Evolutionary Design of a Fuzzy Classifier for EMG-based Control
– Control of a Multi-DoFs Underactuated Hand Prosthesis –

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While the human hand is a marvelous example of very fine mechanics and control, its current artificial replacements (especially hand prostheses) suffer from several limitations, in particular poor functionality and poor control interface. The first aspect can be solved by developing a new generation of hand prosthesis. The lack of practical control interfaces, instead, is still an open issue. Among several possibilities, surface electromyographic signals (EMG) are considered an interesting source of information to allow human beings to control robotic artifacts. In this paper, a novel approach for the automatic generation of fuzzy classifiers from raw EMG data through genetic evolution is proposed and tested. The preliminary results show the validity of the proposed approach for the control of a multi-DoFs hand prosthesis.

Keywords: Human-Robot Interface, Hand Prosthesis, EMG-based control

1. Introduction

The replication of the sensory-motor capabilities of the human hand (i.e. its combination of a large number of degrees of freedom (DoFs), proprioceptive and exteroceptive sensors, a highly hierarchical architecture control, which result in a complex and adaptable system capable of both delicate and precise manipulation and power grasping of heavy objects) is still an open challenge for scientists and engineers [1]. The results, in fact, are quite far from the original, either in terms of dimension, sensors, DoFs, and so on [2].

Two are the most critical aspects in current hand prostheses:

- **poor functionality** (currently only one or two degrees of freedom, controlled either by harness – kinematic prostheses – or by electromyographic signals (EMG) – myoelectric prostheses);
- **poor control capabilities** (mostly due to the lack of a good control interface).

Surveys on using such artificial hands, in fact, reveal that, due to the above limitations, 30 to 50% of the upper extremity amputees users prefer to use simpler (and therefore lighter, and less expensive) cosmetic or kinematic prosthesis instead of the myoelectric ones [3].

A possible solution to the first problem is the enhancement of the current design of prosthetic hand, for example by the introduction of advanced underactuated mechanism, biologically-inspired sensors, and so on [4][5]. These new generation of hands could provide the user with much more functionality and capabilities.

As for the poor control interface, instead, among several different possibilities [6], more or less invasive, the EMG signals recorded using surface electrodes are considered as interesting source of information to allow human beings to control robotic artifacts. In fact, these signals are very easy to record in a non-invasive way, and provide an important access to the neuro-muscular system of the user, i.e., indirectly to the brain voluntary activity. In recent years several architectures have been developed and tested for the control of artificial prostheses by using EMG signals [1][4][5][7][8]. All these systems tried to solve the need for coding the different actions of the robot. For example, the extension of the fingers of a prosthetic hand must be coded by using different muscular activities such as the ones of upper arm or forearm in case of hand prostheses.

In order to increase the number of controllable DoFs, traditional control techniques are not sufficient. Current systems, in fact, are limited to the control of only one or two DoFs with two electrodes; they need more electrodes if they want to control more DoFs.

A possible solution to overcome this limitation is the use of soft-computing techniques for the construction of the classifier. In particular, a novel evolutionary approach for the generation of a compact fuzzy classification scheme directly from EMG data, based on [9], is implemented and tested.

2. Methodology

Objective of this work is to prove the effectiveness of the proposed approach for the development of a robust and reliable control system for four different types of grasping by using only two differential electrodes.

The target hand for this control system is CYBERHAND [3] (Fig. 1), an advanced prosthetic hand with 16 DoFs (6 Degrees of Motion, underactuation factor = 10) capable of replicating the most useful grasps. In particular:

- Cylindrical Grasp;
- Spherical grasp;
- Lateral grasp;
- Tip pinch.

Each grasp is associated with a label (Table 1); two additional classes (C1: no movement; and C6: co-contraction) are necessary for a smooth transition between the different classes during normal use.

Table 1: definition of the six classes of movement discriminated by the multi-level classifier and of the tasks associated to each class.

Label	Definition	Task
C1	no contraction;	no movement
C2	biceps at a low contraction level	pinch grasp
C3	biceps at a high contraction level	lateral grasp
C4	triceps at a low contraction level	palmar grasp
C5	triceps at a high contraction level	spherical grasp
C6	co-contraction of biceps and triceps	stop closing (while grasping) and then opening

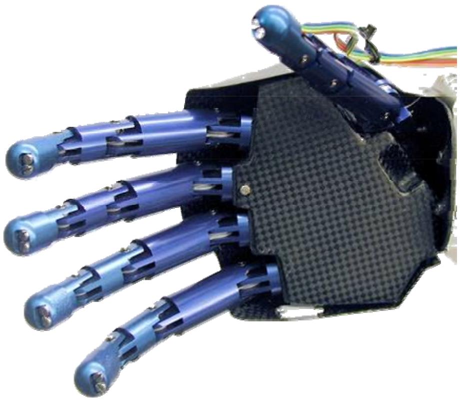


Fig. 1: Picture of the first prototype of CYBERHAND. The size is the same as a standard Japanese adult male.

2.1 Architecture of the classifier

A three–level classifier (Fig. 2) is implemented in order to increase the robustness of the system:

- **L1**: detection of activation
- **L2**: discrimination between biceps contraction, triceps contraction, and co-contraction;
- **L3**: discrimination between high level and low level of activation (both for the triceps and for the biceps).

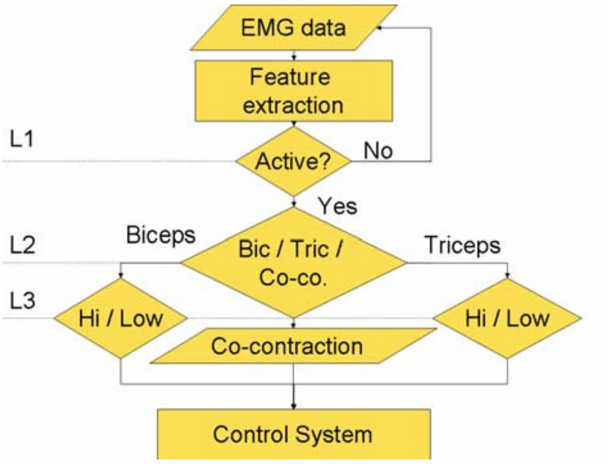


Fig. 2: multilevel classifier’s architecture.

2.2 Experimental protocol

After providing informed consent to the experiments, each subject sits or stands with the right arm relaxed on his side, looking at the computer monitor for visual feedback concerning the EMG level. The counterlateral arm is used to block the movement of the arm, thus generating isometric contractions. A Delsys Bagnoli EMG system is used to capture the surface EMG signal from the *biceps brachii* (BB) and *triceps brachii* (TB) of the user prevalent arm (Fig. 3). The signals from BB and TB are acquired by using two DELSYS DE-2.1 Single Differential Electrodes (2 contacts each 10.0x1.0 mm spaced by 10.0 mm, and made by 99.9% Ag; CMRR @ 60 Hz > 80 dB, Input Impedance > 1015 // 0.2 pF). The electrodes are interfaced with the skin by using the Delsys’ skin interface adhesive. A reference electrode (DERMATRODE HE-R part 00200-340) is attached to an electrically neutral area (usually the belly of the user).

The user is trained to contract the BB and TB in order to generate the different control signals. The visual representation of the EMG signal and its variance helps the user to learn how to control the hand.

The experiments are divided into 3 main phases:

1) experimental set-up:
   a) positioning of electrodes;
   b) gain regulation;
   c) zero regulation;
2) data acquisition;
3) feature extraction.

2.2.1 Experimental Set-up

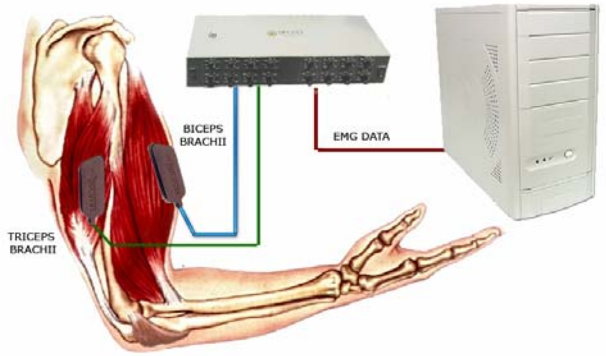


Fig. 3: Schematic drawing of the setup of the experiment.

2.2.2 Data acquisition

The user is asked to generate each class for 5 times. Each epoch lasts 2 seconds and there are 5 seconds of relaxation between one epoch and the following one, in order to prevent muscle fatigue. This sequence is repeated twice. Thus, a total of 60 epochs (120 seconds in total) is collected.

2.2.3 Feature extraction

The feature chosen for these first experiments are (the mathematical definitions can be found in [1] and related articles):

- Integrated Absolute Value (IAV);
- Variance of the EMG. (VAR);
- Zero Crossing (ZC);
- Kurtosis (KUR).

Their values in the 6 different classes are shown in Fig. 4.

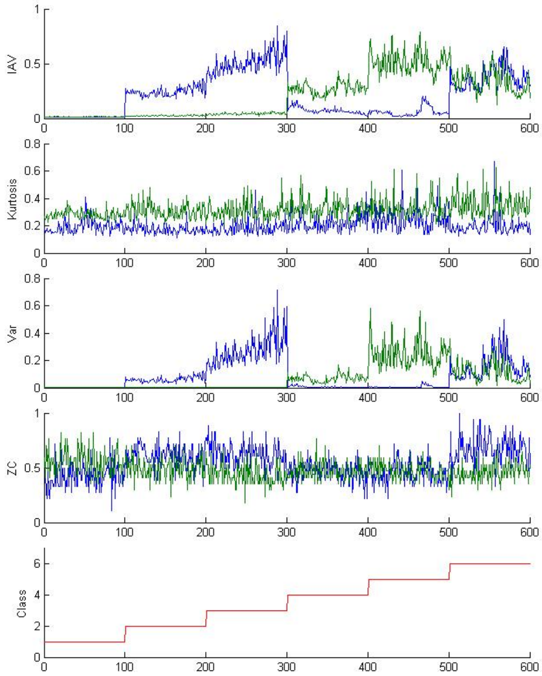


Fig. 4: IAV, Kurtosis, Variance and Zero Crossing for the 6 classes.

2.2.4 Classification

Two classifiers have been implemented and tested:

Threshold classifier

The threshold is carefully chosen by analyzing the variance σ_{ch} and the mean value μ_{ch} for the IAV of each channel *ch* (*ch* = {biceps, triceps}) during the 6 classes of contractions. For each subject the thresholds are chosen in order to maximize the classification ratio.

Evolutionary Fuzzy Classifier

Fuzzy classifiers usually lead to performance similar to neural networks or statistical measurements. Their advantage is the interpretability of their rule-base structure. A small number of rules can be easily interpreted and examined by users; moreover, few fuzzy rules mean also an improvement of performance and robustness of the classification.

Several methods have been proposed in literature for the design of compact and interpretable fuzzy systems. The algorithm chosen for this paper, named VISIT (Variable Input Spread Inference Training), is derived from [9]. It can extract a Mamdami fuzzy system directly from data. This algorithm tries to classify the new patterns into the appropriate class by comparing the features of the unknown new patterns with the features of the patterns which have already been classified. Rules and membership functions are automatically created and optimized by means of genetic algorithms [10] by using a Performance Evaluation Index PEI = f(MCE, II). The Classification Error (MCE) is used to measure the resolution of the fuzzy classifier, while II (Interpretability Index) takes into account the interpretability of the generated system (i.e. he lower the number the rules in relation to the number of lasses, the higher the interpretability II).

3. Results

3.1.1 Classification results

The data from 8 subjects (male, average age 26) have been acquired and analyzed. The results of the comparison between the threshold classifier and the fuzzy classifier are shown in Fig. 5. As can be seen from the figure, the fuzzy classifier always outperforms the threshold classifier.

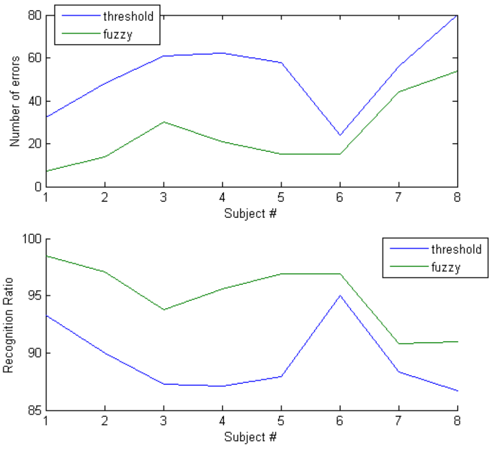


Fig. 5: (top) number of error of the threshold and the fuzzy classifier; (bottom) correct recognition ratio of the two classifiers.

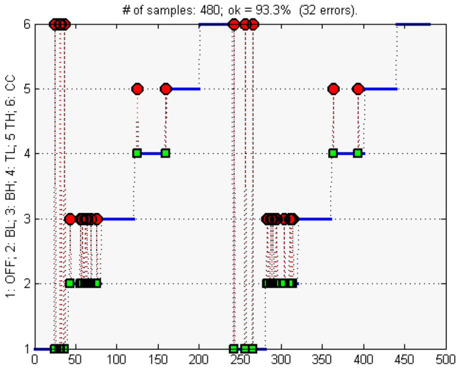


Fig. 6: classification result for the threshold classifies: 480 samples, 32 errors (correct recognition ratio = 93.3%)

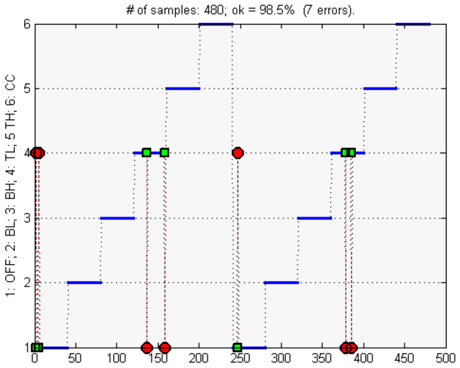
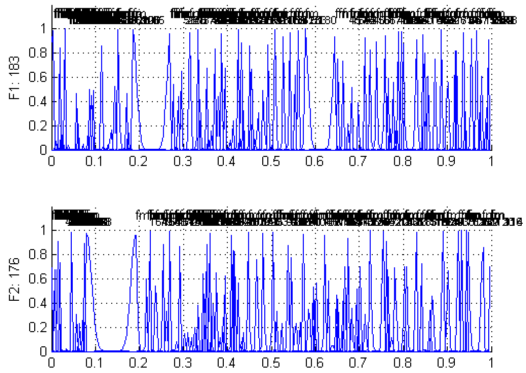


Fig. 7: classification result for the fuzzy classifies: 480 samples, 7 errors (correct recognition ratio = 98.5%)

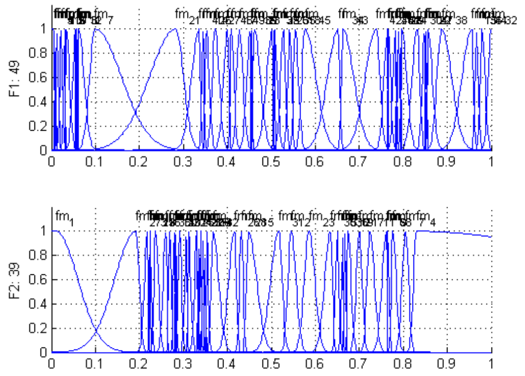
The correct classification rate in case of the threshold classifier ranged from 86.7% to 95.0%, depending on the subject. The results of the fuzzy classifier, instead, were slightly higher, ranging from 90.8% to 98.5%. In Fig. 6 and Fig. 7 the classification result for the threshold classifier (correct recognition ratio = 93.3%) and the fuzzy classifier (correct recognition ratio = 98.5%) on 480 samples for subject #1 are shown.

3.1.2 Evolution of the fuzzy classifier

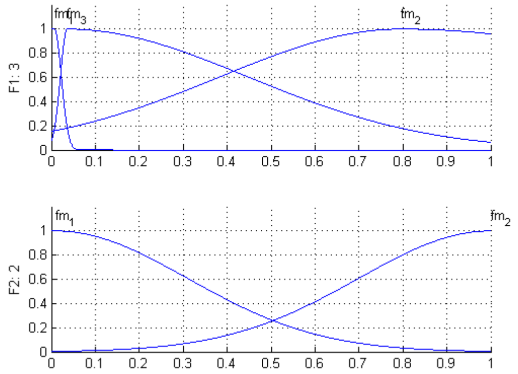
The experimental results proved the effectiveness of the use of PEI for the selection of the best classifier (Fig. 8).



(a) Beginning of the evolution: 183+176 rules, RR = 5%.



(b) intermediate phase: 49+39 rules, RR = 92%



(c) final classifier: 3+2 rules, RR = 98.5%

Fig. 8: Evolution of the fuzzy classifier. At each stage the classifier becomes more reliable (i.e. higher recognition ratio) and more compact (i.e. lower number of rules)

Starting from a system with a huge number of rules and poor recognition ratio (Fig. 8(a), PEI = 0, Recognition Ratio RR =5%), the classifier progressively evolves through Fig. 8(b) (PEI=75, RR=92%) to Fig. 8(c) (PEI=75, RR=92%).

4. Discussion and Conclusion

Although several progresses have been made in the realization of artificial hands, the state of the art is quite far from replicating the performance of the natural hand. Current prosthetic hands, in particular, suffer from the drawbacks of poor performance and poor controllability. In order to address the second problem, this paper presented a novel approach for the generation of the control system directly from the electromyographic data generated by the user.

The preliminary results showed that the fuzzy classifier at the end of its evolution always outperforms a traditional threshold classifier, thus confirming the validity of the proposed approach.

Although the performance of the current system is quite good, the evolution is still too slow. The conversion from a Matlab™ routine to C++ will probably solve this problem. The next steps include also some tests of the algorithm with EMG data from amputated persons, and the implementation of the control of the real hand.

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