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Prediction of EMG Activation Profiles from Gait Kinematics and Kinetics during Multiple Terrains

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Abstract— **Continuous myoelectric prediction of intended limb dynamics has the ability to provide transparent control of a prosthesis by the user. However, the impact on these models of adding a human user into the control loop is less clear. Here, the ability of a User Response Model (URM) to continuously predict EMG activity from gait kinematics and kinetics collected during three mobility tasks (level-ground walking, stair ascent, and stair descent) was examined. Multiple-input, multiple-output NARX-based URMs were developed with two outputs (ankle plantarflexor and dorsiflexor) and variable inputs (ankle kinetics, and shank and/or ankle kinematics). Accuracy in predicting the tibialis anterior and medial gastrocnemius EMG was comparable across URMs regardless of the number of inputs. Stair descent had the lowest accuracy among the mobility tasks. No significant differences in normalized root-mean-square error and cross-correlation were found between URMs with five and nine inputs. A URM that continuously predicts EMG activity from gait kinetics and kinematics could be used to simulate human-in-the-loop myoelectric control of a transtibial prosthesis and examine the stability of the system to changes in the environment or due to control errors.**

I. INTRODUCTION

Approximately fifteen percent of the world's population has a disability [1], with more than fifty million requiring an orthosis or a prosthesis [2]. Moreover, the number of people with lower-limb loss is predicted to increase substantially by 2050 due to chronic diseases [3]. To regain a certain level of functionality while executing different mobility tasks (e.g., walking at variable speeds, slopes, stair ambulation), lower limb amputees typically rely on mechanically passive prosthetic legs that do not provide the power needed to fully restore gait [4]. Powered prostheses commonly use finite state (discrete) impedance control to mimic human gait over specific intervals (e.g., loading response, swing) and achieve a more natural gait across mobility tasks by generating power at the joint [5], [6]. However, discrete control has limited modes and often does not deal with transitions between terrains [7]. To bring out the full potential of powered prostheses, a controller that continuously detects the user's movement intention is needed to provide sufficient time for the system to process the signal and actuate the prosthesis.

Feedforward (open-loop) nonlinear autoregressive model with exogenous inputs (NARX) can be used to predict prosthetic joint kinematics continuously (i.e., ankle angle) from natural residual muscle activity of transtibial amputees during treadmill walking [8]. In doing so, they have demonstrated the feasibility of an EMG-based model to predict intended ankle angle which can overcome delays in signal processing and actuation of the prosthesis to provide a more biomimetic response. Recent work has demonstrated the feasibility of using open-loop and closed-loop architectures to provide accurate and robust predictive continuous estimates of ankle kinematics and ankle kinetics during multiple mobility tasks (level-ground walking, stair ascent, and stair descent) [9], [10]. For real-time implementation a recurrent (closed-loop) NARX architecture is ultimately required to predict ankle dynamics based on the actual, rather than desired, state of the limb and prosthesis. While it is possible to simulate the forward stability of the closed-loop NARX model for predicting intended limb dynamics, the impact of adding a human user into the feedback control loop is less clear. In order to explore the impact of human-in-the-loop control, the objective in this study was to develop an inverse model capable of simulating the user's EMG in response to changes in ankle dynamics (e.g., control errors, terrain perturbations), referred to here as a user response model (URM). With a URM, human-in-the-loop interactions with a closed-loop NARX model can be tested to ensure stable prosthesis control before testing with an actual human user.

Recent studies have shown that it is possible to predict EMG profiles from various inputs (e.g., physiologic), supporting the feasibility of creating a URM. Gonzalez-Vargas et al. developed a muscle excitation profile (MEP) predictive model that used Gaussian-fitting and nonlinear regression to predict MEP during ramp ambulation based on speed and slope elevation for a desired locomotion condition and the baseline condition [11]. Contreras-Vidal and colleagues used an unscented Kalman filter to continuously predict the low-frequency EMG envelope during walking on multiple terrains from fluctuations in the amplitude of electroencephalography slow cortical potentials [12].

In this study, the feasibility of predicting EMG activity from gait kinematics and kinetics was investigated. A NARX-based URM was employed to predict the low-frequency envelope of tibialis anterior and medial gastrocnemius EMGs from kinetic (ankle moment) and kinematic (shank linear

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velocity and/or ankle angle) recordings across three mobility tasks (level-ground walking, stair ascent and stair descent).

II. Methods

Surface EMG, kinetic, and kinematic data were acquired previously from six healthy participants (S1-S6) as they performed three mobility tasks (level-ground walking, stair ascent, and stair descent). All participants gave written informed consent, and all procedures were approved by Marquette University Institutional Review Board in accordance with the Declaration of Helsinki. Methods for data acquisition and pre-processing relevant to the current study are outlined below. For additional details, see [9], [10].

A. Experimental Setup and Procedures

Each participant completed a minimum of 15 trials per mobility task. To decrease session length and reduce the possibility of fatigue, mobility tasks were not randomized. Participants walked along an instrumented walkway containing four 6-channel force plates (Advanced Mechanical Technology, Inc., Watertown, MA); two embedded in the floor, and two embedded in a modified 4-step instrumented staircase connected to a landing platform. During stair ascent trials, participants traversed the walkway at a self-selected speed, walked over the in-floor force plates, ascended the stairs in a step-over-step fashion, and walked to the end of the platform. Participants then turned, and when instructed, crossed the platform, descended the stairs, and walked across the in-floor force plates to finish at their stair ascent trial starting position (stair descent trial). During level-ground trials, the staircase and platform were removed, and participants walked the length of the walkway (~ 5 m) and over the in-floor force plates.

B. Data Processing

An OptiTrack motion capture system (NaturalPoint, Inc., Corvallis, OR) was used to record kinematic data at 120 Hz. Data from force plates were sampled at 1,200 Hz, low-pass (15 Hz, 4th-order Butterworth) and notch filtered (59-61 Hz, 4th-order Butterworth) to remove noise, and then down sampled at 120 Hz. Kinematic and kinetic data were processed using motion analysis software AMASS and Visual 3D (C-Motion, Inc., Germantown, MD). For each trial, ankle angle (sagittal, transverse, and coronal plane), shank linear velocity (anterior-posterior, medial-lateral and vertical direction), and ankle moment (sagittal, transverse and coronal plane; normalized to the participant's body mass) time series and gait events were extracted. Trigno^{TM} wireless electrodes (Delsys, Inc., Natick, MA) were used to record EMG activity from the tibialis anterior (dorsiflexor) and medial gastrocnemius (plantarflexor). EMG signals were sampled at 1200 Hz, differentially amplified (909 V/V), band-pass filtered (20-499.5 Hz, 4th-order Butterworth), full-wave rectified, and low-pass filtered (5.5 Hz, 4th-order Butterworth) to obtain the low-frequency linear envelope, and then down sampled to 120 Hz. Time series of all data trials (EMG, kinematics, and kinetics) were truncated to only include data between the times where force data were available and normalized as a percentage of trial length. As a result, level-ground trials contained one full gait cycle, and each stair ambulation trial contained three gait cycles including two staircase transitions (i.e., from level ground onto the staircase, and vice versa).

C. User Response Model (URM)

The URM was designed to continuously predict the time course of tibialis anterior and medial gastrocnemius EMG profiles across mobility tasks and their transitions. Specifically, a multiple-input multiple-output (MIMO) recurrent (closed-loop) NARX model was created, trained, and tested in MATLAB R2019b (MathWorks, Inc., Natick, MA) using the Deep Learning Toolbox. The NARX-based URM consisted of an input layer in which windowed inputs (ankle kinetics, and shank and/or ankle kinematics), were passed through tapped delay lines. The URM model outputs (EMG) were fed back through second set of tapped delay lines and fed (together with the inputs) to a nonlinear hidden layer. The hidden layer output was then fed to a linear output layer containing separate outputs for the predicted tibialis anterior and medial gastrocnemius EMG profiles (Fig. 1).

For each mobility task, eleven trials from a single lower limb were used for training and testing. A k-fold cross-validation strategy was used to train and test separate closed-loop networks for each participant. One trial of each mobility task was held back and used to separately test the model performance after training (novel test trials). Eighty percent of the remaining trials (8 complete trials/task) were grouped into contiguous blocks for training, and twenty percent (2 complete trials/task) were used for validation. For each fold of the cross-validation, twenty networks were generated using random initial weights and biases to improve generalization and avoid overfitting. The network with the best performance across mobility tasks was then selected as the fold's generalized network. Each model was trained and optimized to minimize the mean squared error between the experimentally measured muscle activity (targets) and the model predictions. Levenberg-Marquardt backpropagation with a maximum validation failure of 6, and a *tansig* function in the hidden layer were used for training.

Model performance was characterized as a function of the prediction interval (input delay, PI: 8.3, 41.5, 83.3, 124.8, 166 ms), and sampling window (SW: 8.3, 24.9, 41.5, 58.1, 83.3, 99.6, 124.8 ms) specified via the tapped delay lines, and the number of hidden units (N: 2 to 20 in steps of 2). Since performance was minimally affected by the model parameters, the sampling widow and the number of hidden units were fixed at 83.3 ms and 16 units, respectively, to minimize error and complexity. To take into account the delay

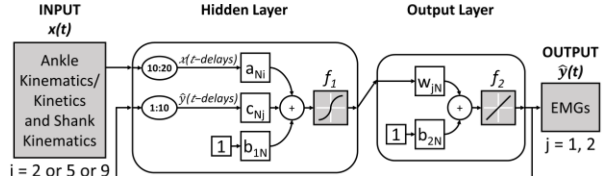

Figure 1. URM model based on a multiple-input multiple-output recurrent (closed-loop) NARX model.

between muscle activity and biomechanical response, the prediction interval (input delay of ankle and shank dynamics) was set to 83.3 ms (10-time steps), and the feedback delay (EMG estimates) was set to 8.3 ms (1-time step).

Several types of URMs were created that differed based on the number of inputs provided to the model. Two MIMO models incorporated ankle angle and ankle moment (sagittal plane) as inputs (2MIMO). Five MIMO models included three additional inputs (shank velocity in all directions) (5MIMO), and nine MIMO models also included ankle angle and moment in the frontal and transverse planes (9MIMO).

All performance measurements and statistical analysis were performed across participants using the novel test trials. Model performance was characterized using normalized root-mean-square error (NRMSE) and squared cross-correlation peak (R^2), calculated between the target and model prediction of each muscle activity. NRMSE was normalized by the range (maximum minus minimum) of the target trial. Separate three-way ANOVA (MATLAB R2019b) analyses were used to identify significant differences ($p<0.05$) in NRMSE and R^2 between MIMO models (2MIMO, 5MIMO, and 9MIMO), mobility tasks (level-ground walking, stair ascent, and stair descent), and muscles (tibialis anterior and medial gastrocnemius). Tukey's honest significant difference criterion ($p<0.05$) was used in all multiple comparison tests.

III. Results

Fig. 2 shows the time series of the target and 9MIMO URM prediction of the tibialis anterior and medial gastrocnemius of the novel test trials for the three mobility tasks (i.e., k-fold with the best performance) of a typical participant (S02). URM EMG predictions in response to changes in gait kinematics and kinetics closely matched the experimentally measured EMG activity for both the tibialis anterior and medial gastrocnemius. For S02, the tibialis anterior NRMSE and R^2 were 12.6±3.2% and 0.91±0.06, respectively, across mobility tasks. Similarly, the medial gastrocnemius NRMSE and R^2 were 11.0±1.2% and 0.92±0.05, respectively. The performance of each MIMO URM across participants is shown in Fig. 3 for each mobility task. The results indicate that EMG prediction was better for 5MIMO and 9MIMO models and was poorest for all models during stair descent.

Three-way ANOVA analysis revealed significant differences in NRMSE and R^2 with main effects of MIMO model (NRMSE: $F(2) = 8.76$, $p<<0.001$; R^2: $F(2) = 14.8$, $p<<0.001$), mobility task (NRMSE: $F(2) = 20.11$, $p<<0.001$; R^2: $F(2) = 67.99$, $p<<0.001$), and EMG (NRMSE: $F(1) = 21.78$, $p<<0.001$; R^2: $F(1) = 9.26$, $p<<0.01$). The performance (NRMSE and R^2) of the 2MIMO URM was significantly worse than the other models (Tukey's, $p<<0.01$), however, there was no significant difference between the 5MIMO and 9MIMO models. There was a significant interaction between EMG and mobility task for both NRMSE and R^2 (NRMSE: $F(2) = 5.49$, $p<<0.01$; R^2: $F(2) = 7.78$, $p<<0.001$). Multiple comparison tests of the tibialis anterior EMG revealed significant differences in NRMSE across mobility tasks (Tukey's, $p<0.05$), with larger errors during stair descent. URM predictions of the medial gastrocnemius had significantly less error (Tukey's, $p<<0.001$) and higher correlation (Tukey's, $p<<0.001$) than the tibialis anterior during stair descent. Both EMGs had significantly lower correlations during stair descent when compared to the other mobility tasks (Tukey's, $p<<0.01$).

IV. Discussion

The URM developed here demonstrates the feasibility of using an autoregressive model to continuously predict EMG activity across mobility tasks and their transitions using prior measurements of gait kinematics and kinetics. In doing so, the results take an important step toward simulating changes in a user's muscle activity (vis-à-vis EMG) that occur in response to changes in terrain and/or errors in intended ankle dynamics. The NARX-based URM model's predictive capability, coupled with its closed-loop architecture, and the use of signals intrinsic to the prosthesis offer an advantage over previous studies [11], [12] for the prediction of EMG activity.

Ankle angle and moment are common targets for the control of powered transtibial prostheses [6]. Often these systems actuate primarily ankle dorsiflexion and plantarflexion, which can be accurately predicted by residual antagonistic muscle activity responsible for sagittal ankle

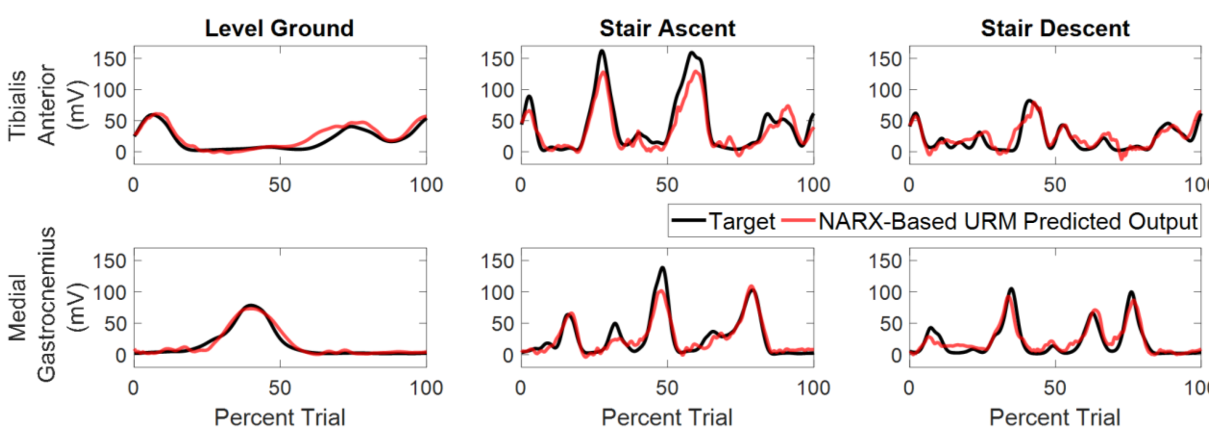

Figure 2. Time series of EMG predictions for level-ground walking, and stair ambulation of a typical participant (S02) (Model: 9MIMO; Parameters: prediction interval = 83.3 ms, feedback delay = 8.3 ms. sample window = 83.3 ms. size of the hidden layer = 16 units). URM predictions are shown for the novel test trials across mobility tasks (i.e., k-fold with the best performance).

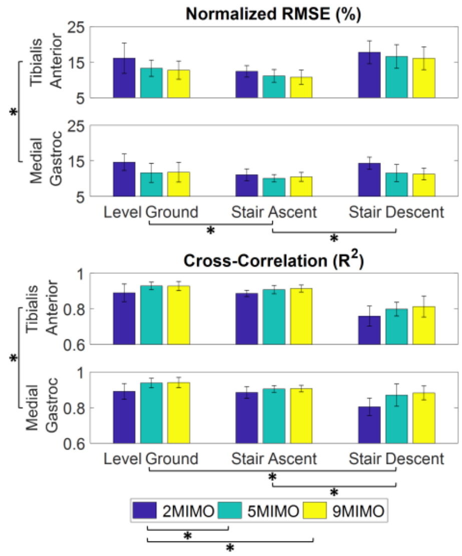

Figure 3. Mean NRMSE and R^2 values of each MIMO URM. Asterisks denote significant main effects of EMGs, model number of inputs, and mobility task (Tukey's, $p<<0.01$). Error bars denote ±1 standard deviation.

movement. Similarly, shank velocities can be measured from intrinsic sensors in the prosthesis, making them readily available as inputs for a URM to simulate human-in-the-loop control. In the simulations reported here, URM performance significantly improved with the addition of shank velocities (5MIMO), and ankle angle and moment outside of the sagittal plane (9MIMO). The comparable levels of performance between 5MIMO and 9MIMO models suggest that shank velocity provided an important source of information about limb state that was used to differentiate the temporal profiles of EMG activity across mobility tasks.

EMG prediction was poorest during stair descent, due in part to the increased variability in plantarflexion caused by a lack of kinematic constraints on ankle angle as the foot moved downward from one step to the next. While the prediction of tibialis anterior activity had significantly higher error and lower correlation than the medial gastrocnemius, there was no significant interaction between the number of model inputs and either the muscle being predicted or the mobility task. Thus, for a given URM (e.g., 5MIMO), predictions of tibialis anterior and the medial gastrocnemius activity were comparable across mobility tasks.

In comparison to Kalman filters and MEP models, the NARX-based URM provided better predictions of continuous EMG profiles. EEG-based Kalman filters had a median correlation (r) of 0.4 for the medial gastrocnemius while walking in five terrains (level, stair and ramp ascent, and stair and ramp descent) [12]. The URMs tested here had comparable or higher average correlations than MEP predictive models ($r = 0.88$), although it is important to note that the MEP was evaluated as a single model that was generalized across participants [11].

While separate URMs were trained for each participant to assess the feasibility of predicting individual user responses for simulating human-in-the-loop control of a NARX-driven prosthesis, it is important to note that the same URM model architecture (prediction interval, feedback delay, sampling window, and hidden layer size) was employed across participants. URM performance could further be improved by optimizing the model architecture to maximize within-subject prediction of EMG in response to changes in gait.

Despite the robustness of the URM model, the absence of pathological muscle activity and corrective responses to external errors are limiting factors in the study. URM performance when predicting EMG from the residual muscles of amputees will be assessed in future studies to account for individual differences in amputee muscle responses that are no longer explicitly tied to gait biomechanics. Prediction of EMG activity in response to external perturbations will also be needed to explicitly model EMG corrective actions in response to perceived errors during gait. Future work incorporating these features will need to determine the required level of model performance to simulate the stability of the interaction between the human-in-the-loop model and the closed-loop myoelectric control of a physical system.

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