Closed-Loop Future Prediction of Continuous Ankle Kinematics and Kinetics Using Residual Muscle Signals of Transtibial Amputees

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Abstract

Background

Despite performance improvements in active lower limb prostheses, there remains a need for control techniques that incorporate direct user intent (e.g., myoelectric control) to limit the physical and cognitive demands and provide continuous, natural gait across terrains.

Methods

The ability of a nonlinear autoregressive neural network with exogenous inputs (NARX) to continuously predict future (up to 142 ms ahead of time) ankle angle and moment of three transtibial amputees was examined across ambulation conditions (level overground walking, stair ascent, and stair descent) and terrain transitions. Within-socket residual EMG of the prosthetic side, in conjunction with sound-limb shank velocity, were used as inputs to the single-network NARX model to predict sound-limb ankle dynamics. By overlaying the ankle dynamics of the sound limb onto the prosthesis, the approach is a step forward to establish a more normal gait by creating symmetric gait patterns. The NARX model was trained and tested as a closed-loop network (model predictions fed back as recurrent inputs, rather than error-free targets) to ensure accuracy and stability when implemented in a feedback control system.

Results

Ankle angle and moment predictions of amputee models were accurate across ambulation conditions and terrain transitions with root-mean-square errors (RMSE) less than 3.7 degrees and 0.22 Nm/kg, respectively, and cross-correlations (R2) greater than 0.89 and 0.93, respectively, for predictions 58 ms ahead of time. The closed-loop NARX model had similar performance when characterizing normal ranges of ankle dynamics across able-bodied participants (n = 6; $RMSE_\theta < 2.7^\circ$, $R^2_\theta > 0.95$, $RMSE_M < 0.11$ Nm/kg, $R^2_M > 0.98$ for predictions 58 ms ahead of time). Model performance was stable across a range of different EMG profiles, leveraging both EMG and shank velocity inputs for the prediction of ankle dynamics across ambulation conditions.

Conclusions

The use of natural, yet altered in amputees, muscle activity with information about limb state, coupled with the closed-loop predictive design, could provide intuitive user-driven and robust control by counteracting delays and proactively modifying gait in response to observed changes in terrain. The model takes an important step toward continuous real-time feedback control of active ankle-foot prostheses and robotic devices.
Background

Advances in robotic systems and human interface design have facilitated the development of rehabilitation devices, exoskeletons, and limb prostheses, including state-of-the-art active ankle-foot prostheses [1–7]. For successful rehabilitation of lower limb amputees, prostheses seek to mimic the biomechanical patterns of gait that occur during daily living activities. In spite of these advancements, most lower limb amputees develop altered muscle activity and biomechanical patterns of gait to maintain stability and compensate for limitations in the prosthesis [8–11]. Despite performance improvements in active (i.e., able to generate power during propulsion) lower limb prostheses over passive designs, there remains a need for robust and accurate control techniques that incorporate user intent to limit physical and cognitive demands and provide a more natural gait across terrains (e.g., level ground, stairs, ramps) and environmental conditions.

Controllers for active lower limb prostheses range from closed-loop finite state machines (FSMs) driven by electromechanical sensors intrinsic to the prosthesis (e.g., inertial sensors, position encoders) [1–5], to continuous proportional myoelectric control [12–16], as well as hybrid strategies combining electromechanical and myoelectric signals [17–22]. FSMs using intrinsic prosthetic sensors have been widely used to control active ankle-foot prostheses [1–5]. However, robust control is constrained to a number of predefined locomotion modes. User intention is deduced indirectly by prosthetic sensors and/or requires the amputee to intentionally switch between modes based on anticipated changes in terrain. Consequently, the system has a limited ability to deal with novel movements and noncyclic activities whereas intentional switching may increase physical and cognitive load on the user, particularly in complex environments [23, 24].

Continuous control approaches using intrinsic prosthetic sensors to unify the gait cycle have also been explored. Joint phase-based methods have been developed to control ankle-foot and multi-joint leg prostheses using shank and hip kinematics, respectively [25–27]. Phase-based approaches can accommodate speed changes of cyclic motion (e.g., walking at different speeds), however, they have limitations for noncyclic and novel movements in which phase planes are not well-defined. Discrete and continuous approaches designed around intrinsic prosthetic sensors provide high fidelity feedback about past limb state but are generally reactive (rather than predictive) to gait and environmental changes, and can introduce undesirable delays in the actuation of the prosthesis. In spite of their higher signal variability, surface electromyography (EMG) signals have been widely examined as an alternate, minimally-invasive source of control signals that incorporate direct user intent about intended movement and upcoming changes in terrain.

Hybrid state-based myoelectric approaches have used EMG signals within the prosthetic socket to select discrete locomotion modes [17–19], or to modify prosthetic behavior within a state (e.g., motor torque gain) [20–22]. EMG-driven FSMs can improve flexibility, allowing amputees to transverse different terrains and adapt to different walking speeds. However, control may not be intuitive, requiring the user to learn novel muscle activation patterns, and remains constrained to the control of predefined locomotion modes.
modes, limiting the amputee’s control over the prosthesis. Continuous proportional myoelectric control (CPMC) does not rely on a FSM, but instead allows the amputee to actuate the prosthesis based on the amplitude of residual muscle activity. Residual antagonistic muscles of a single transfemoral amputee have been used to continuously modulate impedance of an active knee prosthesis during level ground walking [13, 14]. Using CPMC, transtibial amputees were able to control a virtual environment via their residual ankle dorsiflexor and plantarflexor muscles [15, 16], and control an active ankle-foot prosthesis via a single ankle plantarflexor muscle during level treadmill walking [12]. CPMC, especially for impedance control, is a promising approach; however, it can require extensive user training, increase cognitive processing, and can be affected by muscle fatigue.

Many methods to estimate joint dynamics continuously have been proposed to eliminate the need for a discrete state-based control, and in the case of myoelectric control, to reduce user’s cognitive and physical demands and to eliminate the need for high quality, independent muscle signals. EMG signals, ground reaction forces, and hip, knee, and shank dynamics have been used as inputs to continuously estimate (i.e., one-step-ahead estimate) [28–35] and predict (i.e., n-step-ahead estimate) [36–38] ankle kinematics and kinetics. These continuous gait models have proven successful, however, they typically focus on using muscle activity of healthy individuals to estimate ankle angle or moment during a single type of terrain (e.g., level walking).

Autoregressive models, such as nonlinear autoregressive neural network with exogenous (i.e., external) inputs (NARX), have been shown to work well for continuous myoelectric estimation/prediction of limb dynamics [35–37, 39]. The NARX model can be trained in an open-loop mode (feedforward structure; error-free targets as inputs) or closed-loop mode (recurrent structure; model output estimates fed back as recurrent inputs). In previous work, EMG-driven feedforward (open-loop) NARX models have demonstrated the feasibility of continuously predicting future intended prosthetic ankle angle during level treadmill walking using within-socket residual surface EMG of transtibial amputees [36], and ankle angle and moment across ambulation conditions (i.e., level overground walking, stair ascent, and stair descent) in healthy individuals [37]. However, the accuracy and stability of the open-loop NARX model cannot be guaranteed when implemented in a feedback control system [40, 41], commonly used for actuating ankle-foot prostheses. Explicit training as a recurrent (closed-loop) NARX model can overcome these shortcomings. Closed-loop model performance tends to be inferior [40] but model accuracy can be improved by incorporating additional input signals [28–30, 35].

The combination of direct user intent, via EMG signals, and information about limb state, via electromechanical sensor signals, can increase the robustness and accuracy of locomotion mode detection [42–44] and continuous estimation of lower limb kinematics [35, 45]. EMG and kinematic analyses suggest that timing in the local patterns of EMG activity is a key discriminant of gait while traversing different types of terrains [46–48]. The integration of EMG signals with information about limb state in a continuous predictive model of gait would provide intuitive and robust prosthetic control by counteracting delays (e.g., sensing, signal processing, and actuation), and proactively modifying gait in response to unexpected perturbations and upcoming changes in terrain.
The purpose of this study was to determine whether within-socket residual EMG of transtibial amputees could be used to continuously predict future ankle kinematics and kinetics across ambulation conditions including transitions between terrains (i.e., transitions to/from a staircase). Unlike previous approaches [36, 37], here a recurrent (closed-loop) NARX model was used to predict future ankle angle and ankle moment of the sound limb using residual EMG of the prosthetic side, in conjunction with shank kinematics of the sound limb. By overlaying the ankle dynamics of the sound limb onto the prosthesis, the approach takes an important step toward establishing a more normal gait by creating symmetric gait patterns between the limbs. Prediction variability was statistically analyzed at critical points where excessive deviations in model prediction could lead to falls or injury during prosthetic control. Model performance and EMG contribution to model prediction in amputees were compared to models of able-bodied participants as best case characterization of normal gait patterns.

Methods

Participants

Three male unilateral transtibial amputees (TTA) (age = 52.9 ± 6.2; with experimental prosthesis donned: mass = 90.9 ± 26.3 kg and height = 1.78 ± 0.08 m; time since amputation = 11.6 ± 4.8 years) and six able-bodied, healthy young adults (AB) (3 females; age = 21.7 ± 1.8; mass = 69.0 ± 9.0 kg; height = 1.77 ± 0.10 m) participated in the study (Additional file 1: Supplementary Table 1). For both groups, participants were excluded if they presented a neurologic or orthopedic impairment (other than amputation for TTAs) that would affect their ability to walk or follow instructions. All amputees were K3-K4 ambulators (e.g., variable cadence, community ambulator, independent ambulation without assistive devices), and two actively participated in sports activities. All amputees used energy-storing-and-returning feet with a pin-lock gel liner suspension system, and had volitional control of their remnant ankle flexors and extensors with stable residual volume. The study was approved by the Institutional Review Board at Marquette University (Milwaukee, Wisconsin, United States) and all participants provided written informed consent prior to participation.

Electrode-Socket Integration

A plastic electrode-housing test socket and a modified pin-lock gel liner were designed to integrate wireless surface EMG electrodes and allow the acquisition of EMG signals within the prosthetic socket of amputee participants. Prior to participation in the experimental session, each transtibial amputee was evaluated by a certified prosthetist to assess the amputee's ability to independently control their residual tibialis anterior and gastrocnemius medialis and lateralis muscles, and to identify the three muscle sites for recording within socket (the gastrocnemius lateralis site was not used in this study). Amputees were instructed to "point up or down" the toes of their phantom limb. Muscle sites were then palpated, verified with a MyoBoy® (Ottobock, Duderstadt, Germany), and marked on the skin. After amputees donned a gel liner, molds of a Trigno™ wireless surface EMG electrode (Delsys, Inc., Natick, MA, United States) were placed inside the liner at the identified sites and marked on the liner's exterior surface. The marked liner
was used by the prosthetist to transfer the desired electrode locations to a duplicate socket mold which was used to fabricate an individualized test socket for each amputee (Fig. 1A). At each electrode site, the test socket contained openings with protruding walls sized to the thickness of the Trigno electrode, to provide reliefs that enhanced comfort and minimized electrode motion during ambulation. Similarly, the electrode locations in the marked liner were cut out to produce a small aperture for the electrode to make contact with the skin.

At the beginning and end of the experimental session, a certified prosthetist replaced the amputee's original socket with the duplicate electrode-housing test socket, and vice versa, and verified alignment. The test socket was mounted to the amputee's current prosthetic pylon and ankle-foot, and electrode sites were marked on their residual limb. Electrodes were then secured on the residual limb and the modified liner was donned. Electrodes were adjusted to fit properly through the liner holes and EMG signal quality was verified. A prosthetic shrinker was used to apply compression and facilitate donning of the socket. After the donning procedure was completed, the amputee was asked to walk to verify comfort and alignment of the test prosthesis.

**Experimental Procedure**

Participants ambulated at a comfortable, self-selected speed wearing athletic shoes, in three different ambulation conditions, level overground walking (LW), stair ascent (AS), and stair descent (DS). Ambulation conditions were not randomized to minimize set-up time and session duration. The walkway was instrumented with four 3-dimensional 6-channel force plates (Advanced Mechanical Technology, Inc., Watertown, MA, United States), two embedded in the floor, and two built-in under a modified 4-step (60.5 cm width x 17.8 cm rise x 29.1 cm run; 1st step: 46.3 cm width, 26.5 cm run) staircase (Advanced Mechanical Technology, Inc., Watertown, MA, United States) connected to a landing platform (1.22 x 0.91 m) (Fig. 1C). Prior to data collection, participants walked on the walkway to get accustomed to the staircase setup and task instructions. First, participants traversed the walkway (~ 3 m), ascended the stairs in a step-over-step fashion, and walked to the end of the platform (stair ascent trial). When instructed, they walked the platform, descended the stairs step-over-step, and returned to their starting position on level ground (stair descent trial). During stair ambulation, amputees had access to handrails for support and protection, however, their use was minimal. For level ground walking trials, the staircase and landing platform were removed, and participants walked the entire length of the walkway (~ 5 m). Participants completed a minimum of fifteen trials per ambulation condition. Breaks were encouraged to reduce risk of fatigue.

**Data Acquisition and Signal Processing**

Surface EMG activity, kinematic, and kinetic data were collected and synchronized. Trigno™ wireless surface EMG electrodes were placed on clean skin, bilaterally over the tibialis anterior (dorsiexor) and the gastrocnemius medialis (plantarflexor) of able-bodied participants. EMG electrode placement on amputees was performed as described previously (2.2 Electrode-Socket Integration). Surface EMG recordings were sampled at 1,200 Hz, differentially amplified (909 V/V), filtered and rectified to obtain the
linear envelope (band-pass filter: 4th order zero-phase Butterworth at 20-499.5 Hz, full-wave rectified, low-pass filter: 4th order zero-phase Butterworth at 5.5 Hz), and down sampled to 120 Hz. The band-pass filter removed potential within-socket motion artifacts below 20 Hz similar to Hefferman et al. [49]. Kinetic data was sampled at 1,200 Hz, low-pass (4th order zero-phase Butterworth at 15 Hz) and notch (4th order zero-phase Butterworth at 59–61 Hz) filtered, and down sampled to 120 Hz. Seven lower body segments (pelvis, thighs, shanks, feet) were defined based on a modified Helen Hayes marker set using twenty-five reflective markers placed on the participant’s key anatomical landmarks (posterior superior iliac spine and bilaterally on the anterior superior iliac spine, greater trochanters, thighs, medial and lateral femoral condyles, shanks, medial and lateral malleoli, calcaneus, second and fifth metatarsal heads, anterior end of first distal phalanx) (Fig. 1B). Marker locations on the prosthetic limb were approximated based on the sound-limb locations for amputees. Anthropometric measures (height and weight) were taken. Kinematic data were sampled at 120 Hz using an OptiTrack (NaturalPoint, Inc., Corvallis, OR, United States) motion capture system (14 to 16 Flex 13 cameras). AMASS and Visual 3D (C-Motion, Inc., Germantown, MD, United States) were used to extract limb kinematic (shank velocities and sagittal ankle angle) and foot kinetic (sagittal ankle moment, normalized to participant’s body mass) time series and gait events. Pre-processing of kinematic and kinetic time series are explained in detail in previous work [37]. Shank segment center of mass linear velocity was obtained in three axes (sagittal, longitudinal, and frontal) relative to the global coordinate system using the finite difference method [50]. The sagittal axis was defined along the anterior-posterior (AP) direction, the longitudinal axis in the vertical direction, and the frontal axis in the medial-lateral (ML) direction.

All trials were truncated and temporally normalized from 225 ms before the first foot contact on the first force plate to the first foot contact before contralateral toe off on the last force plate (percent trial). Consequently, the level walking trial consisted of one gait cycle, and each stair ambulation trial consisted of three continuous gait cycles including two staircase transitions, as participants traversed from level walking to stair stepping to level walking (Fig. 1D), as detailed in previous work [37]. To overlay the dynamics of the sound limb onto the prosthetic limb to restore symmetric gait using residual EMG, kinematic (ankle angle, shank velocities) and kinetic (ankle moment) trials of the sound limb were temporally aligned with within-socket residual EMG trials of the prosthetic limb to create the dataset for model training and testing. EMG gait cycles of the prosthetic limb (trail limb) were interpolated (piece cubic spline) within a gait cycle to correspond with the length of the gait cycles of the sound limb (lead limb). This method is referred as contralateral gait-cycle alignment (Fig. 1D). Similarly, an additional dataset for able-bodied participants was created where EMG signals of the contralateral limb were aligned and interpolated to the gait cycles of the limb used to train the model (i.e., ankle kinematic and kinetic predictions). EMG of this dataset is referred as contralateral EMG and the participants as \( AB_{cEMG} \).

**NARX Model**

A model of future lower limb state was developed to continuously predict (i.e., future estimates) ankle kinematics and kinetics of the sound limb of transtibial amputees, across ambulation conditions and terrain transitions. Specifically, a recurrent (closed-loop) multiple-input multiple-output NARX model [51,
was created, trained, and tested using the Neural Network Toolbox in MATLAB (R2017a, The MathWorks Inc., Natick, MA, United States). The NARX model consisted of an input layer containing windowed time series of five exogenous inputs and two feedback model outputs (i.e., as recurrent inputs) fed via separate tapped delay lines to a single hidden layer containing nonlinear units. The exogenous inputs consisted of the within-socket residual EMG linear envelopes of the ankle dorsiflexor and plantarflexor and the 3-axis shank velocities of the sound limb. The recurrent inputs corresponded to the prior predictions of the sagittal ankle angle and ankle moment of the sound limb fed back from the model output. The hidden layer output was then fed to a linear output layer containing separate outputs of the predicted ankle angle and moment of the sound limb (Fig. 2).

The prediction of the recurrent (closed-loop) NARX model output, \( \hat{y}_j(t+m) \), at each time point was calculated by the following equations,

\[
v_n(t + m) = f_1 \left( \sum_{q=0}^{d} \sum_{i=1}^{5} a_{ni}(q) x_i(t - q) - \sum_{q=1}^{d} \sum_{j=1}^{2} c_{nj}(q) \hat{y}_j(t - q) + b_{1n} \right),
\]

\[
n = 1, 2, \ldots, N
\]

\[
\hat{y}_j(t + m) = f_2 \left( \sum_{n=1}^{N} w_{jn} v_n(t + m) + b_{2j} \right),
\]

\[
j = 1, 2
\]

where \( v_n(t + m) \) is the output of \( n \)th unit in the hidden layer, \( N \) is the size of the hidden layer, \( d \) is the sampling window length in time steps \( (D = d\Delta t) \), \( m \) is the prediction interval in time steps \( (\tau = m\Delta t) \), \( x_i(t-q) \) is the \( i \)th exogenous input (EMG linear envelopes or shank velocities) for the prior \( q \) time step, \( \hat{y}_j(t-q) \) is the prior prediction of the \( j \)th output (ankle angle or moment), \( a_{ni}, c_{nj} \) and \( w_{jn} \) are the weights of EMG and shank velocity inputs, feedback outputs, and model outputs, respectively, \( b_{1n} \) and \( b_{2j} \) are the bias weights of the \( n \)th hidden unit and \( j \)th output unit respectively, \( f_1 \) is a nonlinear hyperbolic tangent sigmoid function, and \( f_2 \) is a linear function with unit slope. The prediction interval specified the time relative to the current time step for which future ankle angle and moment were calculated. The length of the sampling window specified the number of prior inputs (exogenous and recurrent) used to predict future ankle angle and moment.

Additional to the amputee models, two NARX models were created using the same set of able-bodied participants (AB model and AB\(_{cEMG} \) model). AB models used inputs (EMG and shank velocities) and outputs (ankle angle and moment) of the same limb (i.e., limb used to train the model), whereas AB\(_{cEMG} \) models
models used the aligned contralateral EMG as the EMG input. AB and AB_{cEMG} NARX models served as control models (1) to determine the ability of a single-network, closed-loop model to continuously predict normal ranges of ankle dynamics associated with healthy ambulation, (2) for a normative comparison of amputee model performance, (3) to determine if using contralateral EMG as inputs was a viable approach, and (4) to determine the influence of the contralateral gait-cycle alignment on model performance.

To sample model parameter ranges relevant for the optimization of the model [37], NARX model performance was characterized as a function of prediction interval ($\tau$: 8, 58, 142 ms), sampling window ($D$: 17, 42, 83 ms), and number of hidden units ($N$: 16, 30, 50) using a leave-one-out 10-fold cross-validation procedure. The model was optimized using a supervised learning procedure to minimize the mean squared error (MSE) between the experimentally measured ankle angle and moment (targets) and the model predictions where angle and moment errors were fitted equally. For each participant, all trials were randomized and ten separate model fits, with randomized initial weights, were trained with ten trials of each ambulation condition (80% used for training, 20% for validation). Training trials were organized as concurrent set of sequences and divided into contiguous blocks to avoid discontinuities in the data that would cause inherent training errors, and to ensure that random trials, instead of random points, were used during training. One trial of each ambulation condition was held back (novel test trial) to avoid overfitting and to separately assess model performance after training. All networks were trained and tested in a closed-loop mode whereby model predictions of ankle angle and moment from the output layer were fed back as recurrent inputs rather than the experimentally measured targets. From the ten model fits, the generalized network for that k-fold dataset was determined by the model with the lowest MSE averaged across novel test trials and ambulation conditions. The procedures used for training and testing are explained in detail in previous work [37]. The prediction interval was chosen to be 58 ms (7 time steps) to counteract electromechanical inherent delays (max. 50 ms) of the Marquette University’s active ankle-foot prosthesis [1, 53, 54]. The optimal sampling window and number of hidden units were determined by the network with the minimum MSE averaged over the ten novel test trials of the stair descent condition. Model performance after training was evaluated using this optimized subject-specific network structure to characterize maximal performance for each participant. For each able-bodied participant, optimal sampling window and number of hidden units were selected for each AB and AB_{cEMG} model.

**Model Performance Measurements and Statistical Analysis**

All performance measurements and statistical analyses were averaged across ten novel test trials for each ambulation condition and model output (ankle angle and moment), individually for amputees and averaged across able-bodied participants (AB group and AB_{cEMG} group), unless otherwise specified.

Coefficient of determination ($R^2$; obtained from squaring the cross-correlation peak) and root-mean-square error (RMSE) were calculated between the model prediction and the experimentally measured target of ankle angle and moment to characterize model performance. $R^2$ and time lags were used to
quantify the model ability to reproduce angle and moment profiles and to identify temporal offsets in the model prediction for each ambulation conditions and their transitions.

The effects of prediction interval, sampling window, and number of hidden units on model performance were examined using the average RMSE collapsed along a single dimension (i.e., RMSE averaged across two of the three model parameters). RMSE was averaged across participants for each participant group (TTA, AB, and AB\textsubscript{CEMG}). RMSE was also computed using the optimal subject-specific model parameters, individually for amputees, and averaged across participants for able-bodied groups. Model performance was further investigated by analyzing changes in RMSE distribution within the gait cycles of the ambulation conditions. Each gait cycle was divided into the standard seven gait periods based on gait events [55]: loading response (initial foot contact to contralateral toe off), mid-stance (1–50% of single-limb support), terminal stance (50–100% of single-limb support), pre-swing (contralateral initial foot contact to toe off), initial swing, mid-swing, and terminal swing. The three swing periods represented one-third of the swing phase. RMSE was then computed within each gait period and then averaged across trials.

To evaluate the impact of EMG signals on model prediction, the sum of weighed inputs (SWI) was calculated for each exogenous input using the novel test trials and the trained weights from the input to the hidden layer. The SWI of the $i^{th}$ input, was calculated as,

$$SWI(i, t) = rms\left(\sum_{q=0}^{d} a_{ni}(q) x_i(t - q)\right)_{N},$$

$$n = 1, 2, \ldots, N$$

where for each time step, the windowed input is multiplied by the associated hidden-layer weights, $a_{ni}$, and summed across the sampling window to quantify the strength of the $i^{th}$ input to each hidden unit. The root mean square (rms) was then computed across hidden units to characterize the total contribution of the $i^{th}$ input to the model prediction throughout the trial. SWI was averaged over time and across trials for each ambulation condition to quantify the overall contribution of each input. Similar to the analysis of the RMSE distribution within ambulation conditions, the SWI distribution of the inputs (ankle dorsiflexor and plantarflexor EMG and AP shank velocity) were analyzed within the gait cycles for each ambulation condition (gait cycle 2 for stair ambulation). The SWI over time of each gait cycle was divided into the seven gait periods and then averaged across trials.

Several critical performance points, clearance intervals [56] and stance critical points [57, 58], were selected from literature to verify that the NARX model predictions where within the variability of the targets of each participant at those locations. Leg dynamics of Loverro's et al. staircase steps were matched to the stair steps of this study, and clearance intervals were identified, corresponding to the
minimum foot and toe clearance with the highest tripping risk during normal gait [56]. For each clearance interval, three critical points were identified corresponding to the range of timings of the minimum clearance angle (mean ± standard deviation, i.e., 30 total points). Crucial kinematic (toe off, maximum dorsiflexion, maximum plantarflexion) and kinetic (maximum plantarflexion moment) events for prosthetic design were defined as single stance critical points (i.e., 19 points). For each participant, a paired-samples t-test was performed for each critical point to determine whether NARX model predictions were statistically different from experimentally measured targets across trials. If the Shapiro-Wilk normality test failed, a nonparametric sign test was performed instead. SPSS 22 (SPSS Inc., Chicago, IL, United States) was used for all statistical analyses with a significance level of \( p < 0.05 \). For each participant, the \( p \) values of the critical points (i.e., 49 total points) were adjusted for multiple comparisons using the Benjamini-Hochberg (B-H) procedure with a false discovery rate of 0.05 [59].

Results

Aligned experimentally measured shank linear velocities, ankle angle and ankle moment of the sound limb, and residual ankle dorsiflexor and plantarflexor EMG used during training and testing are shown for an amputee (TTA3, most active amputee) in Fig. 3. Experimental data of the remaining amputees and a typical able-bodied participant (AB3) are provided in the Additional file 1 (Additional file 1: Supplementary Figs. 1–3). All amputees were able to activate both muscles with voluntary sustained contractions. Within-socket residual and able-bodied EMG activation patterns were consistent across trials for each ambulation condition; however, residual EMG showed different temporal profiles among amputees and in comparison to able-bodied participants. EMG activity within the prosthetic socket exhibited different levels of co-contraction between antagonistic muscles (e.g., Additional file 1: Supplementary Fig. 1). Able-bodied participants exhibited a phasic pattern of activity within the muscle pair with minimal co-contraction in each ambulation condition (Additional file 1: Supplementary Fig. 3). When comparing EMG from both limbs of able-bodied participants, the contralateral gait-cycle alignment affected the aligned contralateral EMG patterns (e.g., different shapes), especially during gait cycle 1 and 3 of stair ambulation, but maintained a phased pattern (Additional file 1: Supplementary Figs. 3 and 4). Amputee EMG amplitudes tended to be lower than those of able-bodied participants and tended to have a greater amplitude difference within the muscle pair. Shank velocities and ankle dynamics were also consistent across trials in all ambulation conditions for both amputees’ sound limb and able-bodied participants. The largest shank velocity occurred in the AP direction in all ambulation conditions and participant groups. Across participants, the greatest ankle range of motion occurred during stair descent.

Contrary to the feedforward NARX model developed previously [37], closed-loop model error for the prediction of ankle angle and moment varied nonlinearly with prediction interval across ambulation conditions and participant groups (Fig. 4 and Additional file 1: Supplementary Fig. 5). RMSE had a slightly parabolic shape where 8 and 142 ms had similar values but larger than 58 ms. In contrast, RMSE of ankle angle and moment had a small decrease as sampling window increased across ambulation conditions and participant groups. RMSE were similar with 16 and 30 hidden units but increased with 50 units for ankle angle and moment in all ambulation conditions and participant groups. Amputees had
similar angle and moment RMSE to the AB_{CEMG} group, but both groups had slightly larger errors than the able-bodied group (AB) for all model parameters and ambulation conditions. RMSE of the predicted ankle angle and moment were consistently lowest for level walking and largest for stair descent, but with overlapping standard deviations among ambulation conditions, across parameters and participant groups.

Closed-loop NARX model predictions of ankle angle and ankle moment closely matched the experimentally measured targets in all ambulation conditions and staircase transitions for all amputees and able-bodied participants (AB and AB_{CEMG} models). Figure 5 shows the comparison of model predictions and targets for each amputee using their optimal model parameters (τ: 58 ms, TTA1 - D: 83 ms, N: 50; TTA2 - D: 42 ms, N: 30; TTA3 - D: 83 ms, N: 50). Prediction time series of a typical able-bodied participant trained with same-limb data (AB3) and trained with aligned contralateral EMG as the EMG input (AB3_{CEMG}) are provided in the Additional file 1 (Additional file 1: Supplementary Fig. 6). Table 1 lists average errors (RMSE) and correlations (R^2) of the NARX model predictions of ankle angle (θ) and moment (M) for each ambulation condition, individually for amputees and averaged across able-bodied participants (AB and AB_{CEMG} groups). The results show high levels of accuracy for both ankle angle and moment across participant groups and ambulation conditions and their transitions. For amputees, RMSE and R^2 of ankle angle ranged from 2.06 to 3.74 degrees and from 0.886 to 0.970, respectively, while moment values ranged from 0.096 to 0.213 Nm/kg and from 0.930 to 0.982, respectively. Amputees and the AB_{CEMG} group had similar RMSE and R^2 for both model outputs in all ambulation conditions. Model predictions for the able-bodied group (AB) had lower errors (RMSE_θ = [2.03, 2.65] °, RMSE_M = [0.071, 0.108] Nm/kg) and higher correlations (R^2_θ = [0.954, 0.971], R^2_M = [0.979, 0.992]) than amputees and the AB_{CEMG} group across ambulation conditions. Model predictions accurately aligned with the ankle angle and moment targets where 91% of time lags were within one time step (8 ms) across all trials (i.e., participants and ambulation conditions).
Critical performance points within ambulation conditions are shown in Figure 5. Statistical analysis revealed several critical points that repeated in at least two amputees (i.e., 8 of 49 points) and in more than 50% of AB_{cEMG} participants (i.e., 9 of 49 points), for which NARX model predictions were statistically different (B-H adjusted $p < 0.05$, asterisks in Figure 5 and Additional file 1: Supplementary Figure 6) from the experimentally measured ankle dynamics (see Additional file 1: Supplementary Table 2 for statistical scores). For models trained with same-limb data, no significant differences were observed at critical points in more than 50% of able-bodied participants (Additional file 1: Supplementary Figure 6).

Maximum ankle plantarflexion in the stance phase was significantly different during gait cycle 2 of stair descent in at least two amputees as well as in more than 50% of AB_{cEMG} participants (as double asterisks in Figure 5), whereas level walking was only different for amputees. For ankle moment, six critical points showed significant differences in at least two amputees except gait cycle 1 of stair descent which was only different for TTA3. Similarly, four out of those six peak plantarflexion moments were also statistically different in more than 50% of AB_{cEMG} participants (as double asterisks in Figure 5). During level walking in particular, peak moment predictions were significantly different in all AB_{cEMG} participants ($n = 6$). The percentage difference (absolute difference over mean) between the target and model prediction at all peak plantarflexion moments were up to 19% for level walking, 27% for stair ascent and 24% for stair descent for amputees, 21%, 23% and 28% for AB_{cEMG} participants, and 11%, 10% and 19% for able-bodied participants, respectively. Differences were also observed in four critical points during stair descent in more than 50% of AB_{cEMG} participants but did not occur in at least two amputees (i.e.,
peak dorsiflexion of gait cycle 2; two angle points in the second clearance interval and peak moment of gait cycle 1; Additional file 1: Supplementary Figure 6).

The distribution of RMSE within ambulation conditions showed variations in the accuracy of the predicted ankle angle and moment within and across gait cycles for amputees and able-bodied groups (Figure 6 and Additional file 1: Supplementary Figures 7 and 8). In able-bodied groups, the largest deviations occurred during initial swing for ankle angle and during pre-swing for ankle moment in every gait cycle and ambulation condition. Ankle angle errors also increased during mid-swing for gait cycle 2 and 3 of stair ascent and during loading response for gait cycle 2 and 3 of stair descent. For both able-bodied groups, the patterns of error were consistent across gait cycles but were generally larger for the AB$_{cEMG}$ group, as well as, more substantial moment error at terminal stance. Amputee RMSE patterns were subject-specific and diverged from able-bodied patterns in several cases. Yet, for the most part, the largest errors occurred during the same gait periods as able-bodied groups, including similar error patterns for a subset of gait cycles (e.g., level walking for TTA2 angle and moment in Additional file 1: Supplementary Figure 7). All participant groups had minimal moment errors during the swing phase in all gait cycles. Angle RMSE stayed below 3.4 degrees, 4.3 degrees, and 6 degrees during all gait periods for able-bodied, AB$_{cEMG}$, and amputee participants, respectively, while moment RMSE stayed below 0.155 Nm/kg, 0.255 Nm/kg, and 0.365 Nm/kg, respectively.

The sum of weighed inputs, averaged over time, showed that both residual ankle dorsiflexor and plantarflexor muscle contribution to the model prediction were comparable to AP shank velocity, the largest velocity contributor, for each amputee and both able-bodied groups across ambulation conditions (Fig. 7A). Amputees and both able-bodied groups had similar relative contribution of EMG and AP shank velocity across ambulation conditions. SWI distribution within ambulation conditions showed that EMG and AP shank velocity had alternating contributions within the gait cycle for all participant groups (Fig. 7A and Additional file 1: Supplementary Fig. 9). The contribution of AP shank velocity varied continuously within the gait cycle with a pattern that was consistent across participant groups. EMG contribution predominated during loading response, pre-swing and terminal swing for level walking, swing phase for stair ascent, and during pre-, initial and mid- swing for stair descent for able-bodied groups. While the patterns of EMG contribution differed for amputees, the largest EMG contribution to the model prediction occurred during similar intervals to the able-bodied groups.

Discussion

This study demonstrated that the use of within-socket residual EMG of transtibial amputees can be used, in conjunction with shank kinematics of the sound limb, to continuously predict normative ankle kinematics and kinetics of the sound limb across ambulation conditions and terrain transitions. Additionally, the single-network, closed-loop NARX model had the ability to characterize normal gait patterns of ankle angle and moment of able-bodied participants. The need for explicit identification of gait events or selection of locomotion modes was eliminated due to the ability of the autoregressive
model to continuously predict ankle dynamics within and across ambulation conditions (i.e., level overground walking, stair ascent, and stair descent), including transitions between terrains.

The proposed NARX model could be used in real-time to generate continuous ankle angle and ankle moment commands for the control of an active ankle-foot prosthesis using impedance, stiffness, or similar control schemes [3, 17, 21, 54]. It is believed that this work is the first in which a fully closed-loop model with predictive capabilities (i.e., future estimates) has been developed to continuously predict ankle state. In the closed-loop NARX model, prior model error was directly encoded during training because output predictions were fed back as recurrent inputs instead of using error-free target data (as in open-loop models). A closed-loop structure would make the system robust to model uncertainties (e.g., error accumulation and undesired fluctuations), thus ensuring accuracy and stability when implemented in a feedback control system. Moreover, the prediction of future limb state enables a control system to counteract control and actuation delays, and allows gait changes to be modified proactively in response to terrain changes perceived by the user. Results show that similar performance can be achieved for prediction intervals ranging from 8 to 142 ms (Fig. 4 and Additional file 1: Supplementary Fig. 5) which would accommodate prosthetic delays (e.g., 40–50 ms response time of ankle-foot prostheses [1, 60, 61]) and enable future predictions given the physiological electromechanical delay from onset of surface EMG to the neuromotor drive (4-170 ms for lower leg muscles [62]), while keeping ankle angle error less than 5 degrees [37]. These features make the recurrent (closed-loop) NARX model appealing for real-time feedback control in a wide variety of lower limb robotic devices, including actuated orthoses and exoskeletons.

In lower limb amputees, gait asymmetries between the sound and prosthetic limb are primary attributed to limitations in the prostheses, even active prostheses, and are a major concern in achieving normal gait [58, 63–65]. The practical need to adapt to such asymmetries often leads to differences in kinematics and kinetics of the sound limb when compared to able-bodied controls [66, 67]. The approach presented here, mapping ankle dynamics of the sound limb with residual EMG of the prosthetic side (i.e., aligned), takes an important step toward establishing a more normal gait by overlaying the dynamics of the sound limb onto the prosthesis to create symmetric gait patterns. However, the long-term impact on gait is dependent on the interaction between the model prediction and the human user as they adapt and react to changes (e.g., muscle recruitment, environment, and control errors). In previous work, a human-in-the-loop model was developed to simulate the user’s EMG in response to changes in ankle dynamics [68]. Real-time performance of the autoregressive model during human-in-the-loop control is needed to ensure safety and stability of the physical prosthetic system prior human testing.

Despite amputees in this study having a wide array of residual ankle dorsiflexor and plantarflexor profiles with different levels of EMG activation and co-activation, walking patterns, and foot placement strategies during stair ambulation, the closed-loop NARX model performance was accurate and robust across amputees and ambulation conditions, including terrain transitions ($R^2 = [0.886, 0.982]$), suggesting that the model can be used consistently across amputees. The strength of the model lies in its ability to account for individual’s specific variations of limb dynamics and muscle activity by training and
optimizing the model to maximize performance for each amputee. Similarities in ankle angle and moment RMSE (across gait cycles and ambulation conditions) between individual amputees and the AB.cEMG group suggest that the combination of antagonistic residual EMG along with sound-limb shank motion can effectively predict normative ankle dynamics. Importantly, the contribution of natural residual EMG signals of amputees, to the prediction of ankle dynamics across ambulation conditions, was consistent with normal muscle activity of able-bodied participants (Fig. 7 and Additional file 1: Supplementary Fig. 9). In contrast to proportional myoelectric control systems, the ability to use natural, yet altered, amputee muscle activation profiles, eliminates the need for conscious, intentional muscle contraction, extensive user training, and high quality, independent muscle signals. When implemented in a prosthesis, the cognitive and physical demand on the user is expected to be less than current myoelectric control systems [12, 15, 21, 22].

The use of shank kinematics and antagonistic surface EMG signals allowed for accurate and robust model performance that included information about limb state and direct user intention. While the model developed here used shank linear velocity, other measures of shank kinematics (e.g., angle, angular velocity) could be used as well [25, 29, 42, 69]. A benefit of using shank kinematics in transtibial amputees is that the motion of the residual shank is still governed by the central nervous system and contains information about the limb state in relation to the gait cycle. Furthermore, in real-time application, shank kinematics could be obtained intrinsically from sensors embedded in the prosthesis (e.g., inertial measurement units, gyroscopes, accelerometers), similar to within-socket EMG, minimizing design complexity and facilitating donning and doffing of the prosthesis.

Ankle angle and moment predictions closely matched the experimentally measured targets in all ambulation conditions for all participants. However, deviations in the predicted values were still present, particularly at local minima and maxima. Analyses revealed a number of critical points where predictions of amputee and AB.cEMG models repeatedly fell outside the variability of the targets. While sample size may have been a contributing factor, differences in model predictions may not necessarily correlate with practical disruptions of gait. For example, ankle angle predictions deviated from the targets at one critical point during the stance phase of level walking and stair descent. Studies suggest that foot placement during stair use is not a factor that contributes to a stumble or fall [70], especially if the obstacle is seen beforehand [71]. Since the foot was already in contact with the surface, trip-related fall risk or injury from such prediction errors would be minimal. However, more generally, the impact of critical point errors on prosthetic control during gait remains an underdeveloped area of study in the field, particularly during human-in-the-loop control of an active prosthesis.

While the influence of push-off has not been linked to fall risk [72], limb asymmetry and offsets in the timing of push-off have been associated with increased metabolic rates, excessive limb loading, osteoarthritis, and back pain among lower limb amputees [73–77] and controls [78]. Although significant differences were also found at peak moments for the amputees, the peak percentage differences across ambulation conditions were lower than those present in commercially available ankle-foot prostheses (i.e., active to SACH) compared to able-bodied individuals (LW: 28% [58, 64, 67, 79], AS: 41% [58, 63, 80,
Moreover, timing differences relative to the desired profile were present in the peak moments of those commercial prostheses, unlike the prediction peaks in this study (>84% of moment predictions in amputees were within one time step of the targets). It is known that push-off timing is a key factor to maintain gait stability and stride variability [78]. The ability of lower limb amputees to adapt to these limitations in their own prostheses [82] suggests that the moment prediction errors of the NARX model may not negatively impact the robust control of a prosthesis.

The recurrent (closed-loop) NARX model predicted ankle angles and moments over a wider range of conditions at levels comparable to, and in some instances better than, other continuous gait models [28–35]. Most models have used a feedforward structure to estimate (i.e., one-step-ahead estimate) ankle dynamics of healthy individuals limited to level walking ($RMSE_{\theta} < 4.7^\circ$, $R^2_{\theta} > 0.74$; $RMSE_{\theta} < 0.16$ Nm/kg, $R^2_{M} > 0.86$; [28–32]). In impaired populations, ankle angle errors (RMSE) ranging from 1.2 to 5.4 degrees and from 0.82 to 9.3 degrees have been reported for transtibial amputees [36] and spinal cord injury patients [34], respectively, during level treadmill walking. For the errors of transtibial amputees, ankle angle of their passive prostheses was predicted 100 ms ahead of time using two antagonistic within-socket residual EMG (i.e., same limb) as inputs to an open-loop NARX model [36]. In the current study, even with a greater model complexity, similar errors were achieved in transtibial amputees during level ground walking ($RMSE < 2.8^\circ$ for $\tau = 58$ ms) with the inclusion of shank kinematics as inputs. In comparison to the 2-input open-loop NARX model developed previously [37], while ankle angle and moment errors increased by at least a factor of two across ambulation conditions for the closed-loop model, they remained less than 2.7 degrees and 0.11 Nm/kg for able-bodied participants with correlations greater than 0.95 for both models. Zarshenas et al. obtained favorable results ($R^2 > 0.8$) using a time delay neural network with ankle kinematics and EMG inputs to predict ankle moment of healthy participants up to 1 second ahead of time [38]. Their model exploited the cyclic nature of treadmill walking at a constant speed which resulted in high accuracy over large prediction intervals, although performance was not examined during noncyclic features of gait such as terrain transitions. Gupta et al. estimated (i.e., excluding future predictions) ankle angle of able-bodied individuals during level ground walking ($RMSE = 2.44 \pm 0.45^\circ$, $r = 0.97$), stair ascent ($RMSE = 3.61 \pm 1.00^\circ$, $r = 0.93$), and stair descent ($RMSE = 5.04 \pm 1.56^\circ$, $r = 0.85$) using NARX models trained for each terrain individually [35]. It is believed that the NARX model was implemented as an open-loop model using error-free targets. The closed-loop model presented here had better performance, possibly due to the use of more relevant inputs (shank versus knee kinematics) and the absence of discontinuities in the training data, with the added benefit of being implemented in a single-network model capable of continuous prediction across ambulation conditions and terrain transitions.

The use of contralateral EMG to align residual EMG from the prosthetic side with sound-limb dynamics was a viable approach that yielded accurate predictions of ankle dynamics. While this approach provides a path toward the implementation of sound-limb ankle dynamics in the prosthetic limb, there remains room for improvement. When comparing able-bodied groups, where the only training difference was the use of aligned contralateral EMG instead of data from the same limb (EMG, ankle angle and moment,
and shank velocities), the $AB_{cEMG}$ group had worse performance in all metrics (e.g., higher errors, lower correlations, model predictions that fell outside the variability of targets) than the able-bodied group (AB). Assuming limb symmetry in able-bodied participants [83], large discrepancies in EMG profiles and ankle dynamics were observed during transition steps onto and off the staircase due to differences in step limb dynamics between the lead limb (i.e., limb of ankle kinematic and kinetic predictions) and the aligned trail limb (i.e., limb of contralateral EMG) (Additional file 1: Supplementary Fig. 4). The limiting factor was the lack of EMG trials from both legs as the lead limb. The use of contralateral EMG collected as the lead limb would be expected to improve model performance by more accurately matching step dynamics with EMG signals.

In this study, the impact of post-processing motion artifacts on model performance was not analyzed in depth for the electrode-housing test socket design. Given the consistency of trial-wise variability and the absence of high-frequency, large amplitudes in the EMG linear envelopes across amputees, the potential impact on the current results was considered minimal. Additionally, it has been shown that a similar design using the same EMG electrodes and filtering techniques (i.e., band-pass filter at 20–450 Hz) in a transfemoral amputee produced negligible motion artifacts during level walking and stair ambulation, and produced a high level of user comfort when compared to other designs and electrodes [49]. Furthermore, the effects of variations in EMG signal due to changes in electrode placement and electrode-skin interface were not evaluated. Although studies suggest that these factors can adversely affect myoelectric pattern recognition [84–86], preliminary testing of trained NARX models with EMG from subsequent days suggests the impact may be more limited. However, further research is needed to validate robustness over time. Finally, while the current results demonstrate the feasibility to continuously predict ankle angle and moment across a subset of common ambulation conditions and transitions, additional work is needed to validate the model training and performance with a larger cohort of participants under additional ambulation conditions (e.g., ramps, cadence modulation, noncyclic activities) and in response to untrained situations such as recovering from an unexpected perturbation.

Conclusions

This work demonstrated the ability of an autoregressive model to continuously predict (i.e., future estimates up to 142 ms) desired ankle kinematics and kinetics of the sound limb of transtibial amputees using within-socket residual EMG and sound-limb shank kinematics. The recurrent (closed-loop) NARX model successfully predicted ankle angle and ankle moment during multiple ambulation conditions (i.e., level overground walking and stair ambulation) including terrain transitions. Models of able-bodied participants were presented as a reference for the model performance possible under the same training methodology as amputees, as well as the maximum accuracy possible when predicting normal gait patterns. Model performance was stable and accurate across a range of different EMG profiles, leveraging both EMG and shank velocity inputs for the prediction of ankle dynamics across ambulation conditions. The use of natural, yet altered, muscle activation as inputs could facilitate the design of intuitive and robust control strategies that reduce the cognitive and physical demands associated with
volitional actuation of an ankle-foot prosthesis. This closed-loop predictive model is a step forward for continuous feedback control of lower limb robotic devices, particularly active ankle-foot prostheses, and has the potential to improve prosthetic function for lower limb amputees toward establishing more normal, symmetric gait patterns. Further research is needed to validate the model on a larger cohort of amputees, characterize the impact of EMG signal changes on model performance, and evaluate real-time performance during human-in-the-loop control.

**List Of Abbreviations**

AB: Able-bodied; AB\textsubscript{cEMG}: Contralateral EMG able-bodied; AP: Anterior-posterior; AS: Stair ascent; B-H: Benjamini-Hochberg; cOFF: Contralateral last contact on force plate; cON: Contralateral first contact on force plate; CP: Critical performance point; CPMC: Continuous proportional myoelectric control; cTO: Contralateral toe off; DS: Stair descent; EMG: Electromyography; FSM: Finite state machine; GC: Gait cycle; HS: Heel strike on floor; INIT SW: Initial swing; LOAD: Loading response; LW: Level overground walking; MID ST: Mid-stance; MID SW: Mid-swing; ML: Medial-lateral; MSE: Mean squared error; NARX: Nonlinear autoregressive neural network with exogenous inputs; OFF: Last contact on force plate; ON: First contact on force plate; PRE SW: Pre-swing; RMS: Root mean square; RMSE: Root-mean-square error; SWI: Sum of weighed inputs; TERM ST: Terminal stance; TERM SW: Terminal swing; TO: Toe off on floor; TTA: Transtibial amputee; V: Vertical; Vel: Velocity.

**Declarations**

**Ethics approval and consent to participate**

The study protocol (HR-2804) was approved by the Institutional Review Board at Marquette University (FWA00005844) and all participants provided written informed consent prior to participation.

**Consent for publication**

The participants depicted in Figure 1 and Supplementary Table 1 gave written consent for publication.

**Availability of data and materials**

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

**Competing interests**

The authors declare that they have no competing interests.
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Author contributions

EVZ-G contributed to conception and design of the study, performed acquisition, analysis and interpretation of data, helped in the design of the electrode-housing test socket, and drafted manuscript. TC helped in the design of the electrode-housing test socket, fabricated the duplicate test sockets, and assisted during data collection of amputees. PAV, BS-T, SRK-M, and SAB contributed to conception and design of the study, obtained funding, and supervised the study. All authors contributed to manuscript revision and approved the submitted version.

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References


Figures

Figure 1

Electrode-socket integration and experimental walkway. (A) Individualized duplicate electrode-housing test socket and prosthetic shrinker used during amputee testing. (B) Modified Helen Hayes infrared lower limb marker set and EMG electrode placement on a transtibial amputee. (C) Experimental walkway including (a) embedded floor force plates, (b) stair force plates, (c) staircase, (d) landing platform, and (e) infrared motion cameras. (D) Schematic of step-over-step stair ambulation gait cycles (GC; red, stair ascent; blue, stair descent) used in the contralateral gait-cycle alignment. Gait cycles of the sound limb
(lead limb) whose kinematics (ankle angle, shank velocities) and kinetics (ankle moment) were used as the target movement during training are shown as solid lines. Dashed lines denote gait cycles of the prosthetic limb (trail limb) whose residual EMG was aligned with the target kinematic/kinetic gait cycles.

**Figure 2**

Multiple-input multiple-output recurrent (closed-loop) NARX model for transtibial amputees. The linear envelope of within-socket residual EMG (ankle dorsiflexor and plantarflexor), shank linear velocities of the sound limb, and prior predictions of ankle angle and ankle moment of the sound limb were weighted and fed via tapped delay lines to a single hidden layer containing nonlinear units with hyperbolic tangent sigmoid transfer functions. Intermediate outputs were weighted and linearly combined to provide continuous predictions of future ankle angle and moment over time of the sound limb. Models of able-bodied participants (AB and AB_{cEMG} models) differed in the use of inputs and outputs of the same limb (AB), and the use of the aligned contralateral EMG as the EMG input (AB_{cEMG}).
Figure 3

Aligned experimentally measured trials used to train and test the NARX model of a transtibial amputee (TTA3). Shank linear velocities, ankle angle, and ankle moment of the sound limb, and the linear envelope of within-socket residual EMG (ankle dorsiflexor and plantarflexor) are shown during level overground walking and stair ambulation. Percent trial is normalized from 225 ms before first foot contact on the first force plate to the first foot contact before contralateral toe off of the last force plate. Vertical lines denote gait events (solid: sound limb; dashed: contralateral limb, i.e., prosthetic limb) defined based on force plate (threshold 10 N) and floor contact (ON, first contact on force plate; OFF, last contact on force plate; HS, heel strike on floor; TO, toe off on floor). Contralateral gait events are identified by a lowercase “c” (e.g., cTO, contralateral toe off). Staircase ambulation (black horizontal bar) is defined as the first foot contact on the staircase to the first foot contact on level ground of the sound limb. Staircase transitions to/from level ground are shaded gray. Single-limb support occurs when only one limb is in contact with the ground (cTO to cON or cOFF to cON). Experimental data of the remaining amputees and a typical able-bodied participant (AB3) are provided in the Additional file 1.
Figure 4

Parameter space error of the recurrent (closed-loop) NARX model. RSME between predicted and experimentally measured ankle angle and ankle moment is shown as a function of prediction interval, sampling window, and number of hidden units, averaged across transtibial amputees. RMSE is collapsed across model parameters (i.e., averaged across two of the three dimensions). Shaded regions denote ±1 standard deviation. Results for able-bodied groups are provided in the Additional file 1.
Figure 5

Time series of NARX model prediction of ankle angle and moment for all transtibial amputees. Optimal model parameters were used for each amputee (\( \tau \): 58 ms, TTA1 - D: 83 ms, N: 50; TTA2 - D: 42 ms, N: 30; TTA3 - D: 83 ms, N: 50). Closed-loop NARX model predictions during level overground walking and stair ambulation are shown for the k-fold novel test trials with the best accuracy across ambulation conditions and model outputs. Critical performance points (CPs), used to test for within-subject significant
differences (B-H adjusted $p < 0.05$) between the model prediction and experimentally measured targets, are shown under TTA3 plots (clearance intervals as yellow blocks; stance critical points as green lines). Single asterisks (*) indicate CPs with significant difference in at least two amputees. Double asterisks (**) indicate significance differences in at least two amputees as well as in more than 50% of $\text{AB}_c\text{cEMG}$ participants. Shading and line markers are defined the same as in Figure 3. Prediction time series of a typical able-bodied participant trained with same-limb data ($\text{AB}3$) and trained with aligned contralateral EMG as the EMG input ($\text{AB}3_c\text{cEMG}$) are provided in the Additional file 1.

![Figure 6](image_url)

Figure 6

RMSE distribution within ambulation conditions for the continuous prediction of ankle angle and ankle moment. A transtibial amputee (TTA3) and the able-bodied group (AB) are shown. Each gait cycle is divided into the standard seven gait periods based on gait events: loading response (LOAD; initial foot contact to contralateral toe off), mid-stance (MID ST; 1-50% of single-limb support), terminal stance (TERM ST; 50-100% of single-limb support), pre-swing (PRE SW; contralateral initial foot contact to toe
off), initial swing (INIT SW; 1-33% of swing phase), mid-swing (MID SW; 33-66% of swing phase), and terminal swing (TERM SW; 66-100% of swing phase). Stance and swing phases are shaded light orange and white, respectively. RMSE distribution of the remaining amputees and the $AB_{C_{EMG}}$ group are provided in the Additional file 1.

Figure 7

Exogenous input contribution to NARX model prediction for each ambulation condition. (A) Sum of weighted inputs (SWI) for each input averaged over time. Error bars represent ±1 standard deviation of averaged able-bodied participants. (B) SWI distribution of EMG and AP shank velocity inputs within the gait cycle for level ground walking and the second gait cycle of stair ascent and stair descent for a transtibial amputee (TTA3) and the able-bodied group (AB). Because the network bias (offset) was not included in the SWI calculation, SWI absolute values can vary across participants without affecting the relative contribution among inputs. Gait periods and stance and swing phases are defined the same as in Figure 6. SWI distribution of the remaining amputees and the $AB_{C_{EMG}}$ group are provided in the Additional file 1. Dorsiflexor: tibialis anterior, Plantarflexor: gastrocnemius medialis, ML: medial-lateral direction, AP: anterior-posterior, V: vertical, Vel: velocity.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AdditionalFile1.pdf