG signals we need some additional tools capable of conforming the signals and to allow an online processing. The needing of such tools is even more relevant for the subject-independent approach due to the greater signals variability. A crucial part is committed to the preprocessing phase: it is fundamental to even differences between signals due to noise, muscular and physical fatigue, and so on, but on the meantime to highlight the intrinsic characteristic of the movement. In order to be able to control a prosthetic device we need a twofold approach:

– Obtaining good prediction of the movement, in order to be able to reproduce correctly the requested movement;
– Being able to process the information and the prediction in a short time, in order to be able to work online.

Besides the preprocessing phase, better results can be obtained by implementing new classification techniques. A large number of classification techniques have been proposed during the years to establish a robust interaction with prosthesis devices. In [7] Ju et al. present the classification of 10 different grasps or in-hand manipulations using Fuzzy Gaussian Mixture Model, achieving an accuracy of 96.7%. Bu et al. [2] propose a framework based on Bayesian Networks for motion classification of a cooking task. The manually designed Bayesian Networks extract the statistical dependency between two continuous motions and it is combined with the output of a probabilistic Neural Network classifier, to improve stability and accuracy. In classification frameworks only a limited subset of movements are considered. In real daily applications movements are complex and a single movement is composed by many simpler sub-movements. In [12] Yang et al. study how the composition of a movement affect the movement classification, with the aim of using this technology in real Activities of Daily Living (ADL). They proved that better results can be achieved by including dynamic arm postures and varying muscular contractions in the training phase.

In this paper we present a hierarchical cascade-based classification technique, to both reduce elaboration time and improve the prediction. The results can be achieved by discarding part of the movements while descending into the depth of the tree. Thus, the comparisons are made within a subset of the initial movements. This subset is continually refined and reduced until arriving at the classification between a couple of movements.

The basic idea behind this approach is that two close movements in the taxonomy are more hard to distinguish than two distant movements. At the same time, a misclassification between two close movements is less questionable than a misclassification between two distant ones. This approach is easily generalizable and scalable: new movements can be added in the framework, only by following the taxonomy structure.

In this work we exploit the first results of the hierarchical and dependency relationship between the movements in order to develop a robust classification framework, able to identify online the movement performed by a subject. The proposed solution is subject independent, and it works also with new, unseen subjects. The developed GMM based classification allows an incremental and progressive classification of the samples, granting robust and online results.

The remainder of the paper is structured as follows: Section **??** presents the preprocessing procedure, together with the probabilistic model. In Section **??** we shows and discuss some preliminary results, while Section **??** summarizes the work while proposing some future extensions.

2 Methods

2.1 Signal analysis

In order to be able to process the data online, an appropriate preprocessing of the signal is crucial. The data used in this study come from the NinaPro dataset, a freely online available dataset [1]. A complete description of the dataset can be found in [10], [9], [1]. We used data from N= 40 healthy subjects performing 8 different hand grasps, each movement was repeated 6 times. The dataset contains both information about the muscular activation and the physical movement, but we only focused on the physiological signals from 8 sensors placed around the forearm.

The best classification performances can be achieved if it is possible to detect a clear underlying behaviour between the considered signals. This goal is even more important to reach since we are considering signals from a large number of different subjects. Since the good results obtained in previous studies [11], we started applying at the signal the Wavelet Transform [4] in order to allow an analysis in time and frequency, thus removing the dependence from time and granting online processing. We used the db2 mother wavelet from the Daubechies family and MAV as synthesis function, applying the Wavelet Transform to consecutive windows of 200 samples. Finally data has been smoothed by applying a moving average lowpass filter and normalized, in order to regularize the output.

2.2 Gaussian mixture model and classification

The EMG signals from the selected channels plus the additional information of the movement type, have been used to train offline a probabilistic model, namely a GMM. The GMM approximates the input by using a weighted sum of K Gaussian components which better represent the input data, used to train the model. A complete overview of the GMM and how it is built can be found in [10].

Once built the model, we proceeded with the online classification phase. A classification technique makes us predict the kind of movement the subject is performing starting from EMG signals from the subject's muscles. In particular, after the offline phase of GMM building, we processed online each single EMG signal. Considering the data of a trial performed by a fixed subject, the samples belonging to the trial can be denoted as $\xi_0^t = \{\xi_0, \xi_1, ..., \xi_t\}$. We compute the Probability Density Function (PDF) of each new sample:

$$\rho_m = PDF(\xi_s|\gamma_m) \tag{1}$$

where $1 \leq s \leq S$ is the index of the considered sample within a trial. γ_m with $1 \leq m \leq M$ indicates the index of all the possible class of movements, and M is the number of considered movements. The movement chosen for a fixed sample is the one with the higher PDF Equation 2.

$$\phi_m = m : max\{\rho_m, 1 \leq m \leq M\} \tag{2}$$

At each time instant t we computed the most probable movement up to that moment with 3:

$$\vartheta_s = s : max\{\phi_s, 1 \leq s \leq S\} \tag{3}$$

2.3 Taxonomy

For simplify the work, we considered a subset of 8 movements extracted from the complete taxonomy. The chosen movements are classical every day grasps to interact with common objects. In particular, we have considered the following movements: *Index Finger Extension*, *Medium Wrap*, *Prismatic Four Fingers*, *Stick*, *Writing Tripod*, *Power Sphere*, *Extension Type*, and *Power Disk*. In Figure 3 is represented the considered taxonomy for the subset of chosen movements.

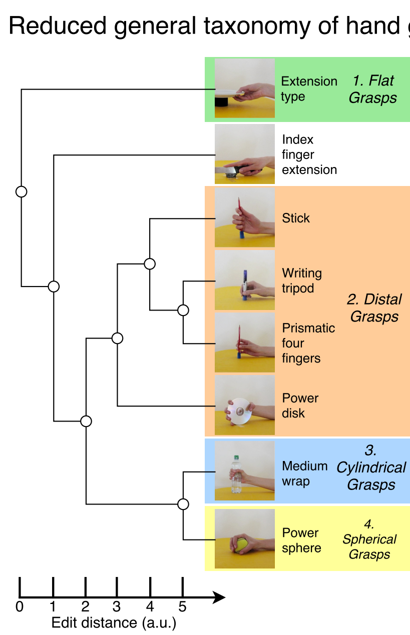

Fig. 1. Subset of the General Taxonomy of Hand Grasps with the movements considered for this experiment.

3 Results

We tested the framework with a Leave-One-Out approach. The model has been built on N-1 subjects and tested on the remaining one. The whole process has been repeated for all the N subjects. The testing phase has been organized in levels of increasing complexity. *Level 0* includes the classification between couples of movement, i.e. *writing tripod* and *prismatic four fingers*, *medium wrap* and *power sphere*. *Level 1* rises of one level in the binary tree and compares a couple of movement with a single one. Particularly, the movements of the previous level are considered as the same "movement group". Therefore, in *level 1* we classified between *stick* vs. *writing tripod* plus *prismatic four fingers*, and so on. A graphical example of this procedure is depicted in Figure 2.

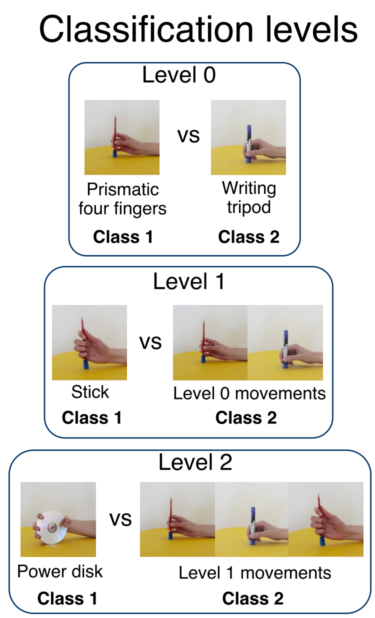

Fig. 2. Example of the levels organization in the taxonomy-based classification.

Figure 2 summarize the achieved results, showing the accuracy obtained for the executed tests. In particular, we computed the accuracy for each trial and movement, in every classification level among all the 40 considered subjects. The final accuracy has been computed by fixing the level and averaging among all the remaining factors. The obtained results are generally good, and they confirmed our expectations. Lower levels achieves the worst results, this probably happens since at this level the two considered movements have the most similar sEMG signals, thus it common to missclassificate them. This hypothesis is supported by the fact that high level reaches higher accuracy. In particular, level 3 reaches an accuracy of 97.29%.

LEV 0		LEV 1		LEV 2	
GROUP A	GROUP B	GROUP A	GROUP B	GROUP A	GROUP B
Medium wrap vs. *Power sphere*	*Prismatic four fingers* vs. *writing tripod*	*Index finger extension* vs. Gr. A-LEV 0	*Stick* vs. Gr. B-LEV 0	*Extension type* vs. Gr. A-LEV 1	*Power disk* vs. Gr. B-LEV 1
80,21%	**57,50%**	**60,56%**	**68,05%**	**77,39%**	**73,12%**

LEV 3	LEV 4	LEV 5
Gr. A-LEV 0 vs. Gr. B-LEV 2	LEV 3 vs. *Index finger extension*	LEV 4 vs. *Extension type*
97,29%	**84,17%**	**90,21%**

Fig. 3. Accuracy obtained among all the considered levels for the subject-independent taxonomy-based classification.

4 Conclusions

In this article we present some preliminar results of a novel approach for the classification of hand grasps by considering physiological signals, namely sEMG. The proposed solution could help amputated subject to gain their lost functionality by allowing them to interact with the outer world and with the objects that populate it. In the framework the critical part is the classification, especially when we want to classify among a large number of groups misclassifications are very common and this comports low accuracy. Our solution aims to limit this problem by exploiting a hierarchical quantitative taxonomy of hand grasps. The binary tree structure of the taxonomy comports a classification between two groups of movements, close to each other. The classification becomes more precise descending the tree and reaching the root, where the classification is restricted between a couple of movements. We built a general, subject-independent framework, able to adapt to new, unseen subject. In particular, we considered data from 40 healthy subjects performing 8 common grasps. The information has been modelized by using the GMM, and the classification process is determined online by using a gaussian-based framework. The obtained results are promising: we obtained a mean accuracy of 76.5%, reaching 97.29% in one of the higher levels. In some future works we want to try a new classification framework, and to compare the accuracy obtained exploiting the taxonomy and the one obtained with the traditional approach.

References

1. Atzori, M., Gijsberts, A., Heynen, S., Hager, A.G.M., Deriaz, O., Van Der Smagt, P., Castellini, C., Caputo, B., Müller, H.: Building the ninapro database: A re-

source for the biorobotics community. In: Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS & EMBS International Conference on. pp. 1258–1265. IEEE (2012)
2. Bu, N., Okamoto, M., Tsuji, T.: A hybrid motion classification approach for emg-based human–robot interfaces using bayesian and neural networks. IEEE Transactions on Robotics 25(3), 502–511 (2009)
3. Castellini, C., Fiorilla, A., Sandini, G.: Multi-subject/daily-life activity emg-based control of mechanical hands. Journal of NeuroEngineering and Rehabilitation 6(1), 41 (2009), `http://www.jneuroengrehab.com/content/6/1/41`
4. Chun-Lin, L.: A tutorial of the wavelet transform. NTUEE, Taiwan (2010)
5. Dimitrova, N., Dimitrov, G.: Interpretation of emg changes with fatigue: facts, pitfalls, and fallacies. Journal of Electromyography and Kinesiology 13(1), 13–36 (2003)
6. Feix, T., Romero, J., Schmiedmayer, H.B., Dollar, A.M., Kragic, D.: The grasp taxonomy of human grasp types. IEEE Transactions on Human-Machine Systems 46(1), 66–77 (2016)
7. Ju, Z., Ouyang, G., Wilamowska-Korsak, M., Liu, H.: Surface emg based hand manipulation identification via nonlinear feature extraction and classification. IEEE Sensors Journal 13(9), 3302–3311 (2013)
8. Matsubara, T., Morimoto, J.: Bilinear modeling of emg signals to extract user-independent features for multiuser myoelectric interface. Biomedical Engineering, IEEE Transactions on 60(8), 2205–2213 (2013)
9. Stival, F., Michieletto, S., Pagello, E.: Subject-independent modeling of semg signals for the motion of a single robot joint. In: Workshop of Robotics: Science and Systems (2015)
10. Stival, F., Michieletto, S., Pagello, E.: Online subject-independent modeling of semg signals for the motion of a single robot joint. In: Biomedical Robotics and Biomechatronics (BioRob), 2016 6th IEEE International Conference on. pp. 1110–1116. IEEE (2016)
11. Valentini, R., Michieletto, S., Spolaor, F., Sawacha, Z., Pagello, E.: Processing of semg signals for online motion of a single robot joint through gmm modelization. In: Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on. pp. 943–949. IEEE (2015)
12. Yang, D., Yang, W., Huang, Q., Liu, H.: Classification of multiple finger motions during dynamic upper limb movements. IEEE journal of biomedical and health informatics 21(1), 134–141 (2017)