Gait Mode Recognition and Control for a Portable-Powered Ankle-Foot Orthosis

Yifan David Li
Department of Mechanical Science and Engineering
University of Illinois at Urbana-Champaign
Urbana, IL, 61820, USA
yifanli4@illinois.edu

Elizabeth T. Hsiao-Wecksler
Department of Mechanical Science and Engineering
University of Illinois at Urbana-Champaign
Urbana, IL, 61820, USA
ethw@illinois.edu

Abstract— **Ankle foot orthoses (AFOs) are widely used as assistive/rehabilitation devices to correct the gait of people with lower leg neuromuscular dysfunction and muscle weakness. We have developed a portable powered ankle-foot orthosis (PPAFO), which uses a pneumatic bi-directional rotary actuator powered by compressed CO_2 to provide untethered dorsiflexor and plantarflexor assistance at the ankle joint. Since portability is a key to the success of the PPAFO as an assist device, it is critical to recognize and control for gait modes (i.e. level walking, stair ascent/descent). While manual mode switching is implemented in most powered orthotic/prosthetic device control algorithms, we propose an automatic gait mode recognition scheme by tracking the 3D position of the PPAFO from an inertial measurement unit (IMU). The control scheme was designed to match the torque profile of physiological gait data during different gait modes. Experimental results indicate that, with an optimized threshold, the controller was able to identify the position, orientation and gait mode in real time, and properly control the actuation. It was also illustrated that during stair descent, a mode-specific actuation control scheme could better restore gait kinematic and kinetic patterns, compared to using the level ground controller.**

Keywords—powered orthosis, gait mode recognition, inertial sensor, exoskeleton

I. INTRODUCTION

Walking is a fundamental part of people's daily routine and an essential component in overall quality of life. Normal gait can be affected by symptoms resulting from numerous neurological disorders, muscular pathologies and injuries, including trauma, incomplete spinal cord injuries, stroke, multiple sclerosis, muscular dystrophies and cerebral palsy [2]. Powered lower-limb orthoses (e.g. robotic exoskeletons) can be used to assist everyday walking activities, as well as gait rehabilitation therapy. There are large populations with neuromuscular impairments that can be treated using a powered lower-limb orthoses. In the United States alone, these include: stroke (4.7M), polio (1M), multiple sclerosis (400K), spinal cord injury (200K), and cerebral palsy (100K) [3]. These populations will continue to grow due to the aging Baby Boomer generation. Therefore, it is important to develop intelligent, energy efficient and affordable lower-limb orthoses to serve these growing needs. Recently, we have developed a portable powered ankle-foot orthosis (PPAFO) at University of Illinois at Urbana Champaign, which can provide modest dorsiflexor or plantarflexor ankle torque at different phases of gait for functional assistance, using a portable pneumatic power system [4]. The untethered design can allow power-assisted walking outside of the laboratory or clinic. Force contact sensors under the heel and toe and an ankle angle sensor allowed an embedded microcontroller to estimate gait state in real time [5].

One of the challenges that can prevent the PPAFO, or any powered orthotic/prosthetic device, from being widely used as an assistance/rehabilitation device for daily activities is the ability to recognize various gait modes (i.e. level ground walking, stairs, ramps, etc.) and adapt to mode changes promptly. For the PPAFO, there were two critical aspects to this problem. First, the original sensor array on the PPAFO had limited sensing ability (it only measured heel and toe contact forces and ankle joint angle), which cannot contain enough information to reliably detect all gait modes (e.g., during stair ascent and level ground walking, the force and angle readings were almost the same). Second, a new gait mode must be recognized at the earliest possible instant to prevent potential misfiring. Failing to adjust actuation for the current gait mode could increase fall risk for the user. Subsequently, with gait mode recognized in real time, the actuation control during each gait mode can be adjusted quickly to match the expected normative gait kinematics and kinetics of the recognized mode.

Currently, manual mode switching schemes are implemented in many applications due to simplicity and reliability. For example, Au et al. [6] required the user to flex the knee before switching modes, and applied a pattern-recognition technique on the EMG signal to recognize this intent. While the EMG approach had the benefit of high robustness and reliability, it had a major limitation that additional EMG electrodes had to be attached to the human body all the time, which would result in increased system complexity and affect the user experience. Additionally, the number of recognized modes was limited by the number of EMG patterns that a user could successfully trigger without misfire or getting confused. Alternatively, Ottobock's C-Leg could switch modes by tapping the heel multiple times continuously [7]. The knee prosthesis could then be locked

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for better stability. These two schemes were not considered ideal solutions for intent recognition, as additional user intervention was needed. Goldfarb et al. [8-11] used mechanical sensors mounted on the powered prosthesis for intent recognition, which was able to successfully detect stand, sit, stumble, different walking speeds and different upward ramps on a transfemoral prosthesis. Their recent ramp walking study also demonstrated that recognizing ramp ascent and controlling the prosthesis differently to adapt to the functional needs can reproduce several kinematic characteristics of healthy ramp ascent that passive prosthesis does not. But they had not yet shown the ability to detect stair activities.

Multiple efforts had been made to develop an autonomous system for gait mode recognition. Zhang et al. [12] used an inertial-measurement-unit (IMU) fixed to the torso and a laser distance sensor to map out the terrain in front of the user to predict gait mode; the shortcoming of this method was the need of a sensor attached to the user's body and intense computer computation cost of combining the IMU with laser data. Although it showed promise in its ability to observe, predict and respond to the terrains in front of the user, the lack of accuracy and reliability in current technology had prevented it from being broadly used. Coley et al. [13] proposed a recognition algorithm that used only a gyroscope attached to the torso, but the detectable mode was limited to stair ascent. Furthermore, that strategy was dependent on future information, thus it was not a causal algorithm that can be implemented in real time.

To sum, there is currently no available automatic gait mode recognition scheme that is capable of reliably detecting all modes in real time and using a minimalist sensor array.

We propose tracking body motion using inertial sensors (IMU) and recognizing gait modes based on tracked position and orientation. IMU based motion tracking has been an emerging topic and attracted much attention thanks to the advantage of not depending on an artificially generated source. Recently, the availability of low-cost and small-size, micro-electro-mechanical systems (MEMS) sensors has made it possible to implement it on compact devices that need orientation and position estimates, including powered prostheses and orthoses.

In this study, an IMU based motion tracking algorithm was implemented and five modes were recognized. Different actuation control schemes were applied based on recognized gait modes and the experimental results of kinematic and kinetic data in the scenarios of with and without gait mode recognition were compared and analyzed.

II. METHODS

A. Ankle Dynamics for Stair Walking Activities

Previous studies had shown that for healthy individuals, ankle dynamics of stair ascent/descent vary significantly from level walking [1, 6, 14-17]. Therefore, it was important to recognize changes in gait mode in real-time, so that the actuation would be provided at the proper time and in the right direction.

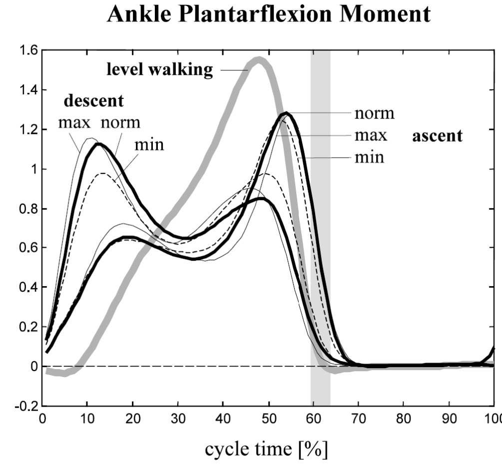

Fig.1 Normal healthy ankle joint moment as a function of percent gait cycle in three gait modes: level walking, stair descent and stair ascent. (From [1], reproduced with approval.)

To better illustrate the necessity for a mode recognition scheme, we discuss normative ankle moment characteristics during stair descent compared to level walking based on the results from [1] and illustrated in Fig.1. During normal level walking, ankle moment gradually increases and peaks at late stance (50% Gait Cycle) to propel the body forward. In contrast, for stair descent, the first peak moment is at the beginning of the gait cycle (about 10% GC, as a toe strike, opposed to heel strike). We note that energy is absorbed during stair descent (or the weight acceptance phase). The ankle joint is also plantarflexed to prepare for the landing. The second moment peak (at 50% GC) shares similar timing as level walking, but with a substantially smaller magnitude. Thus a smaller plantarflexor torque, compared to level walking, should be applied at this portion of the gait cycle. It can be concluded that the functional assistance for different gait modes differs significantly and it is necessary to develop a real-time gait mode recognition scheme. On the other hand, the ankle moment for stair ascent and level walking share similar trends that they do not have to be treated differently.

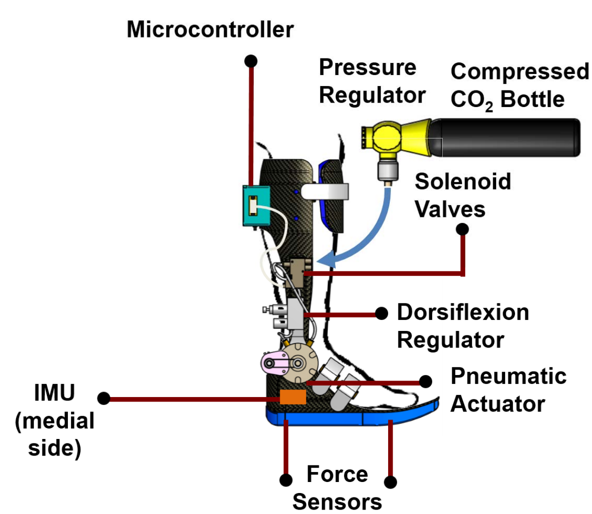

Fig.2 The Portable Powered Ankle-Foot Orthosis (PPAFO). The pneumatic rotary actuator at the ankle is driven by a bottle of compressed CO_2, which is worn on the subject's waist.

B. Introduction of the PPAFO

The portable powered ankle-foot orthosis (PPAFO) was developed from mainly off-the-shelf components to provide powered assistance to an ankle joint (Fig.2) [4]. A compressed CO_2 bottle with embedded pressure regulator (JacPac J-6901-91, 20 oz capacity; Pipeline Inc., Waterloo, ON, Canada) attached to the subject's waist allowed for untethered power assistance. The rotary actuator at the ankle joint is a dual-vane, bidirectional pneumatic actuator (PRN30D-90-45, Parker Hannifin, Cleveland, OH) that was rated for 150 psig and could generate about 12 Nm of torque at 100 psig pressure in both dorsiflexion (toes up) and plantarflexion (toes down) directions. The embedded regulator on the CO_2 bottle controlled the pressure supply for plantarflexor assistance (set to 100 psig), while the additional regulator (LRMA-QS-4; Festo Corp-US, Hauppauge, NY) further reduced the pressure (set to 30 psig) for dorsiflexor assistance based on the needed torque to lift the foot so that this muscle group was not overpowered. Excessive dorsiflexor torque is unnecessary to support the foot during swing and can result in subject discomfort. Two solenoid valves (VOVG 5V; Festo Corp-US, Hauppauge, NY) were used to control the actuation. Three actuation states could be achieved through the combinations of the solenoid valves: dorsiflexion, plantarflexion and passive (no actuation). Actuation was controlled by embedded micro-controller (MCU). The MCU (TMS320F28335, CPU:150 MHz, Sampling Rate: 1 kHz. Texas Instruments, Dallas, TX) read two force resistive sensors located at the heel and the toe of the foot plate (#403, 2" square; Interlink Electronics Inc., Camarillo, CA, USA) and a rotary potentiometer at the ankle joint (53 Series, Honeywell, Golden Valley, CA).

C. Current Control Scheme for Level Ground Walking

In previous studies, we have demonstrated the PPAFO system's ability to provide torque assistance during typical level ground walking [4]. Four functional tasks are defined by different regions of gait (Fig.3): (1) initial contact, (2) loading response, (3) forward propulsion and (4) swing. Each task was determined using a state estimation algorithm that we had previously developed. This algorithm compared the sensor history data (contact forces and ankle angle) to a pre-computed training model to determine the current state and task [5]. During each task, full actuation in one direction was provided.

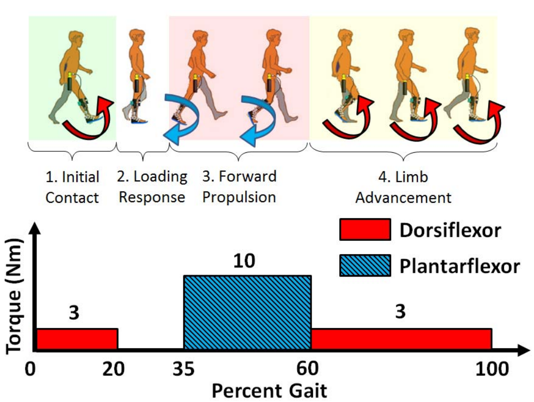

Fig.3 Assistive torque at different times in a gait cycle during level ground walking: dorsiflexor assistance from 0% to 20%, plantarflexor assistance from 35%-60%, and dorsiflexor assistance from 60% to 100%.

D. Tracking Motion using an IMU

We used an IMU (XSens MTi-28A53G35, XSens Technologies. Enschede, The Netherlands) to track the orientation and position of the PPAFO, because they could be directly used to identify gait modes. The stair modes were recognized by comparing the vertical position difference of each step to a threshold (Fig.4), and the ramps modes were detected by examining foot orientation via foot pitch angle when the foot was in full contact with ground.

Only 3-DOF acceleration and 3-DOF angular rate were measured by the IMU at 200Hz. Although the IMU had an embedded magnetometer, due to the complex environment that we have targeted including indoors, outdoors, or inside a clinic or lab while working with other electronic rehabilitation devices, the magnetometer was not used for reliability and safety concerns. Instead, the orientation drift was compensated by identifying certain gait phases in which the relative orientation was known, as described below.

E. Estimating Orientation

In order to track the real-time position, the accelerations had to be rotated into Earth coordinates, which requires pitch and roll angle of the IMU. Thus, the orientation of the IMU had to be estimated first. The orientation was also used to determine the foot pitch angle for ramp recognition. Data from the gyroscopes are used to track the orientation. A quaternion based coordinate system was used to avoid gimbal lock problem.

The initial orientation was inversely estimated [18] by the gravity vector measured during 5 seconds of static calibration at the beginning of the experiment when the subject wore the AFO and stood upright without moving. The yaw angle was ignored because it could not be estimated without a magnetometer. Additionally, yaw angle is irrelevant to measuring vertical position.

With an initial estimate of the orientation, the real-time orientation was tracked from the angular rates. Simply double integrating the angular rate usually does not provide an accurate orientation estimate, due to long-term drift errors. A common approach to avoid drift is to use complementary sensors such as a magnetometer. The magnetometer is often added to the same package of 3-axis accelerometer and 3-axis gyroscope, and the package is referred as a MARG sensor [19]. The 9-DOF data can be fused using a Kalman or complementary filtering algorithm [20-22].

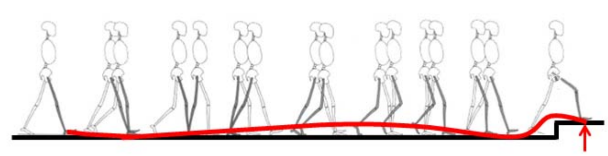

Fig.4 Illustration of tracking position to recognize stair walking mode. The tracked relative change of vertical position for each step (at the heel strike) was compared to a threshold.

However, in this study, due to reliability concerns, the magnetometer was not used. Instead, the calibration was achieved by combining the accelerometer and rate gyro with the heel and toe contact force sensors that already existed on the PPAFO to detect calibration instants, similar to [23]. Zero-rate instants were used for orientation recalibration, while zero-acceleration instants were used for velocity recalibration.

A zero-rate instant was defined as when the PPAFO was in full contact with the ground (with both force sensors compressed). At this time instant, the IMU itself was assumed to be static relative to Earth coordinates, which was equivalent to zero readings from the gyroscope, as in

$$\|\omega\| < \varepsilon_1 \tag{1}$$

where ω was the angular rate from the gyroscope, and ε_1 was a heuristically tuned threshold for determining the zero-rate instant. ε_1 was tuned such that the zero-rate instant would only happen when the controller was certain that the AFO was flat on the ground and not rotating. From the experiment, usually it happened when the subject was standing still before the start of walking, which was sufficient to correct the gyroscope drift.

F. Estimating Position

Once the orientation was known, the real-time position could be tracked. Yun et al. [24] proposed an algorithm for self-contained position tracking for human motion. The cumulative error in tracked velocity due to long-term drift was recalibrated, and the position was compensated at every zero-acceleration instant. A zero-acceleration instant usually happened at every step (Fig.5), but it could be skipped if the criterion was not satisfied. The criterion for determining zero-acceleration was,

$$\|a - g\| < \varepsilon_2 \tag{2}$$

where a was the acceleration from the accelerometer converted to Earth coordinates, g was the gravitational vector, and ε_2 was a heuristically tuned threshold for determining the zero-acceleration instant. The threshold was chosen such that zero-acceleration instant would occur at almost every step, with the exception when the foot was not static enough during stance, where (2) would not be met.

The zero-acceleration instants were identified when (2) is met and the AFO is in full contact with the ground (both force sensors compressed). At each zero-acceleration instant, the tracked velocities were recalibrated to zero, and the tracked positions were compensated,

$$\Delta P_z = -\frac{1}{2} V_z T \tag{3}$$

where ΔP_z was the vertical position compensation based on tracked vertical velocity V_Z. T was the elapsed time from the last zero-acceleration recalibration. The vertical position compensation was derived based on the assumption that there was a constant offset in measured acceleration, which resulted in drifted V_Z. The acceleration drift constant and elapsed time since last zero-acceleration recalibration is used to find the appropriate value based on this theory [24].

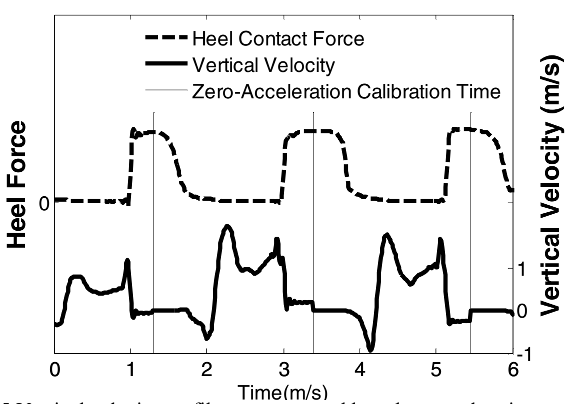

Fig.5 Vertical velocity profiles are re-zeroed based on accelerations and heel contact force.

G. Recognizing Stair and Ramp Modes

Next, the vertical position was sampled by the microcontroller at each time of heel strike (or toe strike), and compared to the vertical position from the previous step to calculate the change. The vertical position change at the n[th] step $Z(n)$ was defined as,

$$Z(n) = P_Z(t_{HS}(n)) - P_Z(t_{HS}(n-1)) \tag{4}$$

where t_{HS} (n) is the nth heel strike time and t_{HS} $(n$-1) is the one before.

Now the gait mode $M(n)$ can be recognized by applying thresholds on $Z(n)$ each time after heel strike

$$M(n) = \begin{cases} \text{Stair Ascent,} & \text{if } Z(n) > T_A \\ \text{Stair Descent,} & \text{if } Z(n) < T_D \\ \text{Level or Ramp,} & \text{otherwise} \end{cases} \tag{5}$$

where T_A and T_D were the thresholds for ascent and descent vertical position, and $M(n)$ represented the gait mode between the n-1[th] and n[th] heel strike.

To distinguish whether a change in vertical position associated with a stair or ramp ascent/descent, the foot pitch angle was also examined. Foot pitch angle was tracked by the IMU orientation at the first instant when both heel and toe force sensors were simultaneously in contact with the ground (roughly about 25% of gait cycle). In the cases when the subject could not activate both force sensors, percent gait state (25% GC) could be used to help identify the timing to sample the foot pitch angle.

The pitch angle was offset to 0 at flat ground during the 5 second calibration trial. Pre-defined thresholds were used to examine the pitch angle to check whether the foot was in contact with an inclined or declined surface, which was considered as a ramp,

$$M(n) = \begin{cases} \text{Ramp Ascent,} & \text{if } C(n) > R_A \\ \text{Ramp Descent,} & \text{if } C(n) < R_D \\ \text{Level or Stair,} & \text{otherwise} \end{cases} \tag{6}$$

where $C(n)$ was the foot pitch angle sampled each step when the foot was in full contact with ground, and R_A and R_D (5° grade used in the experiment) were the pre-defined threshold for ramp ascent and descent. They remained the same values for all trials and subjects.

H. The Optimal Thresholds for Unbiased Recognition

Thresholds were used in both stair and ramp recognition schemes. The choice of threshold values for mode recognition was crucial for reliably detecting a new gait mode and reducing the inaccuracies introduced by the IMU. Intuitively, if the threshold value for level walking to stair ascent transition (T_A) was too high, it was likely that the microcontroller would falsely detect an actual stair ascent as level mode. Likewise, if the choice of T_A was too low, the microcontroller would interpret actual level walking as stair ascent mode. In addition, the choice of thresholds have to do with the accuracy of tracking at different modes (i.e., if we had better accuracy in level mode, the threshold could be chosen to be closer to zero, which would better tolerate the potential errors in ascent mode). Therefore, we derived theoretical optimal threshold values to maximize the reliability of the mode recognition scheme.

A preliminary training session was used to collect vertical position change data and foot pitch angle data in different walking modes. Based on the training data, an optimal threshold was found for unbiased mode recognition.

Vertical position changes in the same mode were assumed to be a Gaussian distributed random variable with fixed mean and standard deviation. Therefore, for level walking mode,

$$Z(n) \sim N(0, \sigma_L^2) \tag{7}$$

where σ_L was the standard deviation for $Z(n)$ in level ground walking mode. Similarly, for stair ascent mode,

$$Z(n) \sim N(h, \sigma_A^2) \tag{8}$$

where σ_A was the standard deviation for $Z(n)$ in stair ascent mode and h is the stair rise for the stairs, assuming one stair traverse for stair walking. Note that technically the mean of the distribution could deviate from their expected values. Nevertheless the expected values are used for ease of derivation.

Two types of error could be described in a null hypothesis: the actual gait mode is level ground mode (Fig.6)

Type I error (false negative) B_A: Mistaking level mode as ascent mode

Type II error (false positive) B_L: Mistaking ascent mode as level mode

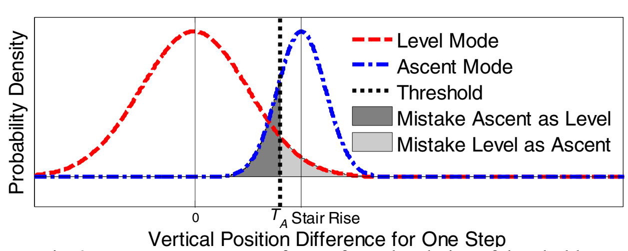

Fig.6 Impact on two types of error from the choice of threshold.

Define the cost function as the bigger value of the two types of error,

$$C = \max(B_A, B_L) \tag{9}$$

Therefore, the optimal threshold can be found as,

$$T_A = \frac{h\sigma_L}{\sigma_L + \sigma_A} \tag{10}$$

I. Actuation Control for Stair Descent Mode

As discussed in the previous section, the actuation control for stair descent mode has to be different from that of level ground walking control, to address the functional needs of stair descent. During stair descent, in order to make sure the ankle joint is plantarflexed before the next step landing, plantarflexor actuation would start in the second half of swing. The torque would remain until the late-stance phase of the next cycle so that the weight impact from stair descent could be absorbed. This actuation strategy was also chosen because it was impossible to fully match the torque needed in Fig.1 using only a set of solenoid valves. A revised actuation strategy provided plantarflexor torque of 10 Nm during 0-50% and 80% to 100% of gait cycle.

J. Experimental Protocol

A preliminary training session was conducted to collect vertical position and orientation data for threshold tuning. One subject wore the PPAFO without actuation, and walked for five trials in five different modes (level, stair ascent/descent, ramp ascent/descent). Training data were collected and processed to compute the thresholds for both stairs and ramps. The thresholds were made available to the microcontroller and remained the same for rest of the study.

Experimental tests were conducted to assess the accuracy of the gait mode recognition algorithms and effectiveness of gait mode control. At the beginning of each trial, 5 seconds of calibration data were collected while the subject stood upright while wearing the PPAFO.

Five healthy male subjects were tested (average age: 23.4yrs, weight: 82.0kg, height 178.6cm). Approval was received from the University of Illinois Institutional Review Board (IRB#12825).

Four scenarios were tested to examine different challenging walking environments: outdoor stairs - one stair traverse (h=14cm, the smallest stair rise), outdoor stairs - two stair traverse (h=28cm), indoor stair - two stair traverse (h=34cm, larger stair rise compared to outdoor), and indoor ramp (6 degrees grade). In each stair (ramp) scenario, the subjects walked over a mixture of level ground, stair (ramp) ascent and descent to test the performance in each mode.

To evaluate the effectiveness of the gait mode controller, three actuation conditions were implemented in each scenario: passive (no actuation), mode controller (stair descent was controlled to have plantarflexion during swing, actuation specific for stair descent) and level controller (always provide dorsiflexor actuation regardless the gait mode, generic actuation used during level walking). The level controller condition was added to examine what would happen if the gait mode was not recognized during stair descent (it would be controlled as level ground instead).

The overall robustness of the algorithm was examined by combining the performance in all the trials of all five subjects. The success rate was defined as,

$$\text{Success Rate} = \frac{\#\text{ of Correctly Recognized Steps}}{\#\text{ of Total Steps}} \times 100\% \quad (11)$$

III. Results and Discussion

A. Experimental Observations

The gait mode recognition algorithm was able to successfully track vertical position changes at each step and used the optimized thresholds to determine stair modes. In Fig.7, on the left, the tracked vertical position was plotted versus time. Position was reset to zero at every step. The estimated change in vertical position (symbols) showed excellent agreement with the true stair rise. In the figure, if an estimated vertical position difference was greater (less) than the threshold value, the algorithm would consider the step to be stair ascent (descent).

Similarly, an illustrative case (Fig.8) demonstrated that the ramp modes could be recognized by sampling the foot pitch angle when both the heel and toe sensors were simultaneously activated (about 25% of gait cycle). On the right, where the foot pitch angle was plotted against gait percent, it can be observed that around the sample time (~25% GC), the two ramp modes could be clearly distinguished from level walking mode.

The results of the success rate of different subjects in different scenarios are found in Table I. The mode recognition algorithm successfully detected the correct mode in at least 92% of the trials. The correct mode was detected in 4 of 5 subjects for 96% of the trials. One subject (subject 2) showed lower success rates than other subjects. This difference may have a result of his gait pattern. (This subject had limited training on the PPAFO and lacked confidence while walking with the PPAFO). For the ramps, although no subjects reached 100% in all trials, the consistently high success rate of over 98.5% illustrated that ramp recognition was in general more robust compared to stair recognition.

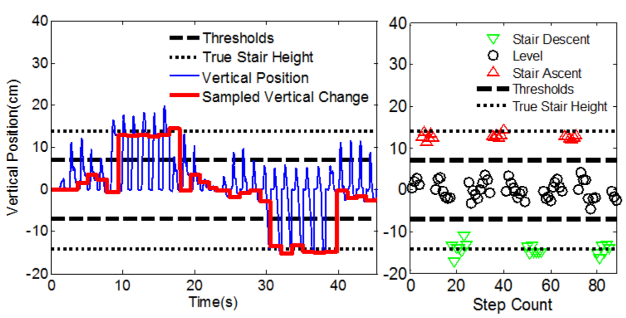

Fig.8 Illustrative case of gait mode recognition of stair ascent/descent mode (indoor, one stair traverse).

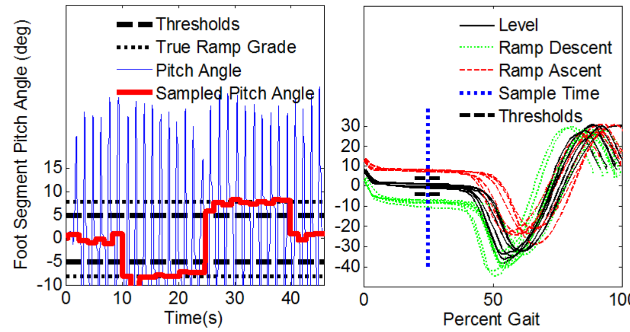

Fig.9 An illustrative case of detecting ramp mode (passive, indoor ramp)

TABLE I. Success Rate for Different Scenarios and Subjects

Subject	Success Rate (%)			
	Outdoor One Stair Traverse	*Outdoor Two Stair Traverse*	*Indoor Two Stair Traverse*	*Ramp*
1	100.0	100.0	100.0	99.0
2	94.7	92.2	97.4	98.5
3	99.6	97.6	100.0	99.3
4	98.5	96.0	100.0	99.0
5	98.8	100.0	100.0	99.6
Avg	98.3	97.2	99.5	99.1

Differences in gait kinematics and kinetics among the three controller conditions were found during stair descent mode (Fig.9). The passive condition represented the natural gait pattern for healthy normal subjects. The mode controller condition represented the result when the stair descent gait mode was correctly recognized and the actuation matched the mode, while the level controller condition described the outcome when the level ground controller was used even during stair descent mode. It was observed from the figure

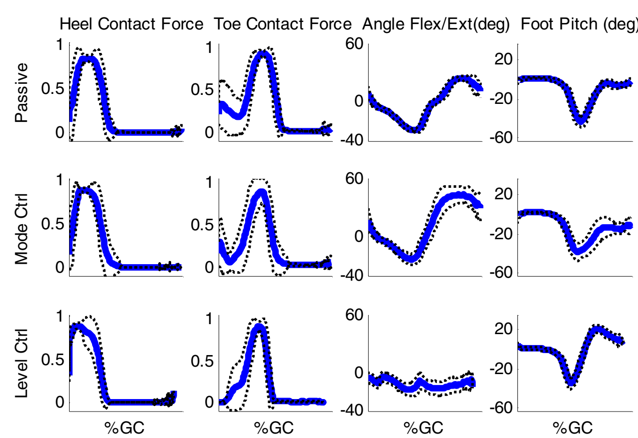

Fig.7 Kinematic and kinetic comparison during stair descent mode (outdoor, one stair traverse) for three controller conditions. The mode controller was better able to reproduce the gait patterns of the passive mode; while the level controller was not appropriate for stair descent.

that the ‘toe strike’ phenomenon in passive condition (significant toe force at the beginning of the cycle) was reproduced by the mode controller. The level controller, however, failed to do so. Compared to the level controller condition, the angle joint angle pattern for the passive condition was also more similar when using the mode controller condition. This incorrect behavior occurred in the level controller condition because when using the level walking controller, the AFO held the toes up during swing, which allowed very little range of motion. Whereas for stair descent, it was preferred to plantarflex the foot to prepare for contact with the next stair.

B. Limitations

Although the mode recognition scheme showed promising success rates and was able to demonstrate that it could produce a more natural gait pattern during stair descent compared without having any mode recognition, it suffered from several limitations, such as one step delay and fall risks that were not accounted for in the cost function. These limitations will be discussed separately in rest of this section.

1) One Step Delay

We made the assumption that the gait mode identified from the immediate past step would stay the same for the current step. Therefore, the actuation could be controlled based on the identified mode as described above. One drawback of this approach is the delay during the mode transition. Due to hardware limitations, the current IMU based scheme could only switch modes no earlier than the end of the first step. In other words, the first step transitioning into a new mode was always unrecognized. This problem could be critical in the scenarios when the subjects have trouble stabilizing themselves. Misfiring in the beginning of a transition can result in a trip or fall. As minimizing the user’s risk is the highest priority of the PPAFO design, to address this issue future studies will explore options to allow for zero-delay, such as instrumenting the contralateral limb, infrared (IR) distance sensing, etc.

2) Defining Weighted Cost Function

We currently use the higher error probability as the cost function. The underlying assumption is to treat the importance of correctly identifying each mode equally. In reality, this simplistic approach might not be the best choice.

Some modes have smaller risk when misidentified. For example, when choosing the threshold for descent/level walking, incorrectly detecting actual level mode as descent mode has a much smaller risk compared to the opposite scenario. For safety concerns, instead of minimizing the chance of error equally, the best solution would be to minimize the expected risk and the potential danger that can be caused by mode switching. Consequently, it would be desirable to redefine the cost function, where the greater risk mode can be emphasized and penalized. Future work will address this weighting.

3) Actuation Control

Currently, as a simplified approach, we have only changed the actuation control scheme for stair and ramp descent modes. It is desirable to customize the control specific to each of the gait mode based on their kinetic characteristics. Ideally, the controller would have an embedded library of kinetic profiles of different modes, and the mode recognition scheme would be able to select a control scheme from the library using real-time recognition results.

4) Developing the Success Rate Standard

In the first section, it was noted that the mode recognition scheme could achieve at least a 92% success rate with an average of over 97%. While these success rates seemed promising, we were not able to justify what success rates are truly acceptable to a user. No prior mode/terrain/intent recognition success rate standard has been established. Other researchers [8, 9, 11-13] have had similar problems. It is obvious that a standard procedure is warranted to set the thresholds for validating the success rate of mode recognition.

In the following studies, the success rate threshold will be estimated based on a simple criterion: the probability of someone losing balance caused by mode recognition misfire should not exceed the probability for the same population without the assist device. Notice that there is a fundamental difference between loss of balance and a misfire due to incorrect mode recognition, the conditional probability of loss of balance as a result of mode recognition misfire (denoted as CD) will also have to be estimated based on experimental data or questionnaire.

For example, one possible approach of estimating CD is to examine the data from this study. According to the experimental protocol, all the trials for stair descent under level controller should be considered as ‘misfire’. It was observed that zero loss of balance was caused as a result of all the misfires. Therefore, it allowed us to estimate the upper boundary for CD. It is also important to differentiate the CD under different conditions. For example, the CD for stair descent is expected to be much higher than the CD for level ground walking, because it is considered easier for people to maintain balance in the event of actuation misfire.

After CD in different conditions are estimated, they can be combined with weightings based on the frequency of their occurrence in average daily walking activities (far more level walking steps than stairs). A final success rate threshold can be calculated based on occurrence frequency weightings and CDs in different conditions.

This loss of balance probability estimation procedure can also be used to redefine the cost function. Instead of being unbiased between different modes, we can choose to optimize the total loss of balance probability based on the likelihoods for each condition (CDs). With the weighted function, a new mode recognition threshold can be selected to reduce the overall loss of balance probability in (10).

IV. SUMMARY

One of the challenges that powered orthotic or prosthetic devices must address is the ability to recognize gait modes (i.e. level ground walking, stairs, ramps, etc.) and adapt to mode changes promptly with proper control actuations. In this study, an inertial measurement unit (IMU) based scheme was proposed to track the real-time 3D position and orientation of the PPAFO for gait mode recognition. A compensation scheme using inertial sensors and force sensors was implemented to correct long-term drift problems. An optimal threshold method was used to minimize error in mode recognition. In different gait modes, actuation control schemes were applied to meet the different functional needs. The experimental results showed that during stair descent, compared to a controller without mode recognition, using the proper mode recognition and actuation scheme to control the device can provide more natural gait patterns (i.e. closer to healthy normal subjects).

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