

Estimating muscle excitations using a reduced sEMG array across a range of walking speeds

Reed D. Gurchiek
M-Sense Research Group
University of Vermont
Burlington, VT, USA
reed.gurchiek@uvm.edu

Anna T. Ursiny
M-Sense Research Group
University of Vermont
Burlington, VT, USA
anna.ursiny@uvm.edu

Ryan S. McGinnis
M-Sense Research Group
University of Vermont
Burlington, VT, USA
ryan.mcginis@uvm.edu

I. INTRODUCTION

Recent research has suggested the possibility of estimating a complete set of muscle excitations from a reduced number of surface electromyography (sEMG) sensors [1], [2]. An estimation method of this sort drastically improves the ability to deploy sEMG sensors to monitor free-living gait mechanics and could enable long-term tracking of muscle activity and joint mechanics important in a variety of clinical contexts (e.g., orthopedic rehabilitation, osteoarthritis). To this end, we recently proposed a novel Gaussian process regression-based solution to this problem (currently under review) and demonstrated its ability to accurately estimate muscle activity during walking. Here we extend the approach to estimating muscle activity during walking for gait speeds not used for model training.

II. METHODS

The sEMG (1000 Hz) of 10 muscles (TA: tibialis anterior, PL: peroneus longus, LG: lateral gastrocnemius, MG: medial gastrocnemius, SOL: soleus, VM: vastus medialis, RF: rectus femoris, VL: vastus lateralis, BF: biceps femoris, ST: semitendinosus), all from the right leg, were recorded from a single healthy female during self-selected slow (0.4 ± 0.03 m/s), normal (0.8 ± 0.03 m/s), and fast (1.2 ± 0.03 m/s) one-minute

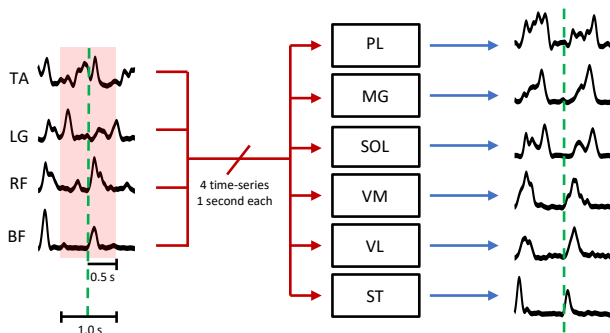


Fig. 1. Graphical representation of the estimation procedure. All sEMG data are high pass filtered at 30 Hz, rectified, low pass filtered at 6 Hz, normalized by the maximum value across trials, and downsampled to 250 Hz. One-second (250 samples) of sEMG data from each of four different muscles (red band) are input to each of six different, muscle-specific “synergy functions,” which map the four, one-second input time-series to the excitation value of the corresponding muscle at the time associated with the middle of the input window (green dashed line). Note that the output of each muscle-specific synergy function is a scalar.

walking trials. The proposed approach uses Gaussian process regression to learn muscle-specific functions which map one-second of sEMG data from each of the TA, LG, RF, and BF to the excitation value of the corresponding muscle at the instant of time associated with the middle of the one-second input time-series (see Fig. 1 for overview). Two experiments were designed to investigate estimation performance for gait speeds that were not used for model training. In the first experiment (interpolation), models were trained using data from the slow and fast walking trials and tested on data from the normal walking trial. In the second experiment (extrapolation), models were trained using data from the slow and normal walking trials and tested on data from the fast walking trial. Both models were also tested on unseen data for gait speeds that were represented in each training set. This served as a baseline for comparison against the extrapolation and interpolation results.

III. RESULTS & DISCUSSION

When estimating for walking speeds that were represented in the training data, the estimation performance across all muscles was best for fast walking, followed by slow and normal walking in terms of root mean square error (RMSE: 3.7%, 4.5%, and 5.9%, respectively) and the percentage of variance accounted for in the true sEMG signal by the estimate (VAF: 93%, 86%, and 75%, respectively). For the interpolation experiment, estimation for the normal walking trial resulted in a slight increase in RMSE (4.5% to 5.3%), and was able to explain 81% VAF. For the extrapolation experiment, the estimation for the fast walking trial nearly doubled the RMSE (3.7% to 7.3%), but it was still able to explain 71% VAF. Some apparent speed-dependent trends in estimation performance may be explained by the number of datapoints input for each predictor muscle and its relation to stride time. For example, an input window larger than one-second may be necessary to increase performance for slow walking speeds. Future research is necessary to understand how these errors influence estimation of other biomechanical variables (e.g. muscle force).

REFERENCES

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