A PRELIMINARY STUDY TOWARDS AUTOMATIC DETECTION OF FAILURES IN MYOCONTROL

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ABSTRACT

Reliability is still the main issue in myocontrol: enforcing (dexterous) grasping, releasing and moving exactly and only when the wearer desires it. One specific path towards the solution of this problem is incremental machine learning, leading to *interactive myocontrol,* in which unreliability is taken care of via on-demand model updates, requested by the experimenter and/or the subject herself/himself. One natural drawback of this approach is that an "oracle" is needed at all times, stopping the prediction and calling for an update whenever this is deemed to be the case; an automated oracle, as reliable as possible, is therefore very desirable.

This work shows the results of a preliminary study in which we tried to find features of the control signals and predictions, as well as environmental information (inertial sensors and motor currents) to automatically identify the failures of the myocontrol system. The outcome is promising, showing that a classifier can match the observer's judgement with an overall average accuracy of slightly more than 75%.

INTRODUCTION

Whenever the scientific community talks about dexterous myocontrol, i.e., natural, simultaneous and proportional (s/p) control of prosthetic artefacts over many degrees of freedom (DoFs), the main issue remains that of *reliability*. An unreliable myocontrol system lets the prosthesis open, close and grasp at times when such an action is not required and vice-versa, which can lead to disastrous results. Even in the case of traditional two-sensors EMG-based myocontrol the situation is far from optimal, mainly due to unexpected changes in the signals (caused by sweating, displacement, fatigue, etc.). There is still a lot of work to do, as has recently been shown during the Cybathlon ARM competition[1]: the winner of the competition, Robert Radocy of TRS Prosthetics, was using a body-powered one-DoF prosthetic arm, which enabled him perform all required tasks without any error, swiftly and elegantly; and he was competing against some of the most advanced academic solutions in the world.

Still, there is now plenty of surveys [Micera et al. (2010), Peerdeman et al. (2011), Ison and Artemiadis (2014), Engdahl et al. (2015)] showing that advanced control is desired, but it is rejected due to poor reliability. Our way towards the solution of the problem is *incremental learning,* allowing for on-demand model updates in real time, leading to *interactive myocontrol:* a natural, s/p control schema which can be "taught" new information whenever the experimenter and/or the subject deem it necessary [Gijsberts et al. (2014), Strazzulla et al. (2016), Nowak and Castellini (2016)]. This concrete possibility of updating represents the main strength of interactive myocontrol; however, the necessity of having an "oracle" at one's disposal – be it the experimenter or the subject – probably constitutes its main weakness.

In this work we propose a step towards automatic updating of interactive myocontrol. In particular, we show that specific features extracted from either surface electromyography (sEMG) signals, the predicted control commands, inertial and/or current measurements, can be used to characterise when dexterous myocontrol would fail. In a preliminary analysis, we engaged an intact subject, equipped with a commercial sEMG bracelet and a multi-fingered 6-DoFs prosthesis, in a complex series of daily-living tasks inspired by the Cybathlon ARM race concourse; the reliability of the myocontrol system would be stressed through the usage of diverse actions (grasping patterns) as well as the necessity to move and walk around. In this specific experiment, an offline analysis reveals that a standard linear classifier could discriminate the faulty situation in 76.71% of the cases.

MATERIALS AND METHODS

Experimental Setup

The experimental setup is visible in Figure 1. It consists of (a) a commercial orthotic splint that was fitted with a custom-design mounting for prosthetic hands; (b) an *i-LIMB Revolution* multi-fingered prosthetic hand manufactured by Touch Bionics; (c) a *Myo* bracelet by Thalmic Labs, embedded with eight sEMG sensors covering the full circumference of the user's proximal forearm. The *i-LIMB* also provides the motor current readings and the "digit

[1] see http://www.cybathlon.ethz.ch/en/cybathlon-news/cybathlon-results/arm-results.html and, especially, the video excerpts in http://www.swisswuff.ch/tech/?p=6670.

status" (opening, closing, stalled), while the *Myo* mounts an inertial device providing the translational and angular acceleration in three dimensions.

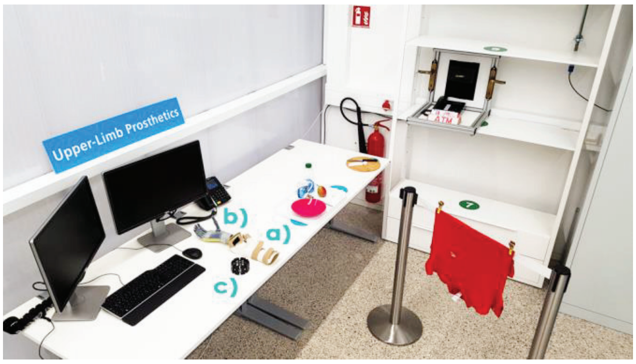

Figure 1: overview of the laboratory setup including a) the *i-LIMB* on an b) orthotic splint, c) the *Myo* bracelet and daily-living objects that were manipulated during the experiment.

Incremental s/p myocontrol was enforced using six parallel instances of *Ridge Regression with Random Fourier Features* (RR-RFF), a method already tested and used for myocontrol in, e.g., [Gijsberts et al. (2014), Strazzulla et al. (2016)]; sEMG data with mild low-pass filtering was taken as the input space, while the output space (ground truth) was obtained through on-off goal-directed visual stimuli administered to the subject (see again the cited references, plus [Sierra González and Castellini (2013)]). The six outputs of the RR-RFF instances were directly fed as (proportionally scaled) current commands to the six motors of the prosthetic hand.

Experimental Protocol

The protocol enforced the execution of a series of nine daily-living tasks inspired by the *SHAP* assessment protocol [Light et al. (2002)] as well as by the Cybathlon ARM competition (see Table 1); notice that the tasks involve walking, standing, sitting and moving around – to this aim, a predefined path was arranged in our laboratory (see Figure 1 again). Figure 2 shows a schematic depiction of our own "concourse", built within the laboratory.

Table 1: tasks involved in the experimental protocol.

Task#	Task description
1	Place objects on a tray
2	Carry a tray with objects on it
3	Place objects on shelves of different heights
4	Cut a mock-up cucumber
5	Pour mock-up water in a mug
6	Hang a piece of clothing on a clothesline using pegs; take it down; fold it
7	Withdraw money at a mock-up ATM
8	Unwrap a piece of candy
9	Shake hands with the experimenter

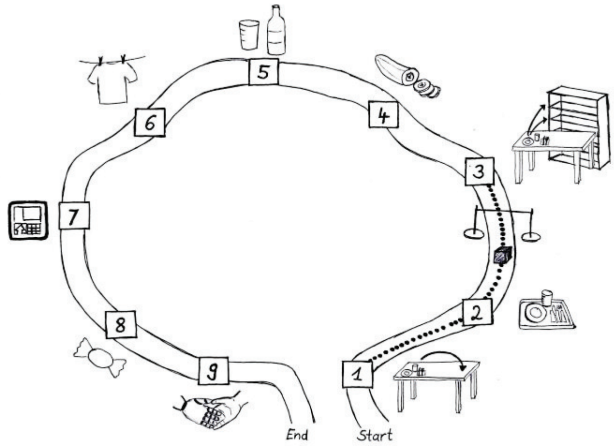

Figure 2: a schematic depiction of the path through the laboratory, including pictograms denoting each task.

The protocol required the subject to use three different hand configurations *(actions),* namely power grasp, tripodal grasp (precision) and pointing index. Initially, the user was asked to perform only one repetition of all these actions (plus the resting action) to train the myocontrol system; such a low number of repetitions was explicitly chosen to potentially induce instability and poor performance in the control system during the execution of the protocol.

During the execution of each task the user was closely observed by the experimenter; the performance of the control system was marked online as *good* or *poor* by the experimenter. When the performance was considered *good*, e.g. the task was successfully completed, the user moved on to the next task; in case the performance was considered *poor*, e.g., objects were dropped or the prosthesis did not behave the intended way, the user was asked to continue to try for a while; then, additional sEMG data was gathered for the intended action (on-demand model update – each update took approximately 15s). After each update the last action was repeated, then the whole task was carried on until successfully performed. This procedure allowed us to gather both *good* and *poor* performance labels even within one and the same task.

Before the experiment started, the single subject signed an informed consent form. The experiment was approved by the Work Safety Committee of the DLR and it was performed according to the declaration of Helsinki.

Observer Model and Feature Extraction

To try and automatically determine the quality of the performance, that is to mimic the experimenter+subject "observer", we offline fed features extracted from the sEMG signals, the myocontrol predictions, the acceleration, the motor current and the digit status signals to a standard linear classification method (*Linear Discriminant Analysis,* see Figure 3).

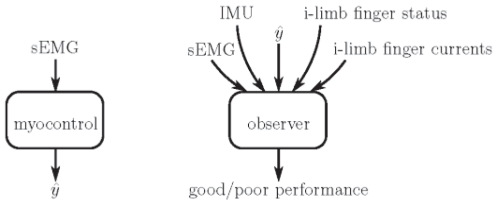

Figure 3: signals fed to the myocontrol system and observer model. In the Figure, $\hat{y}$ denotes the (six-dimensional) output of the myocontrol system itself.

A reasonable assumption is that the myocontrol is unstable whenever its prediction (in turn depending on the input data) displays an oscillatory behaviour; therefore, a Fast Fourier Transformation (FFT) was applied to the sEMG signals as well as to the predictions; the FFT coefficients were then reduced to one using Principal Component Analysis (PCA). Furthermore, a threshold was placed on the derivative of the inertial signals to determine the status of acceleration. The *i-LIMB* digit status was analysed using a derivative and a subsequent count of the zero-crossings, over a moving window of 0.5s. Lastly, FFT was applied to finger currents and reduced to three dimensions, again using PCA. "Leave-one-task-out" cross validation was applied to the extracted features to train the LDA (the observer was trained on all but one tasks and tested on the remaining tasks). This resulted in a 20-fold cross validation, since the user performed 20 tasks in total, including the repetitions of failed tasks.

RESULTS

The classifier showed an overall average accuracy of 76.71%. Since in this preliminary study only one subject was examined, no statistical or comparative analysis could be performed; still, qualitative inspection (an example is found in Figure 4) reveals that some of the features extracted from the available data uniformly match the *good* / *poor* performance, as well as the prediction of the observer evaluating the performance.

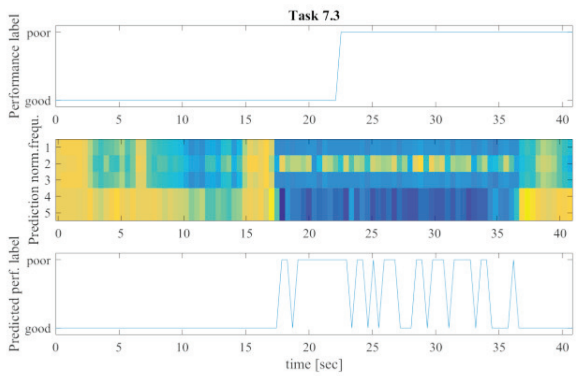

Figure 4: exemplary labels and features for task 7, 3rd trial: labels (top panel); features extracted from $\hat{y}$ (middle panel); labels predicted by the classifier (bottom panel).

Especially, as we expected, features somehow representing the degree of oscillation in the sEMG, prediction and motor current signals seems to match the *poor* performance. This is easily interpreted as the prediction system finding itself in an ambiguous situation (unexpected changes in the input signals, for instance).

More in detail, Table 2 shows the number of attempts performed, and the classifier accuracy, per each task.

Table 2: number of attempts and accuracy in the prediction of the classifier for each task.

Task#	Attempts	Accuracy (mean±std)
1	3	57,15% ± 28,14%
2	2	79,74% ± 13,46%
3	2	65,45% ± 25,59%
4	1	98,15%
5	3	80,67% ± 17,20%
6	1	97,10%
7	6	67,99% ± 16,13%
8	2	60,61% ± 3,85%
9	1	100%

DISCUSSION AND CONCLUSION

Discussion

To a large extent, *poor* performance of the myocontrol, as identified by the experimenter and/or the user, could be automatically identified in more than three quarters of the cases. This was obtained based on sensor information that is already present in advanced myoelectric control, with the exception that most systems lack an inertial sensor.

Arguably, we assume the reported accuracy of the observer is lower than the actual percentage. In Figure 4 one can see the manually labelled performance, the features of the prediction $\hat{y}$ and the labels predicted by the observer. From this figure one can see the delay of the experimenter in labelling the data. While the features and the observer already correctly label the performance as *poor*, there is a reaction time of the experimenter, who draws her/his conclusion based on visual information only.

Conclusion

This results makes us confident that having an observer of the myoelectric performance will provide information on the status of the prosthetic control and therefore allow the user to interact with the control and improve it where needed.

This is a first step towards a truly interactive prosthetic control, where the system can identify shortcomings of itself and ask the wearer for guidance. An example would be a ML-based myocontrol that has been training in a sitting position of the user, who then continues to manipulate objects on a high shelf. Due to changes in the muscular configuration the sEMG signals might be different form the training data and therefore result in a poor prediction. The system could recognise said poor performance and interact with the user to improve the myocontrol.

Postural variations have been identified as a source of poor performance [Fougner et al. (2012)] and to resolve this issues excessive training in different positions coving most of the assumed workspace of a prosthesis was applied to gather as much sEMG data as possible. But one can only train in so many positions. Our work has a similar goal, but the approach is fundamentally different. We only ask for a short initial round of calibration, which is only updated by new data upon demand. This reduces the initial training burden and provides the user with a highly interactive way of controlling her or his prosthesis.

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