Novel Interactive Visual Task for Robot-Assisted Gait Training for Stroke Rehabilitation

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***Abstract*—In this paper, we present an interactive visual task for robot-assisted gait training after stroke. The interactive task is designed as a simple soccer-based computer video-game displayed on a screen, played by moving the ankle in dorsiflexion or plantarflexion to guide a cursor (soccer ball) from its original position towards the goal. This stand-alone game is interfaced with the impedance controlled modular ankle exoskeleton ("Anklebot") that provides assistance only as-needed, as an augmentative tool to further enhance ankle neuro-motor control and whole-body function after task-oriented robot-assisted treadmill walking. Here, we present the design and features of the interactive video game, as well as the underlying biomechanical model that relates patient-to-game performance. Additionally, we embed and bench test simple machine learning algorithms to auto-adjust game parameters in real-time, concomitant to ongoing patient performance during robot-assisted therapy. Finally, we propose human in-loop testing strategies to further validate the video-game performance and its feasibility for clinical use.**

I. Introduction

Stroke is a leading cause of long-term disability, affecting nearly 800,000 people, with 75% being first-time incidences and a mortality rate of ~130,000 people in the United States every year [1]. The effects of stroke depend on several factors including the lesion location, resulting in various neurological complications with the most common one being contralateral hemiparesis [2]. Following hemiparesis, both the timing and magnitude of lower extremity (LE) muscle activity often undergoes radical changes due to impairment in both sensory and motor function [3,4]. For most survivors, this impairment causes a loss or impairment in ambulatory activity indexed by gait and balance dysfunction. This imposes higher energy demands in safe execution of activities of daily life (ADL), leading to a high risk of hip or wrist fractures caused by a fall, often in the first year alone [5-7]. Hemiparetic gait is accompanied by whole-leg (e.g. reduced paretic leg swing phase) and joint-specific (e.g. foot drop) biomechanical abnormalities. For example, a major complication resulting from drop foot is the slapping of the foot ("foot slap") upon contact with the ground (as opposed to heel-first strike) and dragging of the toes during stance ("toe drag"). It is well established that motor rehabilitation in the form of physical therapy improves gait deficits post stroke due to neuro-plasticity and motor learning.

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Conventional gait training methods are targeted towards individual joint-impairment and concentrate on practicing different components of the gait like symmetric weight bearing and weight shifting, stepping training (swinging/clearance) and Push off/Calf rise training. Task specific gait training focuses on stimulating the weakened muscle by repeatedly performing functional mobility tasks like walking and climbing. Yet, most stroke survivors live with residual deficits even after completion of conventional rehabilitative therapy, being forced to rely on assistive devices (ADs). In addition, PT-based gait training is labor intensive, often requiring one or more therapists per patient to manually assist with swing motion. Another gait training modality, treadmill aerobic exercise (TM), has proved to be more effective in improving gait speed and cardio-vascular fitness [21]. However, meta-analyses show that gait interventions, whether PT-mediated or TM-based exercise, produce only modest incremental gains in gait speed in those with mild-to-moderate gait deficits [9,10], enabling stroke patients to "limp" faster, but doing little or nothing to robustly improving underlying gait biomechanics or reduce dependence on ADs.

Rehabilitation gait robots (modular or whole-leg) hold promise to promote lower limb motor recovery. Broadly, these devices fall under to categories: 1) Wearable robotic exoskeletons that propel the paretic leg forward (e.g. Electromechanical Gait Trainer, GT1 [11,12], Lokomat [13], Robot Assisted Gait trainer (RAGT) [14]), and 2) Actuated footplates attached under the sole of the foot that simulate different phases of gait (e.g. Haptic Walker [15]). However, current LE robotics remains controversial, with consensus that current approaches are inferior to usual care, or possibly deleterious [16,17]. Although these technologies are sophisticated, the operating principles are not aligned with contemporary motor neuroscience. In response, we have developed and clinically tested a modular, impedance-controlled, backdrivable, 2-DOF actuated ankle robot ("Anklebot") to improve walking and balance functions after stroke [18], by means of increasing the paretic ankle contribution into task-oriented functional activities such as walking. Numerous clinical studies have shown that the Anklebot can improve paretic ankle motor control while reducing paretic ankle impairments, which translate to whole-body improvements such as higher floor walking speeds (20%) [19,20]. In the most recent clinical study [21], the Anklebot was integrated into treadmill training (TMR) using an adaptive control to precisely time robotic activation to sub-events and ankle directionality across the gait cycle [22]. This approach enabled the customization of robotic therapy to individual gait deficits (e.g., foot drop, weak push-off) and precisely timed impedance control support, in turn affording safety and maximum autonomy during robot-assisted walking practice [22]. The primary finding was that six weeks of TMR (3×weekly) durably improves gait biomechanics and paretic ankle function during independent walking in chronic stroke survivors [21]. Underlying these improvements were a progressive increase in unassisted paretic swing to normal levels with retained improvements 6 weeks after cessation of training, which caused a majority of TMR graduates (85%) self-discard their orthotics or reduce reliance on their ADs. In addition, TMR significantly increased stance propulsive impulses to near-normal levels at retention, which contributed toward ongoing increases in gait velocity after training ended. To our knowledge, this is the first therapy, robotic or otherwise, to therapeutically improve functional dorsiflexion and restore impaired push-off during independent walking in chronic stroke enabling individuals to more ambulatory in home and community settings, by means of greater and better engagement of their paretic ankle. However, few prior studies including ours, have used sensory-motor enhancements like visual tasks as a cueing and motivational stimulus, to augment robot-mediated functional outcomes. And even bigger gap is in "closing the learning loop" that is, to implement co-operative learning in which the robot's performance is continually or periodically updated based on ongoing (step-by-step) human performance (Fig. 1). Our overarching *hypothesis* is that an interactive visual task when integrated with TMR, will further increase the ankle neuro-motor and whole-body functional gains (and learning rates in those measures), and that these performance changes can shape robotic outputs to close the loop. In this paper, we present: a) a novel interactive visual task (videogame) that integrates with TMR to augment previously reported gains in ankle neuro-motor function (i.e. without videogame); b) a simple machine learning algorithm to create a framework enabling "two-way (co-operative) learning"; and c) bench validation results to demonstrate proof of concept, both without (i.e. "one way learning") and with (i.e. "two-way learning") machine learning.

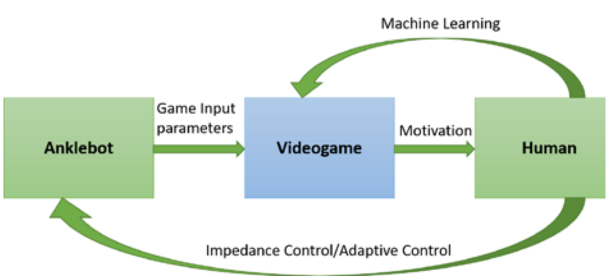

Figure 1. Conceptual model of human-robot-visual task interaction to promote two-way cooperative learning.

II. USE OF VISUAL TASKS FOR GAIT TRAINING

Patient nonadherence in therapy is a major barrier to rehabilitation. Recovery is often limited and requires prolonged, intensive rehabilitation that is time-consuming, expensive, and difficult. Research suggests that video games are beneficial for cognitive and motor skill learning in both rehabilitation science and experimental studies with healthy subjects. Physiological data suggest that game play can induce neuro-plastic reorganization that leads to long-term retention and transfer of skill [23-25]; however, more clinical research in this area is needed. There is interdisciplinary evidence suggesting that key factors in game design, including choice, reward, and goals, lead to increased motivation and engagement [26].

Various studies [26-29] have been conducted to evaluate the efficacy of incorporating a visual task to help in the process of neurorehabilitation –robot-assisted or otherwise. For example, treatments such as robot-assisted repetitive task practice (RTP) and virtual rehabilitation activities [30-35], have been shown to produce improvements in hand function, but have yet to reinstate function to pre-stroke levels—which likely depends on developing the therapies to impact cortical reorganization in a manner that favors or supports recovery. A comparative study between the RTP training and Robot Assisted Virtual Reality (RAVR) rehabilitation suggests that RAVR training leads to different neuro-physical changes when compared with traditional therapy. This effect may be attributed to the influence that augmented visual and haptic feedback during RAVR training exerts over higher-order somatosensory and visuomotor areas.

A fundamental conceptual question in stroke neuromotor rehabilitation is whether to emphasize task specific gait pattern training, or modular and joint specific mass training aimed at specific stroke impairments. Early on, we conducted a 6-week (3×weekly = 18 sessions) seated performance-based robot training to determine initial feasibility for using the ankle robot in extended training in individuals with chronic and sub-acute stroke [19,20]. A performance-based training protocol was implemented with subjects playing a "racer" videogame, adapted from the MIT Manus protocols, that requires repetitive DF and PF of the paretic ankle to move a screen cursor "up or down" in order to pass through "gates" that approached across the screen at different vertical levels. Gate locations were individualized for each subject based on paretic ankle AROM, and level of assistance was set initially to facilitate an 80% success rate, while the level of robotic support was reduced every 2 blocks (160 movements), from 125—75—25 Nm/rad, increasing the volitional movement demands on the paretic ankle. Sessions also included unassisted trials before and after training, bringing the total targeted movements to 560 per day to fit within a one hour training session, including rest intervals between blocks of trials. The primary finding was that this visually-evoked, visually-guided seated Anklebot training significantly improved all robotics measured parameters of paretic ankle motor control and selected spatiotemporal gait parameters in chronic hemiparetic patients that had already completed all conventional rehabilitation options.

While the seated visuomotor approach with the Anklebot showed promise as a motor learning platform for persons with chronic hemiparetic stroke, it represented only the first attempt at gauging the device's feasibility for use across the phases of generally. It seems likely that the greatest impact for this impairment-based application may be for whole-body task oriented gait training, as demonstrated by our adaptive control approach that integrated the Anklebot with treadmill-based walking (see Section III). Moreover, the positive effects of motivation and bio-feedback through visual task integration into robotics has been demonstrated—subjects who trained with the interactive video game using the Anklebot were found to have more efficient cortical dynamics i.e., reduced networking [36]. Whether such an interactive visual task when integrated into robot-assisted walking, can augment neuro-motor outcomes, remains as open question (see Section IV). What is however clear, is that visual stimulus in the form of video games increase patient engagement and motivation, if designed correctly (i.e. balance between game *simplicity* and *flexibility*). Currently, most interactive videogames for robotic therapy require the use of upper-extremities and hence such platforms are more intuitive. In contrast, VR has been preferred for LE rehabilitation but VR-based platforms are accompanied by added costs and equipment, and are not easy to integrate with the robotic device used for therapy.

III. Adaptive Ankle Robotics For Gait training

To meet the requirements for ankle robotic locomotor therapy for stroke and other neurologic diseases, we developed adaptive control to precisely time robotic activation to sub-events and ankle directionality across the gait cycle [22,37]. This customizes robotic therapy to individual gait deficits (e.g., foot drop, weak push-off) and precisely timed impedance control support, in turn affording safety and maximum autonomy to effectively integrate the Anklebot into the context of locomotor learning (Fig. 2). A novel feature of the adaptive controller is the use of robust systems control that tolerates perturbations due to step-to-step variability, thereby increasing operational stability, and accommodates heterogeneous levels of mobility across the spectrum of stroke recovery [22]. The underlying concept is to precisely time robotic assistance, if needed, to gait sub-events derived from real-time signals via bilateral micro-switch insoles. This breakthrough allows, for the first time, the ability to: (1) Differentially target deficits in both stance and swing phases of gait, enabling tailoring of robotic assistance to individual deficits (e.g., foot drop, weak push-off, improper landing) via gait sub-event triggered actuation, (2) Tolerate step-to-step variability to prevent destabilization and ensure patient safety, (3) Progress and dynamically modulate robotic outputs, both in the immediate time frame (step-to-step) and over the course of therapy (inter-visit), as subject performance adapts. This novel *co-robotics* application defines a cooperative learning process between the subject and robot, which over time dynamically shapes robotic outputs to promote and elicit greater volitional effort toward durable locomotor learning. To our knowledge, TMR constitutes the only therapy to reverse foot drop, restore paretic leg propulsion, and correct heel-first landing in persons with chronic stroke. Hence, adaptive control co-robotics holds promise to shift practice paradigms for the care of hemiparetic stroke, providing a bioengineering solution to a previously immutable neurological deficit.

IV. Development Of The Video Game

Here, we present a novel and simple interactive visual task, packaged as a single input (robot torque)—output

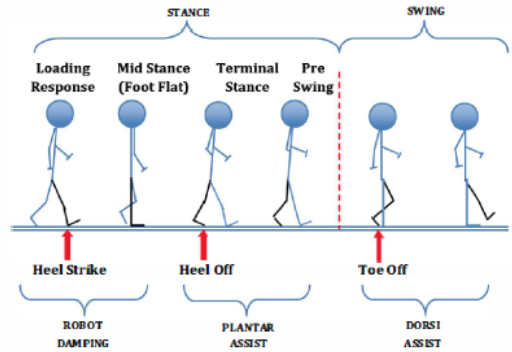

Figure 2. Underlying principle of adaptive Anklebot timing: the robot delivers assistance during key gait sub-events

(screen cursor) computer video game. It is based on the penalty kick scenario in a soccer game. The objective is to provide step-by-step bio-feedback during assisted-walking to facilitate patient's walking performance (e.g. swing DF clearance). A key feature of the game is that it challenges the patient based on their performance by incorporating an adaptive learning algorithm.

A. Task Requirements

The visual task for ankle rehabilitation must be linked directly or indirectly to walking and should also be easily relatable to the geriatric, stroke patients. In addition to providing motivation to the patients through bio-feedback, the visual interface must capture relevant Human-robot interaction (HRI) metric i.e. human vs. robot torque contribution (see Section V-B). The primary requirement was to develop game environment and cursor control such that cursor movement is determined by clinically relevant kinetic or kinematic metric that can be either measured or be derived from the robot (e.g. peak swing angle). Other key requirements of the Visual Task are highlighted in Table 1.

TABLE I. Requirements for the Video Game

Category	Requirement
Functional	Ability to switch directionality of therapy (dorsiflexion/plantarflexion).
	Real-time computation of performance improvement or decline .
User Interface	Multiple layers for performance challenge and calibration (screen-to-torque sensitivity, torque threshold, pixel offset).
	Choice of appropriate machine learning method.
Human Factors	Real-time display of HRI (0-100% of maximum).
	Stride-by-stride cumulative score on task.
	Clear indication of completion of a milestone.

B. Game Architecture

The soccer game is developed to be a standalone entity for universal use with any robot. This gave us the flexibility of the choice of programming language. We used the ubiquitous Python owing to its high portability while consisting of comprehensive package of game development, signal acquisition, statistical analysis, and GUI development. The architecture of the game is shown in Fig. 3. The video game uses footswitch voltage data to detect gait events (e.g. toe-off) and torque data to stimulate the ball position, both in real-time. We established an Ethernet Tcp/Ip connection between the robot host and videogame computers, using used *Netcat* for information flow.

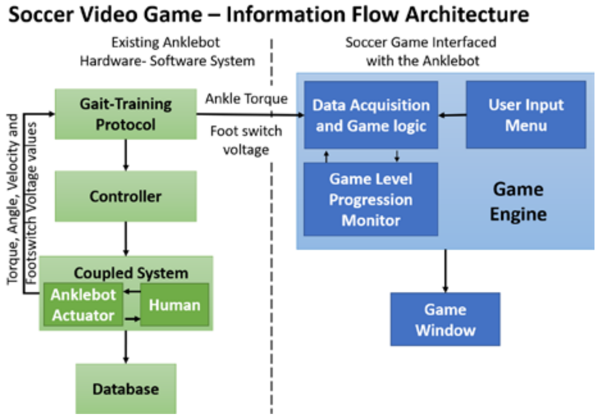

Figure 3. A high-level information flow architecture diagram of the game interfaced with the existing Anklebot hardware-software system.

C. *Game Model*

The soccer game is event-triggered (i.e. activated only for desired events corresponding to gait deficits) with straight forward rules. The ball is initially placed on a red line and traverses linearly towards the goal as the patient starts the robot-assisted gait training exercise (Fig. 4). The game is designed to run in two modes: a) Dorsiflexion, to provide assist during the swing phase (characterized between the toe-off and foot-strike events). In this mode, the biomechanical metric of interest is the peak swing angle (θ_{PSW}); and b) Plantarflexion, to provide supplemental propulsive assist during the stance phase (characterized between the foot-strike and toe-off events). In this mode, the biomechanical metric of interest is the estimated peak human torque ($\vec{\tau}_H$). To make intuitive sense, the PF mode consists of the origin of the ball in the middle of the screen with the ball moving downwards during the stride. Similarly, in the DF mode, the ball starts at the origin and travels upwards.

The model development proceeds along the following lines: the net ankle torque ($\vec{\tau}_{net}$) is the vector sum of the robot ($\vec{\tau}_R$) and human ($\vec{\tau}_H$) vector torques i.e.

$$\vec{\tau}_{net} = \vec{\tau}_H + \vec{\tau}_R. \tag{1}$$

Since the ankle robot is controlled by a simple impedance controller, the net robot torque may be expressed as:

$$\vec{\tau}_R = K\theta + B\dot{\theta}, \tag{2}$$

where K and B are the programmable controller stiffness and programmable controller damping, respectively. Compensating for device stiction (± 1.41 Nm), we can estimate the human torque ($\widehat{\tau_H}$) in absence of a force transducer as:

$$\widehat{\tau_H} = K\theta + B\dot{\theta} - \vec{\tau}_R - \vec{\tau}_{stiction}, \tag{3}$$

The game screen is symmetric about the vertical axis. The initial geometric position of the game screen elements described by their vertical position in pixels is expressed as:

$$y_{start} = \frac{y_{max} - y_{min}}{2} \tag{4}$$

where, y_{start} is the starting position of the red line indicating the origin position of the ball at the start of each trial of the game, y_{max} is the position of the goalpost, y_{min} is the farthest position that the line can take without crossing the bounds of the screen. The movement range of the ball, H is defined as:

$$y_{max} - y_{min} = H \tag{5}$$

In-sole foot switches that generate a discrete cumulative foot-switch voltage determine the "state" of the videogame (i.e. active functionality, or not). The DF or PF human ankle torque causes movement of the screen cursor. Hence,

$$y_{ball} = \alpha\,\widehat{\tau_H} + y_{start} \tag{6}$$

where, y_{ball} is the absolute position of the ball during the gameplay and α is a sensitivity scaling constant (pixels/Nm) that relates τ_H to y_{ball}. In practice, we conduct a seated isometric test before the actual TM based gait training to evaluate the patient's maximum torque capability, thus enabling the therapist to set the sensitivity α_{calib} for each patient. This performed by patient exerting maximum volitional DF or PF torque ($\tau_{H|max}$) against a "stiff" spring whose impedance is characterized by the controller programmable stiffness and programmable damping. Hence,

$$\alpha_{calib} = \frac{H/2}{\tau_{H|max}} \tag{7}$$

The underlying algorithm kicks in when the footswitches indicate an event of interest. The algorithm checks for the peak estimated human torque during phase of interest (e.g. stance for PF assist or swing for DF assist) and continually updates per the following rule:

$$\tau_{max,i+1} = \begin{cases} \tau_{max,i} \ , & \tau_{i+1} \leq \tau_{max,i} \\ \tau_{i+1} \ , & \tau_{i+1} > \tau_{max,i} \end{cases} \tag{8}$$

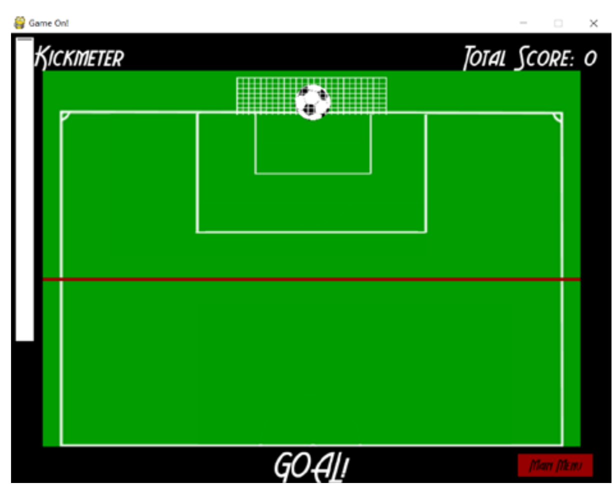

Figure 4. Soccer game rudiments window showing its UI.

with $\tau_{max,1} = \tau_1$. Hence, for each sample during the phase of interest, the position of the ball is given by (Fig. 5):

$$y_{ball} = \alpha\tau_{max} + y_{start} \tag{9}$$

D. Machine Learning for Game Progression

In the seated training protocol of the Anklebot using the "racer game" [19,20], the game parameters did not dynamically adapt to human performance within an ongoing trial. In the soccer game for robot-assisted gait training, we have embedded machine learning that dynamically auto-adjusts videogame parameters (e.g. difficulty indexed by y_{start}) based on ongoing improvement or decline in the patient's performance within the same robot-assisted session. We embed two machine learning methods—a simple average or the correlation coefficient (r)—of the peak human torque ($\widehat{\tau_H}$) across individual gait cycles. To be specific, the difficulty is increased (or decreased) by moving the cursor (ball) starting line further away (or closer) from the goal post. The extent to which the starting line is moved depends on the relative improvement (or decline) in performance over a user-specified fixed analysis window (N), which is numerically calculated either using an average over past (N-1) cycles compared to the N^{th}-cycle, or by examining the sign and magnitude of the correlation coefficient (r). For instance, for the regression method, the start line is moved away or towards from the goal post depending on improvement (r > 0) or decline (r < 0), respectively (Fig. 5). The new position of the starting line (y^*_{start}) is given by:

$$y^*_{start} = y_{start} + sgn[r]\Delta y_{start} \tag{10}$$

$$\Delta y_{start} = |\beta r|.$$

where β is user-specified scaling factor that amplifies the improvement (or decline) to a change in the starting line.

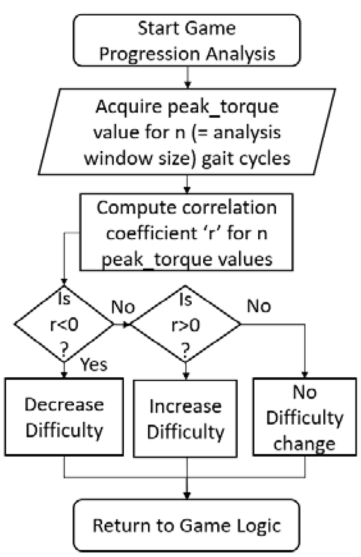

Figure 5. Flowchart describing the machine learning algorithm using the correlation coefficient as the determinant parameter. Difficulty refers to starting line position with respect to the goal post, as defined by Eq. (10). A higher value indicates further away from the goal post (i.e. more difficult or challenging), and vice versa.

V. Validation and Testing of the game Model

As proof-of-concept, we bench tested the videogame integrated human-robot system. This consisted of: a) validating the accurate capture of footswitch signals and comparing model-derived stiction-compensated torques against angular acceleration (derived from positional encoder data [18]); and b) verifying "causality" i.e. that the peak torques across gait cycles accurately predict and move the soccer ball on the screen per Eqs. (6) and (8).

A. Physical Signal Validation

Data was collected from the robot placing it on the bench (i.e. no human) programmed for DF deficit (target event: toe-off) and replicating gait cycles by repeatedly stepping on and off the footswitches (Fig. 6). This was done to verify that the torque profile corresponds to the commanded angle trajectory. Figures 6 shows approximate angular acceleration profiles from ankle angle data. We then compared the net torque profile ($\vec{\tau}_{net} \approx \vec{\tau}_R, \vec{\tau}_H = 0$) from Eq. (3) to verify that the sign of the stiction-compensated torque and angular acceleration are in close resemblance. The stiction-compensated torque was filtered using a Lowess smoothing filter in Matlab™.

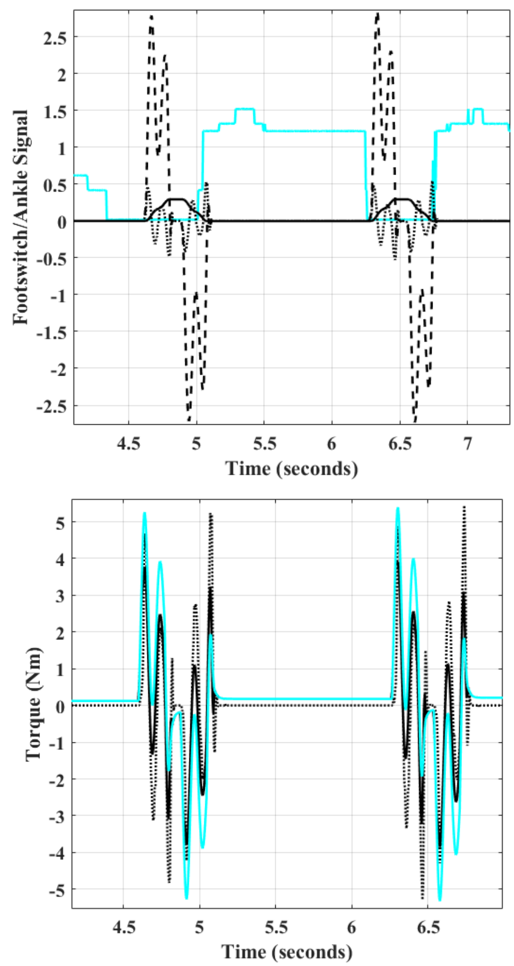

Figure 6: Bench tests of the human-robot interface with event-triggered robotic actuation (Top) Raw traces of footswitch voltage (—), ankle angle (—), velocity (--), and angular acceleration × 0.005 (…); (Bottom) Comparison of stiction-compensated torques vs. scaled angular acceleration × 10, both shown for two simulated gait cycles.

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B. HRI-Videogame Validation: "Causality"

We used the stiction-compensated peak torque values as an offline input to stimulate the videogame. The real-time on-screen ball position was predicted by Eqs. (8) and (9) within and across gait cycles, and was in concordance with desired behavior (Fig. 7)—either the ball position saturated with respect to the previous position (when differential torque did not increase) or moved closer to the goal post (when differential torque increased).

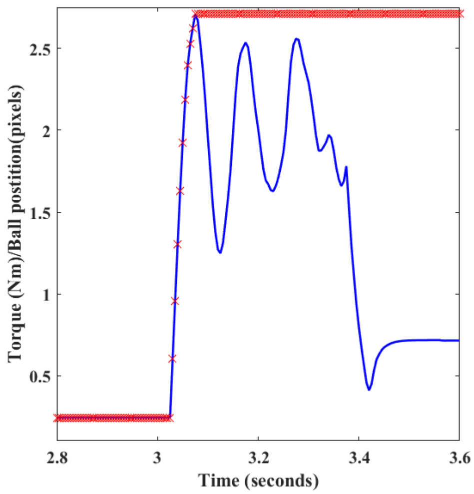

Figure 7: Input-Output characterization of the HRI-videogame system. The ball position conforms to Eqs. (8) and (9) for $\alpha_{calib} = 1$.

C. Machine Learning Validation

We next tested the machine learning correlation-based model. Correlations were performed every 5 cycles—if the coefficient was positive (i.e. improvement, or $sgn[r] > 0$), the start line position increases (Δy_{start}) (i.e. moves away from the goal post providing a challenge). Similar, if the coefficient was negative (i.e. decline, or $sgn[r] < 0$), the start line position decreases (Δy_{start}) (i.e. moves closer to the goal post providing less difficulty). Figure 8 shows an example when there was consistent decline in performance in human torque ($\widehat{\tau_H}$), causing adjustments to the task difficulty (i.e. monotonic decrease in the starting line with respect to the goal position).

VI. Conclusions and Future Work

The work presented here is a first step towards developing a fully-integrated video-game for robot-assisted locomotor therapy. The model and validation procedures show that gait parameters such as dorsiflexion and plantarflexion torques are reflected meaningfully in the game environment and have the potential to evaluate gait improvements in addition to its motivational and bio-feedback value. As this is ongoing work, the next step entails testing the game while interfaced with the human walking with Anklebot, first in able-bodied adults followed by persons with hemiparetic gait. Results will be compared against subjects who underwent TMR training but without the interactive visual task. In the future, we envision adding supervised learning techniques to better predict human performance to modulate task parameters.

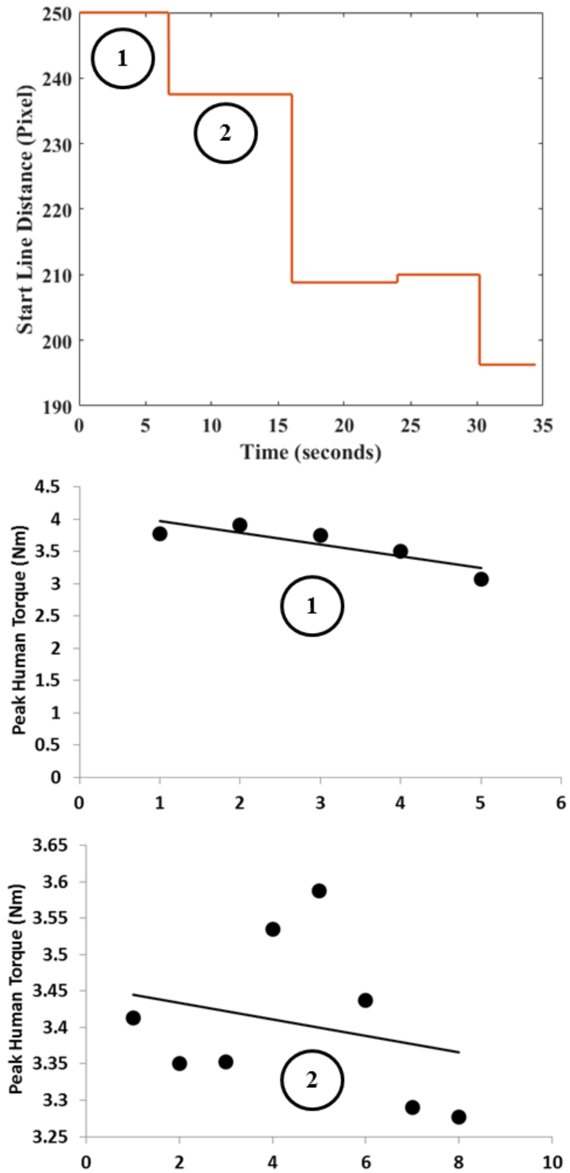

Figure 8: Machine learning mediated (correlation method) adjustments to the task difficulty (starting line) with changes in peak human torque across gait cycles. Starting line is initially set at 250 pixels and correlations are computed over an analysis window N=5 cycles (shown by region "1") and N=8 cycles (shown by region "2").

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