A Novel Mechatronic Approach for Functional Recovery of Human Locomotion

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ABSTRACT

Objective: To retain the locomotive ability after neurological or orthopaedic impairments, consistent and functional training should be emphasized to recover the motor function of the extremities. The aim of this study is to develop a novel mechatronic approach in which kinematics and kinetics of human locomotion have been incorporated into an optimum motion algorithm for robot-enhanced gait rehabilitation.
Methods: Our mechatronic system has two personalized, gait trajectory guided and programmable foot-boards equipped with force sensors. First, human locomotion was analysed to generate personalized gait parameters, using various gait databases. Then, dynamic motions were modelled to be programmed in the system. Finally, we implemented the dynamic motion models to a gait trajectory guiding device for simulating precise, subject-oriented and smooth motion.
Results: The mechatronic system simulated varied stride length, step time and its distribution among double and single support phase, according to the patient's height and average walking velocity. As the walking speed increases, the duration of double support phase approached zero. Horizontal velocity, the values of z1F (t), z2F (t) and their corresponding velocities presented different phases of the walking cycle on the backward and forward plates of the device.
Conclusions: By changing the values of patient's height and velocity, we can simulate person-specific, ideal trajectory for the foot-boards. In conclusion, our developed system is an automated tool that can provide patients a natural walking practice and also guide them to follow an ideal pressure distribution and postural control through visual biofeedback.

KEY WORDS: **Neurological Rehabilitation**
Gait pattern simulation
Patient-specific walking database
Gait trajectory guiding device

Introduction

For rehabilitation to be effective in helping an individual to regain optimal functional recovery, more emphasis should be placed on encouraging the use of injured limbs and providing task-focused experience and training [1]. There is a lot of evidence that neural reorganization reflects patterns of use. Even at the peripheral level, an exercise program with a specific goal has been shown to enhance recovery in both acute and chronic neuropathies. For retaining the walking ability, a task-specific repetitive approach has proven to be an effective measure for gait rehabilitation of no-ambulatory hemi-paretic patients [2]. It is hypothesized that the technique works in part by stimulating the remaining force, position, and touch sensors in the legs during stepping in a repetitive manner and that residual circuits in the nervous system learn from this sensor input to generate motor outputs appropriate for stepping [3]. So far, a small number of people around the world have worked with gait rehabilitation devices based on gait trajectory guided foot-boards [4-7]. However, some gait rehabilitation devices have limitations.

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The design of the existing devices have problems in simulating realistic walking patterns; some of the devices do not consider the variations in walking patterns of people of different ages, height, gender. Researchers have suggested designs with unnecessary sophistication which have made the ultimate devices complex, large in size and expensive for mass installation. Researchers have suggested unnecessarily sophisticated designs, which resulted in large and expensive devices for mass production and easy installation. Aiming for a device for recovery of locomotive function, we have designed and developed an automated mechatronic system that uses computer simulated, gait trajectory guided foot-boards. Two hypotheses have led us to this work. First, if we can study a patient while suspended from a body-weight support harness with his/her feet on guided foot boards, a patient‘s other joints like ankles and knees can also be studied to obtain a realistic gait pattern in different phases of a complete walking cycle. Second, allowing the legs to move freely in different degrees of freedom is more effective for optimal muscular activation during the guided training that can help the patient regain his/her normal walking. In our gait trajectory guiding device, we have simulated the walking pattern on two mechanized foot-boards where the subject will place their feet during the training session and a therapist will supervise the total training session for controlling the paretic limb. Also, the foot-boards must have the provisions of multidimensional movement both horizontally and vertically with adequate degrees of freedom and variable velocity for supporting the total simulation of natural gait pattern of a normal subject in design approach. First of all, we concentrated on developing an optimal motion algorithm for the foot-boards to accommodate patients of different ages, heights and genders, the design has to be quiet, cost-effective and compact so that the device can be easily installed in any physiotherapy centre or infirmary without making any extra arrangements or structure. Each footplate should be controlled for swing speed to get smooth motion when the motion direction has to change. To obtain smooth and precise motion from the plates, sufficient sensors have been installed to control the motion at each degree of freedom. Every mechanical device shows different kind of kinetic or static inertia for different loads. These sensors help the foot-boards to correct their motion in each step through an iterative learning algorithm and follow the actual gait trajectory.

During the training session, we need to collect feedback from the subject continuously through the pressure sensors mounted on the foot-boards for analysing how the subject is reacting to the foot-boards, the change in the centre of pressure (COP) and the improvement of the training over time. In retraining gait in patients with walking disability, having a percentage of their body weight supported results better walking abilities than gait training while the patients bear their full weight [8]. The harness provides support for the patient‘s pelvis and trunk during the gait cycle. That is why a suspension system for supporting the partial weight of a subject is important. It should also have proper adjustments for varying the weight support according to the subject‘s acuteness of disability and pressure-feedback from the foot-boards. Finally, as the motion control and synchronization of this system need a computer, the software interface should be comprehensive and user-friendly so that physiotherapists can operate it with ease. The software system should store all the training histories of patients and show them both in tabular and graphical forms. It should also have some built-in intelligence to generate some further training prescription, analysing the history of the patients.

Materials and methods

Personalized Human Locomotion Analysis

While analysing various kinds of gait databases [9-10] and previous research works regarding natural walking patterns, [11-13] our major focus was to interpret those data and research outcomes in terms of our planned mechatronic system. We have reached the following observations from these analyses- (1) With respect to the sagittal plane, foot trajectory can be expressed by vector T_f = [x_f (t), z_f (t), θ_f (t)] $^{\mathrm{T}}$, T where (x_f (t), z_f (t)) represents the coordinate of the heel position and θ_f (t) denotes the angle of the foot. That is why from our perspective of gait simulation in foot-boards vertical elevation, horizontal progression of heel and angle of feet during walking are three very important parameters. (2) Though normal human locomotion is a series of recurring movement with the natural period of locomotion cycle, walking is possible at a wide variety of combinations of step length sl and step frequency s_f ($velocity\ v = s_l \times s_f$). Inman et al. [12] have suggested an empirical formula by linearly relating the stride lengths s_l with body height h of a person: $sl = 0.004 \times s_f \times h$, where s_l and h are measured in meter and s_f in steps/minute. This equation can be re-written in terms of average velocity of walking $s_l = \sqrt{0.004 \times v \times h}$. (3) Moving average trend line for the horizontal distances between feet over time follows an almost sinusoidal nature. This is called step symmetry. This property of human locomotion means that the forwarding and the back-warding foot-boards should travel the same length of path, for the same duration with the same horizontal velocity pattern. (4) Stance phase of a gait cycle comprises of two double limb support intervals and one single limb support [11]. For maintaining step symmetry, the variable horizontal velocity pattern should be the same for both foot-boards. In other words, gait cycle should be equally divided between the forward and backward progression. The foot placed on the forwarding foot-boards should act as *Swing limb* and at the same time *Single limb Support Phase* will be simulated in the back-warding plate. (5) The Double Support Phase starts with the initial loading of one foot and continues until the other foot terminates the pre-swing phase. That is why Double Support Phase should be simulated in both foot-boards at the same time for the same duration. Inman et al. [12] has established another linear relationship between the step frequency and the duration of the double support state t_{ds} as a percentage of a gait cycle time period t_{cycle} based on experimental data: $t_{ds} = -0.16 \times s_f + 29.08 \times t_{cycle}$, where $t_{cycle} = 2 \times t_{step} = 2s_f$. The horizontal displacement for both feet during the Double Support Phase is quite insignificant and therefore can be ignored. However, during double support phase both foot-boards have motion in vertical direction. (6) During the swing phase the horizontal velocity follows an elliptical shape $Vhorz\,(t) = \sqrt{b^2(1-t^2/a^2)}$ where, a and b represents the X and Y-axes intercepts respectively. After integration we can determine that,

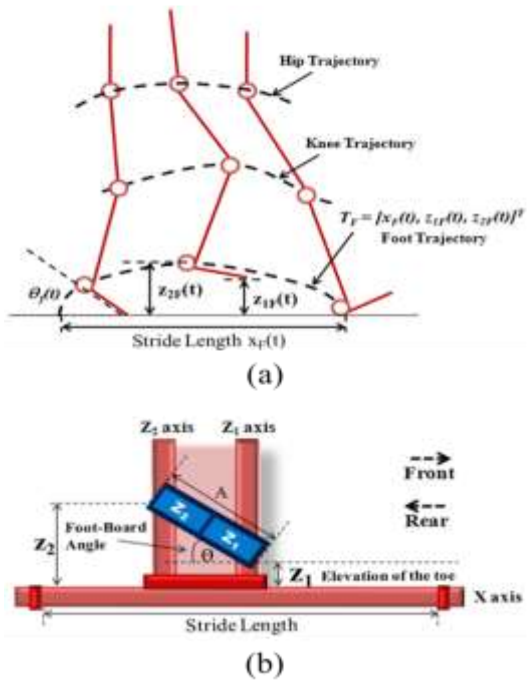
$$xf\,(t) = \frac{b}{a}\left(\frac{t\sqrt{a^2-t^2}}{2} + \frac{a^2}{2}\sin^{-1}\frac{t}{a}\right) \qquad (1)$$

From user input of step frequency or average velocity and height of particular subject, the value of x and step duration ($t_{max} = x \,/\, average\ velocity$) can be calculated. Plugging the value of x = *step length*, $t = a = t_{step} - t_{ds}$ in (1), elliptical shape of the horizontal velocity pattern and acceleration for the forwarding foot-board during the swing phase can be calculated. Due to step symmetry, same velocity patterns will be implemented in the back-warding foot-board during its Single Support Phase.

Dynamic Motion Planning for Foot-Platform

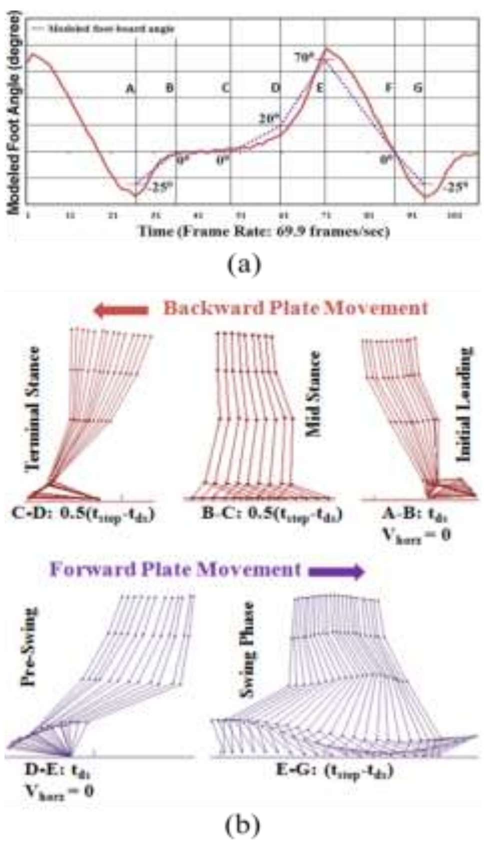
To simplify implementation of our mechatronic system, we have changed the trajectory vector $T_f = [x_f\,(t), z_f\,(t), \theta_f\,(t)]^T$ to $T_F = [x_F\,(t), z_{1F}\,(t), z_{2F}\,(t)]^T$ which supports all the components of T_f. Figure 1 (a) shows the various walking parameters and 1(b) depicts the adopted axis configuration of the foot-boards based on vector T_F.

Figure 1. (a) Parameters of Human Locomotion, (b) Axis-configuration of the Foot-Boards based on Parameters of Human Locomotion.



Defining the values of the components of T_f with respect to time and the variable velocity patterns along X, Z_1 and Z_2 directions based on the anthropometric parameters of a subject are the two major challenges for simulating walking in a task specific repetitive manner for motor relearning. Assuming the period necessary for one walking step is t_{step}, the time for n^{th} step is from n. t_{step} to (n+1). t_{step}, where n=1, 2, 3… N, N is the number of step. Empirical equations discussed before for finding step length shows that, if a velocity is defined, a subject specific step length and step frequency can be determined. Value of s_l is equal to x_F (t) at t = n.t_{step}. Previous research on gait analysis also suggests that, at heel strike or initial contact, the Metatarsophalangeal (MP) joint is in 250 dorsiflexion with the toes up, followed by a total contact with the ground at the end of the loading response- the toes drop towards neutral alignment and maintain this position throughout mid stance. With heel rise in terminal stance, the MP joint dorsiflexes up to 20^0. This motion continually increases throughout pre-swing to a f position of 700 extension [11]. Based on these findings, we can model the values of θf (t) with respect to time which leads us to find the values of z_{1F} (t) and z_{2F} (t). Figure 2(a) indicates the modelled θ_f (t) on the basis of the foot-angle derived from the coordinate data of [10]. Figure 2(b) shows the simulation of foot-boards trajectory in forward and backward progression cases on the basis of the modelled angle. From the length of the foot-board, modelled angle values and % duration of different phases of a complete walking cycle suggested in [11], values of z_{1F} (t)and z_{2F} (t) for t= n.t_{step} to (n+1). t_{step} can be easily calculated.

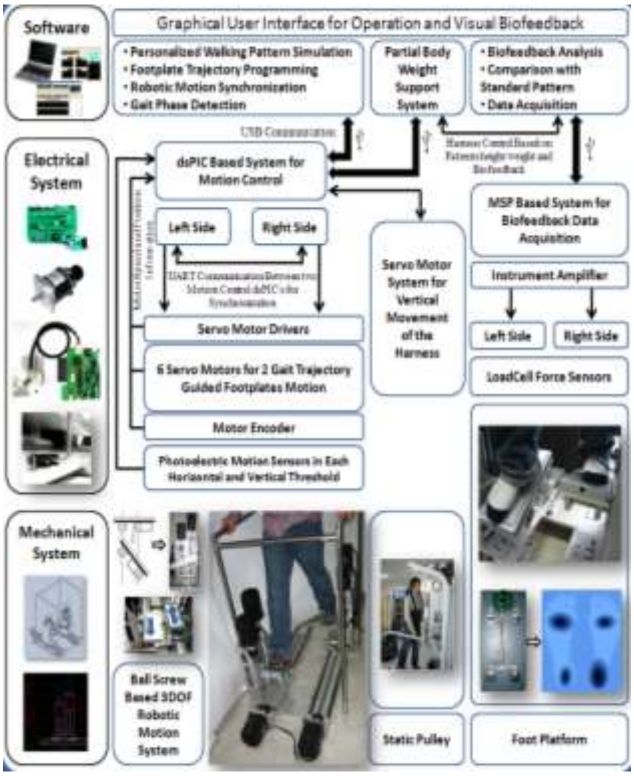
Figure 2. (a) Data modelling for foot-board angles over time, (b) MATLAB simulation of foot-plate movement for our gait trajectory during device according to modelled walking parameters. Sampling frequency = 69.9 frames/sec for figure (a).



Design and Development of the Mechatronic System

The important aspects that a gait trajectory guiding device should have are simulating precise, subject-oriented, smooth motion through the foot-boards that replicate the natural human gait trajectory with sufficient degrees of freedom and the capability to support the weight of a moving human body. From a gait study we know that 40 percent of a normal gait cycle consists of a single-support phase. When the heel strikes the ground while shifting the pressure from one foot to another, the corresponding foot strikes the ground with about 10% more vertical force than the subject‘s weight [10]. With that in mind, our goal was to design a system that has driving motors of the foot-boards corresponding to different axes to support the required torque with necessary tolerance limit. One of the major design goals was to keep the system simple but suitable for the best interaction between a patient and a therapist. The main concern regarding the mechanical design was to find out how to support all the kinematic features such as horizontal and vertical displacements and velocities of human locomotion. In designing the system, we tried to incorporate all of our goals for the perfect design. The base of the system consists of two plates placed parallel to each other. A horizontal screw is positioned in each plate in the longitudinal direction. Rotation of the motor coupled with a horizontal screw will provide the foot-board-holders motion along the x-axis. Each of the foot-board-holders contains two vertical guide ways with vertical screws in the Z_1 and Z_2 axes. Rotation of the motors connected to the vertical screws render upward and downward movements of the foot-boards along the Z_1 and Z_2 axes. In summary, movement of each foot-board along the three axes X, Z_1 and Z_2 is accomplished by three motors with one horizontal and two vertical screws placed in the guide ways. To overcome the inertia variability to which the motors are subject due to an uneven load distribution during different phases of a gait cycle, we have used the data provided by motor encoders and photoelectric motion sensors to keep track of the foot-boards moving along the axes, so that we can check the motion in the desired gait trajectory. After a thorough analysis of motion pattern, we installed three sensors along the x-axis movement and two sensors at two ends of the Z_1 and Z_2 guide ways. In addition to these motion sensors, four load-cell pressure sensors were also mounted on each foot-board. During a training session our software continuously takes information from the pressure sensors to read the patient's progress and produces a graph so that therapists can make a better training strategy. The data obtained are used to control the motor of the Body-Weight Support Suspension System for varying the percentage of weight support. Figure 3 shows a comprehensive overview of the system.

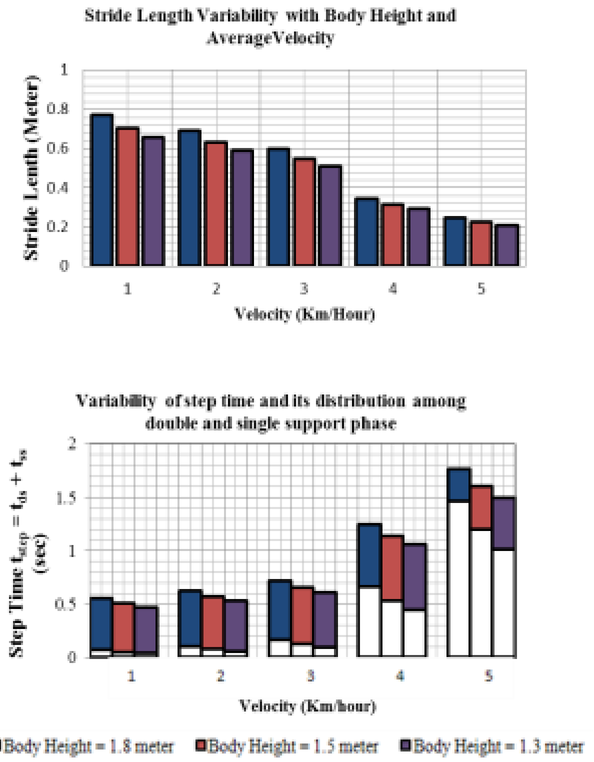
Figure 3. Overview of the Complete System.



Results

With the software input of patient's height and desired average speed of walking, the first task is to determine the stride length of the subject. From the stride length and average speed, the other parameters, such as Step Length, Step Frequency, Step Time, Double Support Phase Time, Single Support Phase Time, elliptical shape of the horizontal velocity pattern, vertical velocity variation in Z1 and Z2 directions with respect to time can be determined. The parameters should be controlled at certain limits to keep the parameters within anatomical limits defined by locomotion attribute e.g. s_{fmax} = 182 step/min or s_{lmax}= 1.08m [13]. Figure 4(a) shows the Stride Length Variability with Body Height and Average Walking Velocity, and Figure 4(b) describes how step time and its distribution among the double and single support phase vary in terms of Body Height and average horizontal velocity. The graphs in Figure 4(b) depict that as the walking speed increases, the duration of double support phase approaches zero. Simulating such a time division in a heavy mechanical device may be difficult.

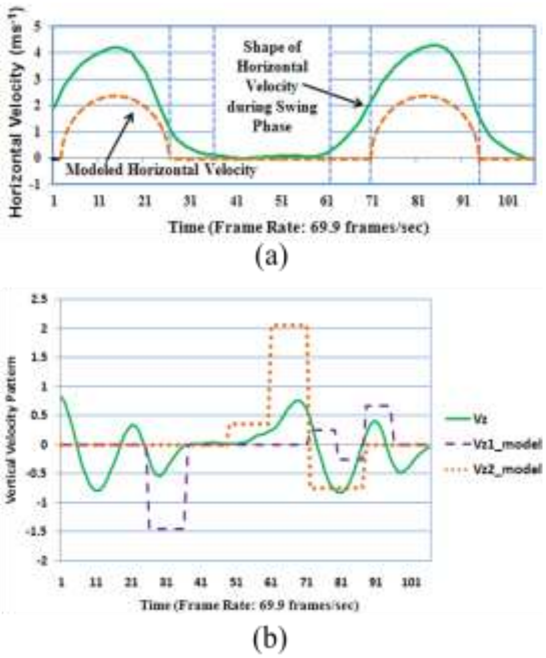
Figure 4. Variability of (a) Stride Length, (b) Step Length with Body Height and Average Walking Velocity.



However, we can use the personalized walking parameters by using the ratio of step time distribution among double and single support phases.

Table 1 shows the elliptical shape of horizontal velocity and the values of z_{1F} *(t)*, z_{2F} *(t)* and their corresponding velocities for simulating different phases of a walking cycle on the backward and forward plates of the device. This calculation was done on a subject of height = 1.8m and the desired walking speed = 5kmph. In Figure 5(a) and 5(b), the shapes of the horizontal and vertical velocities are shown with references to original velocity patterns derived from sample data [10]. By changing the values of the subject's height and velocity, we can simulate person-specific, ideal trajectory for the foot-boards. The modeled velocity in Figure 5(a) during swing phase shows some discrepancies in the original velocity of the sample data. Although we considered horizontal velocity as insignificant before toe-off and after the heel-strike, this graph shows some horizontal velocity in those regions.

Figure 5. Model data of (a) Horizontal velocity along X axis and (b) Vertical velocity of foot-boards along Z1 and Z2 axes in comparison with original velocities of foot from a sample data. Modelled velocity VX, VZ1 and VZ2 were calculated considering v = 5kmph and body height = 1.8m. Sampling frequency = 69.9 frames/sec.



of the upward velocity of feet along Z1 or Z2 direction. These horizontal components have also contributed to the sample data velocity measured during the swing phase. That is why the modeled velocity in Figure 5(a) appears smaller than the original one. In addition to speed and position control of the motor, speed-pulse output information from the motor encoder proved to be useful when setting the footplates in the initial position, controlling the motion. Figure (6) presents Speed-Pulse output information from one of the two horizontal motors. Variability of the duty cycles of this pulse shows how variable speed has been implemented for horizontal movement of the footplate.

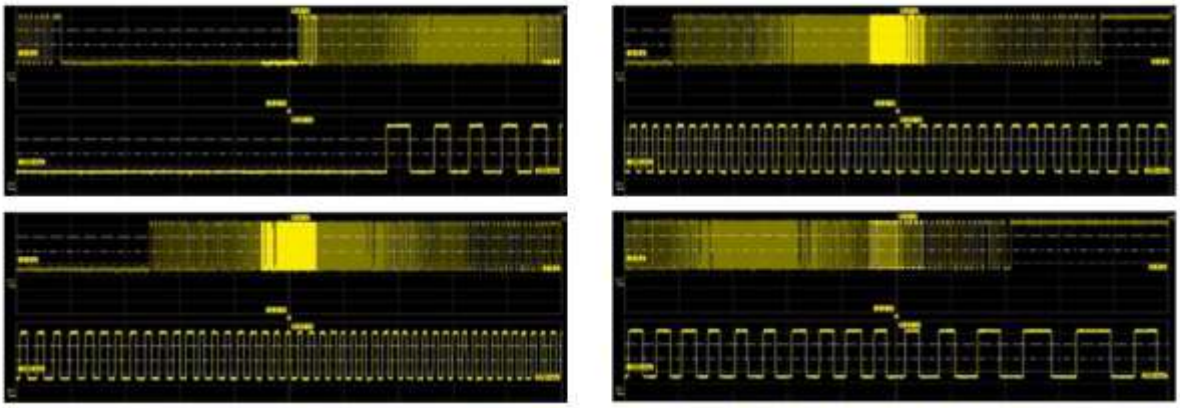
Table 1. Velocity Pattern (For Body Height = 1.8m and Average Walking Velocity = 5kmph)

Length of Foot-Boards of the device = 25.4 cm
X Axis Intercept for Elliptical Shape of Horizontal Velocity = a = 0.48
Y Axis Intercept for Elliptical Shape of Horizontal Velocity = b = 2.04
tstep= 0.56, tds = 0.07, tss = 0.48

		Time		**Angle**	***z_{1F} (cm)***	**V_{z1F} (ms^{-1})**
B	A-B	t_ds	0.074	-25 to 0	-10.72	-1.45
P	B-C	1/2 of t_ss	0.242	0	0	0
M	C-D	1/2 of t_ss	0.242	0	0	0
	D-E	t_ds	0.074	0	0	0
F	E-EF	1/3 of t_ss	0.159	Ascend 4 cm from gnd	4	0.250
P M	EF-F	1/3 of t_ss	0.159	Descend 4 cm from gnd	-4	-0.250
	F-G	1/3 of t_ss	0.159	0 to -25	10.72	0.671
		Time		**Angle**	***z_{2F} (cm)***	**V_{z2F} (ms^{-1})**
B	A-B	t_ds	0.074	0	0	0
P	B-C	1/2 of t_ss	0.242	0	0	0
M	C-D	1/2 of t_ss	0.242	0 to 20	8.68	0.358
F	D-E	t_ds	0.074	20 to 70	15.17	2.056
P	E-F	2/3 of t_ss	0.319	70 to 0	-23.86	-0.747
M	F-G	1/3 of t_ss	0.159	0	0	0

BPM: Backward Plate Movement, FPM: Forward Plate Movement

Figure 6. Elliptical Horizontal Velocity Pattern (output taken from Speed-Pulse output information of servo encoder). The second pulse output represents the zoomed version of the first pulse-train in each picture.



Discussion

In a gait trajectory guiding device, apart from being coherent with the patient-specific perfect gait pattern, precise time division of the total movement is necessary for keeping track of a patient's biofeedback in different phases of the cycle. Although the Ground Contact Force (GCF) signals do not directly provide feedback signals for controlling assistive devices, they do provide a foundation for detecting human motion phases and enable assistive devices to adaptively change the algorithms for each motion phase for better estimation of the feedback signals [14]. They will also be used for reducing tracking errors by a trial-and-error procedure. After each repetition of the gait cycle the feed-forward control signal can be improved by some learning rule. The photoelectric motion sensors installed along every axis of movement and encoders inside the Servo Motor will provide the speed and position information. Conventional therapy requires a lot of physical efforts from at least two therapists to set the paretic limbs and to control the trunk movement of a neurologically disabled patient. When physiotherapists have to work in uncomfortable positions that require a lot of physical exertion, they may find it difficult to treat patients. Our system is an automated tool that can assure patients a natural walking practice and also guide them to follow an ideal pressure distribution and postural control through visual biofeedback. For returning back to a normal life after neurological rehabilitation, it is also important for everyone to restore a full-fledged gait ability. The mechanical architecture of our system also allows us to simulate walking on uneven ground, perturbed gait and stair walking. In later phase we will extend our study to these kinds of gait patterns and simulate them so that after being trained with our system, a patient can acquire all the capacities to perform basic activities of daily living. Furthermore, as we will collect patients' biofeedback information from all of their training sessions through our vertical ground reaction force measurement system and store them, this will help us to include a knowledge-based physiotherapeutic system which can set optimal training algorithms for individual patients.

Conflict of Interest

We declare that we have no conflict of interest.

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