Machine Learning for Advanced Electromyographic Prosthesis Control

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***Abstract*— We present our work on performing robust simultaneous proportional electromyographic control of a hand prosthesis with multiple degrees of freedom. Our approach is based on state-of-the-art machine learning using a sophisticated neural network. On an offline dataset, we achieve a reduction of the Mean Squared Error by almost 40%, online tests with prosthesis wearers are currently in progress.**

I. INTRODUCTION

Surface electromyographic (sEMG) signals have been considered for control of hand prostheses for decades (see e.g. [1]), and it has been shown that these signals allow to distinguish a large number of different movements for both able-bodied persons and amputees [2]. Yet, the vast majority of hand prostheses which are in practical use are much less versatile than laboratory results suggest to be possible, in particular, simultaneous and proportional control of multiple degrees of freedom (DOF) is typically impossible [3]. This goes along with the observation that commercially available prostheses mostly use rather simple algorithms for sEMG-based prosthesis control, e.g. a small number of sEMG channels is recorded, and signal energy thresholding is used to control a small number of functions.

We present our ongoing research on creating a robust and efficient system for real-time simultaneous control of a prosthesis with 4 DOF. We use a state-of-the-art *neural network* (see sections II and III) to directly perform simultaneous regression of up to seven movement commands (which translate to up to 4 DOF) without explicitly modelling the properties of the EMG signal. Here we report results using an *offline* system based on pre-recorded data. An *online* system is currently being tested on patients, see section IV.

II. MACHINE LEARNING & NEURAL NETWORKS

Machine Learning (ML) deals with automatically solving certain tasks without being given *explicit rules* describing the problem. Instead, the system *learns from examples*: In the *training* stage, the system receives samples of the given task and the desired solution as input; for evaluation, or for practical application, the trained system is then *tested* on *unseen* samples. For example, modern computer vision systems can distinguish hundreds to thousands of image categories [4] without any explicit description on what makes up a certain object: the system learns the correspondence between images and class labels solely from examples.

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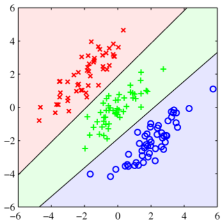

Fig. 1: Fitting straight lines to training data to solve a classification task (source: [5])

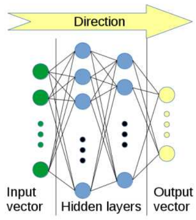

Fig. 2: Schematic diagram of a feedforward neural network

The ML system can be described as a function from the (vector) space of input samples into the output space, likewise represented as a vector space. This allows training algorithms based on fitting a function to the available data, like in figure 1. In contrast to naïve approaches which directly use the input samples, the fitted function can be evaluated efficiently, possibly meeting real-time application constraints, and (if suitably set up) it *generalizes* well, i.e. it works well on unseen data.

Among the variety of machine learning algorithms (see e.g. [5]), *Neural Networks* have recently gained huge popularity for many tasks, including biomedical signal processing. Neural networks perform a *distributed* computation of the mapping from input data to output hypothesis, using a large number of small units (called *neurons*). Each neuron is very simple, it just performs a weighted summation of its input data followed by a nonlinear transformation. The computational power of neural networks lies in the *weighting* of the connections between neurons; these connection weights are optimized during the training stage using the *backpropagation* algorithm [6]. The neurons are commonly organized in layers, as shown in figure 2.

III. SYSTEM, EXPERIMENTS & RESULTS

Data corpus The offline system is based on a dataset of 8-channel sEMG recordings of 11 able-bodied subjects performing seven common movements which are used in prosthesis control: Wrist Flexion/Extension, Wrist Pronation/Supination, Key Grip/Fine Pinch/Hand Open, plus a No Movement baseline. With a proportional control task in mind, these movements were performed in three different target strengths, namely at 30%, 60%, and 90% MVC (maximum voluntary contraction). Each single movement follows a trapezoid structure (1s increase, 3s hold with the target MVC, 1s decrease) Each subject recorded 15 recording sessions with varying electrode positions; each single recording session consists of 5 repetitions of the entire

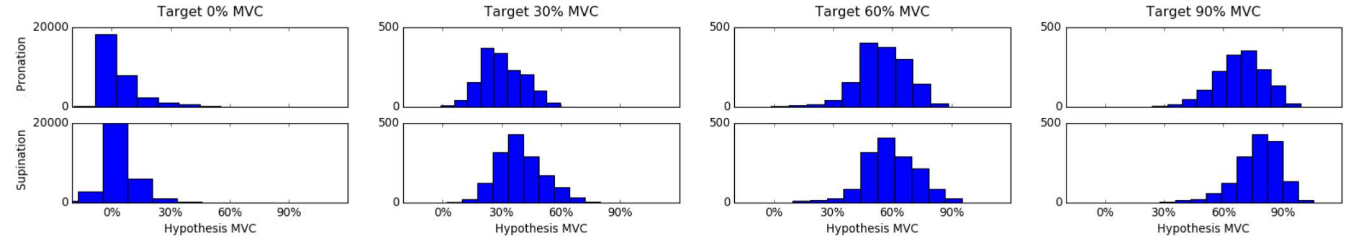

Fig. 3: Histograms of regression results for two complementary classes (subject 1, best neural network). Note that the histograms for 0%MVC also show values for all other movements

set of movements and strengths, i.e. of $5 \times 8 \times 3 = 120$ recordings. The total amount of data per subject is thus 1800 recordings (around 2.5h). The raw EMG data were preprocessed using the standard Hudgins features [7]. For increased exactness, we cut the movement onset and offset of each sample and retained only the part where the subject held the target MVC. Experiments were run *subject-dependently*. From each subject, 10 sessions were chosen for training the regression system, and the remaining 5 sessions were chosen for testing: thus the electrode positioning between recordings varies slightly, which reflects the intended practical usage.

Systems Many current systems for proportional prosthesis control use some sort of linear control scheme, either linear regressor, or a linear classifier (e.g. LDA [8]) combined with a separate estimator for the desired movement speed. In light of this, we use linear regression as our baseline, which is compared with a neural network with the following parameters: The network has two 100-dimensional hidden layers with a $\tanh$ nonlinearity, followed by the seven-dimensional linear output layer (corresponding to the possible movements). The output Mean Squared Error (averaged over all seven movements) is optimized using backpropagation with early stopping.

System	MSE	Correlation
Linear Regression	0.033	0.59
Neural Network	0.020	0.74

TABLE I: Mean Squared Error (MSE) and correlation between target and hypothesis for baseline linear regressor and neural network, on the test data

Results Table I shows the results of our experiments on the test data subset, averaged over all seven movements and all subjects. It is clear that the neural network is substantially better: The reduction of the mean squared error is almost 40% relative. We also computed the correlation between reference target and regressor hypothesis, as a means to quantify the most important parameter for practically controlling a prosthesis, again obtaining an improvement. Finally, figure 3 graphically shows the results of our regressor for a subset of two complementary movements, as a histogram depicting the target MVC (in columns) and the hypothesis, i.e. the output of our system. One sees that the movements are practically always correctly recognized, and that the target strength is quite well estimated. Note that the leftmost column shows the regression output for all other movements, indicating that there are few “false positives” (and that these can easily be removed with thresholding).

IV. CONCLUSION AND ONGOING WORK

We have reported first results on our ongoing work about state-of-the-art prosthesis control. Our current research deals with using these results in a challenging *online* scenario, in particular, in real-life situations with actual prosthesis users. For this purpose, we have developed an online system with the same set of movements and the same training procedure as the offline system. This system is currently undergoing first clinical tests, differences to the offline system described above include the translation of regressor results into movement commands, using versatile postprocessing for improved control. We note in particular that the training data (single muscle contractions) has very different properties from the data accrued in the test situation (real-life movements), a discrepancy which is well-known [9]. In the future, we expect that our neural network paradigm allows an improved training procedure which is closer to the intended usage.

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