Gait Analysis and Visualization in a Fall Risk Assessment System

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ABSTRACT

Falls are a major health concern among elderly populations. There is a critical need to develop automated systems for assessing a patient's fall risk although the methodologies for determining this risk vary in efficacy, accessibility, and comfort. With advancements in smart home technology, aging in place and accurate fall risk assessment are no longer mutually exclusive. This paper presents a user friendly fall risk assessment system designed for care providers to non-invasively but continuously monitor their patient's risk of falling. The proposed system employs a pressure sensor-embedded floor - a SmartFloor - installed in the patient's home to monitor trends in gait parameters like gait speed, stride length, and step width. The system allows care providers to visualize dangerous changes to their patient's gait 24/7 and without disturbing the patient. To facilitate diagnoses and fall risk assessment, the system also reconstructs a skeletal visualization of each recorded walking segment. This is done using a motion similarity algorithm and a database of SmartFloor and Microsoft *Kinect* data. We tested the accuracy of several variations of the motion similarity algorithm using a small pool of seven participants and the results are presented in this paper.

CCS CONCEPTS

• **Computer systems organization** → *Embedded systems*; • **Human-centered computing** → **Information visualization**; • **Applied computing** → **Bioinformatics**.

KEYWORDS

fall prevention, gait analysis, smart home, motion similarity, data visualization

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1 INTRODUCTION

As the average human lifespan increases, the ways in which society monitors and treats the aging population must adapt alongside this demographic change. Older adults and the elderly are often most susceptible to injuries and accidents.Unintentional injury is the seventh leading cause of death for older adults and falls account for the largest percentage of those deaths. Approximately one in four U.S. residents aged 65 or older report falling each year [3]. Even nonfatal falls can be debilitating and limit an elderly person's mobility and freedom for years.

Systems for fall prevention and fall prediction can be designed to address this crisis and facilitate aging in place in graceful manner. Fall prediction is a reliable estimation of fall risk and development of pre-fall alert systems. Fall prevention involves techniques and interventions that mitigate fall risk factors, improve mobility, and prevent future falls [14]. The key to lowering the number of falls is the ability to assess an individual's risk of falling and monitor changes to that risk consistently. There are several ways that care providers do this. Most popular among these are balance and mobility tests conducted by healthcare providers in a clinical setting. These tests usually require a combination of physical evaluations and health history questions. While these tests are quick and accessible, their infrequency leaves lengthy gaps where changes to a patient's health could increase their fall risk dramatically.

Thus, monitoring systems that continuously assess fall risk have become an important field of smart-health research. These systems rely on networks of sensors that collect data passively on the patient. These sensors can either be wearable or ambient and can be designed to monitor a variety of things like sleep hygiene, activity level, medication consumption, blood pressure, balance, posture, and gait - all of which inform a patient's fall risk [14]. These physiological parameters can then be analyzed alongside information about the patient's environment, demographic, and behavior to achieve a holistic estimation of their fall risk.

The next section provide relevant background on pertinent technologies. Section III describes the technical challenges. Section IV describes previous work in the related problem. Section V describes various components of the proposed system. Section VI present the results and the last section concludes the paper with some final remarks.

2 BACKGROUND

This section introduces some areas of study intertwined with fall prevention and fall risk assessment. Many of the following technologies and ideas are either referenced directly later in this paper or informed the system we introduce in a major way.

2.1 The Internet of Things, Ubiquitous Sensing, and Smart Environment Technology

The Internet of Things (IoT) is a system of interrelated computing devices or digital machines with the ability to transfer data over a network without requiring human input. One major application of the IoT is smart home technology. Recent development in the field of smart technology and IoT has allowed for applications that incorporate ubiquitous sensing in clinics, assisted living centers, and people's homes. SmartCare is a project that uses smart environment technology to facilitate aging in place [7]. In a SmartCare apartment, ambient sensors of many kinds monitor the activity of elderly residents in real time. One article theorizes a home equipped with unobtrusive pressure sensors to monitor older adults [8]. These and other smart environments provide the infrastructure required for the type of fall prediction systems mentioned in [14]. Developing a user interface (UI) to extract, analyze, and display the sensor information collected in these smart environments is crucial for successful fall prediction.

2.2 Non-Ambient Fall Risk Assessment

There are several methods to monitor fall risk. Mentioned previously are clinical fall risk assessments [13]. Another popular genre of fall risk assessment tools are wearable sensors that monitor some kind of physiological characteristic. These wearable sensors include pressure sensor-embedded shoes, accelerometers, and SmartWalkers [14], [9], [15], [6], [5]. The third common type of fall risk assessment tools rely on ambient sensors which can include sensor-embedded furniture, occupancy sensors, and camera systems.

2.3 Gait Analysis

Of the many risk factors that such interfaces can compile, gait is one of the most commonly measured factors in popular fall risk assessment tools. Indeed, clinical tests like the Tinetti-test, the Morse Fall Scale, the Schmid Fall Risk Tool, and more use gait parameters in their overall fall risk calculation [11]. Researchers have identified that low gait speed (<1 m/s) is strongly associated with several well-known fall risk factors including history of multiple falls, depressive symptoms, and heavy medication use [10]. For these reasons, continuously measuring a patient's gait helps both patients and healthcare providers stay up-to-date on the patient's fall risk and overall health. Researchers are currently using cameras, accelerometers, pressure sensors, Kinect motion-tracking, and more to measure gait. Raw data from these sensors is convoluted and requires summarization of important gait parameters and recreation of skeletal visualizations of patient gait.

Throughout this paper, several terms associated with gait and gait analysis will be used. Gait is defined as a person's manner of walking. Figure 1 shows a diagram of one gait cycle. A gait cycle has two main phases: the stance phase, when the first foot is on the ground, and the swing phase, when the foot is not in contact with the ground. Combined among those two phases, are eight subphases that Figure 1 labels.

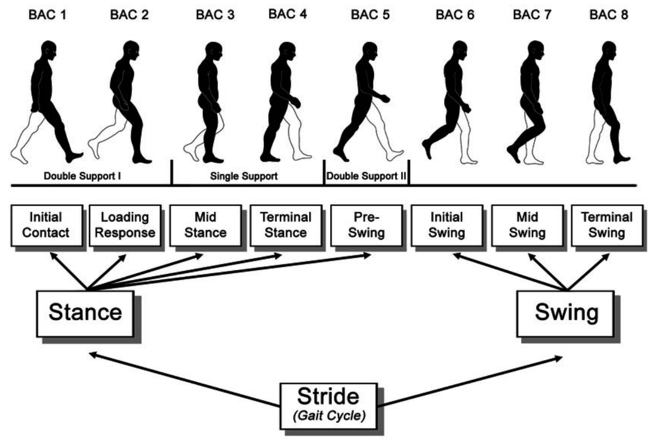

Figure 1: A diagram of one human gait cycle. Source: [16]

Different aspects of these base units of gait can be measured to serve as a robust informer of fall risk. In this paper, the gait parameters measured for our fall risk assessment system are detailed in Table 1.

Table 1: Description of Gait Parameters

Parameter	Definition
Stride length (cm)	Distance between successive ground contacts of the same foot
Average speed (cm/s)	Total distance traveled divided by elapsed time
Double support time (s)	Amount of time spent on both feet during one gait cycle
Stride length variablity (CoV)	Ratio between the standard-deviation and mean of stride length, expressed as percentage
Step width variability (CoV)	Ratio between the standard-deviation and mean of step width, expressed as percentage
Step length variability (cm)	Absolute difference between left and right step length in one gait cycle

3 PROBLEM STATEMENT

We propose a gait monitoring and visualization system integrated with the SmartCare project [7]. Through this system, the SmartFloor would unobtrusively provide insights into the gait patterns and anomalies of an individual. This analysis is paired with a 3D visualization of the individual's gait, better equipping clinicians to perform frequent, personalized fall risk assessments.

4 OVERVIEW OF RELATED RESEARCH

4.1 Ambient Health Monitoring

Past work has investigated the opportunities for ambient health monitoring in a smart home.

Jones et al. considers the implications of a fully pressure sensitive home environment (floor and furniture) as it relates to information relay for caregivers [8]. Using a pressure sensitive mattress with 24 pressure sensors they could monitor parameters such as bed occupancy, restlessness, and respiratory rate. They then provided patients with visual sleep reports including a calculated restlessness index and a timeline of bed entries and exits. This gives patients a window into their sleep quality, which can affect fall risk, through unobtrusive monitoring.

This system was based heavily on previous research performed for the SmartCare introduced in [7]. One of the many ambient sensors that the SmartCare SmartApartment is equipped with is the SmartFloor - a floor underlain with an array of pressure sensors designed to be installed in someone's home to passively and continuously monitor gait and balance parameters.

Work has been done to extract gait parameters from the SmartFloor using the center of pressure (COP). Even though the SmartFloor is relatively low-resolution (about 10 pressure sensors per square meter of floor), it is possible to find the approximate locations of individual footprints during any given walking segment by finding maximums and minimums in the COP velocity and acceleration. This fall risk assessment system uses algorithms described in [12] to extract gait parameters, to segment walking data, and to isolate individual gait cycles from walking segments.

4.2 3D Pose Reconstruction from Foot Pressure Data

A few researchers have demonstrated 3D pose reconstruction from foot pressure data.

FootSee is a full body animation system operated through a high resolution pressure sensor pad [18]. The system uses a foot pressure database linked to a motion database. When the user performs an action on the sensor pad, the most similar reading in the foot pressure database is selected along with the corresponding motion data.

GravitySpace is an interactive installation that senses pressure readings on the floor surface and infers the 3D scene above it, projecting the results onto the floor as a sort of mirror image of reality [2]. Pressure readings are captured using frustrated total internal reflection (FTIR) with a 12 megapixel camera located below the 8 m^2 floor, yielding a pressure reading for each 1×1 mm pixel.

Imprints on the floor are grouped as pressure clusters and recognized as points of contact for furniture and humans in various positions. They use a feed-forward neural network trained on 16 features including image moments, structure descriptors based on Gaussian differences, and details about the bounds of each pressure cluster in order to classify them as a shoe, knee, hand, etc. The under-floor camera system that powers the pressure sensing would make it unfeasible to install *GravitySpace* in someone's home for gait monitoring.

5 SYSTEM COMPONENTS

Our prototype consists of two components: a data processing module and a web based UI.

5.1 Data Processing

5.1.1 Raw Data Format. The SmartFloor unit consists of a 16x8 grid of tiles with a Tekscan FlexiForce A401 pressure sensor installed at the bottom right corner of each tile. This grid is split into four 4x8 boards laid side by side.

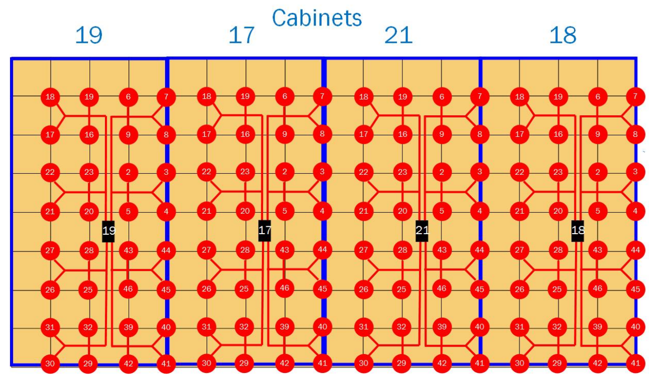

Figure 2: Layout of the boards and sensor grid on the SmartFloor

The unit is connected to a BeagleBone Black microprocessor which records data at around 25 Hz. Each of the four boards takes separate readings. The raw sensor readings from the SmartFloor are stored in CSV format on a host Ubuntu laptop. The file consists of chunks of four lines representing readings from the four boards. Each line is time-stamped and contains columns for the 50 possible sensor connections. Only 32 of these spaces are occupied by actual readings. A reading is represented as a 10-bit integer (i.e., 0—1023).

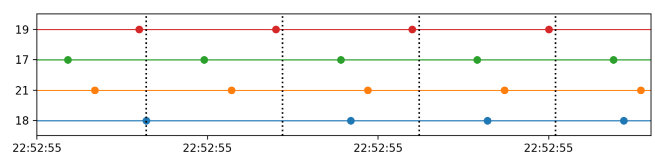

Figure 3: Each horizontal line represents the time domain of one of the boards. A dot on the line marks a reading for that board. The vertical dotted lines mark the interpolated samples we take across all boards.

5.1.2 Initial Interpolation. The time-stamps for each board are not the same over the whole four-chunk reading. Additionally, the recording mechanism does not keep a clean 25 Hz sample rate for all boards as seen in Figure 3, leading to some variation in sample order. To address these issues we perform linear interpolation of the combined matrix of readings across time and resample to an even 25 Hz.

5.1.3 Noise Removal. Noise on the floor is addressed by two means. First, the initial floor readings (when it is unoccupied) are subtracted from all readings, and the result is clamped at zero. This is not sufficient because there is still some stochastic behavior of the sensors over time which can have a significant impact on the center of pressure. Therefore we additionally build a mask that is rectangular in shape, centered around the point of maximum pressure. The mask discards all readings that are farther than a three tile radius from the point of maximum pressure.

5.1.4 Center of Pressure Trajectory. The COP calculation at each time step follow the formula for center of mass:

$$COP_x = \frac{\sum_{x,y} xP(x,y)}{\sum_{x,y} P(x,y)}$$

$$COP_y = \frac{\sum_{x,y} yP(x,y)}{\sum_{x,y} P(x,y)}$$

The center of pressure provides a sub-tile position metric that would otherwise be hidden behind the 16x8 floor resolution. From this spatiotemporal data we can then calculate higher order derivatives such as velocity, acceleration, jerk, etc. For example, the centered velocity approximation is calculated as:

$$V(t) = \frac{COP(t+1) - COP(t-1)}{(t+1) - (t-1)}$$

5.1.5 Footstep Detection. The COP motion provides clues into where and when steps take place. Oluwadare presents a Double Support and Single Support Detection (DS-SD) Algorithm for identifying heel strikes and toe-offs [12]. We have made some modifications to this process.

First, they use the peaks in COP speed as heel-strike markers. However, results from a synchronized video feed suggested to us that peaks in the *change* in speed (i.e. magnitude of acceleration in the direction of motion) are more appropriate markers of heel strike times.

Second, it appears that his interpretation of double support position for stride length calculation as outlined in Algorithm 5.4 is flawed. If the COP is at its peak speed (as it is where he defines the start of double support) then it is not a very reliable indicator of support position, instead it is marking some position between the feet. We use local minima in the smoothed COP speed occurring just prior to a heel-strike as markers for support position. At these positions we know the speed is lowest so the foot is effectively planted.

5.1.6 Cycle similarity. The cycles are rotated, normalized and resampled; they then act as our COP trajectory paths. To find a similar skeleton recording, we want to match an arbitrary query path to our bank of known paths and find the most similar match. We tested a few different path similarity metrics, detailed later in the results section.

5.2 User Interface

Our fall risk monitoring system is designed to be used by the care providers of elderly patients and of other mobile patients at risk of falling. Our system relies on the installation of a SmartFloor above into the home of the patient like the SmartCare SmartApartment [7]. Data is monitored continuously and unobtrusively as the patient walks around on their home. Data is continuously segmented to contain only data from straight-line walking segments. Stops, starts, turns, and standing in place are not helpful in gait analysis. Each walking segment is timestamped and analyzed automatically

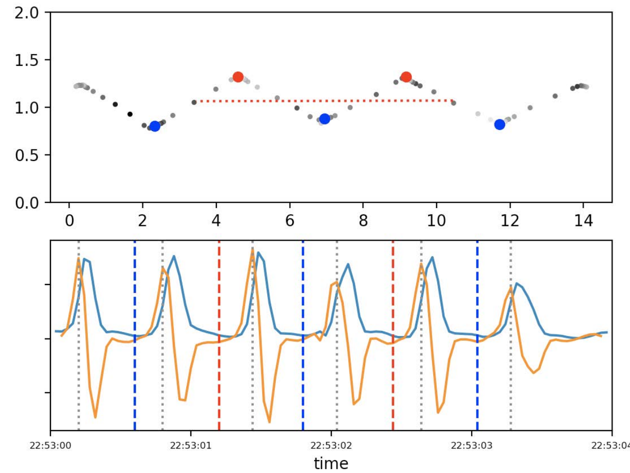

Figure 4: The top plot shows the extracted and classified support positions (footsteps) with a gait line drawn between them. The bottom plot demonstrates how heel strike times (colored dashed lines) and support positions (gray dotted lines) are extracted from COP spatiotemporal data. The blue line represents COP speed while the orange represents change in COP speed (not to scale). Note that the plot shows raw values while the extrema are calculated on smoothed data, hence the slight offset

to extract values for six different gait parameters. These gait parameters were chosen because past research has shown a statistically significant difference in these parameters between fallers and non-fallers [17] [1] [4]. These walking segments and their associated gait parameter values form the basis of our UI.

5.2.1 Web Application Setup. Our UI is hosted on a web application built with basic HTML, JavaScript and CSS. Many of our styling attributes are provided by the *Bootstrap* framework which we incorporate. Other stylistic attributes that we include are *FTLabs* and *SlideReveal*. For plotting, we use the *Plotly* plotting library. For the skeletal animation, we rely on the *ThreeJS* 3D and WebGL renderer library.

5.2.2 Gait Parameter Plotting. Figure 5 shows the homepage of our web application. We plot six different gait parameter trend lines in total. Each data point in a given subplot represents the daily average for that subplot's corresponding parameter. One day may have any number of walking segments depending on that person's activity level for that day. The side bar on the left side of the homepage has switches to toggle the display of each subplot. The plots are interactive and allow dragging and clipping to change your view. We designed the subplots to be connected so that changes to the view/scope of one subplot changes the view/scope of all subplots.

Each subplot is equipped with a visual alert system. Whenever a patient's daily average for any given gait parameter reaches an unhealthy or abnormal level (demarcated with red highlighting) that day's marker turns red. The red demarcations and marker color change allow the care giver to visualize changes to a patients gait that might be signaling a change to that person's fall risk. The

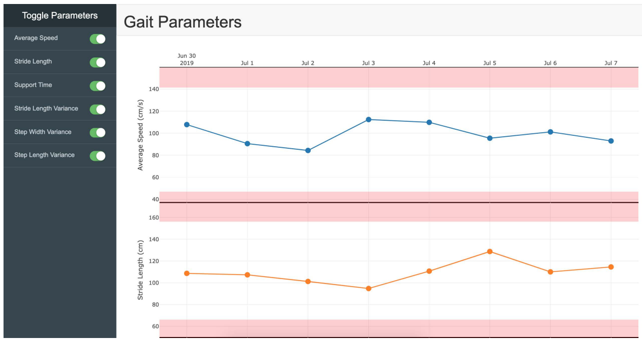

Figure 5: The homepage of our UI. Displayed are two of the six plots that represent the daily averages of a particular gait parameter. The plots are interactive and allow you to drag and clip to see data from different dates.

thresholds deemed as unhealthy and abnormal were calculated using data summarized from [17] [1] [4] in Table 2. Any value beyond two standard deviations of the healthy value is marked as unhealthy or abnormal.

Table 2: Summary of Healthy Gait Parameters

Measure	Mean [healthy]	Std. Dev.
Stride length (cm)	111.15	22.53
Average speed (cm/s)	94.25	23.60
Double support time (s)	0.29	0.07
Stride length variability (CoV)	2.63	1.62
Step width variability (CoV)	19.6	16.6
Step length variability (cm)	0.69	0.157

5.2.3 Skeleton Animation. The second main feature of our UI is a skeleton reconstruction of what someone's gait most likely resembled for any recorded walking segment. Each walking segment corresponds to timestamped data from the SmartFloor. At data processing time, each walking segment is further segmented into gait cycles and each gait cycle is matched to the most similar gait cycle from a prerecorded database of gait cycles. The gait cycles in this prerecorded database were collected while the participant's skeleton was tracked using a Microsoft Kinect so each gait cycle is mapped to a corresponding set of skeletal data. When a user clicks on one of the segments inside daily view, the slider reveals a rendering window displaying a skeletal visualization of that walking segment. This visualization is constructed by piecing together the most similar gait cycle's *Kinect* data into one animation loop. The rendering window and animation is created using the *ThreeJS* library. Figure 6 shows the UI after a click to a segment while in daily view. One can return to regular daily view be pressing the "Hide Visualization" button.

6 EXPERIMENTS AND RESULTS

We tested the accuracy of our nearest neighbor motion matching algorithm on a set of walking data from N=7 participants. Each participant walked along a 16 foot straight segment of SmartFloor.

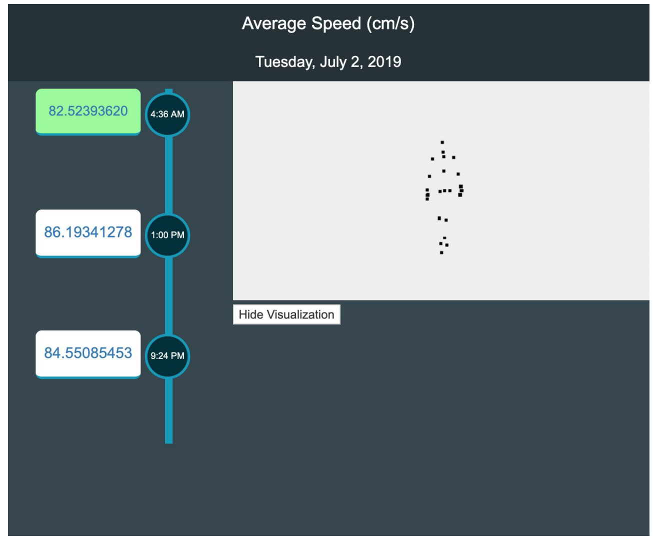

Figure 6: The skeletal visualization of a walking segment after a click on a walking segment in daily view

Each time, the participants were asked to modify their gait in different ways after being given an explanation and short demonstration of each of the six gait styles. The participants were recorded by a Kinect for a demonstration of the prototype - the skeleton data was never used to gather results.

The seven participants and six gait styles yielded 42 different walking segments that were further segmented into a total of 177 gait cycles. In order to test the nearest neighbor algorithm on as many gait cycles as possible, we used 7-fold cross validation where each "group" in our 7-fold was one participant and all of their gait cycles. For each gait cycle in the testing data, we recorded the closest match found by our nearest neighbor algorithm. If the closest match came from a gait cycle of the same gait style in the training set, we marked that matching as correct.

We tweaked our definition of "closest match" (and subsequently our nearest neighbor algorithms) to test whether different input parameters yielded different accuracies. These different similarity metrics are detailed in the Results section.

We tested a few similarity metrics when performing our nearest neighbor queries. We know that the COP trajectory holds the relevant gait information for a cycle. Our first metric involves building a high dimensional feature vector containing the time series of the mediolateral and anteroposterior position and velocity. Similarity is measured by the euclidean distance between each cycle's feature vector.

Table 3 summarizes the accuracy calculations using this euclidean distance metric.

The next distance metric involves a weighted sum of the distances between COP velocity and COP position. This computes the average pairwise euclidean distances of the COP position and velocity at each time step, and takes a weighted sum of the two. Essentially, it is a measure of the space between each path in the position and velocity spaces.

Table 3: Results of Euclidean Distance as a Similarity Metric

Raveled feature distance

	Correct	Total	Accuracy
Normal	10	16	62.50%
Slow	8	23	34.78%
Hunch	15	33	45.45%
Steppage	3	28	10.71%
Left Hobble	40	42	95.24%
Right Hobble	29	35	82.86%
Average			55.26%
Overall	105	177	59.32%

Table 4: Results of Custom Similarity Metric

Weighted path distance

	Accuracy		
	All position	All velocity	Mix
Normal	56.25%	68.75%	68.75%
Slow	30.43%	39.13%	21.74%
Hunch	39.39%	48.48%	51.52%
Steppage	32.14%	10.71%	17.86%
Left Hobble	100.00%	97.62%	100.00%
Right Hobble	85.71%	80.00%	82.86%
Average	57.32%	57.45%	57.12%
Overall	62.15%	61.02%	61.58%

Table 4 shows the result of this similarity metric. We tested the results with all of the weight in the positional distance, then all in the velocity distance, and lastly a fairly even mix of the two. The results across each distribution of the weights was surprisingly insignificant.

Note that the overall accuracy values are inflated by the high number of hobble cycles extracted from our sample data. This style of gait was much easier to classify correctly, so treating each gait style as independent and taking the average of each style's accuracy serves as a better indicator of general performance.

It's important to note that the accuracy values for our classification experiments are significantly bottlenecked by the quality of data we were working with, and the disparity between participant interpretations of each gait style is likely the cause of the underwhelming classification accuracies. Future work should increase the number of subjects to better estimate the accuracy of this model.

7 CONCLUSIONS

In this research, we performed the data cleanup, normalization and gait cycle nearest neighbor lookup necessary to extract similar skeletal data from incoming floor pressure readings, and found it to perform moderately in classification of gait style. We also designed and built the foundation necessary to relay gait parameter trends and walk segment visualization to care providers through a web app. During our work we were able to adjust the DS-SD algorithm presented in Oluwadare's thesis [12] to more accurately reflect the behavior of the gait cycle.

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