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Accelerometer-based step initiation control for gait-assist neuroprostheses

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Abstract—Electrical activation of paralyzed musculature can generate or augment joint movements required for walking after central nervous system trauma. Proper timing of stimulation relative to residual volitional control is critical to usefully affecting ambulation. This study evaluates three-dimensional accelerometers and customized algorithms to detect the intent to step from voluntary movements and trigger stimulation during walking in individuals with significantly different etiologies, mobility limitations, manual dexterities, and walking aids. Three individuals with poststroke hemiplegia or partial spinal cord injury exhibiting varying gait deficits were implanted with multichannel pulse generators to provide joint motions at the hip, knee, and ankle. An accelerometer integrated into the external control unit was used to detect heel strike or walker movement, and wireless accelerometers were used to detect crutch strike. Algorithms were developed for each sensor location to detect intent to step to progress through individualized stimulation patterns. Testing these algorithms produced detection accuracies of at least 90% on both level ground and uneven terrain. All participants use their accelerometer-triggered implanted gait systems at home and in the community; the validation/system testing was completed in the hospital. The results demonstrated that safe, reliable, and convenient accelerometer-based step initiation can be achieved regardless of specific gait deficits, manual dexterities, and walking aids.

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Key words: accelerometer, gait, neuroprosthesis, rehabilitation, spinal cord injury, step, step initiation, stimulation, stroke, trigger.

INTRODUCTION

Neuroprostheses employing electrical stimulation can restore or enhance walking function in people with paralysis from spinal cord injury (SCI) [1–2] or stroke [3]. Applying small electrical currents to the intact peripheral nerves can elicit contractions from the paretic or paralyzed muscles resulting from interruption of descending control due to central nervous system trauma or dysfunction. Coordinating the actions of one or more muscles can assist or generate useful motions of the entire limb, including standing and walking movements.

Originally, electrical stimulation was applied with electrodes placed on the surface of the skin [1]. Due to inability to recruit deep muscles (i.e., hip flexors) and inconvenience and difficulty in applying multiple surface electrodes [3], fully implanted stimulation systems were developed. The original implantable devices were single-channel systems

Abbreviations: AIS = American Spinal Injury Association Impairment Scale, AP = anterior-posterior, ECU = external control unit, EMG = electromyography, FSR = force sensing resistor, FVA = foot velocity algorithm, IMU = inertial measurement unit, IPG = implanted pulse generator, iSCI = incomplete spinal cord injury, LHS = left heel strike, ML = mediolateral, RHS = right heel strike, SCI = spinal cord injury.

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developed for the common peroneal nerve stimulation to correct foot drop in people with stroke by activation of dorsiflexors [4]. It was soon realized that for effective gait correction, hip and knee flexion, in addition to hip stability, were also important. This led to development of a multichannel percutaneous system to define the most effective muscle set for an implanted system with a limited number of channels [5]. Such multichannel implanted pulse generators (IPGs) were successfully tested in a number of case studies in people with incomplete SCI (iSCI) [6–7] and stroke [8]. Concurrently, a number of peroneal nerve stimulators for surface [9–11] or implanted stimulation [12–13] were developed and commercialized, while multichannel implanted pulse generators are still limited to research use [6–7,14–15].

An important consideration for systems designed to assist gait is step initiation. Detecting and controlling gait events using sensors is a rapidly emerging field that has a wide range of applications. From fitness, prosthetics, orthotics, and other exoskeletal devices, it is important to detect gait events accurately and repeatedly. It is especially important in applications for which it is necessary to combine control of an assistive device with the user's volitional control. The step initiation should come from conscious effort of the user, for example, from trunk orientation detected by a level sensor [16] or accelerometer, volitional activity of muscles as detected by electromyography (EMG) [17–18], or simply pressing a switch [5]. Foot switches, force sensing resistors (FSRs), or level sensors are the main source of heel strike or foot-off detection for commercially available systems. Their reliability can vary based on the placement of the device in the shoe, the type of footwear worn, the terrain walked on, and the type and severity of gait impairment. Thus, stimulation timing can be affected by false triggering, foot strike mechanics, or large delays between when the heel actually leaves or strikes the ground and when the heel sensor detects it. In long-term use, foot switches have been shown to deform and malfunction from mechanical breakage of solder joints or sticking contacts [19]. In addition, foot switches require extra equipment that must be donned, which can be difficult for subjects with stroke who have upper-limb impairments and poor manual dexterity. This equipment can also interfere with gait. Alternatively, steps can be initiated automatically as in free cycling or can be based on sensor inputs to a finite state controller [20]. In users with partial paralysis, stimulation can be activated by detecting movement of their less-affected leg. However, it is important that the stimulation is seamlessly integrated with proper timing with their volitional function [5] so that it does not inhibit their volitional effort or interfere with their balance.

In recent years, researchers have been investigating alternative means for the detection of gait events based on accelerometry. Accelerometers are small, relatively inexpensive, and can detect the rapid movements that are seen in gait [21–22]. Accelerometers have also been shown to produce reliable and repeatable signals that can be used for closed-loop control of gait [23–28]. While accelerometers are as reliable as heel contact sensors or FSRs, most accelerometer-based systems still required additional equipment that must be worn or attached to the foot [27–28], shank [26], or thigh [25]. As an alternative to body-mounted sensors, which may be difficult for users with limited manual dexterity to don, we implemented accelerometers for step initiation that are seamlessly integrated into the external control unit (ECU) or walking aids for ease of use. Since many patients use assistive devices such as canes, crutches, or walkers, the movement of which are coordinated with their gait, instrumenting these devices provides an opportunity for an effective means to estimate gait intentions.

In this study, we explored various ways of initiating steps based on each individual subject's specific ability to interact with a multichannel electrical stimulation device while walking. This is particularly important for many system users with hemiplegia or partial paralysis who often have difficulty coordinating their voluntary movements with stimulation since manual (button press) triggering is not an option because of limited hand function, simultaneous use of walking aids, and the additional cognitive burden involved. Free cycling stimulation patterns can be difficult to synchronize with volitional effort, especially when varying walking speed or encountering obstacles and inclines. In this study, three different accelerometer-based step initiation control algorithms were implemented for three unique neuroprosthesis users with different impairments. The algorithms were customized and differed in structure and operation based on the individual presentation of each user. We hypothesized that a safe, reliable, and convenient step initiation could be achieved in these individuals with varied hip, knee, and ankle gait deficits; manual dexterities; and use of walking aids by means of appropriate choice of accelerometer location and processing algorithm.

METHODS

Participants with Implanted Multichannel Systems

Three participants, each with a unique gait deficit, level of manual dexterity, and ability to use a walking aid, were evaluated in the study. All three participants received an 8-channel IPG that was surgically implanted subcutaneously in the abdominal region with implanted intramuscular electrodes at nerves to activate the muscles required to best address their individual gait deficits [6–7,29]. Surgically implanted intramuscular electrodes [30] were inserted into the body via a minimally invasive procedure to excite the targeted motor nerves and connected to the IPG so nothing crossed the skin. A 16-gauge needle probe was inserted at the motor point, with test stimulation applied to ensure activation of the target muscle. A 12-gauge cannula was slipped over the probe to the same depth. The probe was then removed and an intramuscular electrode was introduced via a lead carrier through the cannula to the nerve to activate the target muscle. The electrode lead was then tunneled subcutaneously to the lower abdomen and connected to the IPG by means of intralead connectors [31]. A rechargeable ECU controlled the IPG via an inductive link provided by a transmitting coil taped to the skin over the implant to provide power and control parameters for the stimulation (**Figure 1**).

Constant current stimulus pulses 20 mA in amplitude at a frequency of 20 Hz were pulse-width modulated (0–250 µs). Preprogrammed stimulation patterns were triggered by events detected by the accelerometers (i.e., pelvic acceleration or walker or crutch movement). For example, a walker movement would indicate intent to step, which would activate stimulation to the hip and knee flexors and ankle dorsiflexors to initiate a step followed by the quadriceps for terminal knee extension in preparation for heel strike. Stimulation parameters and timing were tuned heuristically [32] by a physical therapist and engineer for each participant during initial training sessions. Stimulation patterns for walking or exercise can be selected either with a wireless finger switch or buttons on the ECU enclosure. Once the gait stimulation pattern is selected, the step initiation control is based on events detected either by an accelerometer located inside of the ECU, packaged into a separate wireless inertial measurement unit (IMU), or mounted on a walking aid.

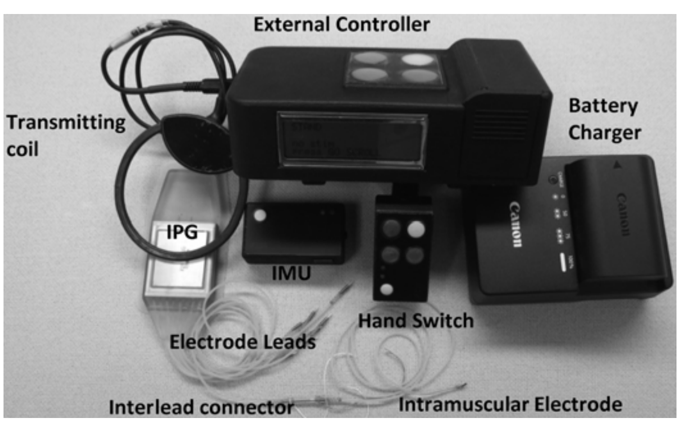

Figure 1.
Implantable multichannel gait system. IMU = inertial measurement unit, IPG = implanted pulse generator.

Subject 1 (male, 193 cm, 107 kg, 54 yr old, average volitional walking speed of 0.5 m/s) with hemiplegia (left-side affected) due to stroke had deficits marked by stiff-legged gait and foot drop (**Table 1**). He walked with a single-point cane. Volitional gait was characterized by compensation strategies including hip hiking and circumduction for toe clearance during swing. Electrodes were implanted for activation of his left sartorius, gracilis, iliopsoas, and tensor fasciae latae for hip and knee flexion; quadriceps for knee extension; and tibialis anterior and peroneus longus for ankle dorsiflexion. Quadriceps were implanted to extend the knee for heel strike with the ankle dorsiflexed to mitigate the tendency to engage the stereotypical hemiplegic flexion synergy.

Subject 2 (male, 178 cm, 68 kg, 28 yr old, average volitional walking speed of 0.05 m/s) with C5 iSCI (American Spinal Injury Association Impairment Scale [AIS] C) had significant functional upper-limb deficits including weakness in finger movements, hand grasp, and elbow extension (**Table 1**). His gait was marked by extensor tone, which made it difficult to consistently initiate steps at will while walking with a front-wheeled walker. Electrodes were implanted bilaterally by nerves innervating hip flexors (right tensor fasciae latae and sartorius; left tensor fasciae latae and iliopsoas), knee extensors (quadriceps), and ankle dorsiflexors (tibialis anterior and peroneus longus).

Subject 3 (female, 169 cm, 53 kg, 51 yr old, average volitional walking speed of 0.2 m/s) with C6 iSCI (AIS C) had gait marked by significant plantar flexion tone and knee recurvatum resulting in toe dragging while walking with forearm crutches (**Table 1**). Electrodes were implanted bilaterally for activation of tensor fasciae latae and sartorius (hip flexion), short head of biceps

Table 1.
Subject overview.

Subject	Injury	Deficits	Gait Speed (m/s)	Assistive Device	Muscles Implanted	Sensor Location
1	Stroke	Hemiplegia	0.5	Cane	L ST, L GR, L IL, L TFL, L TA/L PL, L QU	ECU on hip
2	iSCI	C5, AIS C, UL	0.05	Walker	B TFL, R ST, L IL, B QU, B TA/B PL	Walker
3	iSCI	C6, AIS C	0.2	Forearm Crutches	B TFL, B ST, B SHB, B TA/B PL	Crutch tips

AIS = American Spinal Injury Association Impairment Scale, B = bilateral, C = cervical, ECU = external control unit, GR = gracilis, IL = iliopsoas, iSCI = incomplete spinal cord injury, L = left leg, PL = peroneus longus, QU = quadriceps, R = right leg, SHB = short head of biceps femoris, ST = sartorius, TA = tibialis anterior, TFL = tensor fasciae latae, UL = upper limb.

femoris (knee flexion), and tibialis anterior and peroneus longus (ankle dorsiflexion).

Step Detection Instrumentation and Data Acquisition

Instrumentation

For Subjects 1 and 2, the step trigger was based on accelerometer signals from a 3-axis LIS344ALH (ST Microelectronics; Geneva, Switzerland) linear accelerometer in the ECU with the accelerometer range set at ±2 *g*. The accelerometer signals were low-pass filtered at 10 Hz with a passive, first order, onboard resistor-capacitor filter. For Subject 3, the accelerometer portion of an LSM330DLC (ST Microelectronics) IMU was used in a wireless sensor with the accelerometer range set at ±2 *g*. This wireless sensor also contained a CC430F6137IRGC (Texas Instruments; Dallas, Texas) microcontroller with integrated 915 MHz wireless transceiver, which allowed it to wirelessly communicate with the ECU. The sensor circuitry used in this study had a size profile of 45 mm × 23 mm and a current consumption of 65 μA.

Data Acquisition

The accelerometer signals from respective location for each subject (**Table 1**) and FSR insoles (B&L Engineering; Santa Ana, California) were collected simultaneously with motion capture data for step trigger control algorithm development. The motion capture data were acquired with a 16-camera Vicon MX40 (Vicon Inc; Oxford, United Kingdom) system over an 8 m walkway. Reflective markers were placed on the sacrum and bilaterally on the anterior-superior iliac crest, thigh, knee, tibia, lateral malleolus, calcaneus, and second metatarsal. The accelerometer data were acquired at a minimum frequency of 50 Hz, with laboratory data acquisition software developed in the Simulink/xPC real-time environment (The MathWorks Inc; Natick, Massachusetts).

Data Analysis and Algorithm Development

A customized accelerometer-based step initiation algorithm was developed for each subject by following the process shown in **Figure 2**. The accelerometer placement was based on impairment, type of walking aid, and individual gait characteristics. Data collected during automatic cycling stimulated walking were analyzed for peak accelerations using Simulink to identify the corresponding gait events and walking aid movements. Simulations were performed using subject's data to test the accuracy of gait or walking aid event detection. This process was iterated upon by adjusting thresholds to achieve a near 100 percent true positive rate. Once a final algorithm was developed, it was programmed onto the subject's ECU or wireless sensor for evaluation during walking with stimulation. If needed, minor adjustments to the algorithm were made after testing real-time event detection. Then, the accuracy of step initiation was evaluated for each subject based on true and false positive rates.

Subject-Specific Step Initiation Algorithm: Subject 1

Because the subject had full control of his right leg, it was decided that left step would be initiated relative to the right heel strike (RHS). Thus, if the subject wanted to stop walking he would end with the left step. The RHS was detected with the accelerometer within the ECU strapped around subject's waist on his right side (**Figure 3(a)**) [8]. As shown in **Figure 3(b)**, the anterior-posterior (AP) acceleration signal is periodic and contains peaks at left heel strike (LHS) and RHS (as determined by the motion analysis data) and the medio-lateral (ML) signal

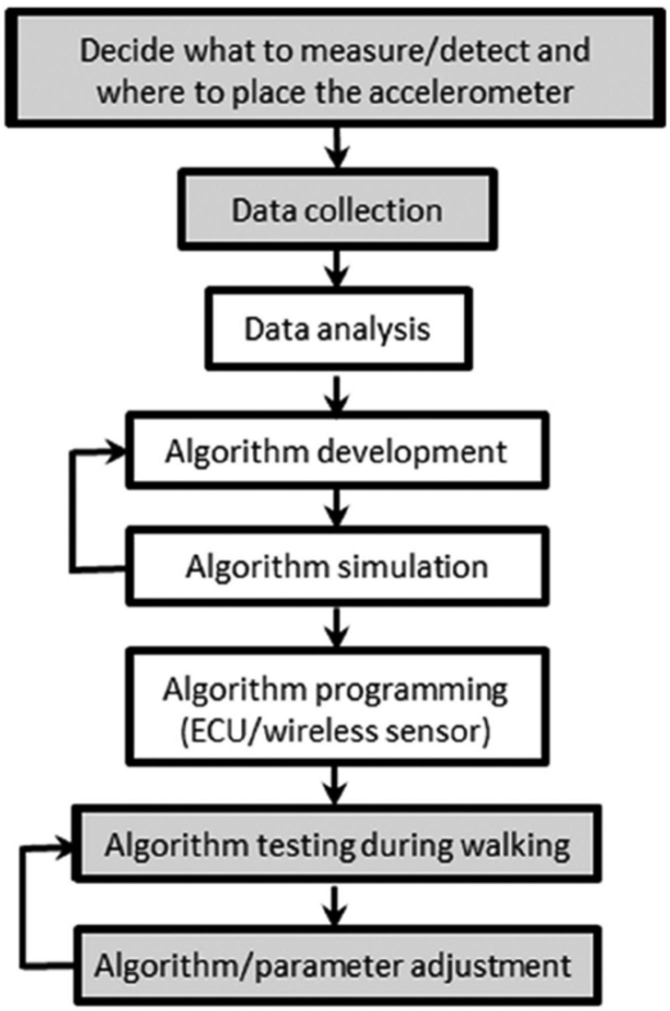

Figure 2.
Algorithm development process; shading indicates subject participation. ECU = external control unit.

alternates between low and high at LHS and RHS, respectively. To determine gait events, we processed the motion analysis data using the foot velocity algorithm (FVA) [33]. The FVA is an accurate way to determine gait events using kinematic marker data. The FVA calculates the foot center vertical velocity, and from the peaks and valleys in this signal, heel strike and toe off can be determined. The algorithm was implemented in Simulink to detect peaks in the filtered (second-order Butterworth 3 Hz low-pass filter) AP signal to determine when a heel strike occurred. The ML signal was compared against a standing calibration baseline to determine whether it was in a high or low state to indicate whether it represented a RHS or LHS, respectively.

The algorithm only searched for peaks in the AP signal that were above a threshold to eliminate low magnitude noise. The initial threshold was determined from the baseline data collection and updated during walking based on a moving average of the peak AP acceleration values that were taken at the previous three heel strikes. Thus, the threshold was continuously adjusted to account for variations in the acceleration signals due to change in walking speed, terrain, or movement of the ECU. Each time the system was used, an automatic calibration was performed during standing to remove the gravitational component of acceleration (which was considered as a constant vector) to adjust for variation in ECU placement. Upon startup, a 2 s average of the 3-D accelerometer position served as baseline. The baseline gravitational/positional component values were subtracted from accelerations during walking to get the values due to movement. We assume that LHS occurred at the end of left step and RHS occurred at the end of right step. Since the stimulation pattern was known, the algorithm only looked for LHS or RHS during the latter part of the respective step, thus eliminating potential false triggers occurring from foot drag during swing. A decision tree of the algorithm is shown in **Figure 3(c)**. For Subject 1, stimulation was triggered by the RHS to initiate stimulation for left hip flexion and ankle dorsiflexion. However, analyses were done for both legs to show that for future participants both heel strikes can be detected with an accuracy of 98 percent from an accelerometer in a single location and stimulation can be applied to either or both limbs [8]. Step accuracy for Subject 1 was determined from data collected in the laboratory and outdoors, as well as at home using a data monitoring system in the ECU.

Subject-Specific Step Initiation Algorithm: Subject 2

Since the subject was unable to use a finger switch because of limited hand function and unable to reliably initiate left or right step without stimulation, it was decided to detect movement of his walker, which he was able to move at will prior to each step. Thus, the forward movement of the walker was used as intent to make a step, and the algorithm tracked whether the left or the right step needed to be initiated next. Forward walker movement was detected with an accelerometer within the ECU placed inside a pouch attached at the front of the walker (**Figure 4(a)**). ECU placement in the pouch resulted in the accelerometer's z-axis being approximately aligned with the AP direction, which allowed for detection of forward movement of the walker. Due to the orientation of the accelerometer's

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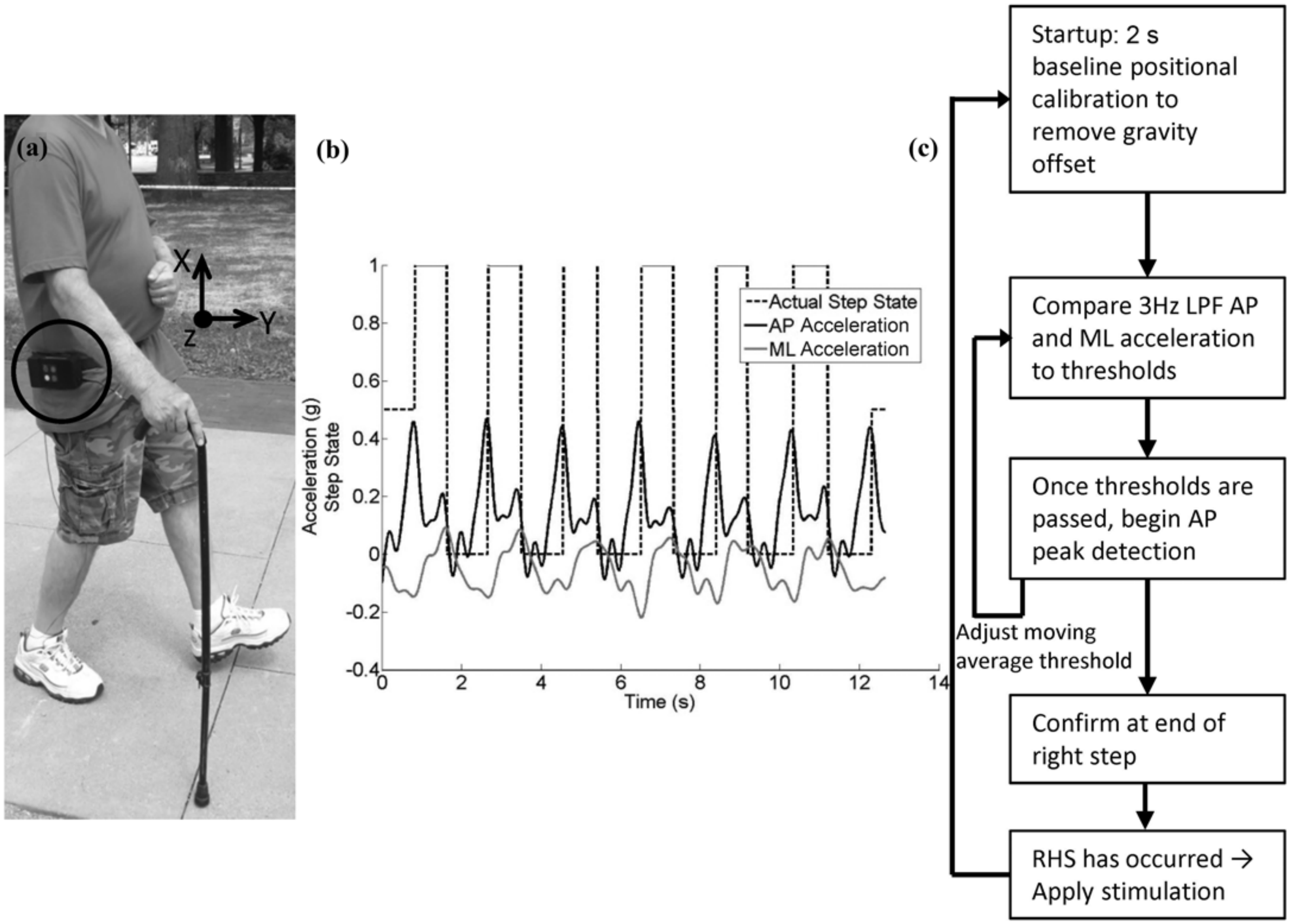

Figure 3.
(a) Subject 1 wearing external control unit (circled) at the right hip. **(b)** Anterior-posterior (AP) and medio-lateral (ML) acceleration. A high-to-low transition of the step state indicates a right heel strike (RHS) and a low-to-high transition is a left heel strike. **(c)** Decision tree of the algorithm. LPF = low-pass filter.

z-axis, a forward movement of the walker caused a negative acceleration followed by a positive acceleration. A backward movement resulted first in a positive followed by a negative acceleration. The sequence of the signs of successive peaks allowed movement direction to be identified. To categorize the walker movement, the algorithm shown in **Figure 5** first filtered the *z*-axis acceleration signal with a second-order bandpass digital filter (0.3 Hz to 2 Hz). The lower band limit of 0.3 Hz was selected in order to remove the gravitational component of the accelerometer signal, while 2 Hz was selected as the upper cutoff frequency in order to reduce unnecessary higher-frequency components of the signal. The algorithm then compared the filtered signal to a specified threshold (z_accel_th1) to detect the negative acceleration event that occurred first for a forward walker push. This threshold was determined by looking at the walker acceleration data collected from subject 2 during walker pushes. It was set at –0.05 V, which corresponded to approximately –0.08 *g*. If this negative acceleration threshold was exceeded, the algorithm then checked for a positive acceleration threshold (z_accel_th2) to be exceeded within a set time (t_limit_max). Again, these values were determined by inspecting Subject 2’s walker acceleration data. The positive acceleration threshold was set at 0.11 V, which corresponded to approximately 0.17 *g*, while the time window was set at 0.9 s. If these conditions were all met, the

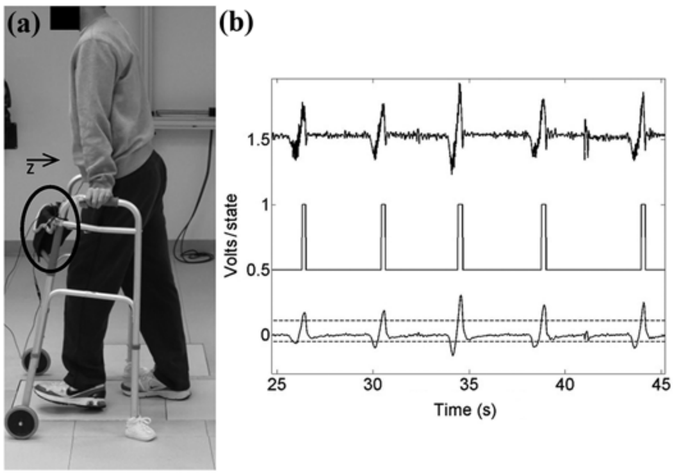

Figure 4.
(a) Subject 2 walking with stimulation triggered by walker push (external control unit circled), and **(b)** raw *z*-axis (anterior-posterior) walker acceleration signal (top) and filtered (bottom). A negative peak followed by a positive peak indicates forward walker movement. Algorithm output trigger for step initiation (middle). Thresholds are shown in dashed lines.

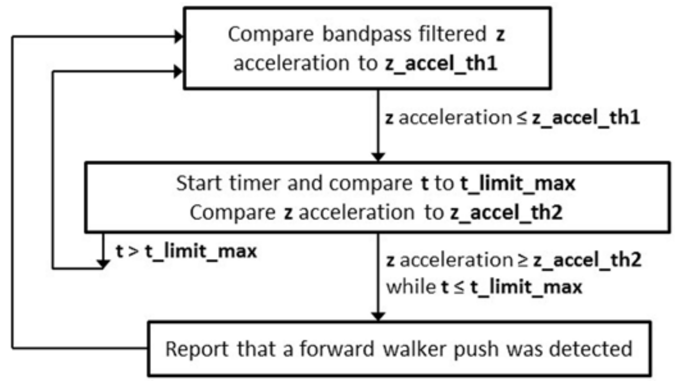

Figure 5.
Flowchart for forward walker movement detection algorithm. z_accel_th1 = –0.05 V, z_accel_th2 = 0.11 V, t_limit_max = 0.9 s.

algorithm reported that a forward walker push was detected, and the ECU initiated the stimulation pattern for the appropriate leg. Note that the determination of the thresholds for this algorithm was an iterative process in which the initial thresholds were selected as 75 percent of the peak accelerations, and then simulations of the algorithm were run using Subject 2's walker push acceleration data and adjusted up or down in 5 percent increments as necessary to achieve 100 percent success rate with no false triggers. Subject 2's forward walker movement acceleration data and simulation results are shown in **Figure 4(b)**. The raw *z*-axis (AP) acceleration signal is shown in the top trace of **Figure 4(b)**, while the bottom trace shows the signal after filtering. The output trigger shown in the middle trace is the result of simulating algorithm performance offline with data collected during walking with cyclic stimulation.

Due to unavailability of Subject 2, the walker movement algorithm was tested in real time by a nondisabled volunteer pushing the walker indoors and outdoors over various terrains and grades with the ECU mounted on the walker and programmed to generate an audible beep each time it detected a walker push. Backward movements were also performed to test the algorithm's accuracy and ability to ignore those movements.

Subject-Specific Step Initiation Algorithm: Subject 3

This subject relied heavily on forearm crutches for her balance and support. She had difficulty volitionally initiating either step, which increased with fatigue. However, she was able to reliably move her crutches at will. Thus, forward crutch placement was used as intent to initiate a contralateral step and trigger stimulation. Crutch strike was detected based on accelerometer signals from wireless sensors placed inside of left and right baby shoes attached at the end of the crutch tips used for increased stability (**Figure 6**). A block diagram of the algorithm developed to detect crutch strike for Subject 3 is shown in **Figure 7**. First, the acceleration in the AP direction (*x*-axis) was compared to a threshold (x_accel_th1). If this threshold was exceeded, it then looked for the acceleration to drop below a second threshold (x_accel_th2) within a specific time (t_limit_min < *t* < t_limit _max). This requirement helped ensure that the crutch was swung forward and not just repositioned in place. The algorithm then looked for crutch strike to occur within another window of time (t_limit2_min < *t* < t_limit2_max) by comparing the AP (*x*-axis) snap and vertical (*z*-axis) snap to specific thresholds (x_snap_th and z_snap_th). Note that snap is the second derivative of acceleration and has been shown to have greater proportional change at impact events and be less prone to alignment errors than acceleration [34]. If all of these algorithm requirements were met, the wireless sensor transmitted a wireless data packet to the ECU, which then initiated the stimulation pattern for the intended left or right step. The algorithm then waited a certain amount of time (t_wait) before it began searching for the next acceleration to ensure completion of the current step. The thresholds and

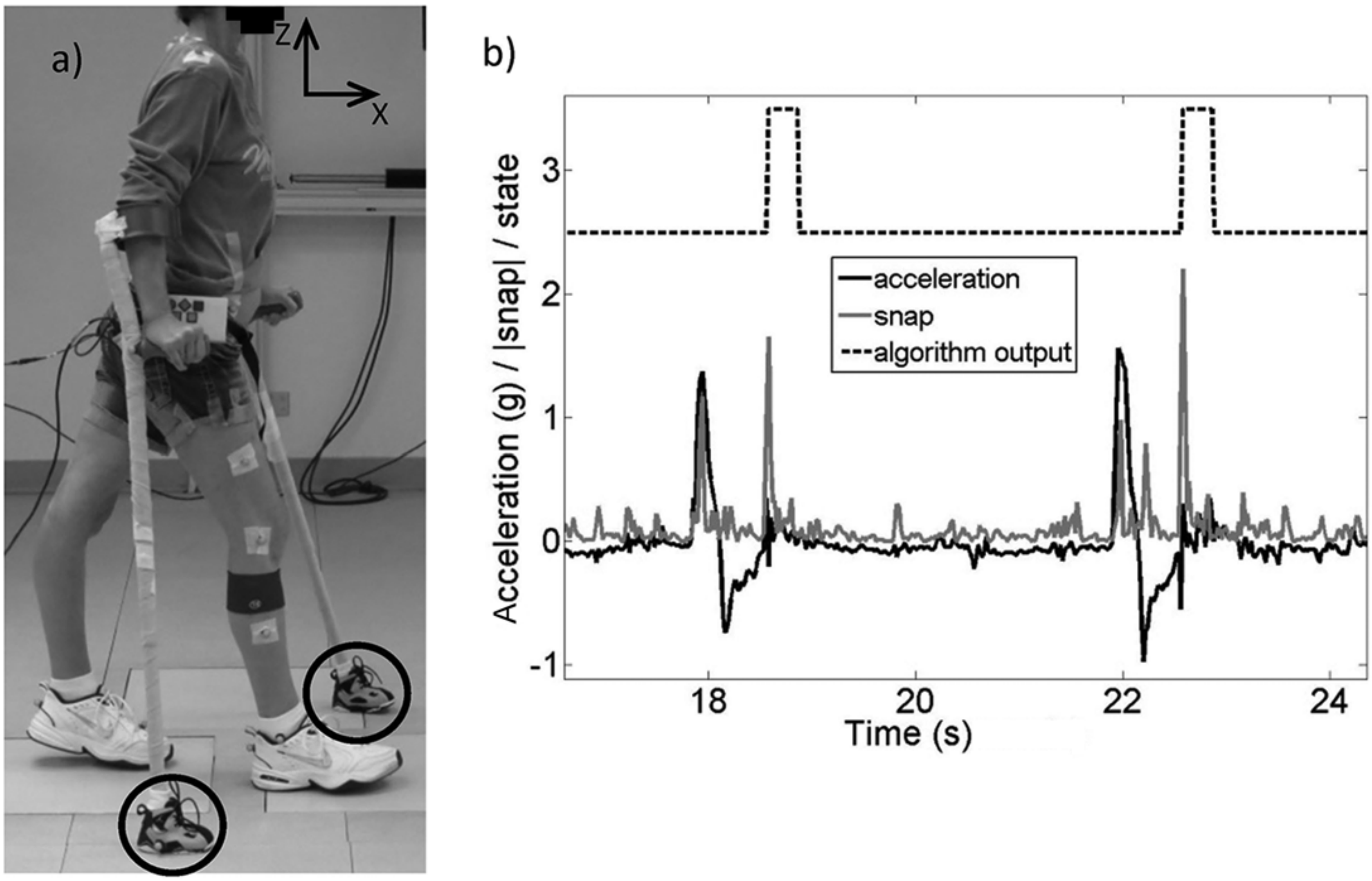

Figure 6.
(a) Subject 3 (S3) walking with stimulation, and **(b)** S3's right crutch acceleration with algorithm simulation results for step initiation. The bottom portion of the plot shows *x*-axis acceleration (solid) and the absolute value of *z*-axis (vertical) snap (dashed). The algorithm output is shown at the top with the low-to-high transitions indicating when a right crutch strike was detected. The wireless sensors were placed in the crutch tips (circled).

timing parameters for this algorithm were initially determined by analyzing Subject 3's wireless sensor crutch acceleration data and setting the values tolerant enough to handle the variances seen in Subject 3's crutch swings/strikes but strict enough to ignore other crutch movements (e.g., repositioning crutch). Using Subject 3's collected wireless sensor crutch acceleration data, we performed simulations to determine the accuracy of the algorithm with different parameter settings. This algorithm with these thresholds and parameters was then implemented in C programming language and downloaded into the wireless sensors using Code Composer Studio (Texas Instruments). The thresholds and parameters were heuristically tuned by increasing or decreasing them by 5 percent of the peak value if too many false positives or negatives were detected, respectively, until 100 percent success rate with no false triggers was achieved. Performance of the algorithm and parameters during testing was measured by noting the number of correctly detected crutch strikes as well as the number of false crutch strikes. These measurements were made possible by having the ECU generate a short audio tone (beep) each time it received a left and right crutch-strike-detect wireless packet from the wireless sensors. A different frequency tone was used for the left and right sides. Delays between when the accelerometer detected the event and when the motion analysis captured the event were also calculated. An excerpt of Subject 3's right crutch acceleration data collected during walking with crutches is shown in **Figure 6(b)** along with the algorithm's simulation results. The accelerometer output during crutch

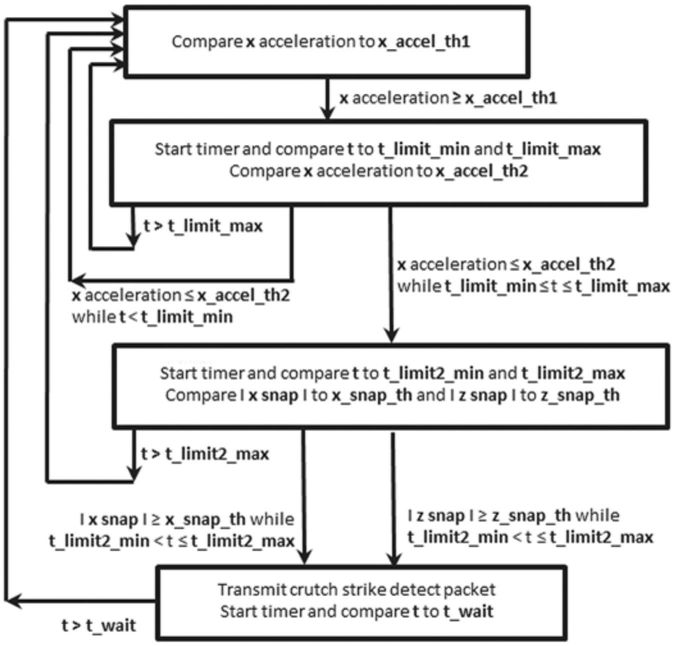

Figure 7.
Crutch strike detection algorithm flowchart.

swing had a noticeable peak of 1.4*g*, with another sharp peak in the calculated vertical snap signal shortly thereafter at crutch strike.

RESULTS

During in-laboratory testing over level ground with Subject 1, the RHS-detect algorithm was found to have a 100 percent success rate of detecting a RHS (225/225) with no false positives. During take-home trials, the accuracy was 99 percent (101/102). During outdoor tests across various terrain near the hospital (on grass, up and down inclines), it was found to have a success rate of 100 percent (72/72) on rolling ground with grass, 91 percent (69/76) for uphill walking, and 94 percent (63/67) for downhill walking. A summary of these results can be found in **Table 2**.

For Subject 2, when using prerecorded data from the subject walking on level ground, the developed algorithm was found to have a 91 percent success rate in detecting forward movement of the walker (41/45). It also correctly ignored 4 out of 4 backward pulls of the walker. This algorithm was also tested using accelerometer data collected from a nondisabled volunteer while pushing and pulling a walker. The nondisabled volunteer used the walker on various outdoor sidewalks, and the algorithm was found to have 100 percent success rate (100/100). Next, the algorithm was tested up and down a 5° ramp. On those surfaces, it was found to have a 100 percent success up the ramp (50/50), and a 96 percent success rate (48/50) down the ramp (**Table 2**). It also correctly ignored 39/40 (98%) backward walker pulls and 9/10 (90%) walker repositions.

Table 2.
Algorithm accuracy for each subject and condition. This represents the number of correct detections out of the total number of steps tested. Subject 3 did not complete uphill or downhill data collections.

Subject	Sensor Placement	Overground	Uphill	Downhill
1	ECU on hip	225/225	69/76	63/67
2	Walker	100/100*	50/50*	48/50*
3	Crutch tips	97/97	NT	NT

*Indicates nondisabled testing in lieu of subject 2 availability. For prerecorded subject 2 data, overground walking successfully detected 41/45 movements.
ECU = external control unit, NT = not tested.

Testing done inside the hospital with Subject 3 walking on a level surface showed the algorithm to have a success rate of 100 percent for detecting the right and left crutch strike (97/97) (**Table 2**). The delay between the actual crutch strike as determined by motion analysis and when it triggered next step stimulation based on accelerometer data was found to be 58 ± 9 ms.

DISCUSSION

Correctly identifying intent to step by detecting gait-related events is critical for assisting or restoring gait with electrical stimulation. Differences in gait patterns among individuals and terrain can make it difficult to use a standard detection scheme that is applicable to all users. Many mechanical sensors (i.e., FSRs and foot switches) are prone to failure and can be difficult for people with limited manual dexterity to don and doff. The participants in this study would have had significant difficulty consistently donning and doffing foot switches. Many users with gait impairments also have upper-limb weakness and limited manual dexterity, which can make manual triggers difficult to use. The participants in this study were either unable to use a finger switch or required their hands to use their walking aids. EMG control is an option when participants retain some volitional control but use during daily living would require additional implanted components. In instances when patients have difficulty even initiating a step (e.g., Subjects 2 and 3), EMG would not be an option and could result in rapid fatigue. Walking aid placement becomes part of the gait cycle; therefore, detection based on walking aid decreases the cognitive load required to initiate a step while EMG would add a movement to focus on. Thus, it is important to integrate the intent to step detection mechanism into a gait-correction system that is easy to use and reliable.

In developing the algorithms and determining the thresholds, the implications of false positives and false negatives need to be taken into account in order to maximize user safety. For each of these subjects, a poorly timed or incorrect trigger (false positive) could lead to a knee buckle if hip and knee flexor stimulation occurred during the stance phase of gait. Because of this, false negatives are the more tolerable of the failure modes, and thus, a more conservative approach to threshold tuning was taken. For Subjects 2 and 3, the action (walker push or crutch swing) could be repeated if the event was missed and stimulation was not activated. For Subject 1, a missed trigger would result in reduced foot clearance without hip and knee flexor and ankle dorsiflexor stimulation.

This study used accelerometers to implement three different gait initiation schemes for three unique users. Each user had a unique gait deficit, upper-limb impairment, and walking aid that led to the stimulation triggering system chosen. While algorithms were custom-developed for each subject because of their specific walking patterns and assistive devices, they may be applicable as a guide to others who fit their profiles. Many users, regardless of their impairment, could make use of the event detect and stimulation triggering algorithms developed here to control their systems if they use an assistive device that is the same or similar to the ones presented here. For example, patients with hemiplegia can use an accelerometer within the ECU described for Subject 1 as a control source for step initiation. Control sources for more impaired users, such as Subjects 2 and 3 who use a walker or forearm crutches, respectively, have not been as thoroughly validated. It is likely that the algorithm thresholds and timing parameters may need to be tuned for each subject.

Limitations of the study include a small sample size. While Subject 2 has been using the system at home for walking, he is using an older version of the walker movement detect algorithm and has not been back in the laboratory for testing with the most recent algorithm. This is the reason for using his prerecorded accelerometer data as well as nondisabled data in order to test this algorithm. Additional testing of these algorithms on other subjects with similar impairments and walking styles should provide further insight into these approaches and their applicability to users with similar gait presentations. A decision tree to classify individuals based on gait deficit, use of walking aid, and manual dexterity could help in the accelerometer placement and algorithm selection to improve the ease and application of this technology. Once a large sample in each category of users has been tested, the range in various thresholds can be determined so a tuning protocol for step initiation can be optimized and automated for ease of implementation.

CONCLUSIONS

In this study, three unique techniques for triggering stimulation for stepping in individuals with varying degrees of lower-limb paralysis and upper-limb impairment from stroke and iSCI were developed and explored. Each participant presented different walking styles and required a unique solution for controlling the stimulation system. Accelerometers were seamlessly integrated into the stimulator or walking aids to coordinate the actions of the assistive device with voluntary movements, thereby minimizing interference and cognitive burden and allowing for easier use. The algorithms and techniques developed here can be used in a variety of applications for other patients who present with similar gait impairments or use assistive devices similar to the ones presented in this study. Each algorithm was found to have a high detection accuracy rate, which should allow them to be used in additional applications. Each subject uses his or her respective algorithm in the home and community on a regular basis and reports high satisfaction and low error rates. Customized applications of accelerometer-based control mechanisms individualized to the specific needs of each user can be robust and reliable, regardless of the etiology of the observed gait deficits, preferred walking aid, the extent of remaining voluntary control, or limitations of manual dexterity.

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