Designing Wearable Sensor-based Analytics for Quantitative Mobility Assessment

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***Abstract*—Wearable sensors are gaining traction in various healthcare domains, including patient mobility assessment performed in rehabilitation environments. Typically, clinical observations by therapists are used to characterize patient movement abilities and progress. More precise quantitative measurements of patient performance can be collected with wearable inertial sensors. Highly useful quantitative information and visual presentations of wearable sensor data are critical in gaining therapist acceptance of the technology and improving the therapy experience for patients. To bridge the gap between design of mobility monitoring technology and actual use of the technology, we report responses from interviews conducted with physical therapy providers at an inpatient rehabilitation facility. The information presented during the interviews includes results from our wearable sensor-based mobility assessment algorithms. Our smart computing algorithms utilize wearable sensor data to extract patient movement metrics, train clinical assessment prediction models, and visualize the data. The interview results indicate therapy providers are interested in using wearable sensors and wearable sensor-based metrics, prediction tools, and visualizations while they provide therapy services for their patients. Based on therapist feedback, we suggest future research directions that may increase the clinical utility and adoption of wearable sensor systems and data visualization for mobility assessment.**

***Index Terms*—Wearable computing; information visualization; technology acceptance; physical therapy; rehabilitation.**

I. Introduction

In recent years, wearable technology has been growing in popularity, with 1 in 10 Americans over the age of 18 owning a wearable fitness device [1]. Wearable sensors are also gaining traction in various healthcare domains, including patient mobility assessment, because of the detailed movement information wearable sensors provide. Typically, clinical observations by therapists are used to assess patient movement abilities and progress. More precise quantitative measurements of patient performance can be collected via pervasive technology, such as wearable inertial measurement units (IMUs). Wearable IMUs contain inertial sensors, such as accelerometers and gyroscopes, that can be used in addition to clinical observations to collect fine-grained movement data from patients as they undergo therapy. Smart computing algorithms operating on inertial measurements can identify subtle performance changes during rehabilitation that are difficult to observe, such as changes in duration of single and double leg support.

By processing wearable sensor data with smart computing algorithms we can provide insight on patient mobility, gait, and rehabilitation. These insights are valuable for validating physical therapy regimens, quantifying patient progress, and determining appropriate patient discharge status. In this paper we bridge the gap between design of mobility monitoring technology and actual use of the technology in rehabilitation environments. To do this, we first present our IMU-based computing approaches to objectively characterize patient mobility performance. Computational components of our system include metric extraction algorithms, training and testing clinical assessment prediction models, and generating metric visualizations. To produce clinically-meaningful metrics, we developed a standardized ambulation performance task, titled the ambulatory circuit (AC), which involves a range of gait and transfer tasks. While inpatient rehabilitation patients perform the AC, they wear three inertial sensors for data collection. We fix the interval of time over which repeated measurements of AC performance is assessed (7 days) in order to quantify changes in movement parameters over one week of rehabilitation. Algorithms statistically analyze the sensor-based metrics to identify clinically significant changes in the repeated measures data.

To evaluate and improve the wearable sensor experience for therapists and patients, we interviewed physical therapy providers regarding the utility of wearable technology and our algorithms for helping provide therapy services for patients. Data collected from the AC wearable sensor study were presented to physical therapists (N = 5) and physical therapy assistants (N = 2) to collect therapy providers' perceived clinical utility of wearable sensor data for mobility assessment. The interview consisted of four main components: 1) general conversation about technology, 2) rating usefulness of sensor-based metrics, 3) questions regarding sensor-based clinical assessment predictions, and 4) evaluating visualizations. We present and discuss the responses received from the therapists and suggest future computing research directions to potentially enhance therapy services and increase the adoption of wearable sensor systems for mobility assessment.

II. Related Work

Wearable IMUs have been utilized for several healthcare applications [2], including gait analysis [3] and rehabilitation [4]. In addition, performance on common clinical assessments, such as the Timed Up and Go (TUG) test, have been characterized with IMUs [3], [5], [6], [7]. Existing commercial systems such as BioSensics [8] offer IMU-based metrics; however, the testing protocols are specific to clinical laboratory-based assessments with a narrow range of ambulatory tasks.

Previous studies have found therapists are open to using wearable technology, particularly when the system provides additional information about their patients [9], when shown evidence that the technology is effective [10], or when the collected health data promotes patient engagement [11]. In addition, medical professionals in hospitals are more likely to use wearable computer systems if the technology improves day-to-day work efficiency [12]. From the patient's perspective, several studies provide evidence that patients exhibit an overall positive attitude regarding the use of wearable sensors, even in their daily life [1], [13], [14], [15]. Several groups have generated tools that visualize sensor data [16], [17], [18], [19]. When presented to therapists, visualizations were deemed helpful in drawing insightful conclusions from data about patients' rehabilitation progress [19]. Recently, commercial products have been introduced for use with rehabilitation that generate movement metrics and visual representations of patient performance [8]. The aforementioned studies have investigated the acceptance of wearable technology for various healthcare applications. To our knowledge, the clinical utility of individual wearable sensor metrics and visualizations for physical therapists assessing patient mobility during rehabilitation has not been explored. This is the goal of the study we present here.

III. Methods

To better understand the clinical utility of wearable sensor-derived metrics and visualizations for mobility assessment, we conducted interviews with physical therapists and physical therapy assistants at an inpatient rehabilitation facility. The interview content was based on an ongoing study at the facility that utilizes wearable inertial sensors, named the ambulatory circuit wearable sensor study [20].

A. Ambulatory Circuit Study

For the ambulatory circuit sensor study, three inertial sensors (Shimmer3 [21]) are attached to the bodies of patients (N = 35 to date) undergoing inpatient rehabilitation. Participants in the study are mostly recovering from stroke and non-traumatic brain injuries. One sensor is placed on the participant's center of mass (COM) and one sensor is placed on each ankle. The accelerometer range is set to $\pm 2g$ for the COM sensor and $\pm 4g$ for the ankles. The gyroscope ranges for the ankle and COM sensors are set at 500 $°/s$ and 250 $°/s$, respectively. The data are collected at a sampling frequency of 51.2 Hz for all sensor platforms.

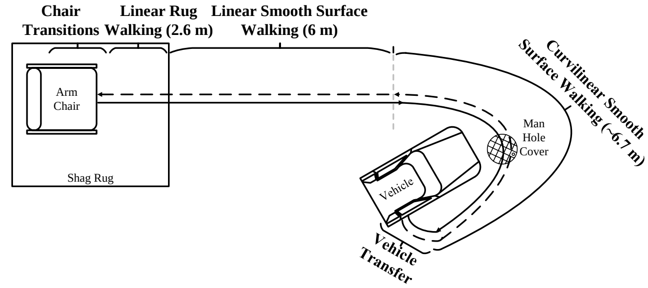


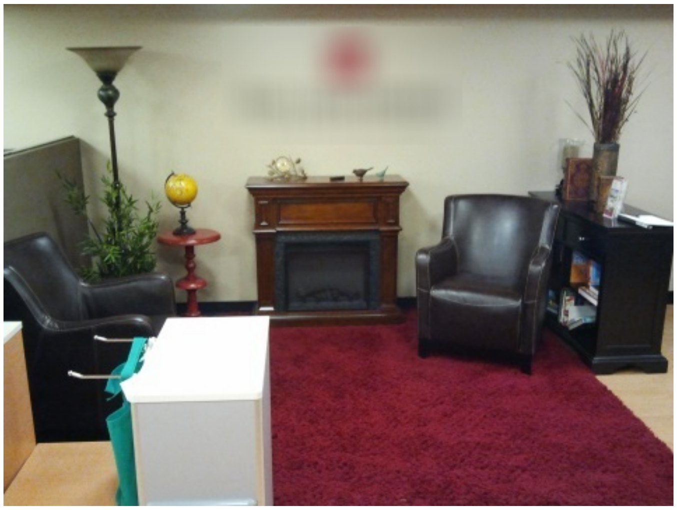
Fig. 1: The ambulatory circuit. The solid line represents the circuit path and the dashed line represents the mirrored return portion.

While wearing the sensors, participants perform an ambulatory circuit (see Fig. 1 for a diagram of the AC), a continuous sequence of activities in a simulated community environment at the rehabilitation facility (see Fig. 2 for images of the AC environment). The AC includes rising from a seated position in a chair, moving with both linear and curvilinear gait, surface transitions, a transfer into and out of a sport utility vehicle, and sitting back down in the chair. AC data are collected at two different testing sessions, with each session collecting data from two trials of the AC. The first session (S1) occurs shortly after the participant became physically able to walk the distance required of the gait task. The second session (S2) occurs one week later, a date that is typically close to their discharge. In summary, the AC is an extension of the common clinical assessment, the traditional TUG test [6], including a greater range of functional tasks (e.g., car transfers) and situational challenges (e.g., different flooring surfaces; a curvilinear pathway). Although the AC environment is unique to the facility, the majority of the AC mobility metrics we report (see Table I) can be computed from any assessment in any environment involving a chair transfer and walking (5 Times Sit-to-Stand, TUG, etc.).

The inertial movement data collected from the AC sensors 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 ankle sensors, the sensor local coordinate system is transformed to the body coordinate system [22]; 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 4^{th} order zero-phase band pass Butterworth filter using cutoff frequencies of 0.1 Hz and 3 Hz for the COM accelerometer [23] and 0.1 Hz and 10 Hz for the ankles [24]. The gyroscope signals for all sensors are low passed filtered at 4 Hz [25]. Fig. 3 outlines the AC sensor data processing sequence.

B. Physical Therapy Provider Interviews

Data collected from the AC wearable sensor study were presented to physical therapists (N = 5) and physical therapy



(a) The hotel lobby.

(b) The vehicle transfer.

Fig. 2: The simulated community environment at St. Luke's Rehabilitation Institute.

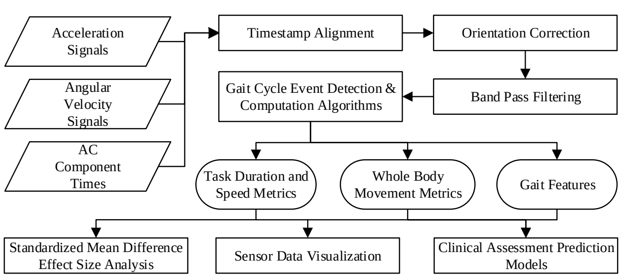


Fig. 3: Sensor data processing. Wearable inertial sensor data are timestamp aligned, oriented, and filtered before metrics are computed and analyses are performed.

assistants (N = 2) to collect their perceived clinical utility of the information. The group had a mean age of 40.14 ± 9.49 years (M = 1, F = 6) and had been working in rehabilitation for 11.86 ± 12.56 years. Interviews were audio recorded and later transcribed independently by two researchers. The interview consisted of four main components:

1) Familiarity with technology: Conversation related to the following topics:
   - Their level of comfort with technology
   - Their willingness to learn new technology
   - The current technologies they use
   - What technologies they wish they had
   - What visualizations they use
   - How they evaluate patient gait and transfer ability
   - How they evaluate *change* in patient gait and transfer ability
2) Metric rating: Evaluations on a scale from 1 (not useful) to 5 (very useful) for the following two ratings:
   - To rate the metric for how useful it is for providing therapy services for patients
   - To rate the metric for how useful it is as an indicator of the Functional Independence Measure (FIM) [26] motor score at discharge
3) Prediction usefulness: Questions related to the utility of a system providing discharge FIM motor score predictions:
   - How useful would you consider the prediction?
   - Would you make use of a technology-assisted prediction of FIM motor score to help you provide therapy services? Why or why not?
4) Visualization evaluation: Evaluation of three wearable sensor data visualizations: 1) task duration bar plot (see Fig. 4), 2) gait cycle bar plot (see Fig. 5), and 3) effect size forest plot (see Fig. 6). Evaluations on a scale from 1 (strongly disagree) to 5 (strongly agree) for the following three ratings related to each plot:
   - I think that I would use this plot frequently
   - I thought the plot was easy to understand
   - I would image most patients would learn to use this plot very quickly

   Additional questions were asked to facilitate dicussion about each plot, including:
   - How do you foresee using the plot to help you provide therapy services for your patients?
   - What might you change about the plot?

Metrics presented to interviewees for evaluation of their clinical utility were selected to be representative of the metrics computed by the research community and commercial sensor systems (see Table I for a list of the metrics). The presented metrics are grouped into three categories: task duration and speed, whole body movements computed from the COM sensor, and gait features derived from the ankle sensors. During the interviews, each metric was explained to the therapy provider. Evaluations on a scale from 1 (not useful) to 5 (very useful) were collected for the following two ratings: 1) to rate the metric for how useful it is for providing therapy services

TABLE I: Metrics computed from wearable inertial sensor data grouped by category: task duration and speed metrics, whole body movement metrics, and gait features.

Metric	Units	Description
Duration	s	Total time to complete the ambulatory circuit or an individual task of the ambulatory circuit.
Floor surface speed ratio		Measures the effect of walking speed on two different floor surfaces.
Walking speed	m/s	Walking speed as determined by distance divided by time.
Center of mass peak angular velocity		Maximum rotational velocity of the center of mass (COM) around the Z-axis.
Movement intensity	$m/s^2/s$	Square root of the mean of the squares of each COM acceleration signal (normalized by time). Represents acceleration magnitude [27].
Walking 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 [28].
Ankle peak angular velocity	$^\circ/s$	Maximum rotational velocity of the ankle around the Z-axis during the gait cycle. This occurs during the swing phase.
Ankle range of motion	$^\circ$	Range of integrated Z-axis angular velocity for each gait cycle. Provides an estimate of the degrees of ankle movement [3].
Cadence	$steps/min$	The average number of steps taken per minute.
Double support percent	%	Percentage of the gait cycle that both feet are in stance phase. Computed as the sum of the initial double support time and the terminal double support time [3].
Gait cycle duration	s	Duration to complete one stride (time between two consecutive initial contacts of the same foot) [3].
Number of gait cycles		Total number of complete gait cycles (strides) that occurred.
Step length	m	Distance between initial contacts of opposite feet [29].
Step regularity	%	Regularity of the acceleration of sequential steps. Computed using the autocorrelation of the vertical Y-axis of the COM acceleration [30].
Stride regularity	%	Regularity of the acceleration of sequential strides (see step regularity) [30].
Step symmetry	%	Ratio of step regularity to stride regularity [30].

for patients and 2) to rate the metric for how useful it is as an indicator of the Functional Independence Measure [26] motor score at discharge. The FIM rating refers to previous research studies investigating the predictive ability of wearable sensor-derived metrics for estimating clinical assessment scores [20], [31], [32].

In our previous work, we investigated the predictive abilities of features derived from wearable inertial sensor data to predict discharge FIM scores without re-administering the FIM assessment battery [20]. The FIM is administered at admission and discharge from inpatient rehabilitation by clinical staff who are credentialed to administer the instrument. The FIM is a well-validated assessment measuring functional status on a 0-7 rating scale for 18 items representing 6 domains: self-care, sphincter control, transfers, locomotion, communication, and social cognition [26]. In addition to a total FIM score, separate scores are developed from the motor function items and cognitive function items. The results of our previous work include leave-one-out-cross-validation correlations between actual and predicted discharge FIM motor scores as high as r = 0.97 (normalized root mean square error = 5.80%) for 20 AC study participants. To gather insights about the utility of such wearable sensor-based FIM predictions, during the interview therapists were instructed to consider a system that provides a highly accurate prediction of their patients' discharge FIM motor scores. The predictions would be available at any point between admission and discharge.

Three wearable sensor data visualizations were presented to interviewees for evaluation. The first visualization presented was the task duration bar plot (see Fig. 4). Task duration plots show AC task durations for performances one week apart (S1 and S2) for an individual patient. The X-axis lists

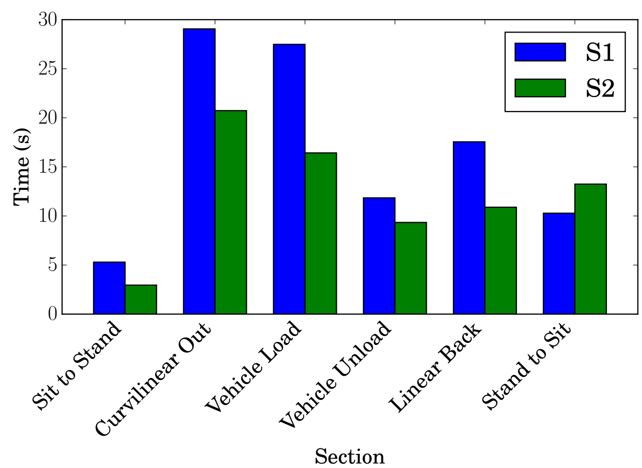
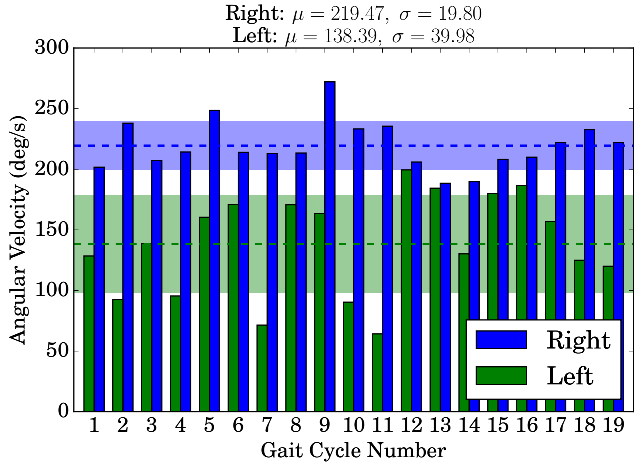


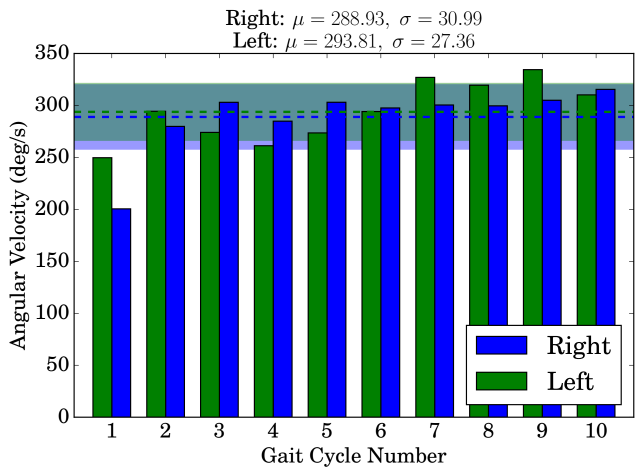
Fig. 4: The task duration bar plot shows a patient's ambulatory circuit task durations for session 1 (S1) and 2 (S2), one week later.

the the ambulatory circuit tasks and the Y-axis shows task duration, measured in seconds. A bar represents the time to perform the task. Blue bars correspond to S1 and green bars correspond to S2, one week later. This plot was chosen because of its simplicity; the amount of time to complete a task is a commonly used clinical assessment of progress, as is the case with the TUG. Bar plots are also a common visual representation of data that many people are proficient in reading.

The second presented visualization was a gait cycle bar plot (see Fig. 5), which plots gait cycle metrics derived



(a) Patient A.



(b) Patient B.

Fig. 5: The gait cycle bar plots visualize ankle peak angular velocities for patient A (top figure) with a left side impairment and patient B (bottom figure) with no paresis. The colored horizontal band around the dashed line mean (μ) is ± one standard deviation (σ).

from sensors attached to both ankles. The gait cycle plot in Fig. 5 shows a patient's left and right ankle peak angular velocities. On the X-axis are the gait cycle (stride) numbers during the linear walking section of the ambulatory circuit. The Y-axis represents peak angular velocity, measured in degrees per second. A bar represents the peak angular velocity for a gait cycle. Blue bars correspond to the right ankle peak angular velocity and green bars correspond to the left ankle peak angular velocity. The dashed horizontal lines correspond to the mean peak angular velocity values. The colored horizontal band around the mean is ± one standard deviation. The plot was selected due to its similarity to graphs included in commercial reports [8]. To facilitate discussion with the therapy providers, two gait cycle bar plots were presented,

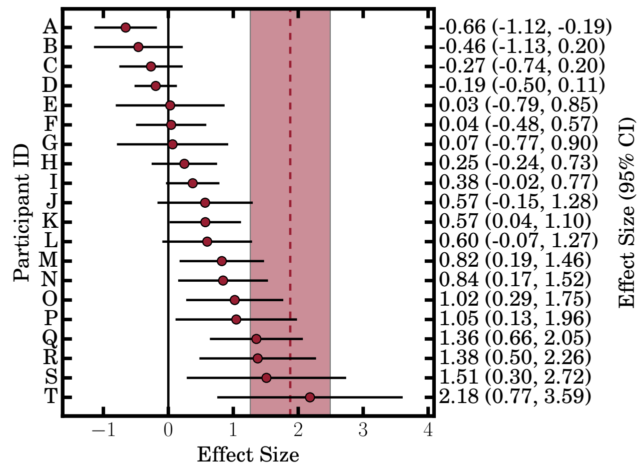


Fig. 6: The forest plot visualizes walking smoothness index effect sizes after one week of physical therapy. The whiskers represent the 95% confidence interval (CI). The vertical dashed line is the group effect size and the surrounding band is the group 95% CI.

each from a different patient. Fig. 5 shows the two gait cycle bar plots, one for a participant with a left side gait impairment (patient A, see Fig. 5a) and one for a participant with no paresis (patient B, see Fig. 5b).

The last plot presented was the effect size forest plot (see Fig. 6). The effect size forest plot displays effect sizes quantifying change after one week of physical therapy for individual participants and for the participants as a group. Before explaining the effect size forest plot, we will first provide an overview of the statistical methods we applied. An effect size based on Cohen's d for repeated measures (RM) data is used to quantify the strength of changes in each of the computed metrics [33]:

$$d_{RM} = \frac{\overline{X}_{S2} - \overline{X}_{S1}}{S_D} \tag{1}$$

Where $\overline{X}_{S1}$ is the mean group score from data collected at S1, $\overline{X}_{S2}$ is the mean group score from data collected at S2, and S_D represents the standard error of difference between S1 and S2 scores. In cases where the S1 and S2 scores have equal variance, S_D is calculated using the formula [33]:

$$S_D^{=} = s_{S1}\sqrt{2(1-r)} \tag{2}$$

In Equation 2, s_{S1} is the standard deviation for the S1 participant pool and r is the test-retest reliability coefficient measured between trial 3 and 4 at S2 testing. An unbiased estimation of population test-retest reliability is derived using r [33]. When S1 and S2 variances are not equal, as determined by the Levene's test of equal variances, an adjustment is applied to the estimate of S_D [33]:

$$S_D^{\neq} = \sqrt{s_{S1}^2 + s_{S2}^2 - 2r s_{S1} s_{S2}} \tag{3}$$

TABLE II: Average therapy provider-rated metric usefulness for providing therapy services for patients and as an indicator of the discharge Functional Independence Measure (FIM) score. The scale was 1 (not useful) to 5 (very useful). Standard deviations are in parentheses. Horizontal lines divide the metric categories (task duration and speed metrics, whole body movement metrics, and gait features.

Metric	Usefulness	FIM Indicator
Curvilinear walking duration	3.71 (1.38)	3.29 (1.38)
Floor surface speed ratio	3.57 (1.27)	3.14 (1.35)
Sit-to-stand duration	4.14 (1.46)	3.29 (1.70)
Stand-to-sit duration	3.86 (1.46)	3.29 (1.60)
Total ambulatory circuit duration	3.71 (1.38)	2.71 (1.11)
Vehicle load duration	3.14 (1.07)	2.43 (1.13)
Vehicle unload duration	3.14 (1.07)	2.43 (1.13)
Walking speed	4.00 (1.41)	3.29 (1.89)
Center of mass movement intensity	3.14 (1.07)	2.57 (1.40)
Center of mass peak angular velocity	2.86 (1.07)	2.29 (1.25)
Walking smoothness	3.71 (1.25)	2.71 (1.60)
Ankle peak angular velocity	3.43 (1.40)	2.14 (1.07)
Ankle range of motion	3.71 (1.38)	2.43 (1.27)
Cadence	4.00 (1.00)	2.86 (1.21)
Double support percent	3.43 (1.40)	2.29 (1.25)
Gait cycle duration	3.71 (1.38)	2.71 (1.50)
Number of gait cycles	3.71 (1.25)	2.71 (1.60)
Single support percent	3.86 (1.35)	2.71 (1.60)
Step length	3.71 (1.25)	2.43 (1.27)
Step regularity	3.57 (1.27)	2.29 (1.38)
Stride length	3.71 (1.25)	2.43 (1.27)
Stride regularity	3.71 (1.25)	2.43 (1.27)

The resulting effect sizes, d_{RM} (Equation 1), are used to evaluate 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% [34].

Effect size analysis and the effect size forest plot were included in the interview to facilitate conversation about visual presentations of statistically quantified performance change and to determine whether physical therapy providers consider comparisons between participants useful. The X-axis of Fig. 6 represents effect sizes for the walking smoothness index metric (see Table I for metric descriptions). The effect size values are shown on the right side of the Y-axis for each individual, with the associated confidence intervals in parentheses. Individual participant IDs are on the left side of the Y-axis. The points in the plot are each individual's effect size. The horizontal lines, or whiskers, extruding from the points depict 95% confidence intervals. The vertical red dashed line is the effect size for the group and the vertical red band around the dashed line is the 95% confidence interval for the group.

IV. Results

All quantitative responses were on a scale from 1 (strongly disagree/not useful) to 5 (strongly agree/very useful). The therapy providers were quite comfortable with technology (4.00 ± 0.82), willing to learn new technology (4.29 ± 0.76), and interested in using wearable technology for their patients (4.43 ± 0.53). The technology therapists use to help provide

TABLE III: Average therapy provider-rated responses to questions regarding the presented visualizations. The scale was 1 (strongly disagree) to 5 (strongly agree). Standard deviations are in parentheses.

Task duration bar plot (mean rating 3.62)	
I think that I would use this plot frequently	3.14 (0.90)
I thought the plot was easy to understand	4.43 (0.53)
I would imagine most patients would learn to use this plot very quickly	3.29 (0.95)
Gait cycle bar plot (mean rating 2.29)	
I think that I would use this plot frequently	2.57 (0.98)
I thought the plot was easy to understand	2.86 (0.90)
I would imagine most patients would learn to use this plot very quickly	1.43 (1.13)
Effect size forest plot (mean rating 1.76)	
I think that I would use this plot frequently	1.86 (0.90)
I thought the plot was easy to understand	2.00 (1.00)
I would imagine most patients would learn to use this plot very quickly	1.43 (0.79)

therapy services for their patients included computers, the Lokomat robotic-assistive device, electrical stimulation, the Nintendo Wii, and video cameras. Of the seven interviewees, five stated a desire for technology for balance assessment and gait analysis. To evaluate patient gait and transfer ability, therapists primarily use observation and an estimate of the amount of physical assistance the patient requires to perform certain tasks. To evaluate change in patient gait and transfer ability, therapists use their memory to compare previous observations to current ones. One therapist listed several movements she looks for, "*I kinda compare and contrast step lengths. I will do speed. I will do trunk deviation. If there's any toe drags. If they are using an assistive device or not. If they are using orthoses or not.*" All seven therapists stated they do not currently use visualizations, plots, graphs, or drawings to describe their patients' ambulatory ability.

Table II lists the mean and standard deviation of the interviewees' usefulness and FIM indicator ratings for each metric. Table III contains rating responses regarding the usability of each plot presented to the therapy providers (see Section III-B for an overview of the questions asked and visualizations). Regarding predictions, interviewees were impartial about considering discharge FIM motor score predictions useful (3.43 ± 1.27).

V. Discussion

Of the three metric categories, metrics in the task duration and speed group were rated highly for both usefulness (mean 3.66) and as a FIM indicator (mean 2.98) compared to whole body movement (mean 3.24, FIM mean 2.52) and gait features (mean 3.69, FIM mean 2.49) groups. Of all the metrics, sit-to-stand duration was rated the highest for usefulness (4.14 ± 1.46). Walking speed (4.00 ± 1.41) and cadence (4.00 ± 1.00) were also highly rated. These metrics can be computed *without* wearable sensors, indicating a preference toward familiar metrics with previously established clinical validity. The metrics with the lowest rated usefulness included vehicle load/unload duration, center of mass peak angular velocity, and center of mass movement intensity. For the vehicle duration metrics, two therapists stated a patient's ability to complete these tasks is more important than the amount of time the patient requires. For center of mass movement intensity, one therapist stated, "*I'm not sure what that relates to,*" indicating she was possibly trying to map the acceleration-based metric into an assessment she was familiar with. When she was unable to produce such a mapping, she rated this metric low (2, not useful).

Four of the seven therapists were enthusiastic about discharge FIM motor score prediction from wearable sensor data. One therapist stated, "*It would be very useful, it could help with discharge planning if we needed to steer one way or another.*" Another therapist stated, "*I would make use of [the predictions] as an adjunct.*" One of the three therapists who were not convinced of the utility of such a FIM prediction stated, "*I probably wouldn't [use FIM predictions], mostly because patients are really variable.*" To address the mixed feelings of therapists about clinical outcome predictions, it would be best to present the system as a tool to augment the information available to therapists when making treatment decisions, and not as a replacement of current methods.

For the task duration bar plot (see Fig. 4), all therapists noted the patient was faster for each task except for stand-to-sit. One therapist stated, "*It may have been an improvement in a safety factor, whereas they may have sat down due to a loss of balance.*" This comment suggests quantitative information alone is not sufficient for therapists to determine if a reduction in a value should be classified as an improvement or regression for an individual patient. Perhaps coupling the quantitative results with a video or 3D animation of the patient performing the task would provide sufficient context for the numeric values. Only one therapist suggested changes to the task duration bar plot by recommending the tasks on the X-axis are grouped by activity instead of by location in the AC sequence (e.g. sit-to-stand next to stand-to-sit). The therapists also thought patients could understand the task duration bar plot (3.29 ± 0.95, see Table III). One therapist stated, "*[The plot] would be helpful to get the patient more involved in seeing their progress.*" Another therapist also felt the plot could be useful for engaging patients, "*I could use this as feedback for a patient as to what changes have been made and extrapolate as to why that is important that they are faster on these tasks.*" The other two plots, gait cycle bar plot and effect size forest plot, were deemed too complicated for patients to learn (1.43 ± 1.13 and 1.43 ± 0.79, respectively).

For the gait cycle bar plot, all seven therapists correctly classified left side paresis for patient A (see Fig. 5). They also identified several differences between patient A and patient B's gait, such as the higher variability for patient A's peak angular velocity. Four of the seven therapists stated they would use the gait cycle bar plot, with one therapist stating, "*It would be for my own personal measures to see where they are at. The ankle is really tough to assess when you are by their shoulders.*" This comment suggests additional utility of wearable sensors could be acquired by placing them on the body in hard to observe areas. One therapist advocated placing sensors on the hip, knee, and ankle joints. Changes proposed by the therapists for this plot included increasing the font size and removing the standard deviation information to reduce the plot complexity.

The effect size forest plot (see Fig. 6) was the lowest rated of the visualizations presented to the therapists (see Table III). Since the plot is statistically-oriented and compares patients with other patients, the low ratings were expected. Two of the therapists acknowledged the usefulness of the effect size forest plot for research, "*If I got into a research study to justify what I was doing then yes, but not for direct patient care.*" Suggestions for improving the effect size forest plot included grouping patients by diagnosis, or including only one patient's data to remove comparisons between patients. Effect size forest plots can show single participant change for gait cycle-based features, such as stride length. For example, each AC trial produces multiple stride length measurements, one stride length for each gait cycle. Stride length effect sizes between two AC trials can be computed using Equations 1, 2, and 3. Furthermore, multiple gait feature effect sizes can be plotted on the Y-axis of an effect size forest plot (e.g. left/right ankle range of motion, left/right ankle peak angular velocity, etc.).

A limitation of this study includes the small number of physical therapists and physical therapy assistants that were interviewed. Additional limitations include:

- The interviewed therapy providers were all affiliated with the same rehabilitation facility. Therapist diversity would yield more representative results.
- The interviewed therapy providers experienced unequal exposure to the ambulatory circuit study prior to the interview. Five of the seven therapists were active in the participant recruiting process and observed the data collection protocol.

Future work aims to address these limitations by conducting a larger, multi-facility study to collect physical therapists' feedback regarding wearable sensors for mobility assessment. We plan to incorporate the results obtained from the current preliminary study in the design process.

VI. Conclusions

In this paper, we presented wearable sensor-based computing algorithms for mobility assessment. To bridge the gap between design of mobility monitoring technology and actual use of the technology, physical therapy providers at an inpatient rehabilitation facility were interviewed to collect their opinions on the clinical utility of wearable sensor data and associated algorithms. The responses indicated providers to be interested in using wearable technology and sensor data visualizations. We suggest future computing research directions that may increase the adoption of wearable sensor systems and visualizations, including: 1) computing metrics that map into standard clinical assessments of progress, 2) designing visualizations containing a single patient's information, possibly compared to normative values for their age/etiologic group,

3) motivating patients with simple sensor-based visualizations of their progress, and 4) coupling wearable sensor data with videos and/or animations. We plan to incorporate the feedback received from the interviewees into a smart wearable system to provide useful quantitative data and visualizations to aid therapists in providing therapy services for their patients.

VII. Acknowledgments

We wish to thank our therapist collaborators at St. Luke's Rehabilitation Institute, Vladimir Borisov, and Jordana Dahmen for their insights and help in data collection. This work is supported by the National Institutes of Health under Grant No. R25AG046114.

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