Measuring Changes in Gait and Vehicle Transfer Ability During Inpatient Rehabilitation with Wearable Inertial Sensors

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***Abstract*— Restoration of functional independence in gait and vehicle transfer ability is a common goal of inpatient rehabilitation. Currently, ambulation changes tend to be subjectively assessed by clinicians. To investigate more precise objective assessment of progress in inpatient rehabilitation, we quantitatively assessed gait and transfer performances over the course of rehabilitation with wearable inertial sensors for 20 patients receiving inpatient rehabilitation services. Participant performance was recorded on a sequence of ambulatory tasks that closely resemble everyday activities. We developed a custom software system to process sensor signals and compute metrics that characterize ambulation performance. We quantified changes in gait and transfer ability by performing a repeated measures comparison of the metrics one week apart. Metrics showing the greatest improvement are walking speed, stride regularity, acceleration root mean square, walking smoothness, shank peak angular velocity, and shank range of motion. Wearable sensor-derived metrics can potentially provide rehabilitation therapists with additional valuable information to aid in treatment decisions.**

***Key words*— Accelerometry; ambulatory monitoring; inertial measurement units; signal processing; wearable sensors.**

I. Introduction

The fundamental goals of inpatient rehabilitation are to restore function, mobility, and independence. Monitoring of motor recovery is typically accomplished by clinical observation using standard clinical rating scales, such as the Functional Independence Measure (FIM), to determine independence in activities of daily living at admission and discharge [1]. Between the admission and discharge FIM assessments, observations by therapists typically characterize progress and influence treatment decisions. Because this approach relies on intuition and subjective observations, it lacks detailed quantifiable information to characterize patient movement patterns. To gather more objective measurements of patients' abilities, standardized clinical assessments, such as the Timed Up-and-Go (TUG) test [2], are administered by trained clinicians. The TUG test measures the time required to rise from a seated position in a chair, walk out 3 meters, walk back to the chair, and sit down. Assessments like the TUG provide a high level overview of patient mobility, but are not sensitive enough to capture individual limb movements or changes in mobility and gait features [3]. More precise quantitative measurements of patient performance during rehabilitation can be collected via pervasive technology, such as wearable inertial measurement units (IMUs). Computations based on data collected from wearable IMU sensors can provide therapists with measures that are not open to the potential for inter-observer bias possible with subjective clinical judgments. These supplementary measurements can identify subtle performance changes during rehabilitation that are difficult to observe, such as changes in duration of single and double leg support. Furthermore, IMUs are an ideal technology for tracking changes in movement because of their low cost, portability, reliability, and ease of attachment to the body. IMUs operate as a self-contained wireless network which can enable testing outside the lab and for any sequence of tasks. Also, IMUs do not interfere with the wearer's movement.

In this paper, we report on a study that utilizes metrics and visualizations obtained from IMU data to characterize patient performance in an objective fashion. To produce clinically-meaningful metrics, we developed a standardized ambulation performance task, titled the ambulation circuit (AC), which involves a range of gait and transfer tasks. We fixed the interval of time over which repeated measurements of AC performance would be assessed (7 days) in order to quantify changes in movement parameters over one week of rehabilitation.

II. Related Work

Wearable IMUs have been utilized extensively in healthcare applications [4], particularly for gait analysis [5] and rehabilitation [6]. To date only a few studies have focused on utilizing IMUs to quantify changes in mobility and gait parameters of impaired populations. These studies have investigated improvement in gait following surgery, such as hip arthroplasty surgery [7]; changes in gait after treatment for a specific injury or illness, such as Parkinson's Disease [8], [9]; the relationship between changes in longitudinally collected gait parameters and changes in falls risk [10]; and changes in daily walking time over the course of rehabilitation for stroke inpatients [11]. Based on these findings, research quantifying fine-grained gait and transfer ability changes exhibited during

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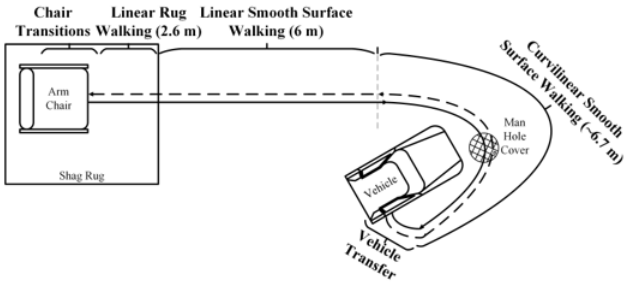


Fig. 1. The ambulation circuit. The solid line represents the way out and the dashed line represents the mirrored return portion. Key circuit subtasks are labeled with distances in meters.

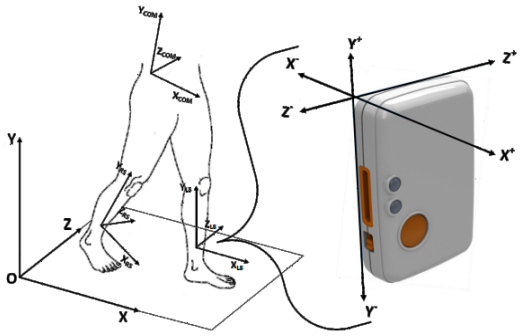


Fig. 2. Sensor placement and axes orientation. Sensor units were mounted on the center of mass (COM), left shank (LS), and right shank (RS).

rehabilitation with wearable inertial sensors represents a new direction to investigate. Consequently, the current study extends several areas of research, including IMU data processing, gait analysis, and rehabilitation research. More specifically, our work presents the following contributions:

- Design and application of an ecological version of the TUG test (the ambulation circuit).
- Computation of novel sensor-based metrics related to ecological gait and transfer ability (e.g. vehicle transfer and floor surface metrics).
- A framework for measuring changes in IMU metrics for individual participants and participants as a group.
- Insight into the recovery process for a multifarious population of inpatients (e.g. stroke, brain injury, etc.).

III. Methods

The study followed a single-arm prospective cohort design with repeated measures of participant performance on standardized gait tasks on two different testing sessions separated by 7 days. The first test session (S1) occurred shortly after the participant became physically able to walk the distance required of the gait task (11.15 ± 4.75 days from admission). The second test session (S2) occurred within the final week of care (2.65 ± 2.25 days before discharge). During each test session, participant performance on the ambulation circuit was recorded two times, producing two separate trials at S1 and two separate trials at S2. In addition, physical measurements and information regarding participants' rehabilitation impairment and other diagnoses were collected.

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. Twenty participants (Male = 14, Female = 6), between the ages of 52 and 88 years old (71.55 ± 10.62 years), participated in both testing sessions of the study. The majority (70%) of participants required a wheeled walker during both testing sessions. Three (15%) participants used a cane during both testing sessions. One participant transitioned from a walker to a cane between the sessions. Medical record review revealed rehabilitation diagnoses were varied, with fourteen (70%) participants undergoing post-stroke rehabilitation. Hemiparesis was present in 11 post-stroke participants.

B. Standardized Gait Tasks: The Ambulation Circuit

We designed a standardized ambulation circuit to assess the mobility and physical ability of the participants during the test sessions. The AC is a continuous sequence of activities performed in a simulated community environment at the rehabilitation facility consisting of several indoor and outdoor modules. The ecological context provided by a simulated environment has been shown to produce a more representative assessment of an individual's functionality than a controlled laboratory setting [12].

Fig. 1 illustrates the AC. The AC begins in a simulated hotel lobby area with the participant seated in a chair on a rectangular shag rug. The chair faces a linear path that leads to an outdoor area with several motor vehicles. On beginning the circuit, the participant rises from the seated position, performing a sit-to-stand transition. Once standing, the participant walks across the remaining length of the shag rug. When the edge of the rug is reached, the participant performs a surface transition from the shag rug to smooth wood flooring. Next, the participant approaches the front of a sport utility vehicle and begins a curvilinear path around the vehicle to approach an open passenger side door. The curvilinear path contains a simulated sewer drain lid (manhole cover) over which the participant has to maneuver. As the participant approaches the vehicle passenger seat, the participant performs a transfer into and then out of the vehicle front passenger seat. After transferring out of the vehicle, the participant walks the AC route in reverse, returning to the chair in the simulated hotel lobby and sits down, ending the AC. Time taken to complete the AC officially stops once the participant's back is fully rested against the back of the chair. In summary, the AC is an extension of the common clinical assessment, the TUG, including a greater range of functional tasks (e.g., car transfers) and situational challenges (e.g., different flooring surfaces; a curvilinear pathway) than is found in more common assessments. This greater range of motor challenges enhances the potential usefulness of the sensor data as a means to show change across time. The majority of the metrics we report can be computed from any assessment in any environment involving a chair transfer and walking (5 Times Sit-to-Stand, TUG, etc.).

C. Instrumentation

Using three Shimmer3 [13] wireless IMUs, we recorded participant motion as they ambulated through the AC. The Shimmer3 platform contains a tri-axial accelerometer and a tri-axial gyroscope. The accelerometers and gyroscopes of all three sensor platforms were calibrated using the software provided by the manufacturer. One IMU was placed centrally on the

TABLE I
METRIC DESCRIPTIONS

Category	Metric	Units	Qualitative Description	Refer -ence
CAP	Duration	s	Total time to complete the ambulation circuit or a subtask of the ambulation circuit.	
	Floor surface speed ratio		Measures the effect of walking velocity on two different floor surfaces.	
	Walking speed	m/s	The walking velocity as determined by distance divided by time.	
WBM	COM peak angular velocity	$°/s$	Maximum rotational velocity of the COM around the Z-axis while rising from a seated position in the chair to a standing position.	
	Root mean square (RMS)	$m/s^2\ /s$	Square root of the mean of the squares of each axes of the acceleration signal on the COM. Represents the magnitude of the signal (normalized by time).	[3]
	Smoothness index		Ratio of even to odd harmonics of the vertical Y-axis COM acceleration signal. A higher harmonic ratio represents a smoother walking pattern.	[17]
	Smoothness of RMS	$m/s^3\ /s$	Root mean square of the derivatives of each X, Y, and Z signal. Synonymous with RMS of jerk (normalized by time).	[3]
GF	Cadence	$steps/min$	Step rate as expressed by the number of steps per minute.	
	Double support percent	%	Percentage of the gait cycle that both feet are on the ground. Computed as the sum of the initial double support time and the terminal double support time.	[5], [16]
	Gait cycle time	s	Duration to complete one stride (time between two consecutive initial contacts of the same foot).	[5], [16]
	Number of gait cycles		The number of complete gait cycles (strides) that occurred.	
	Shank peak angular velocity	$°/s$	Maximum rotational velocity of the shank around the Z-axis during the gait cycle. This occurs during the swing phase.	
	Shank range of motion	°	Integrated angular velocity for each gait cycle. Provides an estimate of the degrees of shank movement.	[5], [16]
	Step length	m	Distance between initial contacts of opposite feet.	[14]
	Step regularity	%	Expression of the regularity of the acceleration of sequential steps. Computed using the autocorrelation of the vertical Y-axis of the COM acceleration.	[14]
	Stride regularity	%	Expression of the regularity of the acceleration of sequential strides (see step regularity).	[14]
	Step symmetry	%	Ratio of step regularity to stride regularity.	[14]

CAP = clinical assessments of progress, COM = center of mass, GF = gait features, m = meters, s = seconds, WBM = whole body movement, ° = degrees.

lumbar spine at the level of the third vertebrae, near the individual's center of mass (COM) [14]. Additionally, one sensor was placed on each shank, above the ankle and in line with the tibia. Positioning the sensor along the tibia reduced mounting error as the sensors were always positioned at approximately the same angle relative to the sagittal plane. The flatness of the tibia bone also prevented the sensor from moving during the activities. The sensor modules were securely attached to the body with elastic straps. Shank sensor mounting locations were measured at S1 and S2 for consistency. Fig. 2 illustrates the shank mounting locations and axes of the sensors. The accelerometer range was set to ± 2g for the COM sensor and ± 4g for the shanks. The gyroscope ranges for the shank and COM sensors were set at 500 $^0/s$ and 250 $^0/s$, respectively. The data were collected at a sampling frequency of 51.2 Hz for all sensor platforms. The inertial movement data and segment times are processed with a custom Python program designed for the AC data. First, the timestamps are aligned from the three different sensor platforms. Next, to correct for the orientation of the shank sensors along the tibia, 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. Acceleration data are filtered with a 4th order zero-phase band pass Butterworth filter using cutoff frequencies of 0.1 Hz and 3 Hz for the COM accelerometer and 0.1 Hz and 10 Hz for the shanks. The gyroscope signals for all sensors are low passed filtered at 4 Hz.

From the processed data we compute metrics representing participants' performance on the AC. AC task durations were recorded by a researcher using a stopwatch. The times are used to segment the data into the different tasks for computing metrics for each of the AC sections. Fig. 3 illustrates the tri-axial COM acceleration and left and right shank gyroscope data from a participant partitioned into the key sections of the AC.

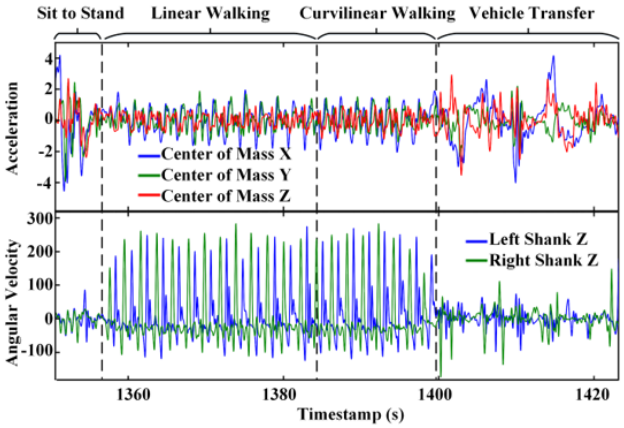


Fig. 3. Sensor signals recorded during the first half of the AC. The center of mass (top plot: accelerometer) and shank (bottom plot: gyroscope) sensor signals were analyzed to quantify the rehabilitation process.

D. *Computed Metrics*

For a unique analysis of sensor-based gait information in a rehabilitation setting, we compute metrics from three main components of the AC: the chair sit-to-stand and stand-to-sit movements at the beginning and ending of the AC, the vehicle transfer, and the ambulation occurring between the chair and the vehicle. This ambulation section includes the linear path on the smooth floor that is used to compute the majority of the gait cycle metrics. For the ambulation section, an algorithm was developed to detect the gait cycle events of initial contact, terminal contact, and mid swing. Initial contact is the moment the heel strikes the ground and terminal contact is the moment

the toes leave contact with the ground. The algorithm operates on the left and right shank medial-lateral (Z-axis) gyroscope data. The algorithm utilizes peak detection and thresholding techniques that were implemented with high accuracy by previous studies [15], [16]. By locating these key gait events, the gait cycle is defined (the time interval between two successive initial contacts of the same leg) and several metrics related to walking are computed. Table I presents the metrics we compute and groups the metrics into three categories:

1. Clinical assessments of progress (CAP). CAP metrics are commonly used approaches for assessing mobility in a clinical setting by recording the duration of a standardized activity, such as walking a fixed distance, rising from a chair, or the TUG assessment.
2. Whole body movement (WBM). WBM metrics are computed from data collected from the COM sensor. An example WBM metric is COM peak angular velocity.
3. Gait features (GF). GF are computed from data collected from the shank sensors. Examples of GF include cadence and shank range of motion, which are based on the aforementioned gait cycle event detection algorithm.

E. Data Analysis

Sensor-based metrics are statistically analyzed to identify clinically significant changes in the repeated measures data. Detected changes in patient performance offer additional insights to clinicians, as well as demonstrate the benefit of sensor-based analysis of rehabilitation. The statistical analyses we apply to the wearable sensor data at the group and individual levels are summarized below.

1) Quantifying Group Changes

An effect size (ES) based on Cohen's d for repeated measures (RM) data is used to quantify the strength of changes in each of the computed metrics [18]:

$$d_{RM} = \frac{\bar{X}_{S2} - \bar{X}_{S1}}{S_D} \quad (1)$$

Where $\bar{X}_{S1}$ is the mean group score from data collected at S1, $\bar{X}_{S2}$ is the mean group score from data collected at S2, and S_D represents the standard error of difference between S1 and S2 scores [18]. The resulting effect sizes, d_{RM}, are used to evaluate group changes in gait parameters over the course of one week of inpatient rehabilitation. Additionally, the confidence intervals for each ES are computed using a small sample size approximation with alpha set at 95% [19].

2) Quantifying Individual Changes

At the individual level, changes in gait metrics one week apart are characterized with the reliable change index (RCI) [20]:

$$\text{RCI} = \frac{x_{S2} - x_{S1}}{S_D} \quad (2)$$

Where x_{S1} is an individual participant's score from data collected at S1 and x_{S2} is the same participant's score from data collected at S2. In addition to numeric RCI statistics, comparison of individuals to the group for change between S1 and S2 are accomplished graphically with RCI plots. Fig. 4 shows an example RCI plot of the walking smoothness index metric (see Fig. 5 for additional RCI plots). The values measured for the smoothness index at S1 (X-axis) are plotted against S2 (Y-axis). The red diagonal line intersecting the plot

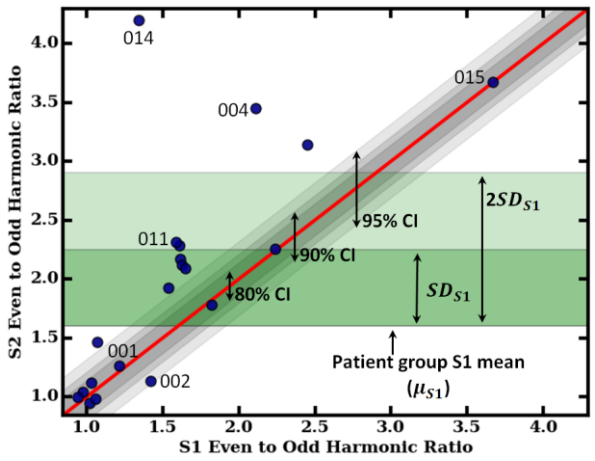
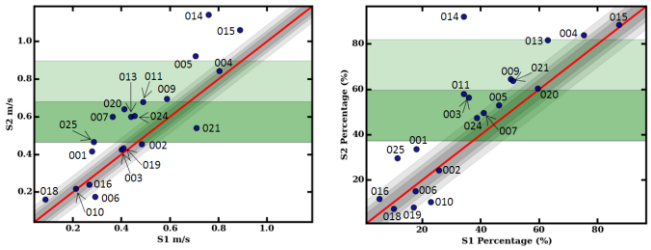


Fig. 4. The smoothness index metric as an example reliable change index plot. Participant session 1 (S1) scores are plotted against session 2 (S2) scores. Also plotted are confidence intervals (CI) and S1 standard deviations (SD). Select individuals are labeled with their participant identification number.



a) Walking speed b) Step regularity

Fig. 5. Walking speed (a) and step regularity (b) reliable change index plots. Individuals are labeled with their participant identification number.

represents an absence of change from S1 to S2. The shaded gray diagonal areas represent confidence intervals based on standard error of measurement and criteria suggested by Wise [21]. The green bands represent the mean value for S1, plus one and two standard deviations respectively.

IV. Results

Tables II-IV contain results for CAP, WBM, and GF metrics, respectively. Reported statistics for each metric include the mean and standard deviation for S1 and S2 (μ_{S1}, SD_{S1}, μ_{S2}, and SD_{S2}) and the standardized mean difference effect size. To facilitate analysis and insights at the individual patient level, smoothness index (see Fig. 4), walking speed (see Fig. 5a), and step regularity (see Fig. 5b) are displayed as RCI plots.

V. Discussion

In this paper we investigate the insights that sensor-based quantifiable measures can supply in addition to observations by clinicians. While analyzing changes at the group level provides information about the effects of therapy from a research perspective, the effects of rehabilitation on an individual basis can be established with wearable sensors and applied directly to patient care.

TABLE II
CLINICAL ASSESSMENTS OF PROGRESS (CAP) METRIC RESULTS

Metric	μ_{S1}	SD_{S1}	μ_{S2}	SD_{S2}	Effect Size
Curvilinear walking duration	24.43	18.14	19.48	12.23	-1.03*
Duration	177.85	129.53	137.36	88.56	-1.08*
Floor surface speed ratio	0.75	0.13	0.80	0.14	0.48*
Sit-to-stand duration	6.84	6.10	4.79	3.03	-0.49*
Stand-to-sit duration	12.94	12.05	11.13	7.13	-0.34*
Vehicle challenge duration	47.81	36.36	34.75	28.10	-0.55*
Walking speed	0.47	0.22	0.57	0.28	1.58*

S1 = session 1, S2 = session 2, SD = standard deviation, μ = mean, * = significant at the 95% confidence level.

A. Group Responsiveness to Therapy

1) Clinical Assessments of Progress

As a group, AC metrics related to CAP demonstrate moderate improvements based on the magnitude of effect sizes (see Table II). For total AC duration, there is a 22.77% decrease in the total time required to complete the AC. Improved functionality is confirmed by increased ambulatory capabilities, completing the curvilinear section of the AC 20.26% faster. Responsiveness on the vehicle load/unload challenge is moderate with 27.32% decrease in duration observed on average. Walking speed is a typical metric for comparison among populations and for indication of ambulatory improvements. Group average performance during both sessions (walking speed S1 $0.47 \pm 0.22\ m/s$; walking speed S2 $0.57 \pm 0.28\ m/s$) as well as the large responsiveness across time (see Fig. 5a for an RCI plot) are in agreement with previous published studies analyzing walking speed in post-stroke populations [22].

2) Whole Body Movement Metrics

Large levels of responsiveness are observed for RMS during linear path gait (see Table III). While there is a relationship between COM RMS and walking speed [17], the large responsiveness across time is due in part to the participant-dictated speed of movement. During the vehicle transfer, the ES for COM RMS during the load and unload tasks suggest substantial progress from one week of rehabilitation therapy. Similar changes in COM RMS are also present on the chair task.

Another WBM metric, the smoothness index of walking (see Fig. 5), characterizes gait harmonics to quantify cyclical movements independent of speed [17]. The calculated ES for change in smoothness index emphasizes the influence rehabilitation has on developing a more stable pattern of locomotion. As a group, the participants demonstrate a 25.63% improvement in the smoothness index.

3) Gait Features

Changes in metrics describing gait quality in terms of symmetry, regularity, and consistency are observed during the straight path portion of the AC (see Table IV). During one week of rehabilitation, the increased walking speed is accompanied by an average increase of 8.72% in cadence. Another important outcome is the 4.74% decrease in the amount of double limb support in the gait cycle. In addition, improvement is observed in gait consistency, measured with stride and step regularity (see Fig. 5b for an RCI plot). These metrics indicate that patients are beginning to produce more consistent walking patterns over one week, increasing the load carried by the affected limb.

Changes are also observed in individual leg movements. Large levels of responsiveness are detected in peak angular velocity, measured at each shank. Along with faster leg movements during the swing phase, there is a strong indication of increased limb range of motion during gait. To perform sub-group analyses of stroke patients with hemiparesis, each limb is re-classified as affected (paretic) or unaffected (non-paretic), instead of left or right. The re-categorization produces a slightly different ES for shank peak angular velocity and range of motion. Tracking changes in the affected side of the body offers additional insight for clinicians treating stroke patients and injuries affecting one side of the body more than the other side.

TABLE III
WHOLE BODY MOVEMENT (WBM) METRIC RESULTS

Metric	μ_{S1}	SD_{S1}	μ_{S2}	SD_{S2}	Effect Size
COM RMS	0.08	0.06	0.11	0.10	1.87*
COM Smoothness of RMS	0.75	0.59	1.10	1.04	1.90*
Sit-to-stand RMS	0.65	0.64	0.85	0.67	0.71*
Sit-to-stand peak angular velocity	84.02	37.96	72.46	44.47	-0.37
Smoothness index	1.60	0.65	2.01	0.97	1.82*
Stand-to-sit RMS	0.38	0.45	0.36	0.30	-0.07
Stand-to-sit peak angular velocity	126.87	36.75	118.45	42.08	-0.26
Vehicle load RMS	0.10	0.11	0.16	0.16	1.37*
Vehicle load peak angular velocity	81.94	36.62	78.27	26.32	-0.10
Vehicle unload RMS	0.16	0.12	0.29	0.37	2.71*
Vehicle unload peak angular velocity	74.45	47.85	68.45	35.89	-0.15

COM = center of mass, RMS = root mean square, S1 = session 1, S2 = session 2, SD = standard deviation, μ = mean, * = significant at the 95% confidence level.

TABLE IV
GAIT FEATURES (GF) METRIC RESULTS

Metric	μ_{S1}	SD_{S1}	μ_{S2}	SD_{S2}	Effect Size
Cadence	64.88	17.67	70.54	20.32	1.38*
Double support percent	33.79	11.97	32.19	13.72	-0.49*
Gait cycle time	1.96	0.66	1.87	0.68	-0.64*
Affected side peak angular velocity	190.09	67.88	208.79	72.50	1.52*
Affected side shank range of motion	47.34	13.22	50.02	11.44	1.20*
Left side peak angular velocity	195.98	61.01	213.09	68.84	1.30*
Left side shank range of motion	47.24	12.66	50.93	12.59	1.73*
Number of gait cycles	18.95	9.32	16.38	5.59	-0.90*
Right side peak angular velocity	217.65	43.80	244.53	51.02	2.02*
Right side shank range of motion	50.41	10.91	54.70	9.43	1.45*
Step length	0.21	0.07	0.23	0.06	0.64*
Step regularity	37.29	22.36	46.91	28.11	1.31*
Stride regularity	40.88	22.73	51.53	24.45	0.55*
Step symmetry	63.57	27.50	70.80	26.31	0.35
Unaffected side peak angular velocity	231.38	39.33	255.20	40.62	1.91*
Unaffected side shank range of motion	51.91	11.96	55.69	8.40	1.56*

S1 = session 1, S2 = session 2, SD = standard deviation, μ = mean, * = significant at the 95% confidence level.

B. Individual Responsiveness to Therapy

RCI analyses suggest that recovery is not consistent for all patients over one week of inpatient rehabilitation (see Fig. 4 and 5). For example, participant #014 experienced a substantial amount of recovery compared to the rest of the participants as assessed through RCI plots. This finding is corroborated by the conventional method of using the FIM to characterize functioning at admission. By contrast, participant #015 did not demonstrate significant change in smoothness of walking or step regularity. At admission to the inpatient facility the functional capabilities for this participant were close to independent, rendering a small window for improvement.

The RCI visualization of performance at the individual level can track progress by assessing performance on multiple metrics. For example, a few participants with moderate responsiveness for walking speed (#007, #015, and #020) did not show change in the smoothness index metric and vice versa (#004). Therefore, analysis of multiple metrics, such as smoothness index along with walking speed, highlights the differences in individual recovery.

A limitation of this study is the metric computations have not been laboratory validated; however, all of the algorithms are derived from previously-published and validated sources. Another limitation includes the use of human-operated stopwatch times to segment the AC into its subtasks. The times recorded by the researchers could impose non-systematic error. Future work includes recruiting healthy individuals to perform the AC to provide reference data for comparison to patient data.

VI. Conclusion

Inpatient rehabilitation contains a wide spectrum of challenges that are tackled uniquely by different patients, depending on their pre-morbid state, injury, drive to improve, and compensatory strategies. Changes measured in movement profiles over the course of one week of therapy indicate wearable IMUs provide a viable platform for gaining insight into these complex recovery processes. The ambulation circuit presented in this study allowed data collection to capture performance of real-world challenges in ecological environments. Several gait and transfer features exhibit statistically significant differences in value from session one to session two, which indicates wearable sensor-derived metrics may be practical for clinicians to use in addition to observation to quantify gait and vehicle transfer improvement. Of the significant metrics, only walking speed does not make use of wearable inertial sensor data, indicating that wearable sensors can capture details about changes in movement patterns that cannot be acquired from standardized subjective clinical assessments.

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