An Integrated Neuro-Robotic Interface for Stroke Rehabilitation using the NASA X1 Powered Lower Limb Exoskeleton

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***Abstract*— Stroke remains a leading cause of disability, limiting independent ambulation in survivors, and consequently affecting quality of life (QOL). Recent technological advances in neural interfacing with robotic rehabilitation devices are promising in the context of gait rehabilitation. Here, the X1, NASA's powered robotic lower limb exoskeleton, is introduced as a potential diagnostic, assistive, and therapeutic tool for stroke rehabilitation. Additionally, the feasibility of decoding lower limb joint kinematics and kinetics during walking with the X1 from scalp electroencephalographic (EEG) signals – the first step towards the development of a brain-machine interface (BMI) system to the X1 exoskeleton – is demonstrated.**

I. Introduction

Stroke is a leading cause of neurological disability in the United States [1] and accounts for the poor physical health and the social dysfunction evident in survivors [2]. Gait impairment is a large contributor to long-term disability and ambulatory dysfunction in daily living [3]. Physical rehabilitation tends to remain the mainstay in long-term stroke treatment to regain functional independence. This primarily focuses on harnessing extant neuroplasticity to learn normal, synergistic movement patterns that promote safe, independent ambulation. In this regard, therapeutic approaches, as well as underlying theoretical models to stroke rehabilitation, are diverse. However, continuously increasing healthcare costs tend to limit supervised therapy times and access to rehabilitation clinicians at later stages of recovery, thereby acting as a rate-limiter to functional recovery.

More recently, body-weight supported robot-assisted treadmill training has been shown to lead to better functional outcomes [4-7]. However, the limitation of these devices is that they are largely restricted to the clinical or research setting, owing to their size, and are therefore less amenable to training with other functional tasks such as over ground walking, climbing stairs etc. Therefore, newer therapeutic "wearable" lower-limb robotic devices, namely "exoskeletons," have been developed [8-10]. These augment the user by mechanically actuating joints to completely or partially assist movements of the lower limb segments, depending on the patient needs. However, the neurophysiological (both central and peripheral) mechanisms by which these robotic devices interact with the human body are not yet completely understood. This knowledge is particularly important for designing appropriate therapeutic interventions for neurorehabilitation with these devices. Here, NASA's (National Aeronautics and Space Administration) X1 was used in conjunction with a neural (EEG) and musculoskeletal (goniometry and electromyography (EMG)) interface for the first time, in two healthy individuals as well as an individual with hemiparesis following stroke. The X1 was originally designed for mobility assistance and leveraged technology developed during NASA's Robonaut 2 program and prior work on lower extremity exoskeletons performed at the Florida Institute for Human and Machine Cognition (IHMC). This heritage makes X1 suitable as a rehabilitative tool for use with hemiparetic stroke survivors. Its versatility is also being demonstrated in the areas of exercise and dynamometry, capabilities important to NASA for counteracting the detrimental effects of microgravity during spaceflight. The primary objective was twofold: a) to demonstrate feasibility of implementing a multimodal physiological interface with the X1 device, and b) to decode lower limb movement (in terms of kinematics and kinetics) during over ground walking from scalp EEG signals. This will drive design of an optimal neural interface with the X1, which can be clinically implemented and tested for efficacy in stroke rehabilitation.

II. Methods

A. Participants

Two able-bodied males (H1 and H2; ages 33.75 +/- 0.12 yrs) and one 51-year old male (S1) with right hemiparesis following stroke (Fugl-Meyer Assessment of Lower Extremity Motor function score 12/34; Berg Balance Scale score 38/56; Functional Gait Assessment score 13/30) participated in this study. All participants provided voluntary informed consent and performed study procedures that were approved by the Institutional Review Board at the University of Houston.

B. X1 powered lower limb exoskeleton

The X1 exoskeleton is a 10-degree of freedom (DOF) wearable robotic device created through a partnership between NASA's Johnson Space Center and IHMC [11]. In the configuration used for this study, four DOFs are actuated (knee flexion/extension and hip flexion/extension for each leg; all in the sagittal plane) and six DOFs are passive (hip internal/external rotation, hip abduction/adduction, and ankle plantarflexion/dorsiflexion for each leg). Actuation is achieved via custom-built series elastic actuators powered by electric motors and custom motor controllers. The passive

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DOFs are capable of being mechanically locked in position for applications with people lacking full use of their lower extremities and abdomen. Control modes of the X1 include a dynamic position trajectory generator, which commands hip and ankle joint angles to replicate a desired gait, based on inputs such as step height, step duration, and step length. Another useful control mode is "passive": the motors respond to any knee or hip movement to "match" the user's desired joint angle. In this manner, the device allows the user to walk with his/her normal gait; the X1 simply adjusts its joint angles to match the wearer, making the device relatively transparent to him/her.

C. Experimental Procedure and Data Acquisition

Participants were instructed to walk over ground, with and without the X1 donned, in a large empty indoor area (see Fig. 1). Participants walked for about 5 minutes each in 3 different conditions: *No Robot*; *Robot Off*, wherein the X1 was donned in "passive" control mode; and *Robot On*, wherein X1 was donned in "active" control mode. For safety, healthy participants used assistive devices while walking, namely, a walker or a cane. A mobile harness system with minimal bodyweight support was used for participants while walking with the X1, as an additional safety precaution. Sufficient rest was allowed between trials to prevent fatigue.

Whole scalp 64-channel EEG data were collected (actiCap system, Brain Products GmbH, Munich, Germany) and labeled in accordance with the extended 10-20 international system. EEG data were online referenced to channel FCz. Electrode impedances were maintained below 10 kΩ with bandpass filters set at 0.01-100 Hz with a sampling rate of 1 kHz. EEG signals were digitized using a BrainAmp DC amplifier linked to BrainVision Recorder software version 1.10 and were time-locked with the EMG, kinematics, and X1 data using an external trigger circuit to mark the start and stop of both the rest and walking periods. The trigger signal was transmitted wirelessly using the Pololu Wixel RF transmitter/receiver (Pololu Corporation, Las Vegas, NV) [12].

Surface muscle activation patterns were recorded with a portable 8 channel surface EMG data acquisition system (DataLOG MWX8 EMG data collection unit, Biometrics Ltd., Cwmfelinfach, Gwent, UK) at a sampling frequency of 1000 Hz (bandpass filtered at 20-460 Hz). Bipolar surface electrodes (SX230 EMG electrodes, Biometrics Ltd., Cwmfelinfach, Gwent, UK) with a fixed electrode distance of 20 mm were placed bilaterally over the following muscles: tibialis anterior (TA); gastrocnemius (GA); biceps femoris (BF); vastus lateralis (VL) after adequate skin preparation to reduce impedance (shaved with a razor, softly abraded with sandpaper, and cleaned with alcohol using medical cotton). Six flexible biaxial electro-goniometers (SG150 Gonio electrodes, Biometrics Ltd., Cwmfelinfach, Gwent, UK) were bilaterally mounted on hip, knee and ankle joints to capture lower limb angular kinematics at a sampling rate of 1000Hz. Specifically, the endblocks of hip goniometers were placed on the lateral side of the pelvis (upper endblock) and femur (lower endblock) to monitor hip extension/flexion. Knee sensors were placed on the medial side of femur (upper endblock) and tibia (lower endblock) for knee extension/flexion to minimize interference from the X1 straps

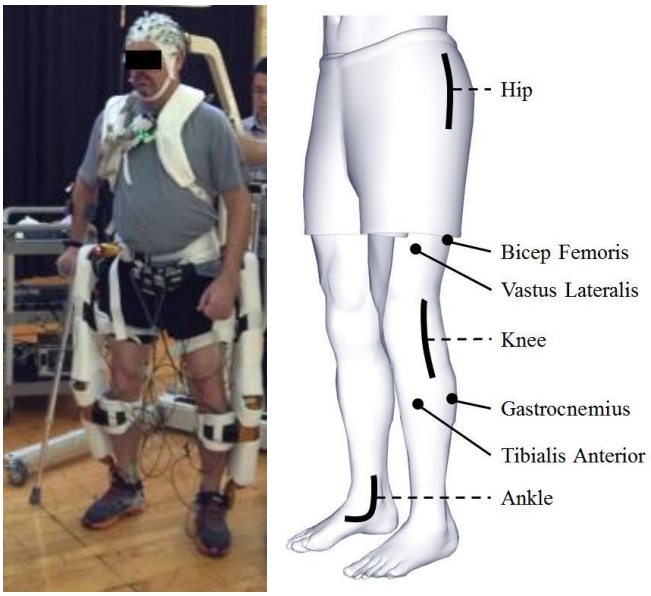

Fig. 1. Left: A stroke subject fitted with the NASA X1 exoskeleton and goniometer, EEG, EMG sensors. Right: A diagram of placement of the sensors. Dot indicates EMG sensor, thick solid line indicates goniometer. Apart from other sensors on left leg, ankle goniometer on right leg is shown here. All sensors come in pairs on both legs. (Picture adapted from https://www.biodigitalhuman.com/)

on the lateral side. Ankle sensors were also medially placed to the lower end of the tibia and medial part of the calcaneus to capture ankle joint plantar/dorsiflexion. Joint angle at hip and knee was also measured internally in the X1 at 200 Hz, and synchronized with other data through the aforementioned trigger. Based on this, goniometer data was substituted by X1 data whenever X1 data existed in the following kinematics analysis. That is to say, kinematics measured by goniometer was used only in ankle (X1 doesn't have ankle joint measurement) and in no-robot condition.

D. Signal Processing and Decoding Algorithms

Pre-processing: Peripheral EEG channels were immediately removed for offline analysis as they are most susceptible to artifacts from eye-blinks, head movements, and facial/cranial muscle activity [13], namely, most frontal channels (Fp1, Fp2, AF7, AF8, F7, F8), all of the temporal channels (all channels labeled FT, T, TP), and the parietal channels PO9 and PO10. EEG data were then detrended and subsequently common average referenced. EMG signals were further bandpass filtered at 30-400Hz, full-wave rectified, and bandpass filtered at 0.1-2 Hz to extract their linear envelope [14]. Kinematic data were bandpass filtered at 0.1-3 Hz, given that this frequency range contained 90% of the original power in walking [15]. In order to match the sampling rate of other data, X1 data were interpolated to reach 1 kHz offline. EEG data were filtered into the same band as EMG and kinematics data to be later fit into the decoder. All data processing was done offline in Matlab (Mathworks Inc., Natick, MA).

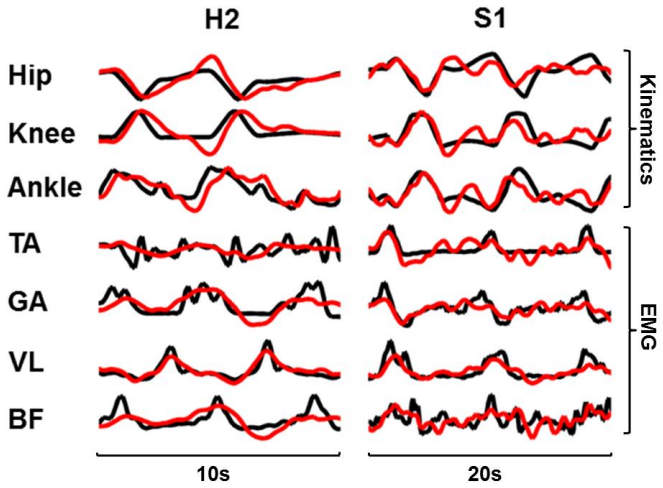

Fig. 2. Exemplary traces of reconstructed joint angular position measured by the X1 and EMG linear envelopes of lower limb muscle activities in the *"Robot On"* condition for one healthy subject (H2) and the affected leg of the stroke survivor (S1). Red traces represent reconstructions (normalized) from the right leg; black traces represent measured data (normalized) from the right leg. TA: Tibialis anterior; GA: Gastrocnemius; VL: Vastus lateralis; BF: Biceps femoris.

Decoding Algorithm: Principal component analysis (PCA) was applied to the EEG data matrix to reduce the high dimensionality (number of channels multiplied by number of time lags), by an approximate factor of 10 while still preserving 99% of the variance. A 10th order unscented Kalman filter was used to separately predict the goniometer and EMG measurements from the EEG signals. This recursive state space algorithm was adapted from the Kalman filter used for neural spike decoding in [16], with a slight variant on the neural tuning model adapted for EEG. The neural tuning models used were two linear functions mapping weights to a vector of EMG voltages at each recorded muscle and to a vector of joint angles and their time derivative, with no other nonlinear augmented terms. Decoding accuracies were assessed via a ten-fold cross-validation procedure. Prediction accuracy of the decoders was quantified by calculating Pearson's correlation coefficient, *r*, between the measured kinematic/EMG signal and the predicted output [15].

III. RESULTS

In this pilot study, the feasibility of using the X1 lower limb exoskeleton on a stroke survivor was established. Particularly, a multimodal, namely neural (EEG), electromyographic (EMG) and motion (goniometers) interface was instrumented in conjunction with the X1 exoskeleton. Here, successful decoding of lower limb joint kinematics as well as kinetics (EMG) from scalp EEG in a stroke survivor fitted with the X1 exoskeleton while walking over ground (Fig. 2) is shown for the first time. It is interesting to note that that the decoder performed reasonably well; similarity between measured and reconstructed kinematic and kinetic traces in hip and knee joint kinematics of the affected (right) leg of the stroke survivor was observed. Since the X1 configuration utilized in this study does not provide ankle measurement data, goniometer data were substituted for them throughout this study. However, offline

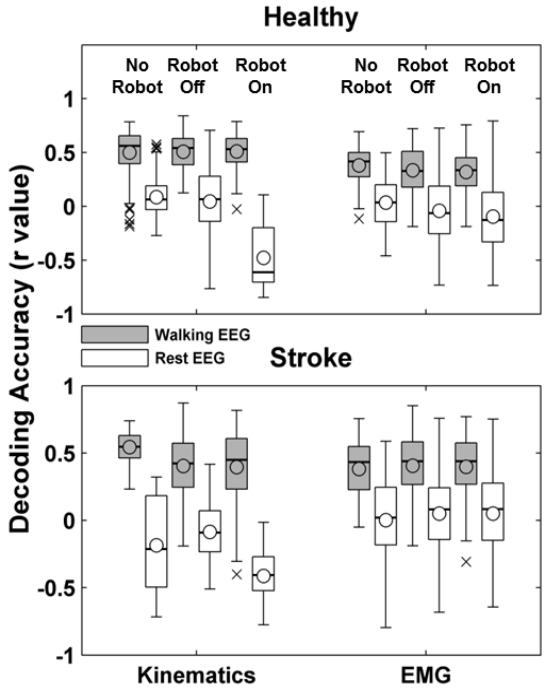

Fig. 3. Boxplots showing decoding accuracies for kinematics and EMG across 10-folds of cross-validation for healthy subjects and the stroke individual, across both lower limbs in different walking conditions. Chance level was established by decoding accuracies obtained for predicting kinematics and EMG from Rest EEG. Note that lack of overlap between the interquartile ranges of boxplots indicates significant difference in medians.

correlation coefficients between joint kinematics measured by X1 (hips and knees) and corresponding goniometers were high ($r \approx 0.9$), indicating reliability of the X1 system in movement assessment and its potential as a rehabilitative tool.

Fig. 3 shows the decoding accuracies for both kinematics and EMG across the 10 different folds of decoding. As seen, decoding accuracies tend to be high and above chance levels (determined by calculating decoding accuracies from Rest EEG), and reasonably consistent across the three conditions. Compared to joint angles, accuracy for decoding EMG activity tends to be slightly lower on average. Moreover, decoding accuracies were comparable across all subjects. Taken together, these findings suggest the feasibility of decoding gait parameters in functional over ground walking in stroke individuals fitted with a powered exoskeleton.

IV. DISCUSSION

Here, preliminary evidence was presented for integrating an EEG-based neural interface with a lower limb robotic exoskeleton, namely the X1, for potential applications in stroke neurorehabilitation. The significance of this system lies in the fact that it can be used for gait rehabilitation in functional environments, i.e. walking over ground versus the treadmill-based operation of existing robotic rehabilitation devices. Specifically, the decoupling of the robotic system from the treadmill allows for easy incorporation into rehabilitation regimens for exercise training other than walking as well.

Next, the feasibility of decoding joint kinematics and muscle activity patterns from scalp EEG during walking with the X1 in healthy participants and a stroke survivor was

demonstrated. Interestingly, moderately high decoding accuracies were observed, averaging around 0.5 for lower limb kinematics from noninvasively recorded scalp EEG. This is very encouraging as these systems can readily be translated to the clinic. However, decoding accuracies for lower limb EMG activities were lower, on average around 0.4. This was probably due to the fact that EMG electrode placement was particularly difficult due to the X1's human-machine interface present in the same anatomic locations. This is a limitation that deserves attention; strategies to overcome this issue via device design modification are in work. For example, interface cuffs and straps with a recessed area for EMG electrodes would greatly help integrating the myoelectric interface with the X1. This modification would help both space and non-space clinical applications of the X1 by making it more equipped for physiological monitoring of user effort during exercise as well as rehabilitation. Another important consideration in the decoding of movement from scalp EEG during walking is the head movement-related artifact potentially contaminating EEG. Currently, work is underway in our lab to systematically characterize this artifact and its influence on the decoding algorithm and we aim to use these data to modify the algorithm by increasing its robustness and reliability.

Clinical Implications and Future Directions

These preliminary findings have important implications in designing neural interfaces that can directly control wearable robotic devices during walking. Unlike classifying discrete commands such as "walk" and "stop", our study demonstrates the possibility of controlling the X1 via continuously decoded trajectories. This can help ensure more thorough engagement of the user and also allows simultaneous monitoring and quantification of internal states and neural plasticity over time. Particularly, such a system can be more readily applied to stroke patients with lesser functional abilities given the assistance provided by the robotic devices, thereby allowing gait training in these individuals while ensuring patient engagement.

An important point to be noted here is that an actuated ankle joint in the X1 would be very clinically relevant to counteract foot drop problems typically seen in stroke survivors. This would significantly help train gait initiation and encourage normal heel-toe gait patterns in these patients. Currently, work is underway to add an actuated ankle to the X1's design. Another area that needs further investigation is the control algorithms or "strategies" that can be incorporated into rehabilitation protocols. These could range from "assist-as-needed" to X1-provided resistance as users perform movements while wearing the robot. In this context, the EEG-based neural and peripheral musculoskeletal interfaces will also serve as monitoring means to observe and quantify user engagement during therapeutic sessions. An appropriate feedback loop can then be set up to incorporate these data into the control algorithm so that it can be modified as needed. Together, this will help create an "adaptive" neurorobotic system that will constantly adapt to the user's needs and promote functional recovery.

In summary, the first evidence was provided for the feasibility of decoding kinematic and surface EMG patterns from scalp EEG during over ground walking of both healthy and post-stroke subjects with a powered robotic exoskeleton. Further research is required to validate this system's clinical utility and to provide insights into design modifications. The authors are currently engaged in a larger study with more stroke survivors to address these important clinical questions to enable translation of this neurorobotic interface to X1 for stroke rehabilitation.

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