University of Genoa

Department of Computer Science, Bioengineering,
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Verification and repair of machine learned controllers: a case study in prosthetics

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To all the people with whom I have been sharing
worries, success and happiness
during these years.

The greatest challenge to any thinker is stating
the problem in a way that will allow a solution.
Bertrand Russell

Abstract

Myocontrol is a hot subtopic of assistive robotics, in particular it is one of the so-far unsolved hurdles in upper-limb prosthetics. It is about swiftly, naturally and reliably converting biosignals, non-invasively gathered from an upper-limb amputated subject, into control commands for an appropriate self-powered prosthetic device. Despite decades of research, traditional surface electromyography cannot yet detect the subject's intent to an acceptable degree of reliability, that is, enforce an action exactly when the subject wants it to be enforced.

In this work we tackle one of the subproblems related to myocontrol reliability, namely activation overshooting, and show that Formal Verification can indeed be used to mitigate it at an acceptable computational cost. Eighteen intact subjects were engaged in two Target Achievement Control tests in which a standard myocontrol system was compared with two "repaired" ones, one using a simple non-formal technique, enforcing no guarantee of safety, and the other using Satisfiability Modulo Theories (SMT) technology to rigorously enforce it. The experimental results indicate that both repaired systems exhibit an improved reliability by reducing activation overshooting. Using the SMT-based system only requires a modest increase in the required computational resources.

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Chapter 1

Introduction

1.1 Context

As testified in Ziegler-Graham et al. (2008) "One in 190 Americans is currently living with the loss of a limb. Unchecked, this number may double by the year 2050": this kind of statistic can easily express how much prosthetic technologies are important nowadays and how big is the market for them. By virtue of the above-mentioned high demand of prosthesis, technological research in the prosthetic domain in the last decades has been very active: ideally amputees would need, as far as possible, prosthesis as functional as real limbs and a great deal of research as been done to try to enhance the performance, the comfort and the appearance of prosthetic limbs. Sadly, even with all the effort done from the scientific community, we are still far from developing this kind of prosthetic limbs: from the low grasping capabilities to the lack of sensory feedback and up to the lack of a "natural", user-friendly control interface [Zecca et al. (2002)], modern prosthesis fall short compared to real limbs. Regarding prosthesis control in particular, during the last few years machine learning has become more and more common as control method: various machine learning model has been used to extrapolate control policy from data provided from disparate type of sensors. One of the most commonly used sensor is the electromyographic sensor, which allows to measure the electrical activity of muscles: this kind of sensor owes its popularity to its (relatively) low cost and to the fact that it can be used without the need of invasive surgical procedures. Although the control methods for prosthesis using EMG signals are constantly improving, from Zecca et al. (2002) to Strazzulla et al. (2017), Formal Methods have never been tried in order to enhance the reliability of the machine learning models used in the control system.

1.2 Goals

In this thesis we are addressing the problem of studying if it is possible to enhance the reliability of the current machine learning models used to control prosthetic upper limbs by means of EMG signals. We will study an unresolved control problems in the system "Interactive MyoControl" currently used at the DLR and then we will try to use state of the art decision procedures, opportunely modified, to solve aforesaid problems, or at least to improve the present system. We will then present the results obtained from an experiment we have designed in order to show the difference between the original control system and the enhanced version.

1.3 Motivations

As testified in Biddiss and Chau (2007b) the mean rejection rate for electric prostheses is 35% for the pediatric population and 23% for the adult population and one of the critical factor for the rejection is the unsatisfactory state of the available technology [Biddiss and Chau (2007a)]. In particular one of the lacking aspect pointed out in Biddiss and Chau (2007a) was the ease of control of the prostheses: whereas the machine learned controllers have grown more and more refined [Strazzulla et al. (2017)] currently there has never been an attempt to use formal methods in order to enhance the reliability of these control system. We believe that, in particular for control system which use EMG signal as inputs, the application of formal methods could truly enhance their reliability and, consequently, improve the confidence on deploying the controller and lower the rejection rate.

1.4 Contributions

In this work we study a open reliability problem in the control of prosthetic hands, we propose a computationally feasible algorithm for the enhancement of the reliability of the system with respect to the above mentioned problem and we show through experimental results that our algorithm indeed manages to limit the appearance of the above-mentioned problem.

1.5 Overview

HERE OVERVIEW

Chapter 2

Background

In this chapter we introduce background notions and survey related work. To be specific section 2.1 briefly present myoelectric control, section 2.2 briefly presents formal methods and in particular the formal verification techniques we use in this thesis. Section 2.3 presents the machine learning methods of interest.

2.1 Myoelectric Control

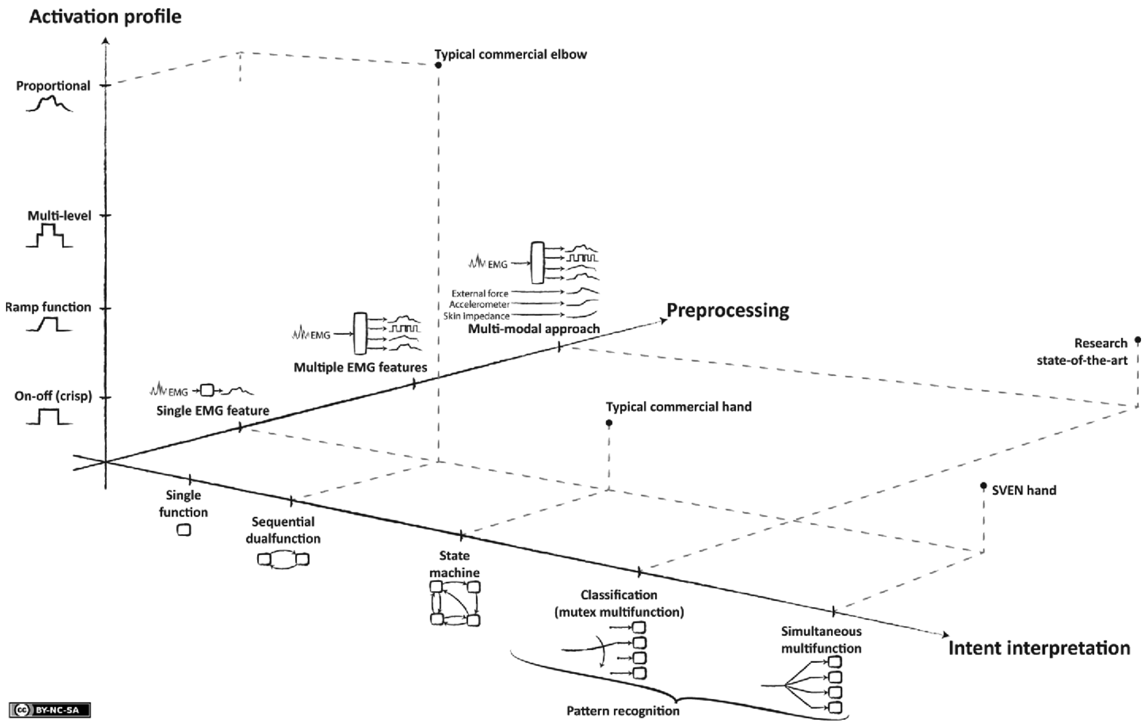

Figure 2.1: Research state-of-the-art of myoelectric control in the year 2012 [Fougner et al. (2012)]

Electromyography (EMG) is an electrodiagnostic technique for evaluating and recording the electrical activity produced by skeletal muscles [Robertson et al.

(2013)]. EMG is performed using an electromyograph which detects the electric potential generated by muscle cells when they are electrically or neurologically activated. This electric potential can be approximatively considered proportional to the force of the muscle activation. Due to the preference for noninvasive prostheses, surface EMG (sEMG) signals have been used for the control of upper limb prostheses prosthetic devices since 1948, as testified in Zecca et al. (2002). The signal produced by the sEMG sensors are fed to machine learning methods in order to control the prostheses: different machine learning models are used in union to different numbers of sEMG sigmals in order to achieve different level of control on the prostheses. A graphical representation of the different control methods and level, considering also non-machine learning methods, can be found in figure 2.1. In this thesis we work on a myoelectric control system characterized by a *proportional* activation profile, a *simultaneous multifunction* intent interpretation and we consider as input *multiple EMG features*.

2.2 Formal Methods

Formal methods are a kind of system design techniques which use meticulous mathematical models for the specification, development and verification of software and hardware systems. The application of these kind of methods to the design of both software and hardware systems is supported by the increased reliability and robustness of the resulting systems. In this thesis we are more interested in the use of formal methods as verification techniques: we will consider a finished system and we will try to use the verification techniques in order to enhance its reliability. In particular the system we will consider is a machine learned controller, therefore in this section we present two of the most popular formal verification techniques used in the verification of machine learning systems: Satisfiability (SAT) and Satisfiability Modulo Theories (SMT).

2.2.1 Satisfiability (SAT)

SAT solving aims to check the satisfiability of a propositional logic formula φ represented as Boolean combinations of atomic (Boolean) propositions. We introduce CDCL-style SAT solving algorithm, being the most commonly implemented in state-of-the-art SAT solvers. The CDCL algorithm starts from a CNF formula and then explores the search space by iteratively assigning truth values to some propositions which are chosen according to some heuristic. After each of these assignment the algorithm applies Boolean Constraint Propagation (BPC) to determine the variable assignments implied by the last decision. If the application of BPC leads to a con-

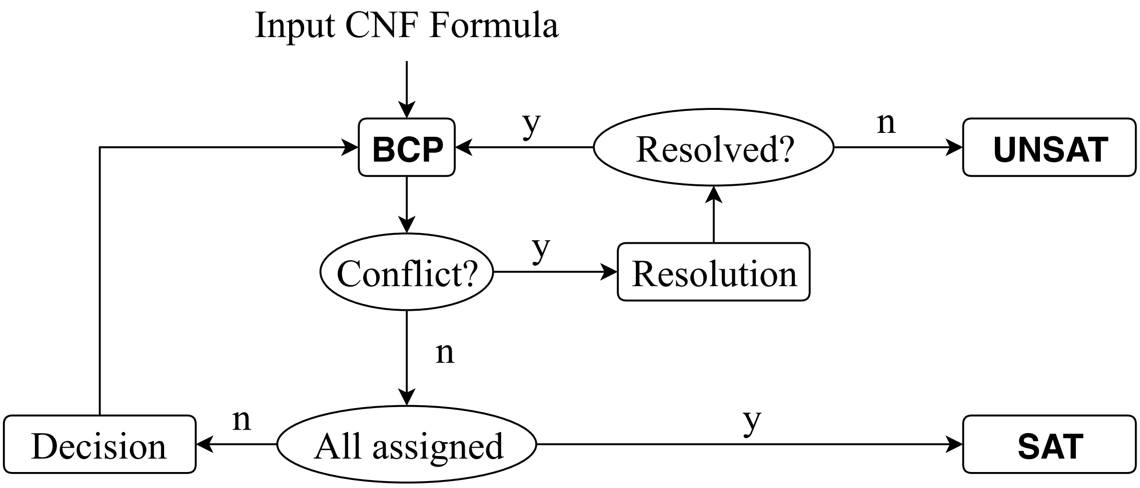

Figure 2.2: The CDCL framework.

flict, which is, if the value of a variable is implied to be both true and false at the same time, then *conflict-driven clause-learning* and *non-chronological backtracking* are employed: the algorithm follows back the chain of implication and applies resolution to infer a reason for the conflict in the form of a conflict clause, which then is added to the clause set of the solver. Backtracking removes previous decisions and their implications until the conflict clause can be satisfied. If the starting CNF formula has clauses consisting of a single literal, the algorithm assign them directly. As consequence the algorithm starts with BCP in order to detect implication. If the application of BCP brings to a conflict, the algorithm tries to resolve such conflict. If the conflict is unsolvable then the CNF formula is unsatisfiable, otherwise the algorithm backtracks and continues with BCP. If BCP is completed without conflicts and there are still unassigned propositions, the algorithm makes a new decision. Otherwise the CNF formula is satisfiable and a solution is found.

2.2.2 Satisfiability Modulo Theories (SMT)

Satisfiability Modulo Theories is the problem of deciding the satisfiability of a first-order formula with respect to some decidable theory $\mathcal{T}$. In particular, SMT generalizes the boolean satisfiability problem (SAT) by adding background theories such as the theory of real numbers, the theory of integers, and the theories of data structures (*e.g.*, lists, arrays and bit vectors). To decide the satisfiability of a CNF formulas φ, SMT solvers usually build a boolean abstraction $abs(\varphi)$ by replacing each constraint by a new boolean proposition.

$$\begin{array}{rl} \varphi & : \underbrace{x \geq y} \wedge (\underbrace{x > 2} \vee \underbrace{y > 0}) \wedge \underbrace{y \leq 0} \\ abs(\varphi) : & \quad A \quad \wedge (\quad B \quad \vee \quad C \quad) \wedge \quad \neg C \end{array}$$

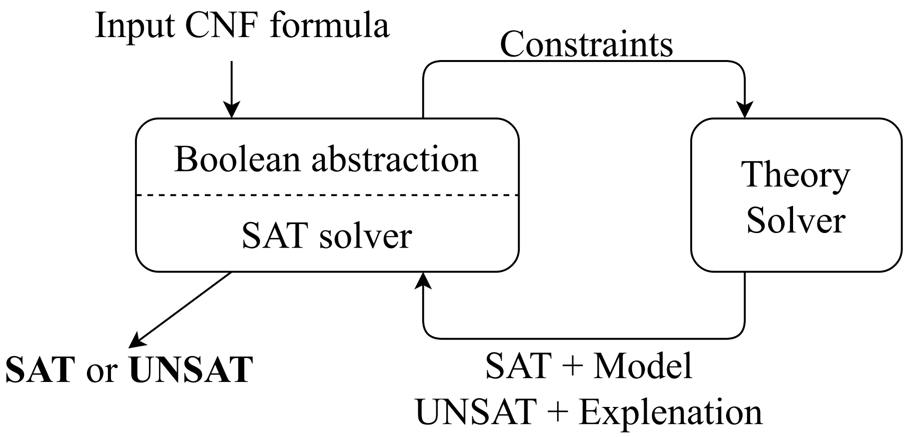

Figure 2.3: The SMT solving framework.

In the example above x and y are real-valued variable whereas A, B and C are boolean proposition. Once the boolean abstraction is built a SAT solver search for a satisfying assignment μ for $abs(\varphi)$ (e.g. $\mu(A) = \bot$, $\mu(B) = \top$, $\mu(C) = \bot$), if there is no satisfying assignment the CNF formula is unsatisfiable. Otherwise the SMT solver needs to check if the assignment is consistent also in the underlying theory using a *theory solver*. If the theory solver comfirm the consistency of the assignment then a satisfying solution (*model*) is found for φ. Otherwise the theory solver provides a set of falsified clauses ϕ_T which gives an explenation for the conflict, such set is then used to refine the boolean abstraction $abs(\varphi)$ to $abs(\varphi) \wedge abs(\phi_T)$. These steps are iteratively executed until either a theory-consistent Boolean assignment is found, or no more Boolean satisfying assignments exist.

2.3 Machine Learning

The machine learning methods we will consider in this thesis is Ridge Regression with Random Fourier Features (RR-RFF), in the following we will briefly explain the above-mentioned model. The simplest form of regression is the least square regression:

$$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} \tag{2.1}$$

where $\mathbf{w}$ is a weight vector and $\mathbf{x}$ is the input feature vector. The optimal values for the elements of the vector $\mathbf{w}$ can be found through the minimization of the sum of the squared error between the prediction $f(\mathbf{x})$ and the correct target label y. The resulting optimization problem is:

$$\underset{\mathbf{w}}{arg\,min} \sum_{i=1}^{n} (y_i - f(\mathbf{x}_i)) \tag{2.2}$$

where n is the number of training samples and y_i is the target label corresponding to the sample $\mathbf{x}_i$. The closed form solution of this optimization problem can easily be found by differentiating equation 2.2 with respect to $\mathbf{w}$, setting the result equal to zero and solving the resulting equation for $\mathbf{w}$. The resulting closed form solution is:

$$\hat{\mathbf{w}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} \tag{2.3}$$

where $\mathbf{X} \in \mathbb{R}^{n \times d}$, n is the number of training samples and d is the number of input features. In order to limit the overfitting of the model and, as consequence, achieve a more stable model, a regularisation term can be used. This term leads to a penalization on the values of the weights and therefore to a smoother model. This particular kind of regression is known as Ridge Regression (RR) [Hoerl and Kennard (1970)], the minimization problem becomes:

$$\underset{\mathbf{w}}{arg\,min}\ \frac{1}{2}\sum_{i=1}^{n}(y_i - f(\mathbf{x}_i)) + \frac{\lambda}{2}||\mathbf{w}||^2 \tag{2.4}$$

where λ is a strictly positive hyperparameter which scales the contribution of the regularization parameter in the equation. The closed form solution for Ridge Regression can be easily found following the same step used for the standard least square regression.

$$\hat{\mathbf{w}} = (\mathbf{X}^T\mathbf{X} + \lambda\mathbf{I})^{-1}\mathbf{X}^T\mathbf{y} \tag{2.5}$$

where $\mathbf{I} \in \mathbb{R}^{d \times d}$ is the identity matrix. Ridge Regression is a linear model: to extend its application to nonlinear dataset, we can map the input space to a higher dimensional space using a nonlinear basis function ϕ:

$$f(\mathbf{x}) = \mathbf{w}^T\phi(\mathbf{x}) \tag{2.6}$$

$$\hat{\mathbf{w}} = (\mathbf{\Phi}^T\mathbf{\Phi} + \lambda\mathbf{I})^{-1}\mathbf{\Phi}^T\mathbf{y} \tag{2.7}$$

where $\mathbf{\Phi} := \mathbf{\Phi}(\mathbf{X}) \in \mathbb{R}^{n \times D}$ and $\mathbf{I} \in \mathbb{R}^{D \times D}$, the number of basis function D is a new hyperparameter of the model.

In this thesis we have followed in the step of the work done in Strazzulla et al. (2017) and therefore we have chosen Random Fourier Features (RFF) as basis function:

$$\phi_{RFF}(\mathbf{x}) = \sqrt{2} \cdot cos(\sigma \cdot \mathbf{\Omega} \cdot \mathbf{x} + \beta) \tag{2.8}$$

$$\mathbf{\Phi} = \mathbf{\Phi}_{RFF}(\mathbf{X}) = \sqrt{2} \cdot cos(\mathbf{X} \cdot (\sigma \cdot \mathbf{\Omega})^T + \beta) \tag{2.9}$$

where $\mathbf{\Omega} \in \mathbb{R}^{D \times d}$, $\beta \in \mathbb{R}^D$, $\mathbf{\Omega} \sim \mathcal{N}(0,\, 1)$ and $\beta \sim \mathcal{U}(0, 2\pi)$ and σ is an hyperparameter which scales the frequency of the distribution.

Chapter 3

Overshooting

Chapter 4

Conclusion and Future Work

HERE CONCLUSION

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