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Trunk Acceleration for Neuroprosthetic Control of Standing – a Pilot Study

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Abstract

This pilot study investigated the potential of using trunk acceleration feedback control of center of pressure (COP) against postural disturbances with a standing neuroprosthesis following paralysis. Artificial neural networks (ANNs) were trained to use three-dimensional trunk acceleration as input to predict changes in COP for able-bodied subjects undergoing perturbations during bipedal stance. Correlation coefficients between ANN predictions and actual COP ranged from 0.67 to 0.77. An ANN trained across all subject-normalized data was used to drive feedback control of ankle muscle excitation levels for a computer model representing a standing neuroprosthesis user. Feedback control reduced average upper-body loading during perturbation onset and recovery by 42% and peak loading by 29% compared to optimal, constant excitation.

Keywords

Rehabilitation; Spinal Cord Injury; Posture; Balance; Functional Neuromuscular Stimulation

INTRODUCTION

Neuroprostheses employing functional neuromuscular stimulation (FNS) can restore basic standing function to individuals paralyzed by motor complete spinal cord injury (SCI). Currently available clinical systems use constant stimulation to activate extensor musculature at the knees, hips, and trunk to provide erect stance (Davis et al., 2001).

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AUTHOR STATEMENT:

This work was conducted at the Motion Study Laboratory at the Louis Stokes Cleveland Department of Veterans Affairs Medical Center (VAMC) in conjunction with the Cleveland Functional Electrical Stimulation (FES) Center and Case Western Reserve University. The Cleveland FES Center aims to develop neuroprostheses to restore function following spinal cord injury. Research at the VAMC strives to improve quality of life of veterans. There is no financial conflict of interest to report.

However, an assistive device such as a walker is necessary for the user to insure postural stability against disturbances through actions of the upper extremities. This study examined the feasibility of utilizing three-dimensional (3D) trunk acceleration (a_{trunk}) as a potential input signal for such a control system.

Center of mass (COM) dynamics are required to effectively determine the limits of standing balance and enact effective *predictive* balance control strategies (Pai & Patton, 1990). For standing with FNS, it is particularly important to incorporate dynamic information into proactive corrections against perturbations due to the non-linear, time-delayed nature of muscle activation (Hill, 1938). Previous closed-loop control systems for FNS standing have focused on joint feedback (Matjacic et al., 2003). Joint feedback requires significant instrumentation and does not directly estimate COM kinematics. It also responds according to configuration changes which may occur too slowly to enact time-delayed, muscle-activated corrections against rapid, unexpected external disturbances. To this end, we hypothesized that a_{trunk} could serve as a useful signal for regulating standing in the presence of postural perturbations. A_{trunk} is measurable using a single tri-axial accelerometer (Mayagoitia et al., 2002) and has previously been utilized to characterize quiet standing (Moe-Nilssen and Helbostad, 2002) and volitional swaying (Betker et al., 2006) for able-bodied individuals. Furthermore, a_{trunk} approximates COM acceleration and analytically predicts a measure of standing control (center of pressure, COP) when the system is represented as an inverted pendulum (Winter et al., 1998). While accelerometers have been previously investigated for FNS standing to detect knee unlocking (Veltink & Franken, 1996), its application as a surrogate of COM dynamics for feedback control of FNS standing has yet to be explored.

In this study, the existence of a natural coupling between a_{trunk} and normative postural control under perturbation was first investigated. An artificial neural network (ANN) was then trained on a_{trunk} inputs to predict future shifts in COP necessary for stabilization during *perturbed* bipedal stance. COP represents fundamental normative control action during either quiet (Winter et al., 1995) or perturbed standing (Krishnamoorthy et al., 2003). To assess potential usefulness of a_{trunk} in an FNS standing control system, the ANN was driven by a_{trunk} feedback to control excitation levels of ankle muscles on a three-dimensional SCI model of stance (Zhao et al., 1998). In simulation, the upper-body effort necessary to maintain upright posture against forward-directed force-pulse disturbances at the thorax with the controller active was compared to standing with optimal, constant stimulation. The overall schematic of this study is summarized in Figure 1.

METHODS

A. Experimental Protocol

Kinematic and kinetic data from three able-bodied male volunteers (age 21 – 26) were collected during standing postural responses to external perturbations. All subjects signed informed consent forms approved by the Institutional Review Board of the Louis Stokes Cleveland Department of Veterans Affairs Medical Center. None showed nor reported a history of orthopedic or vestibular problems. Each subject wore a belt around the lower chest to approximate the level of system COM. The belt was connected to four non-elastic ropes oriented either anterior-posterior (AP) or medial-lateral (ML) to the subject. Manual perturbations were applied using the ropes while subjects stood on instrumented force-plates monitoring COP. Subjects were instructed to stand with eyes closed to minimize anticipation of disturbances. Perturbations were *moderate*, defined as inducing near maximum COP excursions without eliciting corrective stepping. Each subject wore a retro-reflective marker placed on the sternum. The 3D marker position was tracked using a VICON© motion capture system (Oxford Metrics Group, Oxford, UK). All collected data were sampled at 60

Hz. Marker data were double-differentiated off-line and smoothed with a low-pass digital filter (Kaiser & Reed, 1977) to obtain 3D a_{trunk} . For subject 3, a single tri-axial accelerometer (CXL02LP3 *Crossbow Technology*, Milpitas, CA) was obtained and placed adjacent to the sternum marker while aligned to the principal AP, ML directions. The raw accelerometer signals were used as a_{trunk} inputs for subsequent ANN training.

Twenty perturbation sessions were performed for each subject. Each session lasted 90 seconds and consisted of multiple perturbations. Perturbations were *uncontrolled* (i.e., no stipulation on magnitude or duration) and applied through the pulling of each rope by an experimenter instructed to exert singular, impulsive forces displacing the subject's torso without inducing stepping. Each session fell into one of three categories according to perturbation type: 1) AP perturbations (8 sessions): rope-pulls occurring only along AP-axis but in either direction and applied *discretely* (pull, then wait for subject recovery before subsequent pull), 2) ML perturbations (8 sessions): discrete rope-pulls occurring only along ML-axis, and 3) Random perturbations (4 sessions): unsystematic, concurrent pulling of ropes in any direction. For *random* perturbation sessions, experimenters did not coordinate timing of pulls and subjects underwent continuous perturbations without specified order or directions. Sessions across all three perturbation types were presented in random order.

B. Artificial Neural Network Processing

A time-delayed, feedforward ANN using a_{trunk} inputs to predict future changes in COP was created for each subject using the *Neural Network Toolbox* by MATLAB® (*Mathworks, Inc.*, Natick, MA). Prediction performance was measured by the Pearson's correlation coefficient (ρ) between predicted and actual COP output. Preliminary findings indicated better prediction performance by the time-delayed ANN than either a multi-variate linear regressor ($\rho < 0.6$) or ANN without time-delays ($\rho < 0.65$). COP data for each subject were processed to remove the means and create multiple target/output data sets of change in COP (ΔCOP) at various time lags. Each set consisted of taking the difference between the current COP and the COP value at some time (Δt) in the future as:

$$\Delta COP(t+\Delta t) = COP(t+\Delta t) - COP(t) \quad (1)$$

For this study, $\Delta t = 250$ msec was chosen to be the optimal lag for prediction since it represents the average time required for a_{trunk} to reach its maximum value from perturbation onset. Each ANN was trained to predict the two components (AP, ML) of the ΔCOP OUTPUTS from all three components (AP, ML, and inferior-superior) of the a_{trunk} INPUTS.

The ANNs consisted of one hidden layer of six neurons and one output layer of two neurons. Six hidden layer neurons yielded the lowest mean squared error (MSE) upon training convergence. Activation functions for each layer were *tangent-sigmoidal* and *pure linear*, respectively. Time-delays for the a_{trunk} inputs to the ANN were selected using power spectrum density (PSD) of each ΔCOP component. Each PSD displayed Gaussian characteristics with an excellent linear fit to a normal probability distribution ($\rho > 0.9$). The inverse of the PSD mean frequency provided the range over which four equally spaced intervals were defined as input time-delays. It was assumed this time-range represented a fundamental cycle over which each ΔCOP output can be most reliably predicted. A resilient back-propagation algorithm (Haykin, 1999) was used for training. Prior to training, INPUT and OUTPUT data were normalized over the interval $[-1, 1]$. Two-thirds of all data points were used for training with the remaining data equally divided for testing and validation. A maximum of 5000 epochs were specified for training in lieu of an early-stopping criterion specified as 250 consecutive iterations of increasing fitting error to the validation set.

C. Model-Based Trunk Acceleration Controller

A three-dimensional model of human, bipedal stance (Zhao et al., 1998) was used to investigate the potential of a_{trunk} -feedback control. The model included passive joint SCI properties (Amankwah et al., 2004) and sixteen Hill-based (Hill, 1938) muscles (bilateral soleus, tibialis anterior, vastus intermedius, semimembranosus, adductor magnus, gluteus medius, gluteus maximus, erector spinae) targeted for implantation with currently available 16-channel pulse generators (Smith et al., 1998). Maximum muscle forces were reduced by 50% from normative values to reflect SCI (Heilman et al., 2006). Muscle *excitation* is the normalized (0 to 1) command inputs serving as the model analog to stimulation levels. The optimal constant levels of muscle excitation required to maintain erect stance with maximal co-excitation (providing highest static stiffness) were determined by static optimization (Heilman et al., 2006). The static optimization routine assumes excitation is proportional to *activation*, the muscle state variable determining force output level. Each forward simulation commenced with excitations and activations equal at the optimal levels, but excitation-activation dynamics were present for the remaining simulation time. To approximate upper-body loading, proportional-derivative (PD) control was implemented to maintain the left and right shoulder positions. Upper-body loading is ultimately required to stabilize the model against disturbances to compensate for the limited number of paralyzed muscles available for feedback control and provide a performance metric for feedback control of muscle excitation levels compared to constant excitations. Proportional and derivative gains (420 N/m, 920 N/m/sec) were heuristically determined as those minimally sufficient to hold the model in near-erect stance with no muscle support and no external disturbances present during forward simulation. Without muscle support, this PD controller suspends the model COM position within 0.1 meters of erect stance. All simulations were run at 100Hz.

To simulate an ANN-controller that enacts *general* coupling between a_{trunk} and ΔCOP in the model, subject-normalized data across all three subjects were combined to train a single ANN. ANN training followed the same aforementioned subject-specific protocol. Only ANN prediction of AP-COP was employed for controller action in these simulations. Since AP-COP is simply a function of dorsi/plantar-flexion ankle moment (Winter, 1996), it can be *directly* applied through controller modulation of excitation levels of available ankle muscles (soleus, tibialis-anterior). Net ML-COP, however, is a function of ankle and hip moments and ML-COM position [16] and is thereby not strictly a control measure since it also reflects system state. Standing control in the ML dimension requires a more sophisticated control structure to be addressed in future work.

A simple linear mapping was used to determine ankle muscle excitations (E_{sol} , $E_{\text{tib-ant}}$) at each next time step in the simulation according to the normalized ANN-predicted change in AP-COP ($\Delta\text{COP}_{\text{AP+}}$) and the current AP-COP (COP_{AP}):

$$E_{\text{sol}} = E_{\text{sol,opt}} + \left(\text{COP}_{\text{AP}} + \frac{(1 + \Delta\text{COP}_{\text{AP+}})}{2} \right) \times K_{\text{sol}} \quad (2)$$

$$E_{\text{tib-ant}} = E_{\text{tib-ant,opt}} + \left(\text{COP}_{\text{AP}} + \frac{(1 - \Delta\text{COP}_{\text{AP+}})}{2} \right) \times K_{\text{tib-ant}} \quad (3)$$

This mapping ensures that *changes* in ankle excitation levels from the optimal levels (E_{opt}) are within the range [0,1] corresponding to normalized changes in AP-COP over [-1,+1] prior to multiplication with *output* gains (K_{sol} , $K_{\text{tib-ant}}$), which were tuned to further reduce upper-body effort and minimize oscillations (Zheng, 1992). Measured inputs or gain-multiplied outputs were limited not to exceed normalized bounds. Since the model feet are

rigidly fixed to the ground, the ankle moment applied to the model was set to zero if net ankle moment was in dorsi-flexion. This simulates toe-off conditions when the COM is located approximately above the ankle joint given the erect stance position about which a standing neuroprosthesis is expected to operate.

Forward and backward force-pulse perturbations of 250 msec duration and at test amplitudes of 5, 10, 15 and 20% body-weight were applied at the thorax COM of the model in individual simulations. Total upper-body loading (UB_{load}) was computed as the sum of net PD controller forces applied at the left and right shoulders and measured for 0.5 seconds following perturbation onset, capturing the duration of the disturbance as well as a 0.25 second recovery period. Each forward simulation was 1.5 seconds in length and included the model initially at erect stance before one of the aforementioned perturbations was applied at simulation time = 0.5 seconds. These perturbation simulations were conducted with either (1) ankle muscle excitations held constant at the optimal levels or (2) ankle excitation levels under feedback control as defined in equations 2 and 3. The average and peak UB_{load} was compared across these two condition sets.

RESULTS

Typical a_{trunk} and COP data (Figure 2) collected for type 3 trials include notable excursions in all directions. A_{trunk} amplitudes were consistently small ($\sim 1\text{m/sec}^2$) compared to those observed for volitional swaying (Betker et al., 2006) as subjects likely stiffened their system in resisting external perturbations. Since stiffening was a consistent response against external perturbations, this effect was desirably incorporated into the data used to train the ANN for COP prediction during standing perturbations..

Correlation coefficients (Table 1) across all 3 subjects were highest for COP-components that coincided with the direction of the perturbations in trial types 1 and 2. For trial type 3, which included random and potentially most challenging multi-directional perturbations, the mean ρ across all 3 subjects in the AP and ML directions were 0.701 ± 0.053 and 0.734 ± 0.039 , respectively. The ANN predictions closely matched the true ΔCOP targets in both the AP and ML directions across all data sets for all three subjects. Correlation coefficients were between 0.67 and 0.77 for these data, demonstrating ANN ability to simultaneously identify both AP and ML COP when perturbations were applied randomly and concurrently across both dimensions. Using a simple static linear regression model for prediction, correlation coefficients ranged between 0.55 and 0.63 for the same data. Even when training a single ANN to predict data across all three subjects simultaneously, ρ was similarly high (AP = 0.694, ML = 0.704). For subject 3, using the raw accelerometer signals for a_{trunk} inputs yielded nearly identical correlation results as the digital filter estimate. Figure 3 illustrates the high degree of correlation ($R^2 > 0.75$) between actual ANN-predicted ΔCOP for typical type 3 data.

Feedback control of ankle muscle excitation with the ANN reduced the mean UB_{load} of the computer model by 42% compared to constant excitation across all perturbations tested. Controller feedback also reduced the maximum UB_{load} by 29%. Figure 4 shows results for the 15% body-weight perturbation. Final proportional gains ($K_{sol} = 1.47$, $K_{tib-ant} = 0.59$) were only moderately tuned away from unity ($K = 1$) where ANN output is unaltered. This minimal tuning indicates good first-approximation of control action by the ANN itself.

Feedback control introduced oscillations following perturbation offset in the feedback signal (Figure 4B) and corresponding controller outputs (Figures 4C and 4D). The net effect of these oscillations on simulated user stabilization effort (Figure 4A) was minimal. Even with the oscillations, >90% of the power in the a_{trunk} feedback signal was below 5Hz, which is

well below the stimulation frequency of 20Hz typically applied clinically for standing with FNS (Davis et al., 2001).

DISCUSSION

This preliminary study suggests that 3D acceleration may serve as an effective parameter for deploying control action to maintain standing under perturbation. The ANN successfully identified an empirical coupling between a_{trunk} and control action (i.e., ΔCOP) in normative perturbed standing against discrete perturbations applied in either the AP or ML directions or against unsystematic, continuously applied perturbations. Acceleration has previously been related to ΔCOP assuming system behavior approximates an inverted pendulum (Winter et al., 1998), but this assumption can break down during perturbed standing. The ANN was employed since it is a proven and effective mapping technique to identify complex, non-linear relationships (Haykin, 1999) including input-output parameters for neuroprosthetic development (Lan et al., 1994). The ANN outperformed a simple linear regressor in predicting ΔCOP . It is unclear if this improvement in prediction significantly augments net controller action or if a dynamic linear regressor (e.g., Kalman filter) produces similar results. However, this study suggests acceleration feedback inputs for potentially viable neuroprosthetic standing control regardless of system identifier. ANN prediction of COP using trunk acceleration inputs was similarly high whether training subject-specific ANN structures or a single ANN across data for all 3 subjects. For subject 3, using raw accelerometer data as a_{trunk} yielded similar COP prediction capability as a_{trunk} calculated from the derivative filter. This suggests that sensor noise or changes in sensor orientation relative to the gravitational field observed during perturbed bipedal standing do not significantly affect ANN prediction of ΔCOP .

In simulation, this ANN mapping of a_{trunk} input to ΔCOP output was effectively exploited for feedback control of FNS standing by appreciably reducing the upper-body effort required against perturbation in an SCI model of stance. The power spectral density of the simulated a_{trunk} feedback signal was largely composed of sufficiently low frequencies to which clinical stimulation frequencies can feasibly respond. However, higher frequency content of acceleration-based feedback reduces the controller response margin of error compared to position-based feedback. Ultimately, oscillations in the feedback signal (a_{trunk}) and control outputs (COP and muscle excitation) were sufficiently attenuated by proper tuning, delays in activation dynamics, and upper-body interactions with an assistive device to improve performance compared to open-loop stimulation.

Limitations of this study include the reliance on only ΔCOP for control of standing balance. COP was investigated because it represented a fundamental measure of standing control (Winter, 1995) that conveniently reflected COM dynamics for a simplified inverted pendulum model of stance (Winter et al., 1998). While a_{trunk} was effective in predicting ΔCOP in both AP and ML directions, modulation of soleus and tibialis-anterior activity primarily targeted $\Delta\text{COP}_{\text{AP}}$. Muscle actions at other joints only contribute indirectly to changes in COP, although their effects on COM can be profound. For *comprehensive* control of standing that distributes postural corrections simultaneously across all joints, the actions of individual muscles should be mapped directly to COM. In simulation or experiments involving individuals with SCI, data *directly* relating changes in muscle activity to COM-acceleration (a_{COM}) could be optimized to create a synergy for comprehensive control of standing with FNS (Kuo & Zajac, 1993). In clinical practice, accurate estimation of a_{COM} would then require acceleration measurements from other segments (e.g., pelvis, head and arms) in addition to a_{trunk} .

Other limitations are related to the utilization of able-bodied volunteers to represent individuals with SCI. The ANNs were trained on data from individuals with normative muscle strength, which may have contributed to ankle muscles being maximally recruited during SCI model simulations. This could trigger spastic reflexes in some individuals with SCI, and needs to be addressed on a case-by-case basis. The effective maximum stimulation level for a specific individual may need to be set below the threshold for eliciting spasms. This could reduce potential controller effectiveness, but would be necessary to provide some useful measure of disturbance rejection. Other considerations in training controller operation on normative data include able-bodied individuals having a fully intact sensory system and no available support device such as a walker. Ultimately, an SCI standing system should be entirely based on standing responses of particular SCI users, but this study demonstrates that even normative standing control elicited from a_{trunk} feedback can produce improved performance in a general model of neuroprosthetic standing. Furthermore, the usage of a support device with a standing neuroprosthesis allows an FNS control system to be optimized according to the reduction in upper-body loading. This optimization is subject to the limitations in force production capabilities of stimulated paralyzed musculature for particular users. To this end, user-specific FNS and upper-body control systems should be considered for optimal tuning.

In conclusion, 3D acceleration is a potentially effective feedback parameter for control of standing with FNS. It is intrinsically superior to conventional joint-based control due to its rapid onset and dynamic sensitivity to postural disturbances. This study demonstrated the potential feasibility by exploiting an empirical ANN mapping in simulation that produces changes in COP according to a_{trunk} -feedback to considerably reduce the upper-body loading required to resist perturbations. While accurate estimation of actual ΔCOP would be compromised by the presence of passive joint properties and other unaccounted mechanical factors, neuroprosthesis control actions under acceleration feedback can potentially improve standing performance with proper gain tuning. The next steps are developing and testing comprehensive, SCI user-specific control structures in simulation and employ acceleration-based feedback and implementing them in the laboratory setting.

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Figure 1.

Overall flow diagram of Methods. Three-dimensional trunk acceleration ($3D a_{trunk}$) and center of pressure shift (ΔCOP) data collected from external perturbations applied to normative standing participants in “A. *Experimental Protocol*” used to train ANN in “B. *Artificial Neural Network Processing*”. Trained ANN employed to enact feedback control of muscle excitation levels of ankles to minimize upper-body loading required to stabilize against external perturbations in “C. *Model-based Trunk Acceleration Controller*”.

TRIAL TYPE 3: RANDOM PERTURBATIONS

Figure 2.
Sample trunk acceleration, center of pressure data

Figure 3. ANN prediction of ΔCOP versus true (target) ΔCOP at $\Delta t = 250$ msec for 25-sec test sample from a random perturbation (type 3) trial.

Figure 4.

Simulation results for anterior-directed force-pulse (15%body-weight amplitude, 250 msec duration) perturbation applied at thorax. A: Upper-body loading applied to resist perturbation. B: Anterior trunk acceleration for controller feedback. C: Net COP produced with controller. D: Controller-modulation of ankle muscle excitation levels.

TABLE I
Correlation coefficients between ANN-predicted and true Δ COP at $\Delta t = 250$ msec

Subject	COP-component	Type 1	Type 2	Type 3	All Test Data
1	AP	0.668	0.237	0.667	0.666
	ML	0.205	0.742	0.741	0.735
2	AP	0.682	0.353	0.675	0.676
	ML	0.208	0.661	0.692	0.689
3	AP	0.774	0.231	0.762	0.765
	ML	0.207	0.782	0.768	0.774
3*	AP	0.773	0.230	0.762	0.764
	ML	0.206	0.781	0.765	0.774
Combined**	AP	0.697	0.268	0.699	0.694
	ML	0.204	0.726	0.714	0.704

Type 1: discrete anterior-posterior (AP) pulls. Type 2: discrete medial-lateral (ML). Type 3: continuous, random pulls.

* Denotes usage of accelerometer signal to predict COP

** ANN trained and operated across all subject-normalized data for simulation of FNS system