Low-Cost Gait Monitoring as Early Warning for Neurodegenerative Diseases

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Abstract

Every year more than 50 million people suffer from neurodegenerative diseases that impact their lives and wellbeing. These neurodegenerative diseases have many symptoms, some of which manifest in the form of gait (walking) disorders. Measuring these gait disorders and recording changes over time can lead to early detection of possible neurodegenerative diseases. The developed wearable device, EDGAR (Early Detection of Gait AbnoRmalities), utilizes Arduino and external sensors to detect and monitor gait abnormalities. EDGAR is able to detect the small changes in the parameters: stride length, and cadence.

1.0 Introduction

More than 50 million people are currently suffering from neurodegenerative diseases in the U.S. and with an increasingly older population, many more people are expected to develop neurodegenerative diseases (Brown, 2005). Neurodegenerative diseases are one of the leading causes of death in the United States (CDC, 2024). For example, 7 million Americans have Alzheimer's; one out of every three eventually die due to it (Alzheimer’s Association, 2024). Since neurodegenerative diseases are chronic conditions that damage parts of the brain and the nervous system over time, they can lead to symptoms of memory loss, muscle spasms, and coordination issues. In the early progression of the diseases, symptoms subtly progress and often go undiagnosed. The result is that most diagnoses of neurodegenerative diseases take place after traumatic accidents, which can decrease a patient's quality of life and possibly cause more health

complications (Cleveland Clinic, 2023). Early detection of neurodegenerative diseases can allow patients to prepare for living with a neurodegenerative disease and avoid traumatic injuries. Detection and monitoring of symptoms such as physical deterioration can be potentially useful for early detection of the presence of neurodegenerative diseases.

1.1 Overview of neurodegenerative diseases

Common neurodegenerative diseases include Alzheimer's disease, Parkinson's disease, Multiple Sclerosis, and dementia. The causes range from genetics and age to lifestyle and environment; therefore, symptoms may vary for each person. Alzheimer's disease, for example, is the loss of neurons that affects many regions of the brain, including the frontal lobe which is responsible for higher cognitive functions as well as voluntary motor movements (Dugger & Dickson, 2017). Most neurodegenerative diseases will eventually cause cognitive and motor decline which can be identified through the gait of one's walking patterns. As symptoms of motor disability increase, there is a change in gait. These changes in gait can be detected and may correlate to a progression in neurodegenerative disease.

1.2 Gait Parameters and Gait Pattern

The most common gait disturbance symptoms of neurodegenerative diseases are changes in walking speed, step/stride length, cadence, and support time (Grazia Cicirelli et al. 2022). Cadence is measured in the number of steps/minute. Stride length is when one foot's initial contact makes contact with the floor again while step length is the distance between the contact of the left foot and the contact of the right foot (Refer to Figure 1).

Figure 1. *Stride Length, Step Length, and Visual Diagram (Xsens. 2023).*

Gait pattern changes vary with each neurodegenerative disease but share common factors. For Alzheimer's, a patient will exhibit an overall slower gait cycle as the cognitive function deteriorates. Patients with Multiple Sclerosis can experience motor failure. Parkinson's disease has symptoms related to body rigidness, tremors, and posture issues. Depending on the type of neurodegenerative disease, the gait symptoms that change with progression of the disease differ and are shown in Figure 2 (Cicirelli, 2022). A blank in the chart means that the change is not significantly correlated with the disease progression.

	Alzheimer's disease	Multiple Sclerosis	Parkinson's disease
Cadence	↓	↓	↑
Stride Length	↓		↓
Support Time	↑		
Gait Speed	↓	↓	↓

Figure 2. *Specific Neurodegenerative Diseases and Their Gait Related Symptoms Change as the Disease Progresses.*

Neurodegenerative diseases are not the only factors affecting gait change. Age can also cause reduced speed and stride length and an increased step and stride time (Gamwell, 2022). Therefore, changes in gait may indicate presence of a neurodegenerative disease, but it would not be a definitive diagnosis.

1.3 Types of gait detection

Gait analysis can be based on clinical assessment (semi-subjective) or based on device-measured gait parameters (objective). A clinical assessment is usually done in a lab with

a medical professional conducting the testing. An objective analysis can be determined using different types of technology, such as Image Processing, Floor Sensors, and Wearables (Muro-de-la-Herran et al., 2014). Objective analysis can be accomplished outside of a clinical setting and implemented as a normal part of daily life.

Gait abnormalities can be identified using wearable technology or non-wearable technology. Some devices may be challenging for patients to set up, such as image processing devices, or restricted to certain areas, such as floor sensors. In contrast wearable technology can be accessed at any setting or time and it is relatively easy to set up. Inertial sensors such as the accelerometer and magnetometer are used in wearable technology because of their size that can be placed anywhere on the body. To record long-term gait changes and increase accessibility for potential patients, wearable technology is the most fitting.

1.4 Computational techniques

Numerical integration using an accelerometer is possible by integrating acceleration into position (Muro-de-la-Herran 2014) using physics kinematic equations to find displacement. Once displacement is measured, it is possible to find the parameters: stride length, and step length. However, there are concerns with the limitations of numerical integration as integrating can lose accuracy with each interval, due to the maximum decimal place of the Arduino being 6-7 places.

1.5 Literature Review

In 2019, Akpan et. al. published a review of the importance for early detection when treating patients with potential neurocognitive disorders. They note that a major issue when dealing with neurocognitive disorders is that people may not recognize early symptoms until they become worse. An early detection of these disorders is important to allow patients time to

plan for their future and to take measures to slow further decline. This study suggests that long term monitoring of patients would be a solution to help detect early symptoms of neurocognitive disorders by measuring gradual changes in gait. While this study mainly focuses on the cognitive symptoms of neurodegenerative diseases, it demonstrates a need for early detection technology.

In 2023, Ejaz et. al. developed a smart walker to detect gait characteristics in participants with osteoporosis and those without osteoporosis. The smart walker utilizes force sensors on each leg to measure the distribution of force on the participant when the subjects are walking. Using the data from the force sensors the researchers were able to measure key gait parameters and differentiate gait patterns for patients with and without osteoporosis. This study is useful to see that other options need to be available to peple, who for example don't use a walker to walk ando therefore would need a different gait monitoring device.

In 2017, Circirelli et. al. published a review of gait analysis in patients with neurodegenerative diseases. Each neurodegenerative disease reviewed had a predictable set of gait abnormalities. This study provides typical gait parameters for Alzhimer's, Parkison's, Multiple sclerosis, Amyotrophic Lateral sclerosis, and Huntington's. How demographic data (age, gender, etc.) can affect the detection of anomalies in gait in different gait measuring forms is also discussed. For wearable devices, the researchers used different combinations of gait parameters to differentiate the healthy patients from the ones with neurodegenerative diseases, providing a baseline of data that can be used for gait differentiation.

1.6 Problem Statement

Neurodegenerative diseases often show early signs of development in the form of cognitive slowness, gait disorders, and muscle weakness. Clinical diagnosis of subtle gait changes can be expensive and time consuming, and gradual gait changes are only revealed after

long term monitoring. Detection of subtle or gradual gait changes could be a useful early detection of potentially serious neurodegenerative diseases. EDGAR (Early Detection of Gait AbnoRmalities), an Arduino based device, was created, providing a low-cost, portable, and easy to use device that monitors the gait parameters: stride length and cadence.

2.0 Methods

The EDGAR software was developed to utilize two hardware components: the accelerometer and the force sensor. Once the software was working, the components were validated individually. After validation, the components were combined to build the final prototype.

2.1 Hardware and Software

The parameters measured are stride length andcadence. Using an accelerometer, stride length will be calculated. To find cadence, the time between steps is recorded, using a force sensor as the step indicator. Figure 3 shows a full software function flowchart.

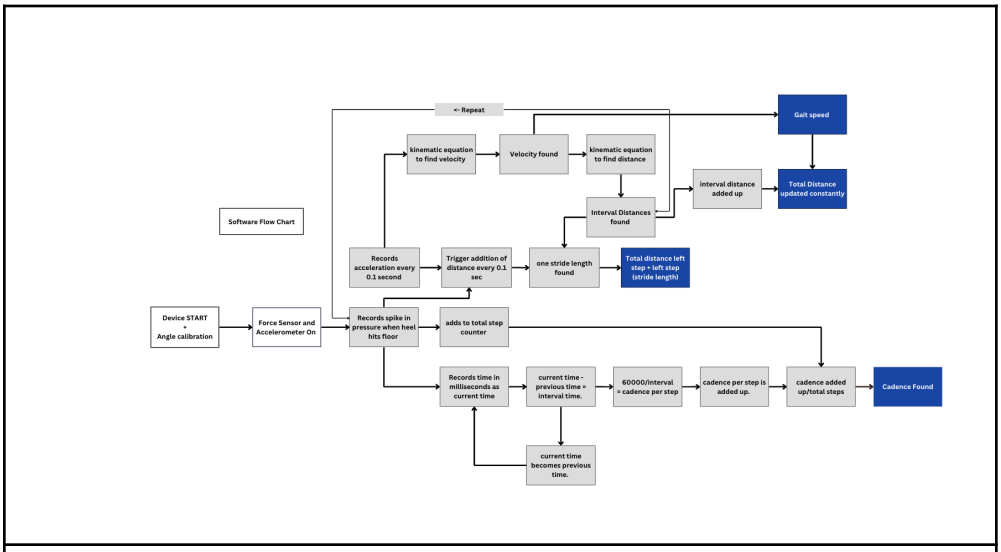

Figure 3. *Software Flowchart.*

2.2 Device Validation

Validation of average cadence was conducted by walking in a hallway for 1, 2, 3, 4 and 5 minutes, comparing software calculations and direct measurement. The accuracy of the distance integration and angle calibration code was verified with simulated acceleration data.

After the codes for angle calibration, net acceleration, and displacement were validated, the individual software components were combined and tested on a one dimensional testbed (Figure 4.). To validate the combined software, the accelerometer was placed onto a 14 inch rail and pulled along the rail to imitate the speed of a step. There were 3 tests, each with 10 trials, for normal speed sliding (1 second), a slightly quicker speed, and one slightly slower speed.

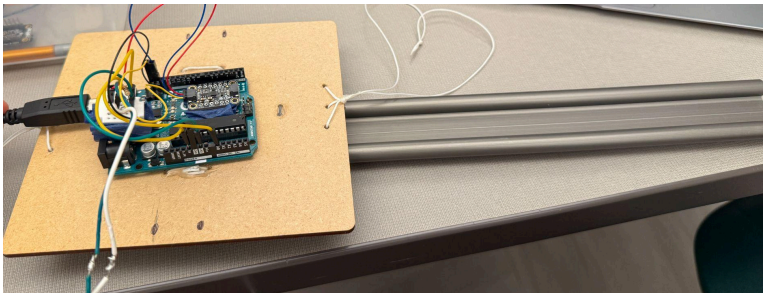

Figure 4. *One dimensional Testbed.*

The first integrated EDGAR prototype was tested by walking down a hallway with a controlled distance for each stride to show consistency of the software distance results. The tested stride lengths were 1 meter and 1.5 meters per stride and the test was performed 5 times each with 20 strides.

Following this test, a blind test was created where EDGAR was worn and walked an stride length, unknown to the data processor, to see the precision of the distance measurements. This test was performed with 2 unknown stride lengths, each repeated 6 times in 18 strides.

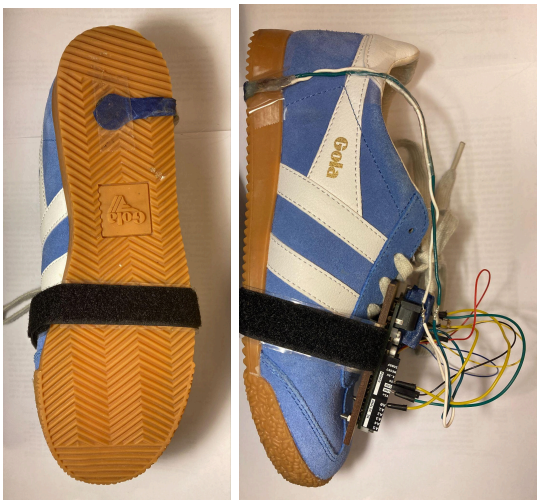

Figure 5. *Final prototype- Force Sensor with Accelerometer and Arduino.*

The EDGAR device (accelerometer and Arduino) were attached on a platform to the front/top area of the shoe with velcro, while the force sensor was taped to the bottom middle sole of the shoe, as seen in Figure 5.

Analysis of the axis locations (ankle, toes, and middle), showed that placing the EDGAR on the tongue of the shoe would be optimal for the least amount of angle changes. The force sensor is placed around the mid-foot sole region to ensure that the sensor is triggered when walking. With Figure 6, it is possible to understand how much angle change affects the uncertainty on acceleration.

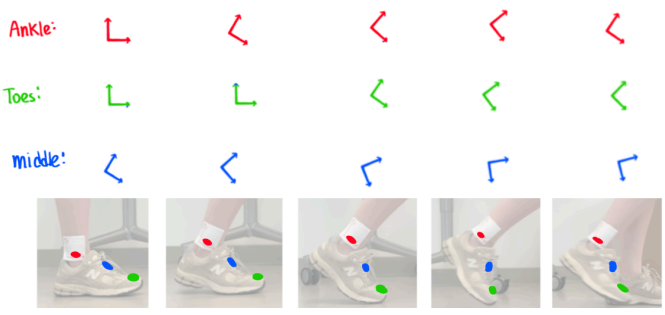

Figure 6. *Axis with Respect to Gravitational Vector on Different Parts of the Foot.*

3.0 Results

3.1 Components Validation

Using kinematic equations, Arduino code can successfully calculate the displacement with simulated constant acceleration data with 0.16% error (±0.003 m).

The 1D testbed demonstrated that the software for distance measurement works with a consistency of 85% and an accuracy of around 63%. The test reveals that EDGAR loses accuracy the faster the accelerometer slides.

Speed	Stride Length (Average)	Standard Dev	Error % (Consistency)	Error % (Accuracy)
Normal	0.243	0.032	13%	17%
Quicker	0.249	0.037	15%	15%
Slower	0.166	0.025	15%	43%

Figure 7. *1D Testbed Data.*

The average cadence code has a percent error of 3.5% to .6%. As the tests increase in time and step count, the percent error decreases (see Figure 8).

Time	# of steps by code	# of steps by hand	Average Cadence Calculation (Code)	Average Cadence Calculation (by hand)	Percent error
1 minute	48	48	46.34	48.00	3.5
2 minutes	98	97	49.26	48.50	1.6
3 minutes	153	153	51.38	51	0.7
4 minutes	207	208	51.67	52.00	0.6
5 minutes	261	261	51.89	52.20	0.6

Figure 8. *FSR Cadence Validation Test Results.*

3.2 Stride Length Test

For the Stride Length test, EDGAR was used to calculate the stride length during a controlled and measured walk. The data shows that the absolute calculated measurements do not match the calibrated stride length. However, EDGAR does appropriately show a difference between a larger and shorter calculated stride length seen in Figure 9 (1.5 m vs 1.0 m).

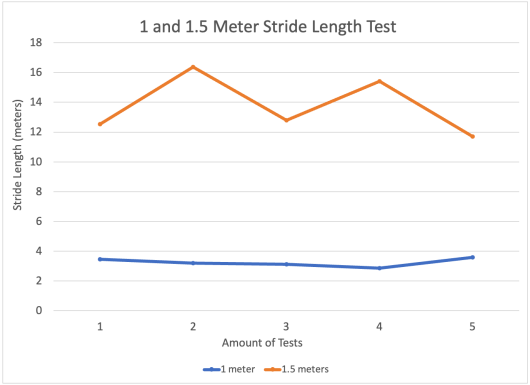

Figure 9. *Average 1 Meter Stride Length Over 5 Trials (blue) and Average 1.5 Meter Stride Length Over 5 Trials (orange).*

For the blind test, EDGAR demonstrates the ability to see a difference in stride of up to the hundredths place with 1.20 meters (Figure 10) to 1.25 meters (Figure 11).

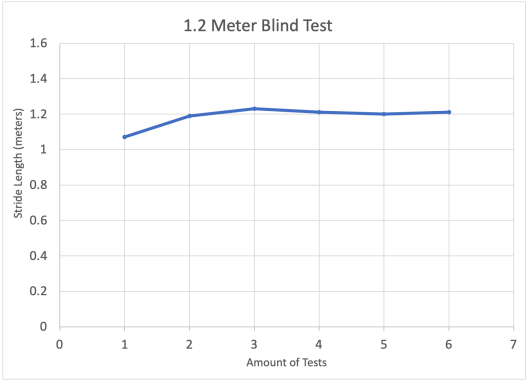

Figure 10. *Average 1.20 Meter Blind Test Over 5 Trials.*

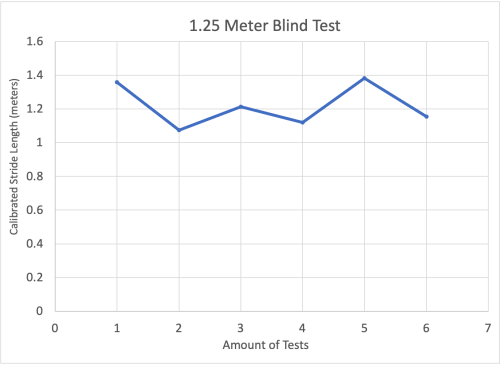

Figure 11. *Average 1.25 Meter Blind Test Over 5 Trials.*

4.0 Discussion

EDGAR was designed to measure stride length and cadence utilizing an accelerometer and a force sensor. Based on the stride length tests (Figure 9), EDGAR was unable to accurately calculate stride length. However, using the calibration data to create an equation it was possible to determine a software correction curve (Figure 12). With this correction curve, in the blind test validation (Figure 10 and 11), EDGAR calculated a stride length of 5.21 and 5.60m (Refer to Figure 13).

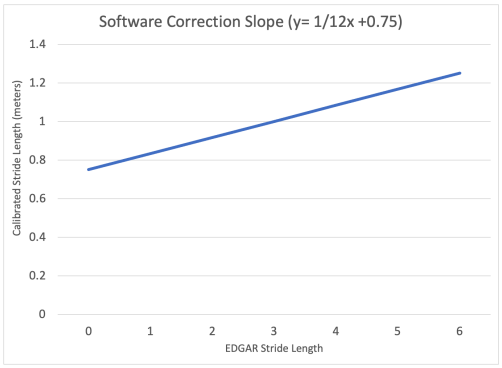

Figure 12. *Software Correction Curve*

Blind Test Stride Length (Calibrated with Correction Curve)	Actual Blind Test Stride Length Walked	EDGAR Original Blind Test Stride Length
1.18 m	1.20 m	5.21
1.21 m	1.25 m	5.60 m

Figure 13. *Table Comparing the Values of Blind Test, Actual Stride, and EDGAR's Stride*

EDGAR can differentiate between shorter and longer strides up to 0.05m accuracy (1.20m to 1.25m) and can calculate cadence with an accuracy of 94% - 96.5%.

The software code is accurate when simulated data is plugged in, however, inaccuracies occur when using the accelerometer. With real-world data, the accuracy of distance calculations decreases. This could be due to: the sensor, angle calibration, or EDGAR placement.

The leading accuracy limitation is the angle calibration. Angle calibration only happens once the device is initialized (at the beginning), but as the foot moves, the angle is continuously changing. Therefore, the device does not calibrate even after many angle changes and causes inaccurate acceleration calculation. EDGAR placement also plays a significant role in accuracy. Although it was placed on the tongue of the shoe, the most stable location on the foot, angle changes were inevitable and were amplified through integration.

The blind test (Section 3.2) proved that the low accuracy caused by uncertainties does not matter, as EDGAR is consistent. The blind test also shows that the prototype is able to differentiate between distances in the hundredths of meters. (Refer to Figures 10 and 11) Despite the fact that EDGAR has significant inaccuracy of 34%, the accuracy is not necessary to detect changes in gait. Change in gait measures the difference in the parameters over time. This means that even with inaccurate data, detecting the difference between different types of gait is possible. After running tests with various distances, the output data successfully demonstrates that EDGAR can detect changes in gait. Using an equation, the inaccurate distance could be calibrated to produce an accurate distance reading.

Future research on this project could include additional testing to provide a more accurate measurement and refining of software to optimise constant angle calibration. Further testing of accelerometer placement, such as the waist, may help to offset the problems caused by angle changes and improve accuracy.

5.0 Conclusion

With 50 million suffering from neurodegenerative diseases in the U.S., diagnosis and management is key to improving the life and well being of those with neurodegenerative diseases. One of the key symptoms of neurodegenerative diseases is the development of gait abnormalities. The EDGAR (Early Detection of Gait Abnormalities) device was developed with low cost materials to monitor and detect gait abnormalities while walking. Using Arduino hardware, EDGAR has an estimated affordable cost of $36-$40 and a ready to wear velcro and force sensor attachment. The device has been shown to be able to detect differences in stride length and cadence, successfully detecting the difference between 1.20 and 1.25 meter strides and a cadence accuracy with 96.5% - 99.4%.

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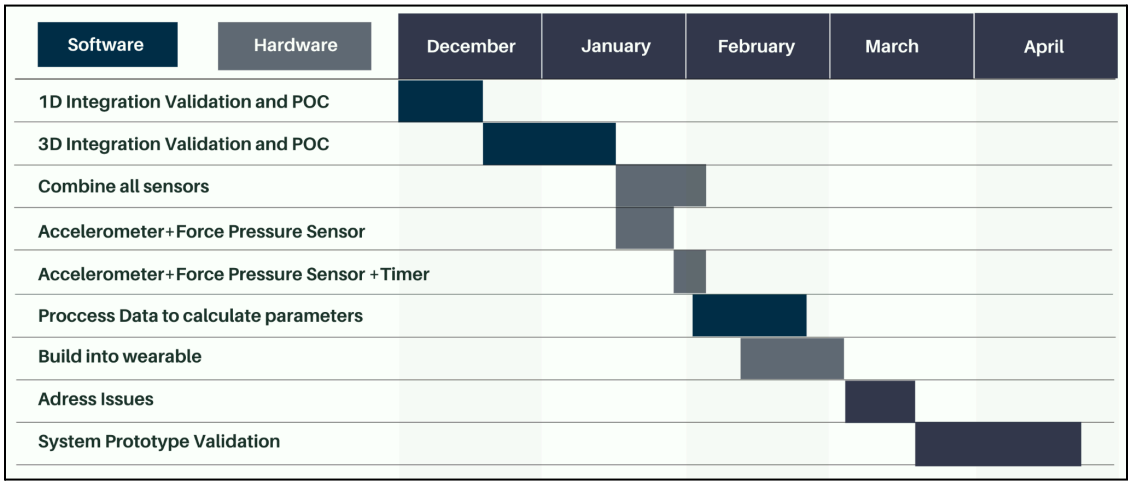
7.0 Appendices

7.1 Gantt chart



7.2 Kinematics Equation Validation Table

acceleration	Hand Calculated	Code	Difference	%diff
20	62.5	62.4	0.1	0.16
1000	3125	3120	5	0.16
-10	-31.25	-31.2	0.05	0.16
1.1	3.4375	3.43	0.0075	
1.4	4.375	4.37	0.005	

7.3 Simulated Data for Angle Calibration

Unknown moving Accel = [ax,ay,-9.8]		Answers	Pitch Roll (Theta,Phi	Moving Accel	Net accel
[-0.614316, 3.351797, -9.242731]			(10°, 20°)	[1,0,-9.8]	1.000000
[-0.584621, 3.821644, -9.074319]				[1, 0.5, -9.8]	1.118034
[-1.077025, 3.821644, -8.987495]				[0.5, 0.5, -9.8]	0.707107