Predicting Elbow Movement from Electromyography Data

Markus Vieth
Machine Learning Group
Bielefeld University
Bielefeld, Germany
mvieth@techfak.uni-bielefeld.de

I. Introduction

Electromyography (EMG) means to measure the electrical activity of muscles, which gives insight into their current state and condition. In medicine, EMG is established as a tool to diagnose various disorders. In the area of machine learning, EMG is e.g. also used to control actuated hand prostheses, by recognizing intended hand gestures [1]. In contrast to such a classification task, the prediction of continuous movement is less researched. Methods that have been proposed to predict continuous movement via EMG use e.g. a combination of convolutional and recurrent layers [2], [3], often in deep architectures, or simple statistical features [4].

II. Proposed Model

This work investigates the prediction of elbow movement. A dataset consisting of elbow movements recorded from 17 persons serves as a basis for experiments. During the movements, EMG measurements were conducted at 4 sensors on the upper arm, two on the biceps and two on the triceps. Additionally, the elbow angle was measured. The test subjects performed slow and fast movements, in three different arm poses (upper arm pointing down, pointing up, and held horizontally). The goal is to create a model that predicts the future trajectory of the elbow angle, online, using this dataset for training and verification. The model is desired to be interpretable and to allow insight into how each muscle influences the movement. It must be computationally inexpensive, so that it can run in real-time even on small hardware. Instead of a one-step prediction, the model should give the prediction as a Taylor polynomial of low order. This has the advantage that the polynomial can be evaluated at any time point, it can even give predictions hundreds of milliseconds in the future, albeit then with less accuracy. For example, a second order Taylor polynomial is described by:

$$f(a) + f'(a)(x - a) + 0.5f''(a)(x - a)^2 \tag{1}$$

Where f is the elbow angle, a is the current time, and x is any time of interest in the future. $f(a)$ is the (known) current angle, and $f'(a)$ and $f''(a)$, the angular velocity and acceleration, have to be estimated by the model.

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The proposed network architecture (fig. 1) has two stages: The first stage reconstructs the level of activity of the muscle or muscle parts from the raw EMG measurements, individually for each sensor. This is done with a convolution over the last 256 EMG measurements. The output function is a sigmoid, so that the activity is between 0 and 1. The second stage is a fully-connected layer which combines the four muscle activities with a gravity component. The gravity component reflects how strong and in which direction gravity acts on the forearm and hand, with regard to the elbow.

The performance of this proposed model is shown in fig. 2. It is visible that the general shape of the angular velocity is well predicted, but the magnitude, especially peaks, are often underestimated. Furthermore, the prediction contains some noise, likely carried over from the noisy EMG signals.

III. Future Work

The proposed model will be refined to give better predictions and then be compared to models introduced in other papers for similars tasks, e.g. [2], [3]. One question is whether the convolution weights should be the same for all sensors, or whether the weights should be learned individually. The latter could be appropriate because the different muscle parts might produce different electrical signals, which are influenced by layers of tissue and skin, but this could also reduce the ability of the model to generalize.

One major aspect to investigate is how the trained model can be transferred to another person. The two stage architecture may facilitate this.

References

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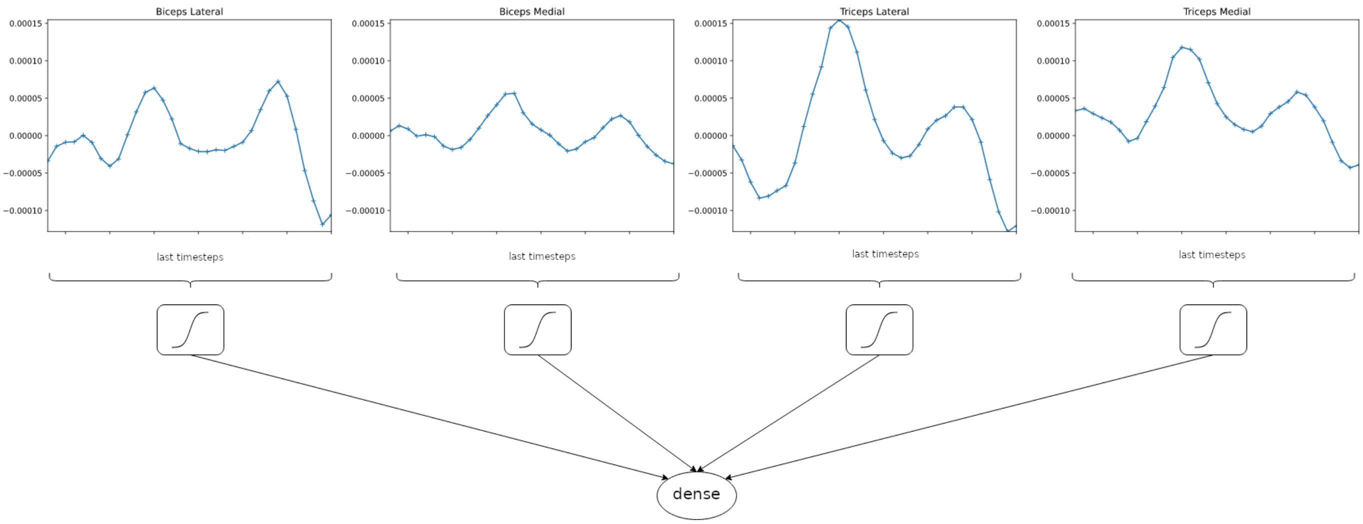

Fig. 1. The two stage architecture of the proposed model. The upper part shows the convolutional layer, activated by a sigmoid function. The lower part combines the four inputs in a fully-connected (dense) layer, together with a gravity component (not shown).

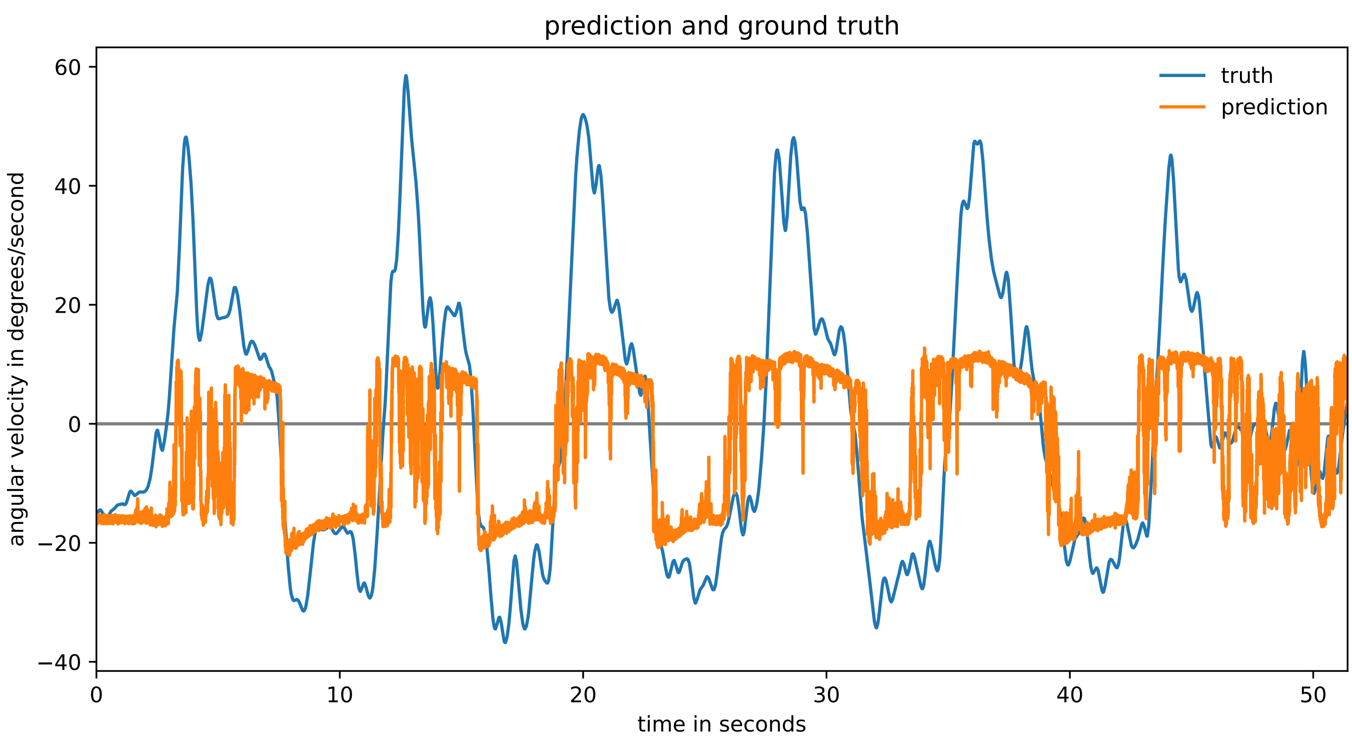

Fig. 2. Current performance of the network in predicting the angular velocity of the elbow.