Quantitative Assessment of Lower Limb and Cane Movement with Wearable Inertial Sensors

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***Abstract*— Individuals with an age, injury, or disease-related mobility impairment often utilize a walking aid, such as a cane, to increase safety and stability during ambulation. Many individuals use a cane incorrectly and demonstrate altered gait patterns. Consequently, measuring the relationship between cane use and gait characteristics has potential to provide users, clinicians, and caregivers insightful information about cane-assisted walking. In this paper, we investigate fine-grained, objective measures of cane movement acquired from wearable inertial sensors. Specifically, we compute quantifications of swing and stance variability for both lower limbs and a cane device. We also introduce a novel visualization, the stance and swing phase plot, to facilitate insights into the sensor data. The computed gait parameters and visualization can potentially inform users and clinicians about assistive device usage over time and provide feedback about correct movement. We demonstrate the utility of the proposed algorithms with inertial sensor data collected from two patients undergoing inpatient stroke rehabilitation.**

I. Introduction

Age, injury, or disease-related mobility impairments can severely diminish one's functional independence. Particularly for walking, moving independently is often necessary to maintain strength, mobility, and a reasonable quality of life. Many individuals with walking impairments use assistive devices, such as canes, walkers, and wheelchairs, during ambulation to increase their base of support. A study from 2011 revealed 8.5 million adults in the United States aged 65 and older reported using a mobility device within the last month [1]. The study found a cane to be the most commonly used mobility device, with 16.4% of adults 65 years and older using one.

Although utilizing a walking aid is intended to help the user, research has revealed this is not always the case. Assistive devices often are used without consultation of a medical professional [2], are set for inappropriate height, or are faulty [3], and may cause an increase in falls risk [4]. Assistive devices are also often used incorrectly. An estimated 28% of cane users incorrectly hold the cane on their weak side, 11% occasionally swing the cane with the ipsilateral leg, and 14% occasionally hold the cane in the air for multiple steps [2]. Furthermore, using a walking aid alters spatiotemporal parameters of gait [4]. Objective assessments describing cane use while walking can offer useful information to users, clinicians, and caregivers. Wearable inertial measurement units (IMUs) are an ideal technology for providing these measures because they can be worn by the user and placed on the walking aid. Additionally, IMUs have several benefits over alternative technologies such as motion capture and gait mats: IMUs are inexpensive, portable, reliable, and can form a wireless sensor network. To extend research on assistive devices and gait analysis, our work utilizes objective IMU-derived measurements of lower limb and cane movement to quantitatively assess assistive device usage in populations with functional walking deficits. More specifically, we investigate the relationship between swing and stance timing and variability in movement to provide insight into assistive device usage and potentially offer feedback to users, clinicians, and caregivers about proper cane movement.

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II. Related Work

Several studies have applied wearable IMUs for monitoring human movement and gait analysis [5]; however, fewer IMU studies have accounted for gait impairments that require the use of an assistive device. These studies can be grouped into those investigating lower limb movement (sensors attached to the user and not to the device) [6], device movement (sensors attached to the device and not to the user) [7]–[9], and the relationship between user and device movement (sensors attached both to the device and user) [10]–[12]. The studies investigating the movement and gait of both the user and device are most relevant to the current study. Hester et al. [10] computed statistical features from an ankle-mounted accelerometer and a cane equipped with two accelerometers and a load cell to train a neural network for activity recognition. Hassan et al. [11] utilized IMUs mounted on a cane and affected limb of hemiplegic participants to estimate the movement intention of the user to control an exoskeleton. Recently, Lancini et al. [12] added several sensors, including an accelerometer, to crutches used by powered exoskeleton users.

While the aforementioned studies have investigated human movement and device usage with several types of technologies, IMU-based gait analysis with respect to cane usage is a new direction of research. In this paper, we present our research in this area with algorithms designed for IMUs attached to both lower limbs and a cane device. The current study extends several areas of research, including IMU data processing, gait analysis, and quantitative assessment of assistive device movement.

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III. Methods

IMU data were utilized from a previous study conducted at an inpatient rehabilitation facility [13]. For the previous study, three inertial sensors (Shimmer 3) were attached to the bodies of patients undergoing inpatient rehabilitation, one sensor on the center of mass and one on each shank. If the patient used a cane or a walker as an assistive device, a fourth sensor was placed on the device. For the present study, we are only utilizing gyroscope data from the shank and cane sensors. The gyroscope ranges were set at 500 $^0/s$ and the data were collected at a sampling frequency of 51.2 Hz for all sensor platforms.

While wearing the sensors, the participants performed an ambulatory circuit (AC), a continuous standardized sequence of ambulation activities. The AC represents a more complex version of the traditional Timed Up and Go (TUG) test that is frequently used for mobility assessment [14]. The AC includes rising from a seated position in a chair, walking a linear path which proceeds to a curvilinear path, transitioning between different floor surfaces, transferring into and out of a sport utility vehicle, and returning on the path to sit back down in the chair. Data were collected from four trials at two different testing sessions (two trials each session). The first session (S1) occurred shortly after the participant became physically able to walk the distance required of the gait task. The second session (S2) occurred one week later, a date that was typically close to their discharge from the inpatient facility.

A. Participants

Participants were recruited from the inpatient rehabilitation population at a large inpatient rehabilitation facility. The study was approved by a regional hospital institutional review board and all participants gave written informed consent. The study is ongoing, with 35 participants tested to date. Of the 35 participants, 2 participants (P1 and P2) who used canes at both S1 and S2 are included in the current analysis. Table I contains information about participant characteristics from medical records, including their Functional Independence Measure (FIM) score, a standardized clinical assessment measuring independence on 18 activities of daily living. Both participants were undergoing post-stroke rehabilitation, with P1 having left sided hemiparesis, and P2 having no paresis but profound imbalance secondary to stroke.

B. Data Processing

The inertial movement data and segment times are processed with a custom Python program designed for the AC data. First, the timestamps from all sensor platforms are aligned. Next, to correct for the orientation of the shank and cane sensors, the sensor local coordinate system is transformed to the body coordinate system [15]; a right handed system with the X-axis along the anterior-posterior body axis, the Y-axis along the vertical body axis, and the Z-axis along the medial-lateral body axis. The gyroscope signals for all sensors are low passed filtered at 4 Hz.

While there are several unique components of the AC (chair transfer, vehicle transfer, surface transitions, etc.), for this study we focus only on the ambulation occurring between the chair and the vehicle. This ambulation section consists of six meters of smooth floor, linear path walking that is used for gait analysis. Future work consists of analyzing assistive device movement during the other components of the AC.

TABLE I
Participant Characteristics

ID	Etiology	Sex	Age (years)	Assistive Device	Dominant Side	Affected Side	FIM_A	FIM_D
P1	Stroke	Male	85	Cane	Right	Left	87	113
P2	Stroke	Male	63	Cane	Right	No paresis	69	107

FIM_A = admission total FIM, FIM_D = discharge total FIM.

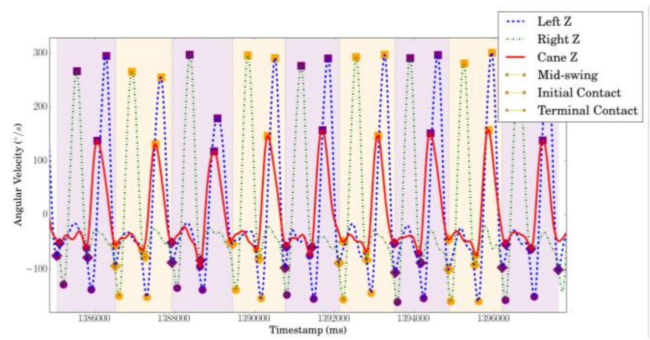

Fig. 1. Participant P1's left shank, right shank, and cane sensor Z-axis gyroscope signals recorded during the linear walking portion of the AC. The individual gait cycles are identified as alternating shaded regions.

C. Gait Parameter Computation

For the ambulation section, an algorithm was developed to detect the gait cycle events of initial contact (IC), terminal contact (TC), and mid-swing (MS) for the lower limbs and cane. Initial contact is the moment the heel/cane strikes the ground and terminal contact is the moment the toes/cane leave contact with the ground. The gait cycle is defined as the time interval between two successive initial contacts of the same leg. The algorithm operates on shank and cane medial-lateral (Z-axis) gyroscope data and utilizes peak detection and thresholding techniques that were implemented with high accuracy by previous studies [15], [16]. Fig. 1 shows Z-axis gyroscope data and the associated gait events for participant P1's left shank, right shank, and cane. The outline of the algorithm is as follows:

1. Detect MS events. MS events correspond to the highest peaks in the Z-axis gyroscope signal (square points in Fig. 1).
2. Detect IC events. IC events correspond to the local minimum after a MS event (diamonds in Fig. 1).
3. Detect TC events. TC events correspond to the local minimum before a MS point (circles in Fig. 1).
4. Identify MS, IC, and TC events corresponding to individual gait cycles for the lead leg. The lead leg is defined as the leg corresponding to the first detected IC event of the linear walking portion of the AC.
5. Identify MS, IC, and TC events for the non-lead leg and cane with respect to the cycles defined by the lead leg.

The algorithmically-detected gait events were visually inspected for correctness. In the case of an incorrectly identified event, the event was manually corrected. In total 11 of the 666 detected gait events were manually corrected.

For each trial t of the AC, there are N_t gait cycles detected during the ambulation section. For each gait cycle i, the following gait features are computed:

- *Cycle duration*. Measured in milliseconds: $Lead\_IC_{i+1} - Lead\_IC_i$.
- *Stance %*. Leg and cane stance periods as a percentage of the total gait cycle.
- *Mid-swing °/s*. Leg and cane MS angular velocity.
- *Cane stance ratio*. Ratio of contralateral limb stance percent to cane stance percent: $\frac{Contralateral\_Stance_i}{Cane\_Stance_i}$. Represents the similarity in amount of time the cane and the contralateral limb are supporting the body.
- *Cane swing offset*. Cane MS temporal offset from the contralateral leg MS: $|Cane\_MS_i - Contralateral\_MS_i|$. Represents how closely the cane swings with the contralateral limb.
- *Double support %*. The overlap in stance phases for the left and right legs as a percentage of the total gait cycle.
- *Triple support %*. The overlap in stance phases for the left leg, right leg, and cane as a percentage of the total gait cycle.

The mean and coefficient of variation are computed for each of the above features for all N_t gait cycles of each trial t.

D. Stance and Swing Phase Plots

To visualize the variability of timing between both legs and a cane, we introduce stance and swing phase plots. Fig. 2 and Fig. 3 show stance and swing phase plots for participant P1 and P2 at S2 testing. For each sensor location, stance (gray) and swing (blue) phases are represented with horizontal bars. The sensor location stance and swing phases are grouped together for each gait cycle (the Y-axis). The X-axis shows an estimate of the percentage of the gait cycle, based on the average gait cycle duration. Overlaid on top of the stance and swing bars are periods of double (star hatch) and triple (cross hatch) support periods.

IV. Results

Computed gait parameter results are summarized in Table II. Reported statistics for each metric include the mean (μ_{S1},μ_{S2}) and coefficient of variation (CV_{S1},CV_{S2}) for S1, the average of the two trials at S1, and S2, the average of the two trials at S2. To facilitate additional insights at the individual gait cycle level, stance and swing plots are included for P1 in Fig. 2 and for P2 in Fig. 3 and Fig. 4.

V. Discussion

In this paper we utilize wearable IMUs to perform fine-grained, quantitative assessment of gait and cane usage for two patients undergoing stroke rehabilitation. The metrics we compute reveal several differences between the two patients. For example, P1 has shorter gait cycles, spends less time in double and triple support, and swings both his legs and cane with higher angular velocity. P1 also generally demonstrates lower variability in gait and cane usage, with the exception of left leg mid-swing angular velocity and the percentage of time spent in double support. Considering P1 has a left side involvement, this anomaly is understandable.

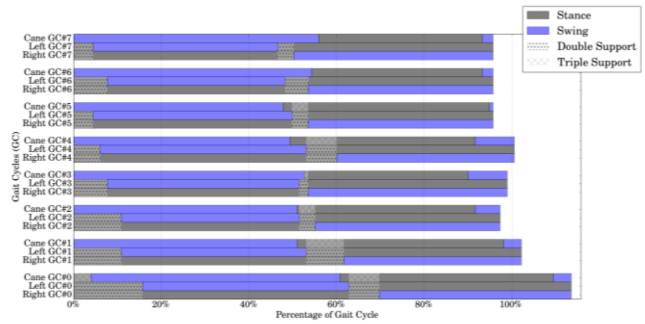

Fig. 2. Stance and swing phase plot for participant P1 recorded from trial 3 at session 2 testing.

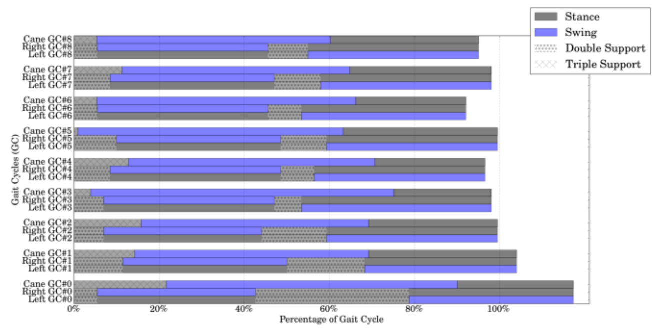

Fig. 3. Stance and swing phase plot for participant P2 recorded from trial 3 at session 2 testing.

TABLE II
GAIT PARAMETER RESULTS

Metric	P1 μ_{S1} (P1 CV_{S1})	P1 μ_{S2} (P1 CV_{S2})	P2 μ_{S1} (P2 CV_{S1})	P2 μ_{S2} (P2 CV_{S2})
Number of cycles per trial	8, 7	8, 7	14,12	9,9
Cycle duration in milliseconds	1377.79 (4.04%)	1221.33 (5.18%)	1398.95 (5.29%)	1308.21 (7.68%)
Left stance %	57.67% (4.45%)	56.44% (3.73%)	63.08% (7.37%)	59.03% (4.53%)
Right stance %	58.82% (4.73%)	58.18% (5.34%)	58.82% (5.58%)	59.26% (6.41%)
Cane stance %	46.91% (6.11%)	43.60% (8.48%)	46.33% (23.04%)	40.26% (13.23%)
Left mid-swing °/s	282.86 (9.79%)	321.70 (14.71%)	249.76 (18.74%)	292.47 (9.93%)
Right mid-swing °/s	286.91 (6.66%)	320.81 (7.53%)	240.43 (14.76%)	276.11 (12.51%)
Cane mid-swing °/s	140.88 (7.94%)	153.24 (13.19%)	58.45 (27.88%)	66.61 (26.38%)
Cane stance ratio	1.24 (7.26%)	1.30 (9.17%)	1.33 (22.88%)	1.49 (13.20%)
Cane swing offset	112.59 (39.43%)	164.21 (30.92%)	94.20 (103.72%)	110.90 (59.80%)
Double support %	16.49% (23.89%)	14.62% (29.08%)	21.90% (16.16%)	18.34% (30.07%)
Triple support %	6.50% (41.04%)	5.72% (74.28%)	7.99% (78.43%)	6.54% (87.39%)

CV = coefficient of variation, P1 = participant 1, P2 = participant 2, S1 = session 1, S2 = session 2, and μ = mean.

Stance and swing plots allow several observations of the timing and variability of individual gait cycles. For example, inspecting Fig. 2 reveals several important characteristics of participant P1's gait and cane usage. First, the cane correctly swings in phase with the affected (left) leg. Second, the initial double support period appears more consistent in occurrence and duration than the second double support period. Fig. 3 reveals P2 has more variable gait. In particular, he swings his cane such that there is only one

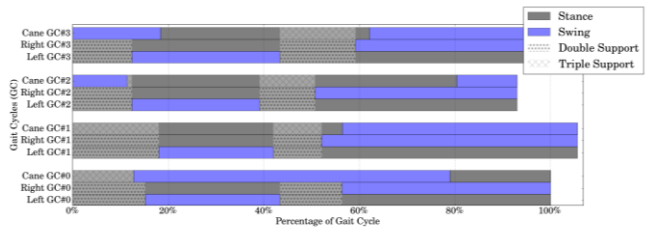

Fig. 4. Stance and swing phase plot for participant P2 recorded from the first four gait cycles detected during trial 1 at session 1 testing.

period of triple support each cycle, indicating asymmetrical cane support between the first and second double support periods. This is different cane movement behavior than P2 exhibited one week earlier at S1 testing (see Fig. 4). Additional analysis of changes after one week of inpatient rehabilitation reveal each participant had a reduction in total cycle duration, 11.4% for P1 and 6.5% for P2. Similar improvements are seen in stance and double/triple support percentages. The observed differences between P1 and P2 are corroborated by P2's lower admission and discharge FIM scores (see Table I).

Wearable IMU data can also be used to detect incorrect cane use. Fig. 4 shows P2 exhibiting incorrect cane use [2] by swinging the cane in phase with the ipsilateral leg for the first detected gait cycle (GC#0) of the first trial. Algorithms operating on IMU data can also automatically detect when cane users hold the cane in the air for multiple steps [2] by detecting a missing cane IC within a gait cycle.

Limitations of this study include the low sample size and that the gait cycle event detection algorithm has not been laboratory validated; however, it is based on previously-published and validated sources. One such study utilizing IMUs from the same manufacturer (Shimmer Sensing), reported mean true errors for gyroscope-based gait cycle event detection of -5.5 ± 7.3 ms for detecting IC points and 40.6 ± 19.2 ms for detecting TC points [16]; therefore, the timings of gyroscope-detected gait events should be interpreted as estimates of the true durations. The value of fine-grained gait parameter estimations from IMU algorithms lies in the additional information provided; information that is unavailable from human observation alone. Our future work aims to address these limitations by collecting IMU data from additional participants using different assistive devices and designing a real-time system to monitor walking aid usage for correctness and changes in variability over time.

VI. Conclusion

With the large number of assistive device users in the United States, technology to monitor device usage for gait analysis and safety is of increasing importance. Consequently, we undertook a study to investigate the application of wearable inertial sensors for fine-grained, quantitative assessment of cane and lower limb movement during straight-path gait for two patients undergoing inpatient rehabilitation for stroke recovery. The gait parameters computed and sensor data visualization introduced in this paper provide a foundation for future IMU monitoring of gait and assistive device movements.

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