Automatic 'Timed-Up and Go' (TUG) Test Segmentation

by Ari M. Green

S.B., Computer Science and Engineering

S.B., Comparative Media Studies

Submitted to the

Department of Electrical Engineering and Computer Science

in Partial Fulfillment of the Requirements for the Degree of

Master of Engineering in Electrical Engineering and Computer Science

at the

Massachusetts Institute of Technology

May 2018

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May 25, 2018

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May 25, 2018

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ABSTRACT

The Timed-Up and Go test (TUG) is a well-known medical test that is used as an indicator of mental and physical health. I developed the TUG-Segmenter, an automatic segmentation tool that can divide recorded TUG test data into the six main phases of the test: Sitting, Standing-Up, Walking-Forward, Turning, Walking-Back, and Sitting-Down. I created an annotation tool as well that greatly speeds up the creation of ground truth from TUG test data. Using both these tools I was able to evaluate the accuracy of the TUG-Segmenter in terms of the duration of the segmented phases (83.4 % accurate) and the start times of the segmented phases (83.6 % accurate). Lastly, I found a 0.3 cm difference for jitteriness and an 8.5 mm/s difference for speed between healthy elderly subjects and healthy young subjects when comparing the features extracted from the individual TUG test phases.

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Acknowledgements

First of all I want to extend a huge thank you to my advisor, Professor Randall Davis. Thank you for taking me under your wing and teaching me how to be a curious and methodical researcher – I sincerely appreciate all your guidance and patience along the way.

Secondly I wanted to thank Dr. Dana Penney for all the wisdom you shared with me on gait and human motion. I am extremely appreciative for the genuine interest you took in my thesis project and all your encouragement as I worked through each part.

I also wanted to thank Zachary Kabelac and Rumen Hristov for your help collecting all the WiGait data and answering my numerous questions, I could not have done it without you. I am also very grateful to Professor Dina Katabi for allowing me to collaborate with her lab and making my thesis possible.

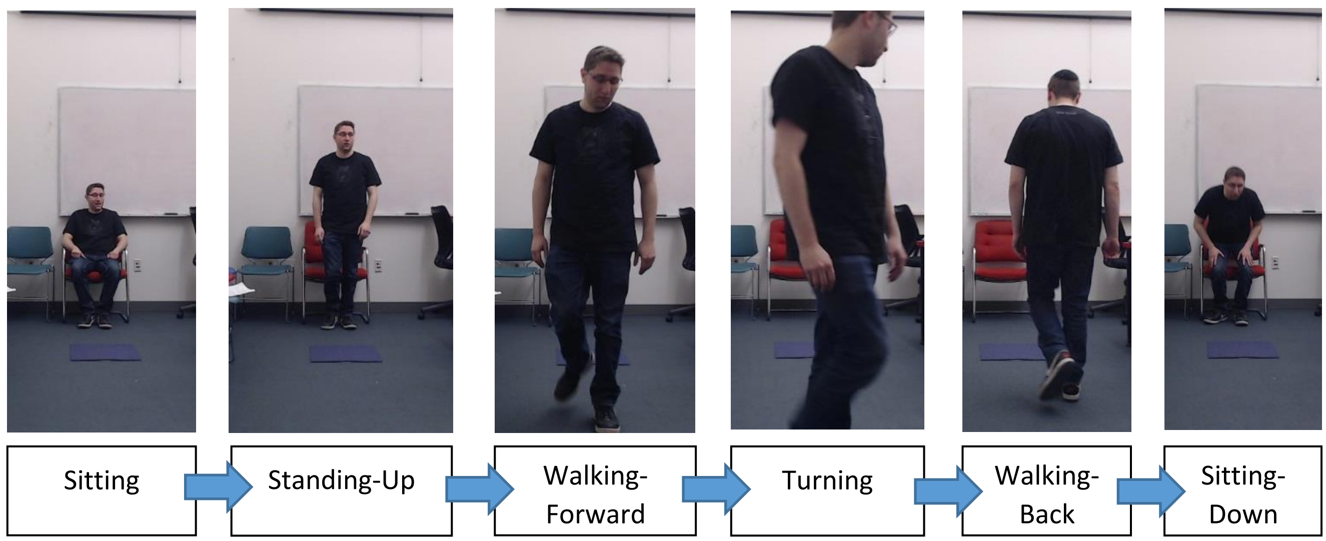
Thank you to Professor Alan Oppenheim for the advice on signal processing, you helped me find a better direction for the project's implementation.

Finally thank you to my Mom and Dad, Elissa and Eliot Green, for the constant support and always pushing me to succeed. Thank you to my sisters, Yael and Rachel, and all my friends and family for your never-ending interest in my life and work.

Introduction

The Timed-Up-and-Go test, also known as the TUG test, is a medical test used to assess the health of people with Parkinson's disease, Alzheimer's disease, and the elderly in general. It can predict several areas of health such as a subject's risk of falling, future cognitive degeneration, and general mobility. During a TUG test the subject stands up from a chair and walks to a point three meters away, then they turn around and walk back to the chair and sit down. An elderly subject is determined to have a four times higher risk of falling in the future if they complete the test in greater than 12.6 seconds (Kojima 2015). Impaired performance on the TUG test, taking longer than 10 seconds to complete the test, has also been shown to predict cognitive degeneration for patients with Alzheimer's in the form of dementia (Lee 2018). Completion of the TUG test under 12 seconds has been shown to correlate with good mobility in communities of elderly women (Bischoff 2003). The TUG test has the ability to predict both physical and cognitive issues and its use is widespread.

I created a tool that automatically segments a subject's motion during a TUG test into the six main phases of the TUG walk cycle. The TUG-Segmenter segments the walk cycle into the phases of Sitting, Standing-up, Walking-Forward, Turning, Walking-Back, Sitting-Down. Previously the result of the TUG test was a single number: the time it takes to complete the whole TUG walking cycle. By breaking the TUG test walk cycle into several phases, the test results can be analyzed in a more detailed way, such as the time it takes to complete each phase. The hope is that this TUG-Segmenter will help in future research such as studies using the TUG test to predict the progression of Parkinson's.



Previous research done by the Multimodal Understanding Group at MIT was able to successfully predict cognitive impairment of subjects with the neurodegenerative disease, Alzheimer's, using the physical motions of a subject drawing a clock (Davis 2015). Parkinson's disease is another neurodegenerative disorder, which means it similarly affects cognition. One way Parkinson's disease symptoms manifest is as an increased difficulty walking. This equates to slower overall walking in addition to a more jittery gait, due to many smaller and irregular steps. Other studies on Parkinson's have shown that when patients are asked to do two movements simultaneously, such as extending an arm while squeezing their fingers together, there is a greater slowing down than when they do one movement after another (Marsden 1989). The greater the cognitive difficulty, the longer it takes to complete the intended movement or movements, thus we can use physical metrics such as speed to indicate cognitive difficulty.

Certain phases of walking are more cognitively difficult than others. For example, the Standing-Up phase in young individuals can be seen as the execution of several overlapping actions needed to go from sitting to walking and therefore is more cognitively difficulty in contrast to the single action of sitting. These overlapping actions during the Standing-Up phase may be rising from the chair, positioning the feet into a walking stance, and propelling the body forward. In younger individuals these separate actions often occur in parallel during the Standing-Up phase; as they rise from the chair they begin extending their foot for the expected walking motion. In older individuals these actions are more sequential, and often the subject is mostly upright before moving their foot forward to begin walking. In the TUG walk cycle, physical symptoms such as slowing or jitteriness may manifest due to the cognitive difficulty of a particular phase of walking.

An automatic segmentation of the phases of walking might enable better analysis of each phase of the walk cycle. I measured two categories of features per phase, speed and jitteriness. I found a 0.3 cm difference for jitteriness and an 8.5 mm/s difference for speed between elderly and young subjects.

Current motion tracking technology is quite cumbersome to wear and deploy, generally taking the form of multiple Inertial Measurement Units (IMU) bands that measure the acceleration of specific limbs, or body suits with unique visual markers so that limb locations can be inferred from captured video. Dina Katabi's lab at MIT has developed a form of radar using a signal comparable to Wi-Fi that is able to track motion without the need for wearables (Hsu 2017). Using this new sensing technology, I measured the walk cycle of healthy individuals to establish a reference for the speed and jitter for each phase of walking. This can then be used in future research as a comparison for individuals with neurodegenerative disorders such as Parkinson's disease.

Some issues surfaced during the data collection of the walk cycles, such as sensor pauses and data discontinuities. I developed strategies and automatic methods for determining when these issues occurred. For sensor pauses and data discontinuities the TUG-Segmenter looks for displacements between two sequential frames of data in which the displacement is greater than what is possible for human motion, and then keeps track of which TUG tests contain these invalid sections of data. Other data issues required manual fixing such as splicing two walking motions together. This was needed when the sensor mistakenly perceived the motion of one person as if two separate people had each performed a subsection of the motion.

I also developed an efficient and fast pipeline for collecting and then annotating the walking data. After recording the subject walking, images captured from the TUG test are put into a user interface that enables easy traversal of the images and quick annotation of specific frames as endpoints of walk cycle phases. This annotation data can then be exported, and combined with the walk cycle motion data, yielding the walk cycle ground truth. I used this interface to manually annotate the walk phases efficiently. By solving data issues along with annotation of the walk phases I created a body of data usable for ground truth.

Through an automatic segmentation of the walk cycle using the TUG-Segmenter, researchers will be able to quickly identify phases of walking for a given subject and also determine if the speed or jitteriness of a particular phase is atypical. Additionally, with a segmentation tool available, the TUG test results can be more granular and perhaps give greater insight into the health of the individual. By understanding typical motion for each phase of the walk cycle during the TUG test I hope to help future research more easily identify erratic or strange motion in patients with Parkinson’s disease.

Related Work

In prior research, TUG tests have been tracked while subjects wear Inertial Measurement Unit (IMU) sensors on specific limbs (Nguyen 2017). Some researchers have noted the importance of minimizing the amount of sensors being used in order to not interfere with a subjects gait (Reinfelder 2015). The importance of automatic TUG test segmentation algorithms have also been because features extracted from individual phases can give scientists more detailed and clinically relevant TUG test results (Reinfelder 2015). There has also been research done combination of TUG test features that improve the discrimination between subjects with a history of falling and those with no history of falling (Ponti 2017).

In one study, twelve elderly subjects diagnosed with an early stage of Parkinson's disease wore a body suit of 17 IMUs while they performed TUG tests over a 10 and 5 meter distance (Nguyen 2017). In this study the TUG test was segmented into 4 phases. The segmentation strategy was to look for several activity peaks in the measured TUG test IMU data and then find the nearest minimum and maximum to the right and the left of that peak. The result of this study was that the strategy of an algorithm developed for segmenting the TUG test data of healthy individuals was transferable to TUG test data for patients with Parkinson's disease.

A second study emphasized the importance of creating a tracking system with as few sensors as possible due to the interference obtrusive sensors can cause to the natural course of motion (Reinfelder 2015). In this study they placed two unobtrusive

IMU sensor on the outside of a pair of shoes. Subjects would then perform a standard 3 meter TUG test using the modified shoes. 121 features were then calculated from the TUG test data and used to classify the TUG data into 6 phases. The best classifier achieved a classification accuracy of 81.8%.

A third study focused on the effect of using various features, such as Euclidean distance, Power Spectral Entropy, Power Spectrum Frequency, and others. The best result (a sensitivity and specificity of 83%) was found by performing feature fusion, a normalized average of all the features, to improve TUG test discrimination between subjects with a history of falling and those without a history of falling.

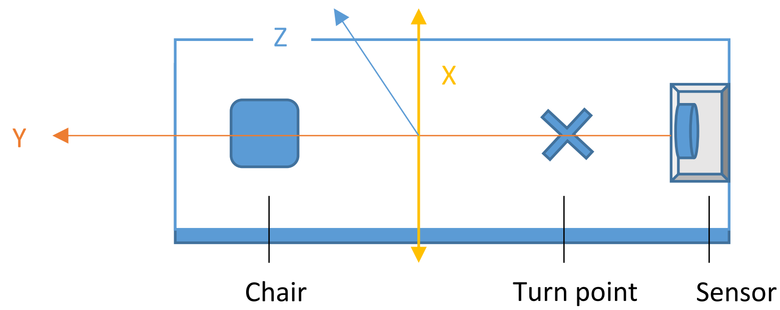
In the two studies that developed and algorithm for phase segmentation, there was an examiner who had to manually mark the frames for the start and end points of phases using visual data, either a 3D representation of the subject or images from a high-speed camera. This is a common pipeline for validation of the segmentation algorithms, and later I will discuss the tools I developed to improve this pipeline.

The WiGait Sensor

The WiGait sensor is a motion sensing technology being developed by the Katabi lab at MIT CSAIL (Hsu 2017). The sensor uses the reflections of a low frequency Wi-Fi signal to track the motion of people. Similar to radar, the sensor emit signals and can identify objects in motion based on the time it takes for multiple signals to return to the sensor. Using the distance changes calculated from transmitted and received signals, it can identify these moving objects. The sensor continuously sends out signals to localize all moving objects and once an object stops moving it is no longer able to be tracked until it begins moving again. This method of motion tracking is ideal for elderly patients because it does not require the subject to wear any heavy or restrictive tracking devices such as markers or bodysuits.

Data Format

The data collected from the sensor is the calculated center of motion at a given time. The sensor was programmed to collect data every 0.02 seconds in the form of **[timestamp: x, y, z]**. For all subjects, the sensor was placed at the far end of the room across from a chair. The subject would rise from the chair, walk 3 meters toward the sensor until reaching the turn point, walk away from the sensor for 3 meters to the chair, and then sit back down. Each of the subjects would perform 30 of these TUG tests consecutively. The axis between the chair and the sensor is the Y axis. The X axis represents the motion perpendicular to the sensor, such as the axis formed by the left and right of a subject. Finally, the Z axis is oriented vertically, along the height of a subject.



A length of continuously collected positions from one person is referred to as a 'tracklet' and defines a sequence of motions. The granularity of changes in motion that the device can perceive is based on its distance from the subject. At the closest the sensor can detect changes on the order of millimeters, such as heartbeats. At the farthest it can detect motion on the order of centimeters, such as breathing (Fadel 2015).

At the same location as the sensor was a camera that could capture images of the scene at 10 frames per second. This camera was recording during the subjects' TUG tests so that I could later determine the ground truth for the start and end of the walk phases.

Device Specifications

	Distance from sensor	Resolution at distance
Minimum range of sensor	1 meter radius	Millimeter changes
Maximum range of sensor	8 meters radius	Centimeter changes

	Field of View
Maximum horizontal angle	± 75 degrees
Maximum vertical angle	± 75 degrees

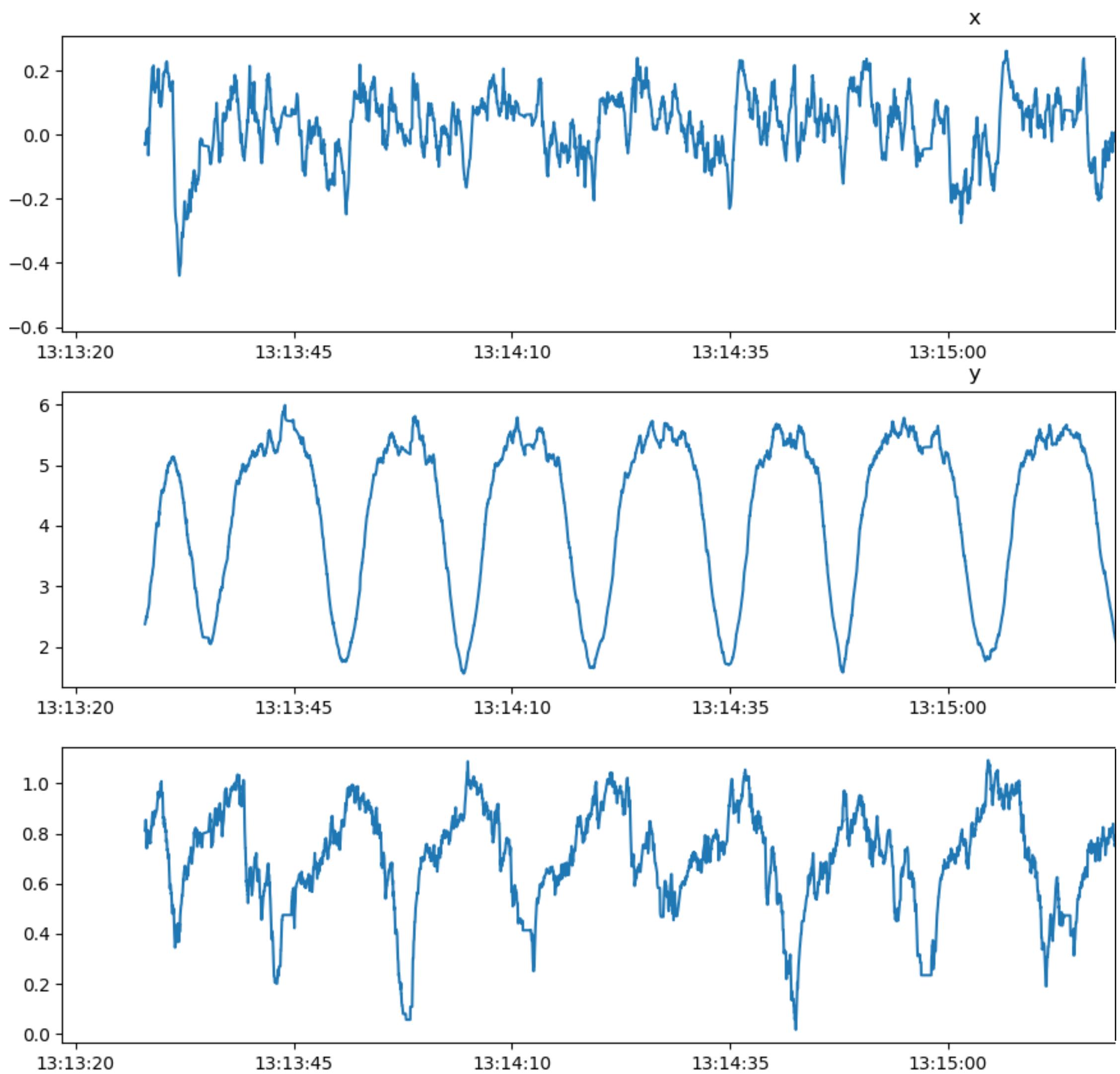
* The sensor has the ability to simultaneously track multiple people if they are at least a few meters away from each other.

Limitations

The WiGait sensor can capture very small motions but is not specific as to the body part that moved. For example, while tracking a person, the sensor may detect a large movement to the right but cannot indicate whether that motion is due to a leg, an arm, or the whole body moving in that direction. Thus, picking a test with a specified series of motions, such as the TUG test, was critical because it allowed for the motions to be more easily categorized into phases.

Data for the X and Z axis turned out to be particularly noisy, likely because of the small difference between the minimum and maximum value for these axes. The X axis had a difference of ~0.6 meters and the Z axis had a difference of ~1.5 meters. On these axes, motions that are irrelevant to the overall walk cycle manifest on a similar scale to meaningful motions, which adds noise to the data. An example of this phenomenon would be a body turning around to the right while also moving a hand out to the left causing a confusing resulting motion on the X axis.

Because of this issue with noise, the Y axis, which has a range of ~5 meters, had the clearest signal and thus it alone was used to determine the segmentation for the phases of walking.

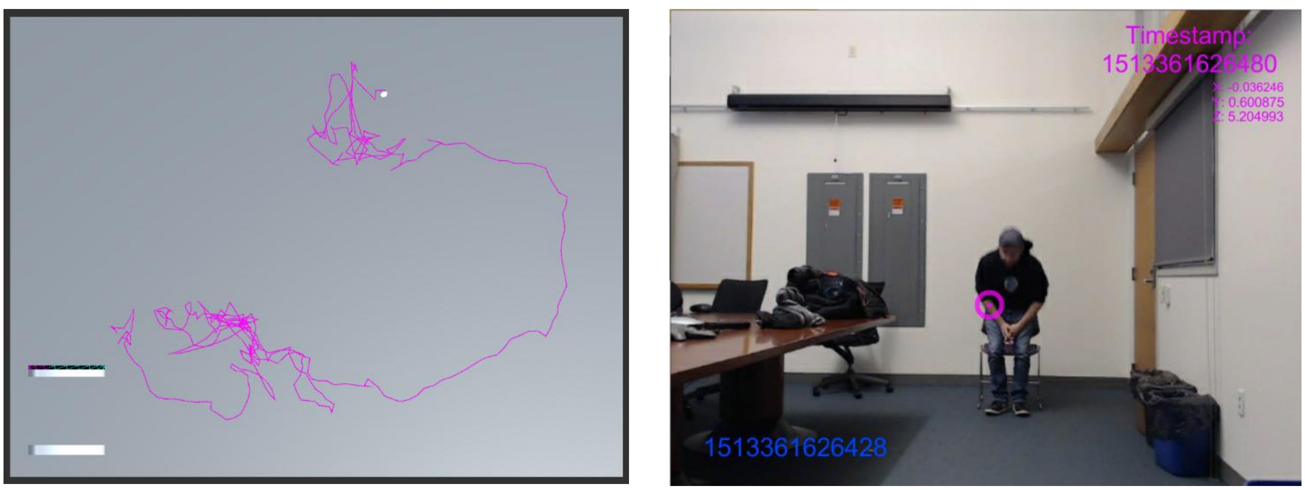


The X axis (top), Y axis (middle), and Z axis (bottom) for a series of 6 TUG tests.

Data Visualization and Jitter

Parallel Data Stream Visualization

To understand the tracklet data I created a visualization program that takes in tracklets and interprets the **[timestamp: x, y, z]** data as a moving 'dot' in a real-time 3D simulation. This dot is then overlaid with the video captured during the data collection. The result is a video with the WiGait sensor output overlaid on the video of the subject.



Early screenshots of the visualizer program. X is left/right, Y is up/down, Z is front/back.

I performed seven tests in order to get a general sense of the sensor sensitivity. I recorded myself:

- Sitting in a chair making no large motions.
- Holding a glass as a physical load while sitting.
- Counting backwards in my head by units of 7 as a cognitive load while sitting.
- Making motions only with my legs.

- Making motions only with my arms.
- Making motions with my right and then left the sides of my body and then full motion.
- Doing a TUG test for walking motions.

All of these tests were run through the visualizer to gain clarity on the amount of motion present in various types of movements and to find insights about fluctuation patterns in the data.

I quickly discovered that the sensor output was not necessarily the position of the center of the body, because the movement of limbs caused large shifts in the output. For example, the output position might follow an arm extended out to the right even while the person remained in the chair. Even small flicks of the wrist or ankles could cause the sensor data location to shift away from the body. The visualizer allowed me to understand that the WiGait sensor could be very sensitive to these small motions. Identifying what phenomena were causing perturbations and changes in the data gave an intuitive sense for how the WiGait behaves and tracks motion.

Images from the jitter tests.

One of the metrics I used to understand the motion of a person and noise of the sensor is ‘jitter’, which I defined as the difference between a motion and a smoothed version of that motion. For example, if one shakes heavily while rising from the chair or walks forward using small irregular steps the jitteriness will be higher than a fluid rising motion or walking motion. I smoothed the motion by applying a Gaussian filter to the sensor output on the Y axis with σ = 0.65. Jitteriness is computed as the pointwise absolute difference the smoothed motion and its corresponding point in the original motion.

$$J(O) = \frac{1}{n}\sum_{i=0}^{n} abs(O_i - Gauss(O)_i)$$

I used jitter to evaluate two types of motion tests, unmoving and moving. The unmoving tests consist of three sitting tests:

- Quiet sitting
- Sitting with physical load (holding a glass of water)
- Sitting with cognitive load (counting backwards by units of 7)

The moving tests consist of three sitting tests and one walking test:

- Sitting with leg movement
- Sitting with arm movement
- Sitting with sides and full movement
- A TUG test

The rounded average jitter amount for the unmoving tests was 1.8 cm and the rounded average jitter for the moving tests was 4.5 cm.

Unmoving Tests	Jitter (meters)	Distance from MIN to MAX value (meters)
Quiet sit test:	0.041	X: 0.43 Y: 0.89 Z: 0.69
Physical load sit test:	0.011	X: 0.39 Y: 0.62 Z: 0.99
Cognitive load sit test:	0.003	X: 0.28 Y: 0.44 Z: 1.62

Moving Tests	Jitter (meters)	Distance from MIN to MAX value(meters)
Legs test: (along Z)	0.025	X: 0.37 Y: 0.62 Z: 0.96
Arms test: (along X and Y)	0.059	X: 0.33 Y: 1.03 Z: 1.00
Sides test:	0.026	X: 0.42 Y: 0.53 Z: 0.45
TUG walk test:	0.069	X: 0.58 Y: 3.51 Z: 0.99

Data Collection Methods

I collected 30 TUG tests from 4 male subjects, two of which were young and two of which were elderly. I asked the subjects to rise from a chair and walk at a comfortable pace to a point 3 meters away and then walk back to the chair and sit. In between each TUG test I would wait 15 seconds before giving them the indication to begin the next TUG test. The WiGait sensor tracked the subjects' motion while the camera captured images of them performing the TUG tests.

By taking a look at a subject's walk cycle frame by frame from the images, I determined ground truth for the segmentation points for each phase of walking. Here are the definitions I used while manually annotating the data:

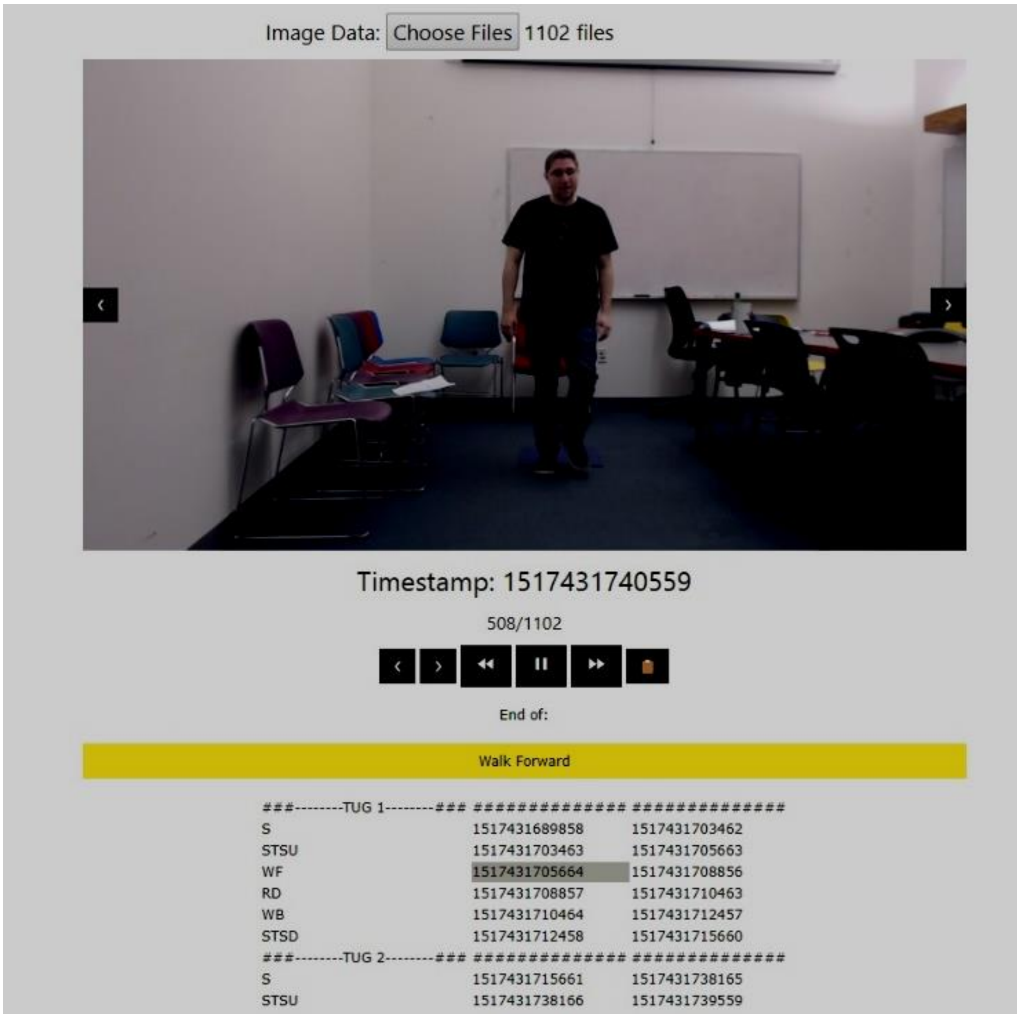
- **End of Sitting:** the frame before a subject moved in anticipation of standing up, this was typically an arm movement.
- **End of Standing-Up:** the frame where the shoulders reached their maximum height. In addition, both feet had to be planted on the ground or one foot could be extended toward the first step of a walking motion.
- **End of Walking-Forward:** the frame where the subject's chest was no longer fully parallel to the sensor, typically this initiation of turning was paired with a leg crossing over another leg.
- **End of Turning:** the frame where the subject's back was parallel to the sensor.
- **End of Walking-Back:** the frame where the subject's back was no longer parallel to the sensor, typically this was paired with one extended foot planted

perpendicular to the walking direction to assist with the turning required to sit down in the chair.

- **End of Sitting-Down:** the frame where the subject's back was against the chair and were no longer moving around in the chair.

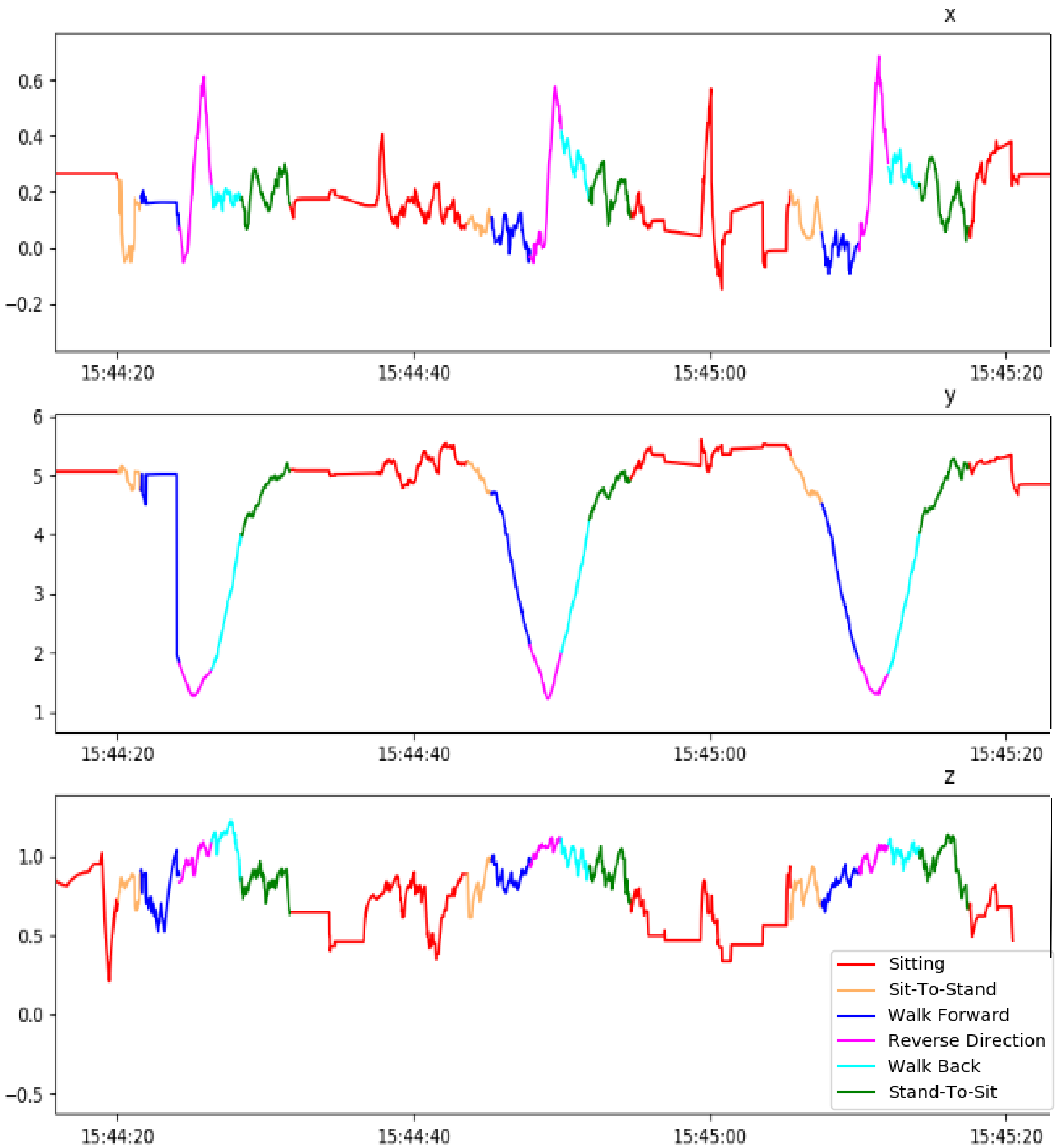
Annotation User Interface

To efficiently and quickly create ground truth from the dataset I developed a user interface that streamlined the annotation process. It prompts users for the end point of each phase in the order they appear in the TUG. The interface allows users to easily traverse the frames, either one by one or at a particular framerate. Once a frame is selected for an end point, the interface automatically fills out the start point of that phase based on the end of previous phase. Previously annotated phases appear in a chart with their associated timestamp. This chart can also be edited in case a frame was mistakenly selected. During edit mode the interface displays a preview of the frame at the segmentation point being edited. This chart, containing the ground truth annotation, can then be copied and exported into a separate file for use by a researcher.



A screenshot of the annotation UI.

Without the interface it took me 40+ hours to annotate 80 TUG tests, about 30 minutes each. Using the interface to annotate the 120 TUGs from the 4 subjects it took me 10 hours to annotate all the data, about 5 minutes each, a significant speed up.



Annotated ground truth for three TUG tests. (top-to-bottom) X axis, Y axis, Z axis.

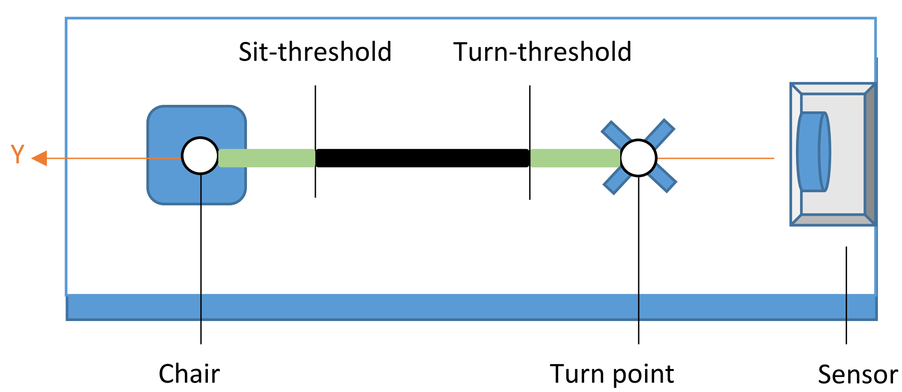
TUG-Segmenter Implementation

The TUG-Segmenter automatically segments the data via a two stage process, segmentation of core phases and then segmentation of transition phases. The core phases of the TUG are the phases where no height change takes place: Sitting, Walking-Forward, Turning, and Walking-Back. The transition phases are the phases that connect a phase at standing height to the phase at sitting height: Standing-Up and Sitting-Down. A two stage process is used in order to segment the phases that are more straightforward to segment, the core phases, before segmenting the more difficult phases, the transition phases. The core phases provide a useful start or end point for the segmentation of the transition phases. During the stages of segmentation the TUG-Segmenter uses only the Y-axis data, the subject's distance from the sensor.

Stage-One: Core Phases

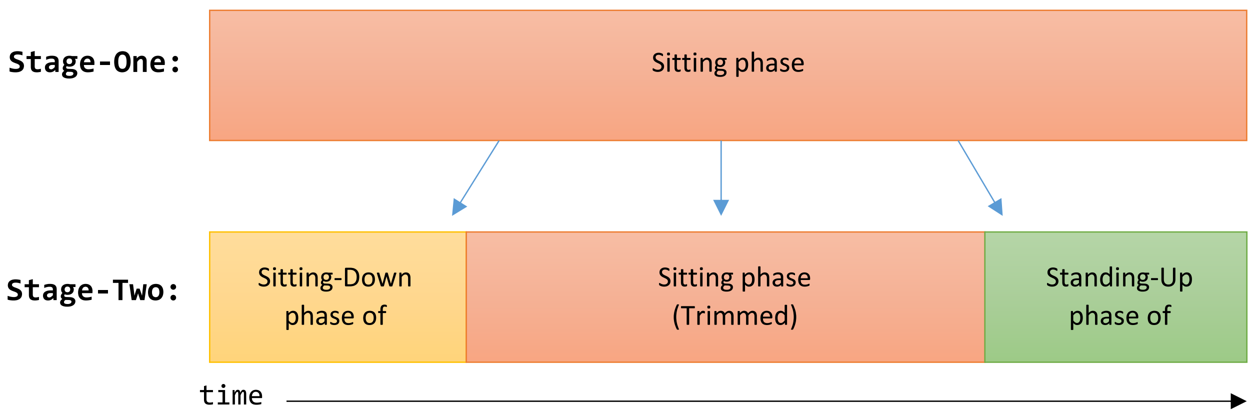
The core phases are segmented based on distance thresholds from two locations, the sit-threshold and turn-threshold. The sit-threshold is the distance from the chair at which a person is determined to have just exited or entered the vicinity of the chair to either walk away or begin sitting down. The turn-threshold is the distance from the turn point at which a person is determined to have just started or finished their turning motion. The sit-threshold has a value of 0.315 meters and the turn-threshold has a value of 0.565 meters. Both of these values were determined by calculating the average Y-position at the beginning and end of all Walking-Forward ground truth phases, for the sit-threshold and turn threshold respectively.

The distance from the sensor to the chair and turn point are measured before data collection. The end frame of a Sitting phase is determined by the TUG-Segmenter when a subject's distance from the chair exceeds the sit-threshold value. Then from that frame until the frame where the subject's distance to the turn point is less than the turn-threshold value is the Walking-Forward phase. The end frame of the Turning phase is then determined when a subject's distance from the turn point exceeds the turn-threshold value. Then from that frame until the frame where the subject's distance to the chair is less than the sit-threshold value is the Walking-Back phase. The following phase is a Sitting phase and the process repeats until all the data has been segmented into a phase. Once this segmentation occurs, the result is a series of TUGs, each segmented into four phases: Sitting, Walking-Forward, Turning, and then Walking-Back.



Stage-Two: Transition Phases

The transition phases are segmented from the Sitting phase determined in the previous stage of the TUG-Segmenter. The sit-threshold value is purposefully large enough such that the Sitting phase from the previous stage includes the beginning of the Sitting-Down phase and the end of the Standing-Up phase. Therefore each stage-one Sitting phase is composed like so:



The first stage-one Sitting phase does not contain a Sitting-Down phase because there is no previous TUG.

Sitting-Down

To determine the endpoint of the Sitting-Down phase I use the gradient of the smoothed stage-one Sitting phase Y-position data with respect to time. The TUG-Segmenter scans from the start time of the stage-one Sitting phase data until it finds the first point where the motion toward the chair plateaus, indicated by the speed being less than or equal to 50 cm/s. When this point is found, the Sitting-Down phase is determined to be all the frames between the first frame of stage-one Sitting and the point found with the speed less than or equal to 50 cm/s. The gradient of the stage-one Sitting phase data is taken using an approximation by central differences, which approximates the derivative using a point sampled from equal distances on its left and right. The smoothing is done by a Gaussian filter with $\sigma = 0.65$.

Standing-Up

To determine a point as the start point of Standing-Up the TUG-Segmenter considers each point from the end point of the Sitting-Down phase to the end of stage-one Sitting, until it finds the first point that satisfies several conditions:

- There must be at least a 2 second motionless sitting period between the end of Sitting-Down and the start of Standing-Up. This is to prevent the start of Standing-Up occurring immediately after the end of Sitting-Down, yielding an empty Sitting phase. Motionlessness is determined by a sequence of points where all the speeds are under 50 cm/s.
- A large movement detected in the unsmoothed data in combination with an overall motion toward the sensor in the subsequent points. This is characteristic of someone rustling in the chair as they begin to get up, and then rising. The large movement is determined by a rate of

displacement less than or equal to -10 m/s in the unsmoothed data. The overall motion is determined by taking the average rate of displacement over the next 0.2 seconds and 2 seconds, if both are less than or equal to -10 m/s the motion is considered to be moving toward the sensor.

- There is no motionless after the large movement that would indicate a false start Standing-Up, such as rustling in the chair but then remaining sitting.

If all these conditions are satisfied then the start point of Standing-Up has been determined. The TUG-Segmenter then marks the interval from the found point until the end of the stage-one Sitting as the Standing-Up phase. If these conditions cannot be satisfied, a more lenient condition is used to find the start point (considering each point from the end of Sitting-Down):

- An overall motion toward the sensor in the subsequent 4 seconds after the point being considered.

If this condition cannot be satisfied, then a constant value of 0.1 seconds is used to determine the duration of the Standing-Up phase. The last 0.1 seconds of stage-one Sitting is then determined to be the Standing-Up phase. The end point of the Sitting phase is appropriately modified.

Once this last stage segmentation occurs, the result is a series of TUGS, each segmented into six phases: Sitting, Standing-Up, Walking-Forward, Turning, Sitting-Down, and then Walking-Back.

Data Issues

Several categories of issues arose with the data due to the WiGait sensor: extreme oscillation, discontinuities, and tracklet fracturing. Each of these issues required a different solution to allow the TUG-Segmenter to process the collected data.

Extreme Oscillation

At times the sensor would seem to stop and then attempt to recover tracking. This would result in the sensor outputting data indicating that the motion of a subject was greater than ~2.5 meters between two frames, usually showing this type of motion multiple times within a single second. This is unlikely behavior as the average walking speed of a human is 1.4 m/s (Browning 2006). To detect extreme oscillations the TUG-Segmenter would look at each two adjacent frames in the data and if the absolute difference between the Y-positions of the two frames was greater than 2.5 meters then that TUG test was marked as invalid.

I do not make use of this phenomenon, but it is interesting to note that the sensor stopping before the occurrence of an extreme oscillation appears as a value that doesn't change until the oscillation occurs. This manifests as a horizontal line and then an oscillation with a high frequency and large amplitude as shown by the graph below.

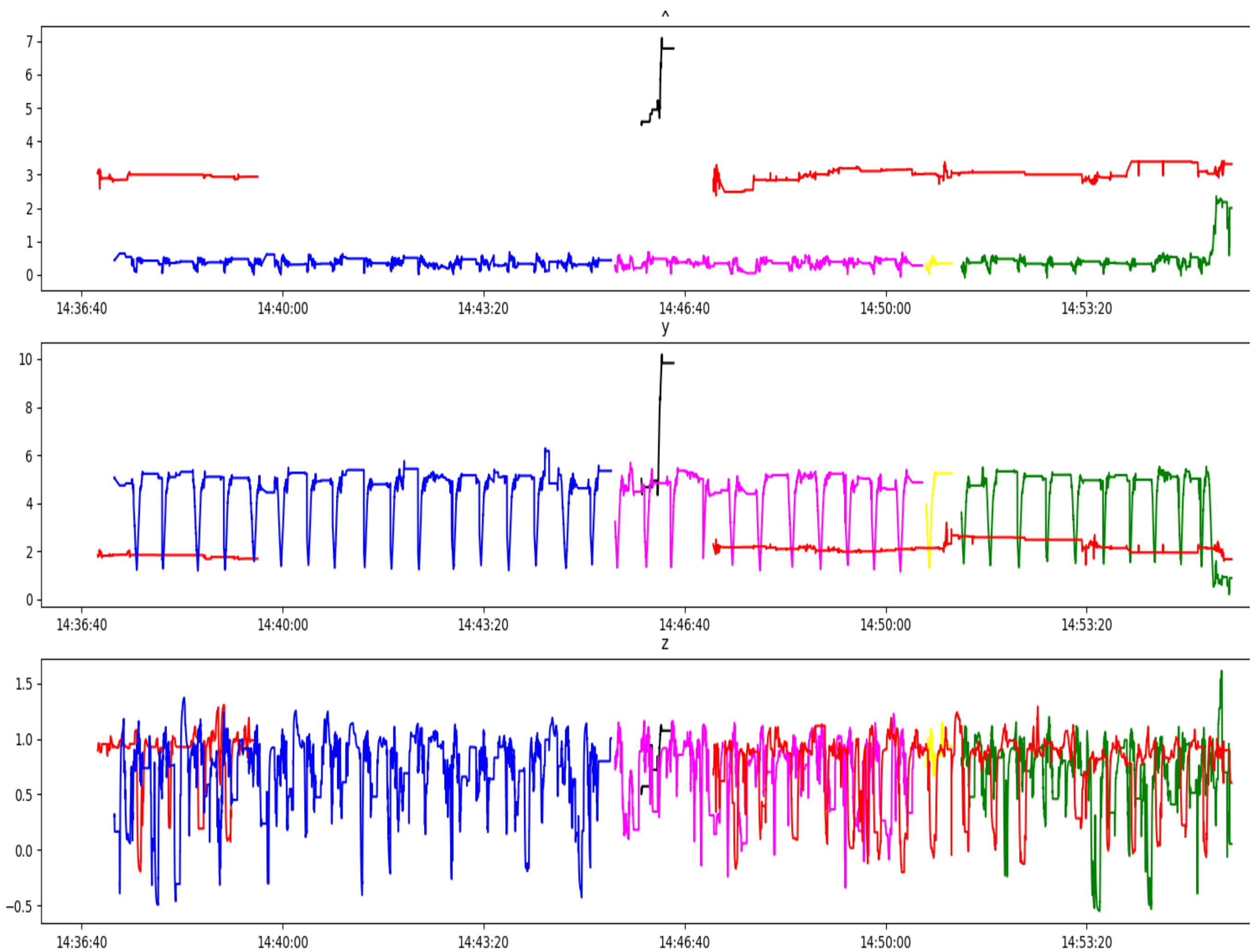
The middle graph shows an example of extreme oscillation between 15:30:18 and 15:30:20.

Discontinuities

Discontinuities in the data likely occurred as a secondary effect of extreme oscillation. They were removed by applying a Gaussian filter to correct the missing points.

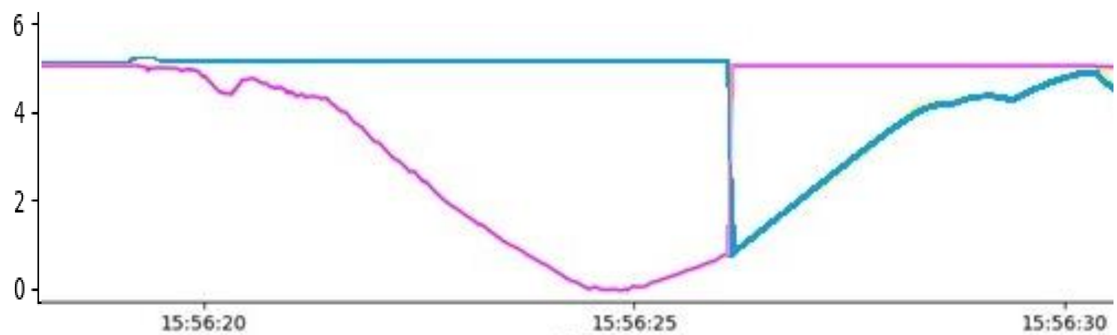
Tracklet Fracturing

Tracklet fracturing occurred in two forms, split tracklets and overlapping tracklets. Both of these issues occurred when the sensor determined certain parts of one sequence of motion belonged to more than one individual. Tracklets are called split if the data has been partitioned into more than one separate tracklet by being partitioned at a single point. Fixing this requires merging the two tracklets.



The blue, pink, yellow, and green tracklets show an example of split tracklets.

Overlapping tracklets result from the sensor interpreting one motion as two distinct motions occurring at the same time and belonging to two moving subjects. This phenomenon requires more effort in order to fix. In this case the tracklet is divided in the middle of a motion and two tracklets together must be spliced together at the correct point to preserve the correct TUG test motion. In the example below, the pink tracklet contains the correct TUG test data until partially through the upward curve of the Walking-Back phase, after which point the yellow tracklet contains the correct data. These two parts spliced together form a full TUG test tracklet. This issue can only be fixed by manually finding the correct splice points in the two tracklets.



An example of overlapping tracklets that spliced together yield the correct TUG test data.

Results

The accuracy of the TUG-Segmenter was evaluated based on two metrics, durations and start points.

Duration accuracy is the percent difference between segmented phase durations and ground truth phase durations. For example, if a Sitting phase lasts from t=1 until t=11 (10 seconds total) and the TUG-Segmenter marks that Sitting phase as occurring from t=1 until t=10 (9 seconds total) then there is a 10% difference from the ground truth phase duration.

Start point accuracy is the percent early or late a segmented start point is compared to its corresponding ground truth start point based on the proceeding phase duration. The full results can be found below. For example, if a Sitting phase lasts from t=1 until t=11 (10 seconds total) and the TUG-Segmenter marks that Sitting phase starts at t=2 then the start point is a 10% off from the following ground truth phase duration.

Ground Truth Durations

Subject 1	Duration (seconds)
Sitting	16.986
Standing-Up	1.533
Walking-Forward	2.41
Turning	1.598
Walking-Back	1.973
Sitting-Down	2.347

Subject 2	Duration (seconds)
Sitting	17.248
Standing-Up	1.91
Walking-Forward	2.569
Turning	2.224
Walking-Back	2.195
Sitting-Down	2.659

Subject 3	Duration (seconds)
Sitting	16.354
Standing-Up	1.677
Walking-Forward	2.745
Turning	1.827
Walking-Back	2.59
Sitting-Down	2.913

Subject 4	Duration (seconds)
Sitting	17.34
Standing-Up	1.785
Walking-Forward	1.586
Turning	1.741
Walking-Back	1.577
Sitting-Down	2.133

Durations

Subject 1	% difference
Sitting	4.5%
Standing-Up	88.8%
Walking-Forward	29.7%
Turning	26.9%
Walking-Back	2.5%
Sitting-Down	1.7%
Full TUG Test	2.6%

Phase durations 25.7% inaccurate.

Subject 2	% difference
Sitting	2.3%
Standing-Up	5.4%
Walking-Forward	13.6%
Turning	22.4%
Walking-Back	24.1%
Sitting-Down	19.1%
Full TUG Test	0.7%

Phase durations 14.5% inaccurate.

Subject 3	% difference
Sitting	12.8%
Standing-Up	16.1%
Walking-Forward	8.0%
Turning	7.3%
Walking-Back	23.7%
Sitting-Down	53.2%
Full TUG Test	2.0%

Phase durations 20.2% inaccurate.

Subject 4	% difference
Sitting	3.4%
Standing-Up	5.3%
Walking-Forward	1.3%
Turning	4.8%
Walking-Back	11.6%
Sitting-Down	9.3%
Full TUG Test	0.4%

Phase durations 5.95% inaccurate.

Start Points

* Negative values indicate the start point was early by that percent.

Subject 1	% late
Sitting	-8.3%
Standing-Up	1.7%
Walking-Forward	25.3%
Turning	-18.1%
Walking-Back	10.1%
Sitting-Down	7.9%

Start points off by 11.9% on average.

Subject 2	% late
Sitting	-0.4%
Standing-Up	43.2%
Walking-Forward	29.3%
Turning	15.6%
Walking-Back	-4.6%
Sitting-Down	13.0%

Start points off by 17.7% on average.

Subject 3	% late
Sitting	-10.3%
Standing-Up	54.6%
Walking-Forward	22.0%
Turning	18.0%
Walking-Back	9.1%
Sitting-Down	27.4%

Start points off by 23.6% on average.

Subject 4	% late
Sitting	2.8%
Standing-Up	21.7%
Walking-Forward	11.7%
Turning	8.2%
Walking-Back	13.0%
Sitting-Down	17.2%

Start points off by 12.4% on average.

Using the ground truth phases, I calculated speed and jitter for each phase and averaged them per subject. Speed was calculated using the 3D distance between sensor location every 1 second, and the duration from the end of Sitting until the end of Sitting-Down. 3D location was used to more accurately get the speeds for phases that involve vertical motion, namely Standing-Up and Sitting-Down. The results of these features can be seen below.

	Age	Average Speed	Average Jitter
Subject 1	Young	2.981 m/s	6.9 cm
Subject 2	Elderly	2.37 m/s	6.2 cm
Subject 3	Young	2.477 m/s	6.8 cm
Subject 4	Elderly	3.105 m/s	6.9 cm

* Young = mid 20's, Elderly = 60+

Results Summary

Overall, the automatically segmented phase durations were 83.4% accurate compared to their ground truth durations, and segmented start points were off by 16.4% of the duration of their proceeding ground truth phase. Standing-Up was the least accurate in both duration and start point. Sitting-Down had the second worst accuracy in the duration category. One of the main causes for the inaccuracy of Standing-Up is due to many false oscillations on the Y axis before the person stands up caused by their hands, feet, or shifting in the chair. This is the reason the TUG-Segmenter contains many conditions that must be satisfied when segmenting the Standing-Up phase, in order to rule out some of the false Standing-Up movements from the correct start of Standing-Up. The second reason is that it is one of the shorter phases (1.5 seconds on average) and thus start point lateness compared to its phase time will be large a percent.

Lastly, when comparing elderly and young subjects, there was a 0.3 cm difference for jitteriness and an 8.5 mm/s difference for speed when these features were averaged over all phases. However, the number of subjects was small and more subjects would be needed in order to generalize these results and see if there is any significant difference between elderly and young subjects.

Conclusions

Overall the TUG-Segmenter can segment TUG test WiGait data with 83.5% accuracy (duarations and start points). Using the TUG-Segmenter and annotation interface, the pipeline has been established for analyzing individual phases of walk cycles. By examining these phases it appears healthy individuals have similar speeds and jitter regardless of age. Using the TUG-Segmenter and annotation interface, one can be more granular with the analysis of the TUG test, an already useful diagnostic test.

Future Work

I used only the Y axis when developing the TUG-Segmenter due to noise on the X and Z axes, however, in the future I think finding methods to clear up the signals on those axes would prove very useful in a more accurate segmentation of the transition phases. Currently these phases are the most inaccurate but with the ability to utilize the Z axis one should be able to more faithfully predict when the rising action out of the chair or the descent into the chair is beginning. One strategy may be to use multiple WiGait sensors to create better estimates of the motion on the Z axis. Another strategy might be to use a camera to track the center of the body in addition to the center of motion from the WiGait.

Lastly, one area I am very interested in is using the TUG-Segmenter to segment the walk cycle of patients with Parkinson's. I think there is much more to be gained in looking at the individual walk cycle phases of those exhibiting erratic movement due to cognitive impairment, than from simply looking at the overall performance on the TUG test.

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