2024

SMS : a smartwatch application suite for mobility assessment

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SMS: A SMARTWATCH APPLICATION SUITE FOR MOBILITY ASSESMENT

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A THESIS

**Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Engineering
in
Electrical and Computer Engineering
to
The Graduate School
of
The University of Alabama in Huntsville
May 2024**

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Abstract

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Regular assessment of mobility can detect changes in physical health over time and discover underlying health issues. Some of these changes in mobility may indicate an increased risk of falls, which can lead to serious injuries. Identifying mobility changes can help prevent these incidents. Wearable technology can facilitate mobility tests at home and alert caregivers or medical professionals to any irregularities and promote proactive healthcare. Adoption of smartwatches with various built-in sensors like accelerometer and gyroscope creates new opportunities for wearable health monitoring. We developed the Smartwatch Application Suite to evaluate functional mobility using standard mobility tests: Timed Up and Go Test, Thirty-Second Chair Stand Test, and Two-Minute Walk Test. The application suite was implemented and tested on the Samsung Galaxy 4 smartwatch. The applications process signals from inertial sensors, generate mobility parameters, and save all signals and results on the medical server. We present implementation and verification of the application suite.

Acknowledgements

I would like to thank Dr. Emil Jovanov for his encouragement and support without which I would not have pursued my thesis and come to the finish point. I would also like to thank all my professors from Electrical and Computer Engineering Department who enhanced my knowledge in various Fields of Computer Engineering like VLSI, Embedded Systems, Network Security and ubiquitous computing.

I would like to thank Dr Paolo Bonato, Luca Spagnuolo and the entire team from Motion Analysis Lab at Spaulding Rehabilitation Hospital, Boston, MA, for their help in validation of the smartwatch application.

I would like to thank Prof. Angelo Bos from Brazil for testing the smartwatch application suite on elderly patients and for providing us the results and data for the verification of the smartwatch applications. He also provided us with constant feedback on improving the application.

I thank my employer ADTRAN INC, who sponsored my graduate program at UAH.

I would like to dedicate this thesis to my parents, who supported me to pursue engineering, my wife and kids who sacrificed their valuable time and encouraged me to pursue a graduate degree and work on this thesis.

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Scientists study the word as it is, engineers create the world that never has been.

– Theodore von Karman

Chapter 1. Introduction

Assessment of mobility is very important for long-term and short-term monitoring of the health of the elderly. The Centers for Disease Control and Prevention (CDC) created the STEADI (Stopping Elderly Accidents, Deaths & Injuries) tool kit [1] for health care providers. This kit includes a set of rules and recommended tests for fall risk assessments and interventions. The CDC recommends the evaluation of gait, strength, and balance using three tests: the Timed Up and Go (TUG) test [2], the 30-Sec Chair Stand (30SCS) test [3], and the 4-stage Balance (4SBT) test [4]. There is another test called the Two-Minute Walk Test [5] that is being used in healthcare centers along with STEADI to assess mobility.

UAH has developed a suite of mobile applications running on smartphone to assess mobility and store the records on the mobile health server from 2013 to 2016 [6], [7]. In addition to smartphones, smartwatches have become increasingly important platforms for health management and ambulatory patient monitoring for several reasons:

- Convenience: strategically positioned on the wrist, smartwatches are very convenient for notifications, interaction, and continuous monitoring without additional devices.
- Accessibility: easily accessible on the wrist, smartwatches facilitate monitoring of possible falls and emergency SOS calls directly from the

smartwatch that is particularly useful for the elderly and people with certain health conditions, providing timely help when needed.

- Sophisticated sensors: smartwatches feature inertial sensors (accelerometers, gyroscopes), vital sign monitoring (PPG, SpO2, ECG, bioimpedance), temperature, UV and light sensors.
- Reminders: smartwatches can be programmed to remind users to take medications or perform other health-related tasks.

The UAH team developed the first smartwatch monitoring application for mobility assessment in 2019 [8]. This thesis presents the design and validation of the expanded suite of mobility assessment applications on a smartwatch:

- STUG – smartwatch Timed Up and Go test. The application allows the user to perform the automated test and calculate the total time, the number of steps, and step duration.
- 30SCST – Thirty-Second Chair Stand Test allows automation of the test, calculate total time of completed stands, the number of stands, and timing of individual stands.
- 2MWT – Two-Minute Walk Test automates the standard test, and calculates the total number of steps, timing of left and right steps, and their symmetry.

The Timed-Up-and-Go (TUG) test is a frequently used clinical test for the assessment of functional mobility and fall risk prediction in the elderly population and people with Parkinson’s disease, neurological and geriatric problems [9]–[11]. To monitor daily activity and to detect changes in the mobility and fall conditions, healthcare professionals administer standardized assessments manually. TUG provides an assessment of walking, turning, and postural transitions, including standing and sitting. It is a reliable and valid measure of fall prediction in older adults [12]. At the beginning of the test, a subject sits in a standard armchair. On the command ‘Go’ the subject stands up from the chair and walks to a 3 meters marker on the floor at a normal pace, turns around, walks back to the chair, and sits down again. Total time from the command ‘Go’ to end of the test is recorded using a stopwatch which is used to analyze subject’s mobility. This test is generally performed manually in the clinic using a stopwatch and results are noted down in the records.

Figure 1.1 Timed-Up-and-Go Test Phases.

The Thirty-Second Chair Stand (30SCS) test is a clinical test for the assessment of the lower body strength and endurance. In this test, a subject sits in the middle of a standard armchair with hands placed on opposite shoulders crossed at the wrists and feet flat on the floor. Back should be straights and arms are against chest. On the command ‘Go’ the subject rises to a full standing position and sits back down again. The subject should repeat stands as many times as possible in 30 seconds. Total complete stands from the command “Go” to end of the test are recorded using a notepad which is used to analyze subject’s strength of lower body. This test is generally performed manually in the clinic using a stopwatch and results are noted down in the records.

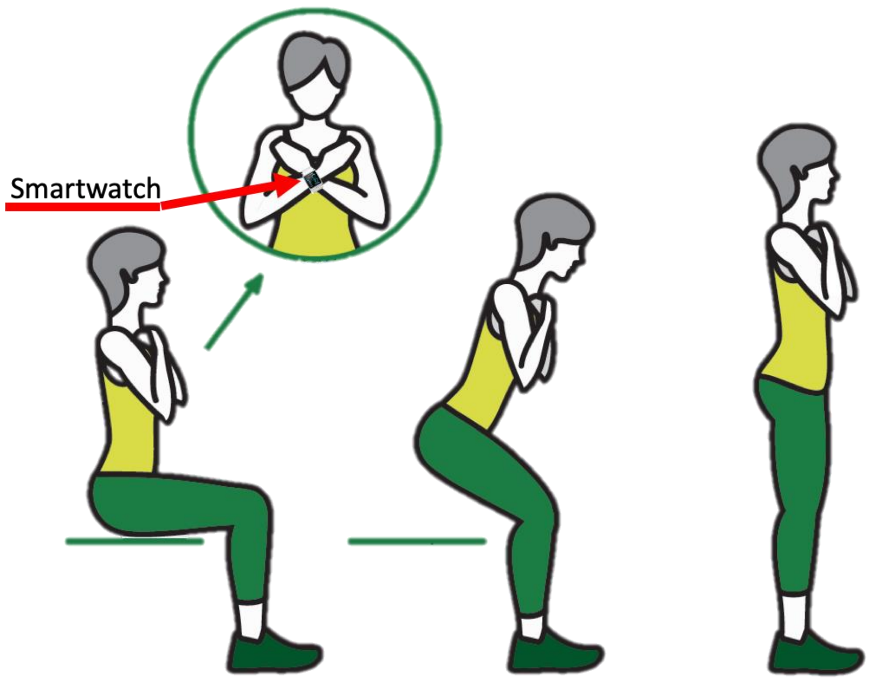

Figure 1.2 Thirty-Second Chair Stand Test.

The Two-Minute Walk Test (2MWT) is measure of self-paced walking ability and functional capacity, particularly for subjects who cannot manage the longer Six Minute Walk Test (6MWT) or 12 Minute Walk Test [13]. In this test the subject walks without assistance for two minutes and the total distance is measured. A subject sits in a standard armchair. On the command “Go” the subject stands up from the chair and walks without assistance for 2 minutes and sits down again. Walking should be at the fastest speed possible. Assistive devices can be used but not physical assistance. Total time from the command “Go” to the end of the test is recorded using a stopwatch. This test is generally performed manually in the clinic using a stopwatch and results are noted down in the records.

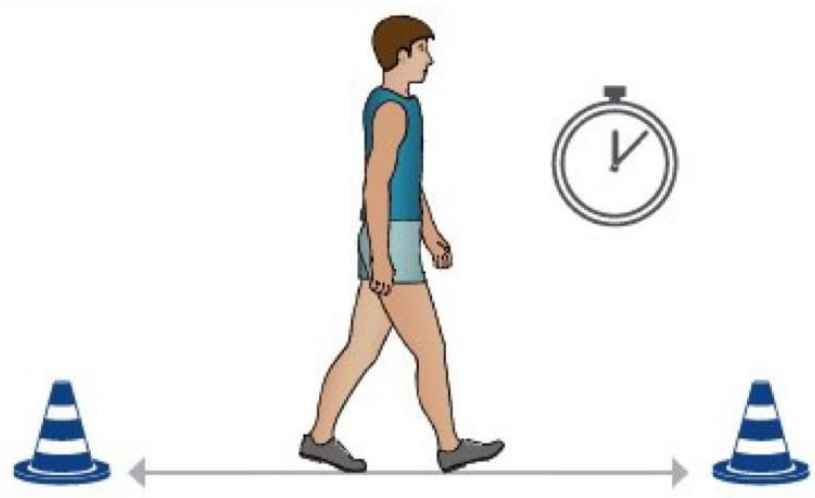

Figure 1.3 Two-Minute Walk Test.

Inertial motion tracking, which uses Inertial Measurement Units (IMUs) or inertial sensors for motion tracking, has been a hot research topic for more than two decades [15]. Typical inertial sensors, such as accelerometers and gyroscopes, are integrated into most mobile and wearable platforms and can provide different types of sensing information in different scenarios such as healthcare, smart home, automation etc.

Leading wearable operating systems like Android, Apple (iOS) and Android WearOS provide Application Programming Interfaces (APIs) that enable the reading of raw data from inertial sensors. These operating systems allow to check availability and features of available hardware sensors, register to read them at certain intervals, and unregister once application completes data acquisition [16], [17]. With increased acceptance and availability, smartwatches became the most popular wearable devices in healthcare applications. Smartwatch applications can be used to automate the manual tests, monitor vital signs and other physiological parameters, store the result on the cloud in personal medical records, administer questionnaires, and generate notifications. We expanded the previously developed 30SCST application to smartphone application suite to support more comprehensive evaluation of mobility of users.

The thesis is organized as follows. Chapter 2 presents a survey of smartwatch technology and the use of smartwatches in healthcare. Chapter 3 presents the hardware and software architecture of the smartwatch-based system used to run the applications. Chapter 4 presents the application mobility suite and details of each application in the suite. Chapter 5 discusses the validation of implemented signal processing algorithms, analysis of experimental data, and algorithms developed based on these data. Chapter 6 concludes the thesis and describes possible future enhancements of the proposed system.

Chapter 2. Wearable Monitoring of Health and Activity Using Smartwatches

Integration of sensors into smartwatches played a very important role in enabling wearable monitoring of health status and activity of the users. There are a variety of sensors available in today's wearable and mobile devices. Some sensors are accessible as physical hardware devices, and some sensors are virtual, with outputs generated in software procedures. For example, Heart Rate sensor (HR) is a software sensor in Android operating system, that will calculate average heart rate using hardware photoplethysmography (PPG) sensor. The most frequently used sensor types according to their Android name are presented in Table 1. A more detailed list of sensors is provided in Appendix A.

Table 2.1 Sensors and their properties.

Sensor	**Type**	**Description**
TYPE_ACCELEROMETER	Hardware	Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity.
TYPE_GYROSCOPE	Hardware	Measures the angular velocity in all three physical axes (x, y, z), in degrees/sec
TYPE_HEART_RATE	Software	The calculated value of the heart rate in beats per minute.
TYPE_MAGNETIC_FIELD	Hardware	Measures the ambient geomagnetic field for all three physical axes (x, y, z) in microTesla.

2.1 Smartphones for Wearable Health Monitoring

Mobile Health (mHealth) created a revolution in delivery and applications of healthcare [18], [19]. Mobile phones are used as personal servers for integration of information from individual sensors. In addition, increasingly sophisticated sensors integrated in mobile phones allow use of mobile phones as sensor platforms for diagnostic and health management.

Major mobile operating systems, such as Android, iOS, and Windows, support frameworks for managing the sensors including continual sampling, thus enabling a wide variety of new mobile sensing applications in different domains. Due to availability of these features, high performing microprocessors, communication facilities (cellular, WiFi, and Bluetooth/BLE) on the smartphone, researchers are extensively exploring smartphone-based solutions for fall detection and prevention.

Milosevic *et al.* [6], [20] developed a smartphone application called sTUG to completely automate and quantify the instrumented version of the Timed-Up-and-Go test, and facilitate testing at home and physician's office. The subject mounts a smartphone on the chest (or) belt and starts the application to capture movement by using smartphone's built-in accelerometer and gyroscope sensors.

Milenkovic *et al.*[21] presented a Smart Wheelchair that uses a smartphone to record physical activity of manual wheelchair with the help of a smartphone's built-in sensors. A Smartphone application called mWheelness was developed to capture and process activity related data and periodically upload to the mHealth server. Along with these data, the smartphone acquires heart rate data from the Zephyr Heart Monitor and logs the heart activity for processing and quantifying results.

Jovanov *et al.* [22] developed a mobile wellness monitoring system (imWell) to continuously assess the dynamic physiological response to posture transitions during activities of daily living. They used a Zephyr Bio Harness3 physiological monitor to continuously report heart activity and physical activity via Bluetooth to a personal mobile device. The personal device processes the signals from the accelerometer to recognize posture transitions in real-time, characterizes dynamic heart response to posture changes, and uploads the event descriptors to an mHealth server.

Wood *et al.*[23] developed a smartphone based mHealth application that can diagnose, track, control infectious diseases and improve efficiency of health system. They propose using either the built-in or externally connected sensors to the phone that can diagnose, analyze a condition and connect to mobile health networks through mHealth app. These data are stored and updated in the public health system and patients are provided remote consultation and care. A comprehensive review of the use of wearable technology during the pandemics was presented in [24].

Wang *et al.*[25] explored the clinical effect of continuous care for patients with type 2 diabetes using mobile health application by comparing traditional discharge nursing using a mobile phone application. Their research concluded that patients using mobile health applications and continuous care showed improvements in disease awareness, blood glucose levels and less rehospitalization.

Weisel *et al.* [26] investigated the efficacy of standalone smartphone apps for mental health. Interventions utilizing mobile apps have several benefits, such as reaching individuals who would otherwise not seek treatment and delivering large-scale interventions in emerging and low-income economies.

While smartphones applications proved to be very valuable in healthcare, they have some significant limitations. For applications to run and collect sensor data from onboard sensors in real time, phones must be attached to the patient, sometimes on body location of interest for the given application. While most of the population uses mobile phones, they are often carried in pockets, bags or placed, which significantly limits possible applications of activity monitoring.

2.2 Smartwatches as Wearable Health Monitoring Platform

A smartwatch is a wristwatch with built-in computer hardware which allows it to run specialized applications, and display information, such as the weather, calendar information, and user's activity. The smartwatch market has grown significantly over the past few years, with global market size USD 30.4 billion in 2021 and is expected to expand at a compound annual growth rate (CAGR) of 8.2 % from 2022 to 2030 [27].

Smartwatches were initially developed as fitness trackers and to complement smartphones to receive notifications from the phone applications. The latest smartwatches are more powerful with many features including support to cellular service which makes it a replacement for the smartphone [28]. The current generation of smartwatches integrates a rich set of powerful physiological sensors: inertial sensors (accelerometer and gyroscope), PPG heart rate monitor, blood oxygen saturation monitor, ECG, body composition/GSR, ambient sensors (barometer, temperature, ambient light, UV sensor), monitor/GSR, digital compass (magnetometer), GPS location, and microphone. Some of the possible uses of smartwatches include [29]:

- Heart Activity Monitoring: Most smartwatches come with built-in PPG heart rate sensors that can continuously or periodically measure heart rate that can be used as a notify users during exercise or assess fitness level. Some watches have integrated ECG sensor that can alert users to potential heart-related issues, such as atrial defibrillation and irregular heart rhythms.

- Sleep Tracking: A combination of activity monitoring and heart rate monitoring provides an assessment of the sleep patterns, including the amount of deep, light, and REM sleep. This can help in understanding sleep quality and making necessary lifestyle changes.
- Activity Tracking: Smartwatches can track various activities like walking, running, cycling, swimming, and more. They can measure steps, distance covered, calories burned, and provide data about workouts.
- Blood Oxygen Saturation (SpO2) Monitoring: Some advanced smartwatches can measure blood oxygen levels, which can be crucial for those with respiratory conditions.
- Fall Detection: Some smartwatches have fall detection capabilities. If a user takes a hard fall, the watch can send an alert. If the user does not respond within a set time, it can automatically call emergency services.
- Stress Monitoring: By analyzing variations in heart rate and other metrics, some smartwatches can estimate user's stress levels and offer relaxation reminders or guided breathing exercises.
- Blood Pressure Monitoring: While less common and often not as precise as traditional cuffs, some smartwatches offer blood pressure monitoring features.
- Environmental Alerts: Some smartwatches can provide alerts about environmental conditions that might affect health, such as high UV levels.

With the growth in smartwatch market and technological advancements like wide range of built-in sensors and support from leading players, smartwatches are becoming very popular in health care sector for regular tracking of various conditions through customized applications, diagnostic applications, and long-term monitoring. In addition to standard applications provided by the smartwatch manufacturers, there are more than 41,000 healthcare and medical applications available in the Apple app store [30].

Smartwatches are developed worldwide on different operating systems, support different hardware and come with standardized and customized applications. The most popular smartwatches include Apple, Samsung, Fitbit, Garmin, and Google. Apple and Samsung dominate the smartwatch market with their rich features, although other manufacturers increase their share of the market, particularly for low-price platforms [31]. A world-wide survey around on the most desired features in smart watches indicates that Fitness/health tracking features are the most important after battery life [32].

SmartMonitor is a company that developed an application called Inspyre that can run on both Apple or Samsung smartwatches and detects seizures [33]. The gyroscope and accelerometer of these watches are used to detect seizure like movements and use the wearer's smartphone to call a caregiver for assistance. Gutierrez *et al.* demonstrated that smartwatch with heart rate sensor and skin temperature sensor could determine if the user's Blood Alcohol Content (BAC) Level is within a certain threshold with a precision of 0.970 ± 0.002.

Lutze *et al.* [34] developed a sensor data collection app and used it to collect sensor information from different activities such as walking, eating, etc. Data mining was used on the sensor data to develop algorithms that could determine when an action performed by the wearer was a drinking motion.

Jovanov *et al.* [8] developed a smartwatch application for automation of the 30 second chair stand test (30SCST). The test measures the number of complete standups a person can perform during a 30s interval. The test is conducted using a straight back chair without arm rests, and a stopwatch. While a standard test provides only the number of completed stands, automated tests provide several additional parameters. They implemented a smartwatch application for Android Wear OS operating system and tested the application on two smartwatch platforms: Fossil Gen 4 and Polar M600. The smartwatch application collects inertial signals (3 axis of acceleration and 3 gyroscope signals) sampled at Fs=100 Hz, and heart rate provided as events in Wear OS.

Matey-Sanz *et al.* [35] present and describe a system capable of automating the TUG test using a consumer WearOS-based wrist-worn smartwatch, which collects accelerometer and gyroscope sensor data, and a paired smartphone capable of measuring and segmenting the TUG test sub-phases in real time, using sliding window feature extraction based on an offline-trained machine learning model.

Christine *et al.* [36] conducted a survey of how smartwatches work in remote health monitoring. The results show that most research on smartwatches has been conducted only as feasibility studies for chronic disease self-management. Specifically, these applications targeted various disease conditions whose symptoms can easily be measured by inertial sensors, such as seizures or gait disturbances.

2.3 Modelling of Step Detection

To analyze steps during walking, different positioning of single or multiple inertial sensors can be used. Godfrey *et al.* [37] used single accelerometers on the chest and used valley points on 3D vector magnitude to detect the start and stop of a step during walking.

Madhushri *et al.* [7] developed algorithms using both raw accelerometer and raw gyroscope signals in the smartphone application STUG to analyze and detect the steps during the test. The application also uses the smartphone's magnetic sensor data to detect turning and the number of steps before the turn.

Troung *et al.* [38] presented the precise stride counting-based method to estimate the walking distance using insole sensors. The insole sensors consisted of a triaxial inertial sensor and eight pressure sensors. The authors estimated the traveling distance based on the number of strides extracted from the phase information. However, they only considered the walking distance estimation of normal walking on flat ground.

Ho *et al.* [39] developed a method of walking distance estimation based on an adaptive estimator of the step length and robust step detection. The presented method successfully estimated the traveling distance at three speed levels and four different distances.

In most common approaches, all processed activities data are directly fed to an adaptive step detector without classifying the performing activities. It is more effective if the activities are classified because the thresholds of the acceleration values depend on the type of activities. Susi *et al.*[40] proposed adaptive step detection by analyzing the characteristics of the gait cycle, which included the hand motion and carrying-mode difference of a pedestrian using a smartphone. The authors detected the motion modes, *e.g.*, swinging, texting, phoning, bag carrying and irregular motion, before applying the step detection algorithm on the collected inertial signals.

Bui *et al.* [41] implemented robust step detection and adaptive distance estimation algorithm based on the classification of five daily wrist activities (phone texting, phone calling, hand in pocket, suitcase carrying and hand swinging.) while walking at various speeds using a smart band. Park et al demonstrated that the arm and foot movements were synchronized during walking [42]. This relationship is used by Troung Bui et al to detect the step events by analyzing the acceleration data from the smart band [43].

Matey-Sanz *et al.*[44] implemented a smartwatch application that allows the user to start the data collection process (for ML model training) or to start the execution of the TUG test. When instructed, the smartwatch starts the data collection process and sends the collected data on a regular basis to the paired smartphone device through Bluetooth. In COLLECTION mode, the smartphone stores the incoming data into a file to offline-train the model later. In TUG mode, the smartphone device processes the incoming data in real time and infers the current activity that the user is performing. Once the smartphone detects that the user has finished the test *(i.e.*, the user sat down), it prompts the smartwatch to stop the data collection process, computes the test results, and sends the total time of the test to the smartwatch to provide feedback to the user.

Chapter 3. Hardware and Software Architecture of the Smartwatch

We used a Samsung Galaxy Watch 4 [45] to develop and test the smartwatch applications in this project.

3.1 Hardware Architecture

The Samsung Galaxy Watch has Exynos W920 (5nm) Dual Core 1.18GHz processor, 16 GB Storage with 1.5GB of RAM. It has all the inertial sensors and connectivity through Bluetooth, Wi-Fi, LTE. It has a Super AMOLED display.

Figure 3.1 Samsung Galaxy Watch 4 Default Screen and App Screen.

The Samsung Galaxy Watch 4 is Compatible with devices Android 6.0 or higher. Watch activation is done after connecting to compatible Android device. This smartwatch needs “Galaxy Wearable app” on the compatible Android device to activate. Later apps on the smartwatch can be managed using this Galaxy Wearable app [Appendix A].

3.2 Software Architecture

Samsung Galaxy Watch 4 supports Wear Operating System (Wear OS) version 4 co-developed by Google and Samsung. Wear OS 4 [46] is based on Android, which allows integrated development environment like Android Studio [47] to develop customizable applications for smartwatches. The availability of all inertial sensors in one device along with various connectivity options makes this smartwatch a powerful embedded sensor platform. This allows developers in various fields to design and create a variety of new and exciting health applications.

This sensor data can be used to design applications based on the needs of the user. Wear OS Application consists of a sequence of activities with each activity consisting of a group of user interface views. Events allow users to create buttons, text boxes, list view and other view objects that are defined using Extensible Markup Language (XML).

The Android Sensor consists of a list of sensor implementation classes. Each sensor implementation class allows the user to acquire and log data from embedded sensors such as accelerometer and gyroscope. The Sensor Coordinate System uses a standard 3-axis coordinate system to express data values. When a device is laid down horizontally, the X axis points to the right, the Y axis points up in the same plane, and the Z axis points vertically from the smartwatch, as shown in **Figure 3.2**.

Figure 3.2 Coordinates of inertial sensors in smartwatch.

The *Sensor Manager* class is the super class which gives primary access to all hardware sensors. Each hardware sensor is listed as a service where the *Sensor Manager* class allows the user to register (enable) and un-register (disable) each service. The Sensor event listener is an interface that provides the callbacks created by sensor related events executed by the user provide procedures. *Sensor Event* is an object that contains all the information that is passed to an application when a hardware sensor has some information to report. A sensor event object is passed from sensor system service to callback methods on Sensor event listener. The listener processes the data in the sensor event object in an application specific manner. It is important that acquiring values from a sensor should not be implemented inside an activity as it might cause time delays and dropped data. This is because Android is not a Real Time Operating System (RTOS) and some measured values might be delayed due to the processing of other tasks at that time (or) system might be busy performing other high priority jobs.

The best practices for accessing and using sensors are the following:

- Verify sensor existence in the device before attempting to acquire data from the sensor.
- Request for necessary permissions to access the sensors.
- Register for sensors (enable) only when needed and un-register (disable) sensors after recording data samples.
- Check and configure sampling rate that is suitable for the application, since the sensors can provide data at high sampling rates, at a higher use of resources (processing time, memory, and power).

3.3 Android Activity Life Cycle

The Android Activity Life Cycle is the set of states that an activity goes through during its lifetime. It is designed as a series of callback methods that the Android framework calls on the activity as the activity transitions from one state to another. The lifecycle consists of seven different states.

- **onCreate():** Called when the activity is first created. Used to initialize the activity and its views.
- **onStart():** Called when the activity becomes visible to the user, but not yet in the foreground and interacting with the users.
- **onResume():** Called when the activity comes to the foreground and is interacting with the user.

- **onPause():** Called when another activity comes to the foreground and the current activity is no longer in the foreground.
- **onStop():** Called when the activity is no longer visible to the user.
- **onDestroy():** Called when the activity is about to be destroyed. Used to cleanup and release resources.
- **onRestart():** Called when the activity has been stopped and is restarting.

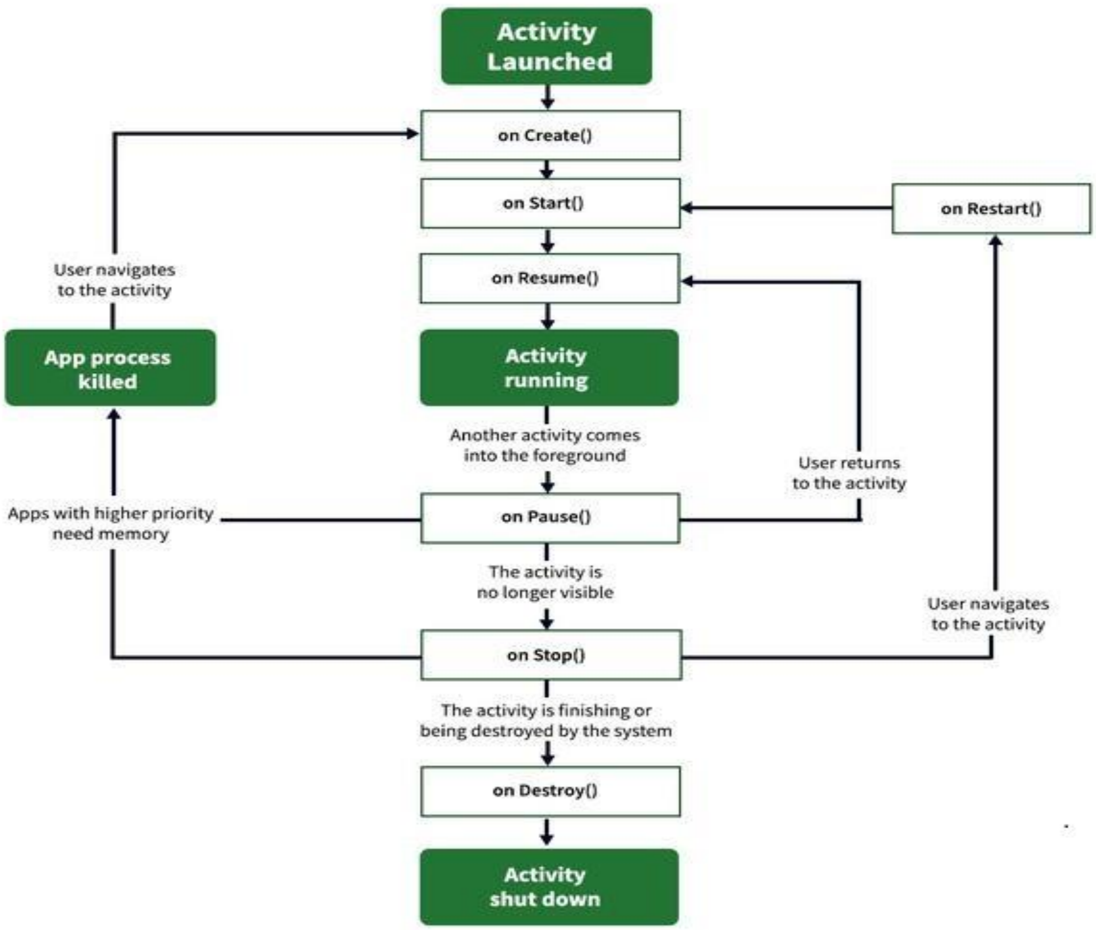

Figure 3.3 Activity Lifecycle in Android.

3.4 Development Environment

Android studio chipmunk version is used as IDE and java as programming language to develop the applications.

3.5 Publishing the Results

Results from each of the applications will be published using Message Queuing Telemetry Transport (MQTT) [48] Protocol. It is designed as an extremely lightweight publish/subscribe messaging transport that is ideal for connecting remote devices with a small code footprint and minimal network bandwidth. It is standard messaging protocol for the Internet of Things (IoT). There are clients which can either publish the messages to broker or subscribe to notifications from broker as shown in **Figure 3.4.**

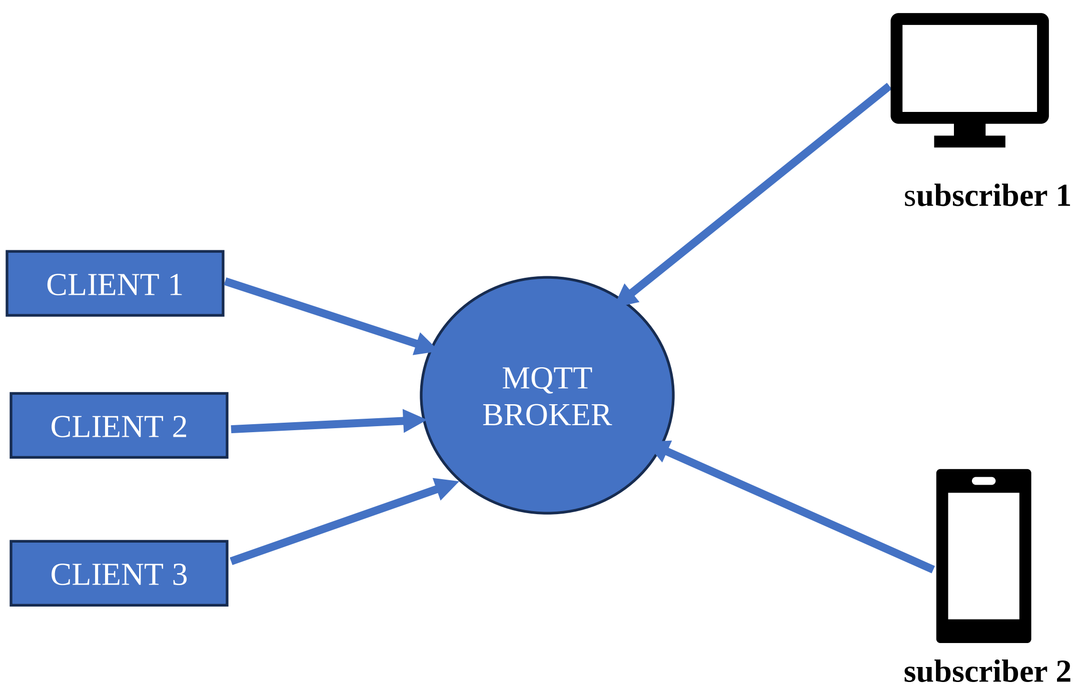

Figure 3.4 MQTT Client Broker Architecture.

These results are displayed instantly when a broker subscribes to the server. We use mosquito [49] server to publish the results and use MQTTAnalyzer phone Application [50] as Broker to subscribe and display the results.

Chapter 4. A Smartwatch Application Suite

A smartwatch Application Suite was developed consisting of the STUG, 30SCST and 2MWT that automate the standard Time Up and Go, 30 Seconds Chair Stand and 2 Minute Walk tests.

4.1 STUG Application

4.1.1 Design and Architecture

The STUG (Smart Timed Up and Go) application is designed and developed to calculate the time it takes to finish TUG test and mean step duration using the sensor values from accelerometer, gyroscope collected during the test at a sample rate of 100Hz. The application contains Start, Stop and Close (Result) Views as shown in **Figure 4.1**.

Figure 4.1 STUG Views.

The Application starts when the user clicks the START button. It registers and starts recording heart rate from the HR sensor. View is changed to display with a 15 second countdown timer and STOP button. Once the countdown timer reaches zero, the application registers for accelerometer, gyroscope sensors and starts recording the signal. It vibrates indicating the user to start the test. After the user finishes the TUG test, the user clicks on the STOP button that will stop recording accelerometer, gyroscope signals and unregister them. The application will continue to record heart rate and physical recovery of the subject for another 15 seconds. During this time, the countdown timer is displayed; at the end the display changes to RELAX. At the countdown of zero, the application generates a vibration to indicate the end of test, stops recording HR data and unregisters the HR sensor. Display changes to CLOSE showing the total TUG time. Clicking on the CLOSE button will take the user to the application home screen with the START option to test again.

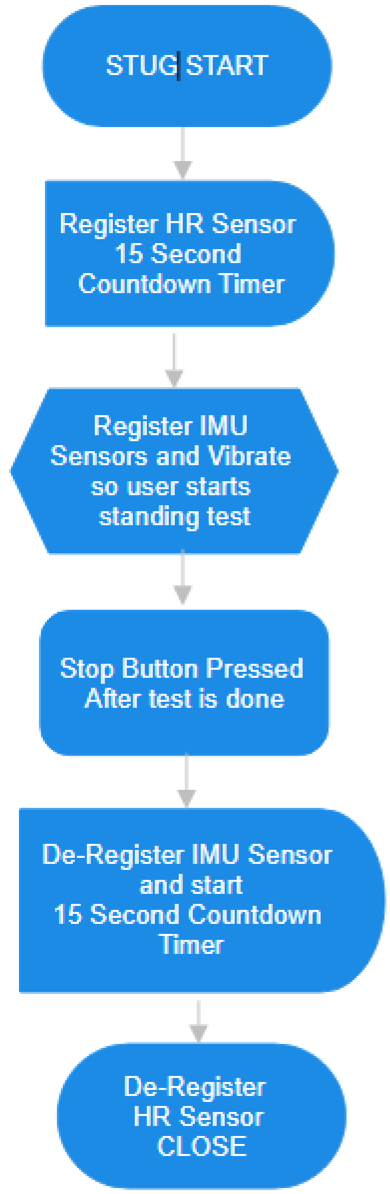

Figure 4.2 STUG Application Flowchart.

4.1.2 Experimental Data Collection

All the sensor data captured during the test is uploaded to a preconfigured ftp server in 3 different text files, one for IMU, one for HR and one to store Result.

4.1.3 Results Data in Health Server

Results from the STUG application are instantly uploaded to preconfigured Health Server using MQTT protocol as shown in **Figure 4.3.**

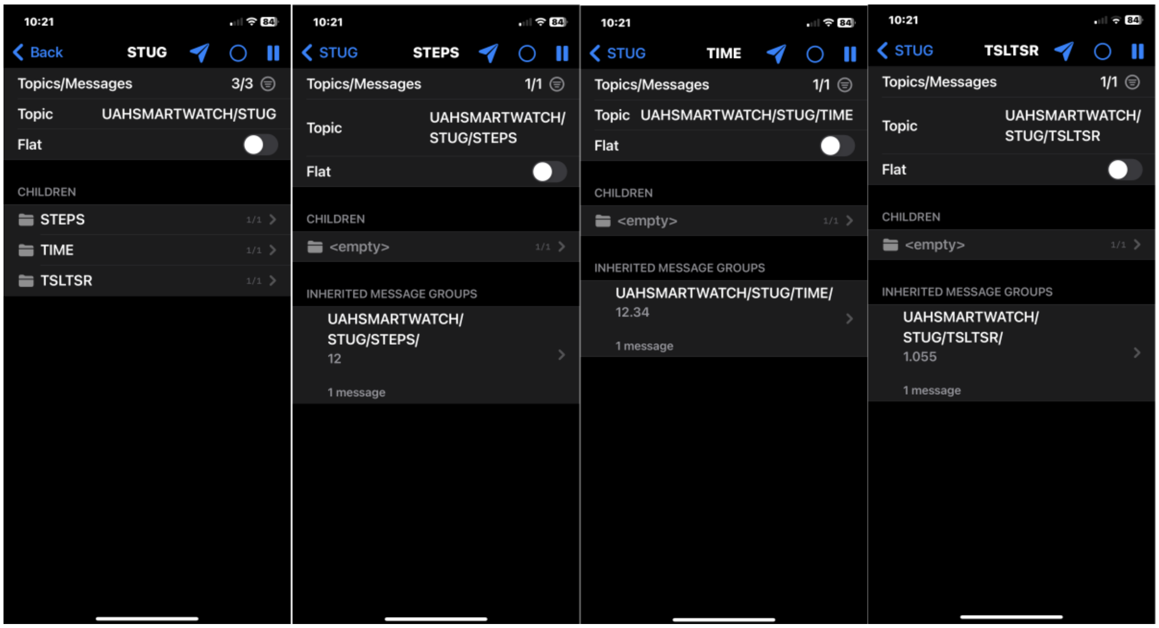

Figure 4.3 STUG Results Stored in Server.

4.2 30SCST Application

4.2.1 Design and Architecture

The 30SCST (30 Seconds Chair Stand Test) application is designed and developed to calculate number of stands a subject can perform from a chair in 30 seconds using the sensor values from accelerometer, gyroscope collected during the test at a sample rate of 100Hz. The application contains Start, Stop and Close (Result) Views as shown in **Figure 4.4**.

Figure 4.4 30SCST Views.

The Application starts when the user clicks the START button. It registers and starts recording heart rate from the HR sensor. View is changed to display with a 15 second countdown timer and STOP button. Once the countdown timer reaches zero, the application registers for accelerometer, gyroscope sensors and starts recording the signal. It vibrates indicating the user to start the test. At the end of 30 seconds, the application will stop recording accelerometer, gyroscope signals and unregister them. It vibrates indicating user to stop the test and rest while continuing to record heart rate and physical recovery of the subject for another 15 seconds. During this time, the countdown timer is displayed. At the countdown of zero, the application generates a vibration to indicate the end of test, stops recording HR data and unregisters the HR sensor. Display changes to CLOSE showing the total time and number of stands calculated by Algorithm. Clicking on the CLOSE button will take the user to the application home screen with the START option to test again.

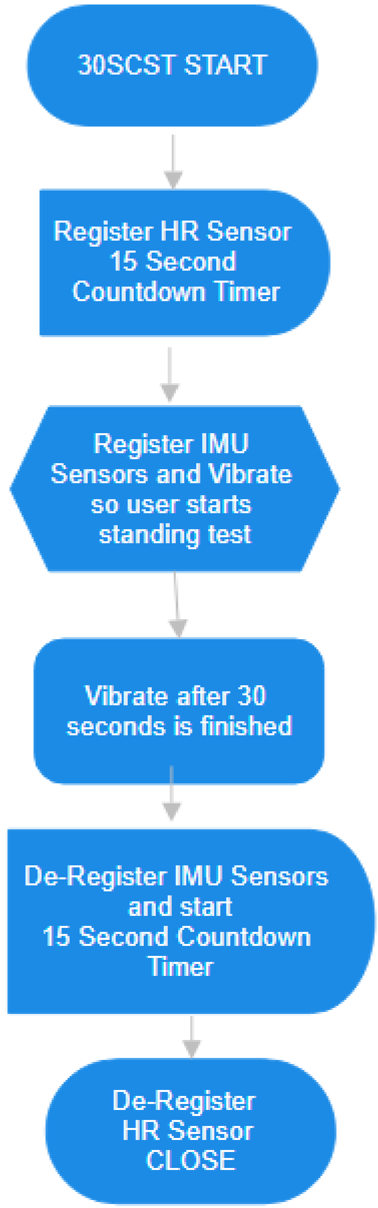

Figure 4.5 30SCST Application Flowchart.

4.2.2 Experimental Data Collection

All the sensor data captured during the test is uploaded to a preconfigured ftp server in 3 different text files, one for IMU, one for HR and one to store Result.

4.2.3 Results Data in Health Server

Results from the 30SCST application are instantly uploaded to preconfigured Health Server using MQTT protocol as shown in **Figure 4.6**.

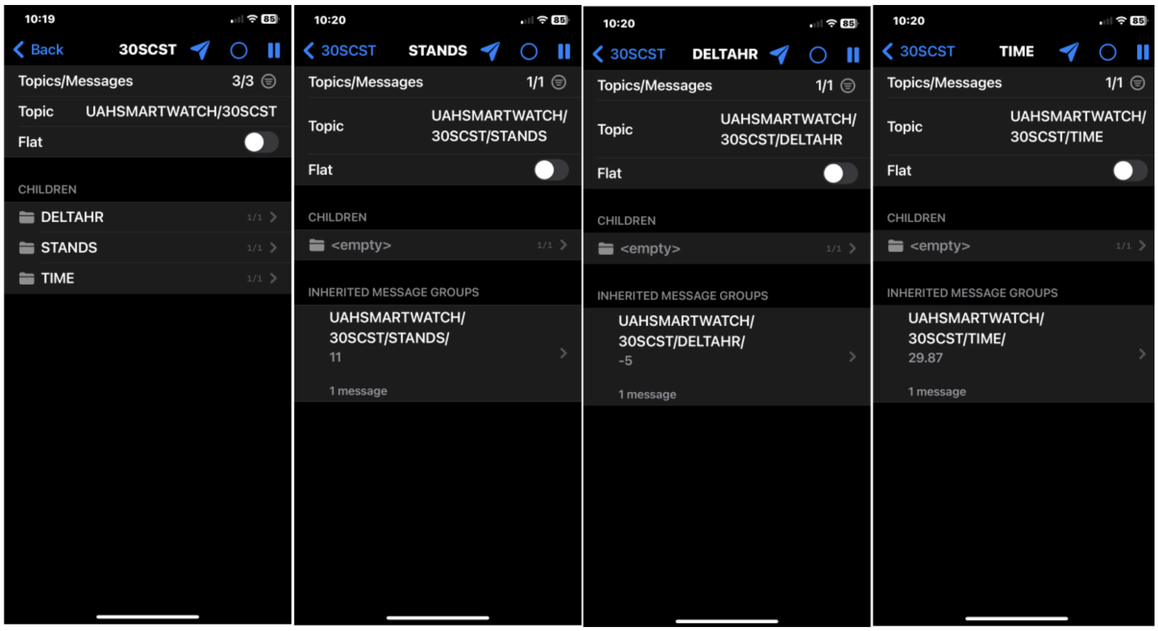

Figure 4.6 30SCST Results Stored in Server.

4.3 2MWT Application

4.3.1 Design and Architecture

The 2MWT (2 Minute Walk Test) application is designed and developed to calculate the total number of steps taken in 2 minutes and mean step duration using the sensor values from accelerometer, gyroscope collected during the test at a sample rate of 100Hz. The application contains Start, Stop and Close (Result) Views as shown in **Figure 4.7**

Figure 4.7 2MWT Views.

The Application starts when the user clicks the START button. It registers and starts recording heart rate from the HR sensor. View is changed to display with a 15 second countdown timer and STOP button. Once the countdown timer reaches zero, the application registers for accelerometer, gyroscope sensors and starts recording the signal. It vibrates indicating the user to start the test. At the end of 30 seconds, the application will stop recording accelerometer, gyroscope signals and unregister them. It vibrates indicating user to stop the test and rest while continuing to record heart rate and physical recovery of the subject for another 15 seconds. At the countdown of zero, the application generates a vibration to indicate the end of test, stops recording HR data and unregisters the HR sensor. Display changes to CLOSE showing the total steps. Clicking on the CLOSE button will take the user to the application home screen with the START option to test again.

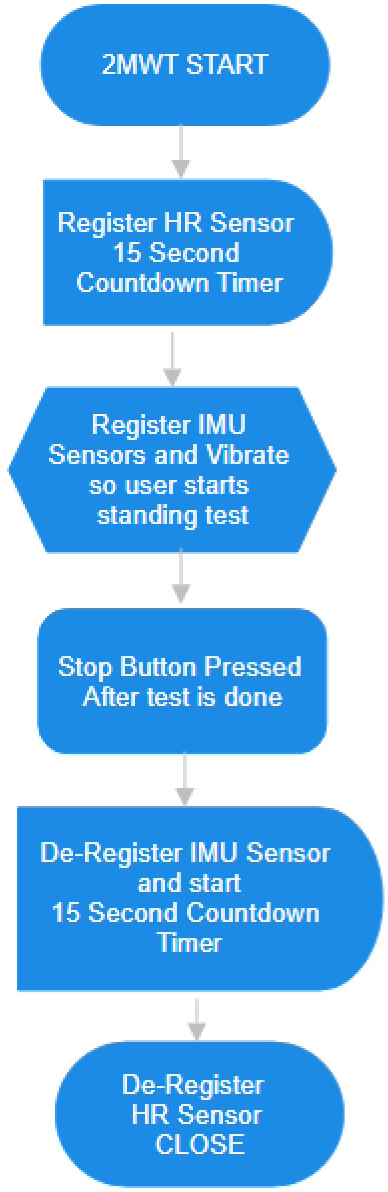

Figure 4.8 2MWT Application Flowchart.

4.3.2 Experimental Data Collection

All the sensor data captured during the test is uploaded to a preconfigured ftp server in 3 different text files, one for IMU, one for HR and one to store Result.

4.3.3 Results Data in Health Server

Results from the 2MWT application are instantly uploaded to preconfigured Health Server using MQTT protocol as shown in **Figure 4.9**.

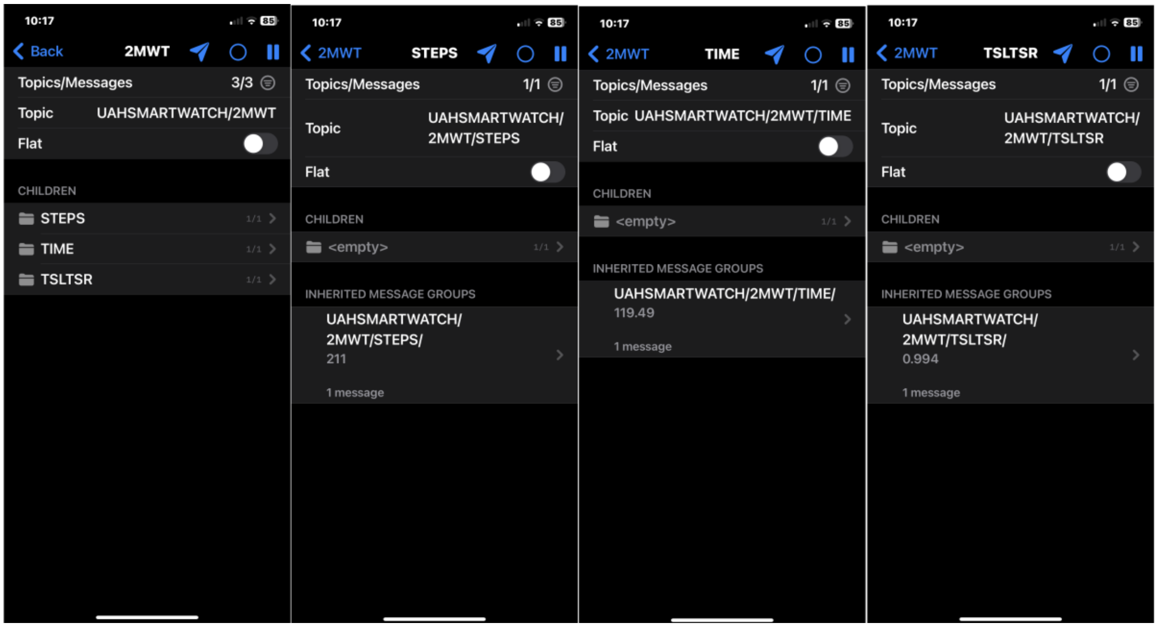

Figure 4.9 2MWT Results Stored in Server.

Chapter 5. Validation of Mobility Application Suite

Validation of the smartwatch applications requires sophisticated monitoring of absolute position of body segments during the test. Clinical standard is the use of high precision optical systems that track reflective markers on the body with high spatial (<1mm) and temporal (<10ms) resolution. One of the best optical systems for motion tracking is Vicon [51]. A low-tech option is analysis of synchronized video recordings of subjects during the test. However, maximum time resolution in that case is limited to the frame rate, typically 33 ms, and it is highly subjective, different experts may annotate different frames as actual events (*e.g.* end of standup, or actual moment when leg touches the ground).

Spaulding Rehabilitation hospital as a part of Harvard Medical School in Boston, MA, uses Vicon system for clinical evaluation of mobility of patients, mostly stroke and Parkinson's patients. We asked Dr. Paolo Bonato, Director of the Motion Analysis Laboratory at Spaulding Rehabilitation Hospital [52], Boston MA, for simultaneous recording of body markers and inertial signals from our smartwatch application. Dr. Bonato is an Associate Professor in the Department of Physical Medicine and Rehabilitation, Harvard Medical School, Boston MA, an Adjunct Professor of Biomedical Engineering at the MGH Institute of Health Professions, Boston MA, and an Associate Faculty Member at the Wyss Institute of Biologically Inspired Engineering at Harvard University, Boston, MA. The Motion Analysis Lab (MAL) at Spaulding Rehabilitation Hospital brings state-of the art technology and internationally recognized expertise to the study and treatment of mobility-limiting conditions, including cerebral palsy, stroke, traumatic brain injury, spinal cord injury and Parkinson's Disease. The lab is one of the country's pre-eminent research labs in the development of ground-breaking robotics and wearable technology for patient rehabilitation. We were not able to test smartwatch applications on real patients at the hospital until a dedicated IRB approval of the Spaulding hospital.

Accurate testing of mobile applications requires testing on real subjects, because of the unique motion patterns. UAH established close collaboration with Prof. Ângelo José Gonçalves Bós, Professor of the School of Medicine of Pontifical Catholic University of Rio Grande do Sul (PUCRS). Prof. Bos is a Researcher at the Institute of Geriatrics and Gerontology (IGG) where he coordinates de Research Project Multiprofessional Care for the Oldest-Old. He also coordinates the Program "Assumindo o Controle de sua Saúde" for the Pan American Health Organization (Brazilian branch). He was the President of City Council of the Older-Adults of Porto Alegre (2014-2016) and the Brazilian Society of Geriatrics and Gerontology RS Branch between 2012 and 2014. His expertise includes longitudinal data analysis. Prof. Bos used our smartwatch applications to collect smartwatch recordings from subjects in his studies using standard mobility tests. We had to analyze records using video recordings of subjects during the test, synchronized with the smartwatch recordings. However, these recordings were very valuable as they represent real elderly subjects and capture unique motion patterns.

5.1. Methods

MAL uses Vicon systems with 10 cameras that allow absolute positioning of 3D markers with millimeter resolution and sampling frequency of 120Hz. We simultaneously recorded the position of markers as shown in **Figure 5.1**, and the stream of data from the inertial sensors on the smartwatch in our application.

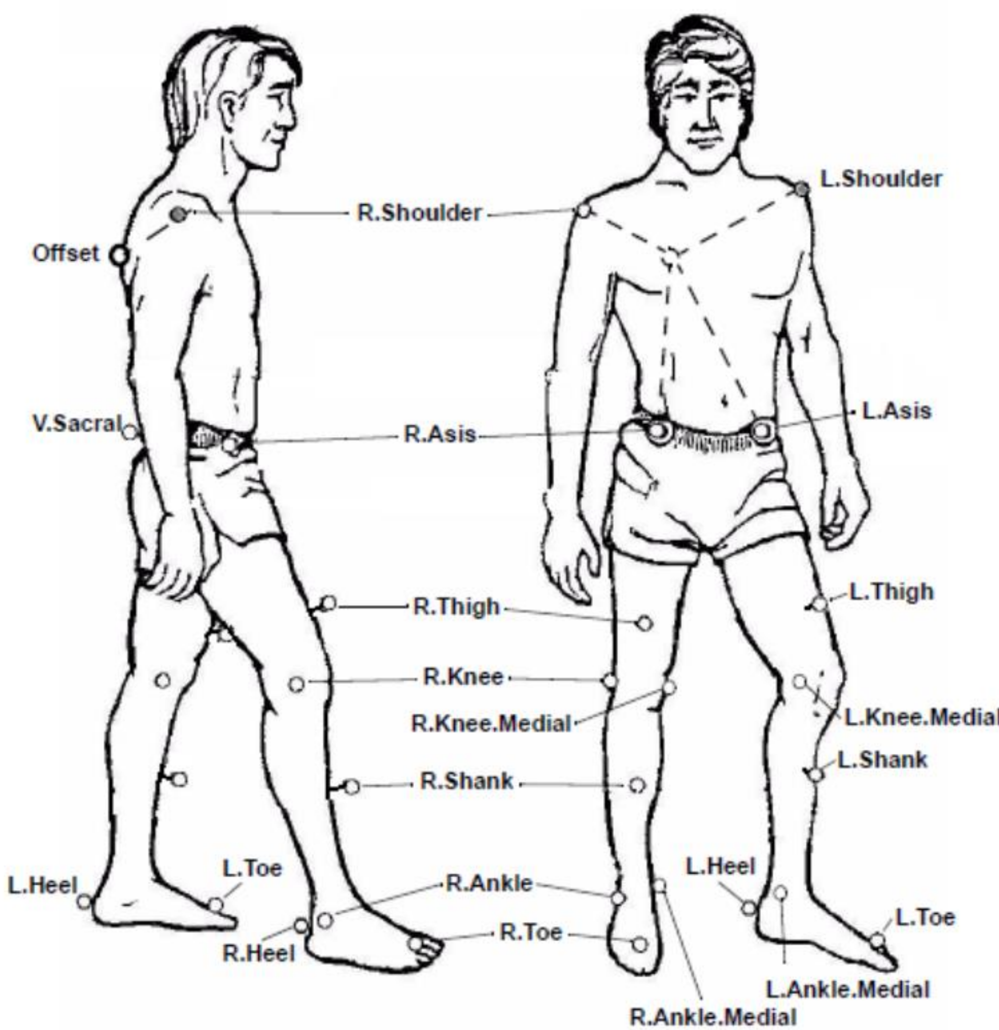

Figure 5.1. Position of markers for monitoring of motion during STUG and 30SCST validation in MAL Laboratory.

The recording data from all the sensors is captured simultaneously along with the smartwatch data. Since applications on the smartwatch are running at 100 Hz, accelerometer and gyroscope signal is resampled at 120 Hz to synchronize with MAL data.

Prof. Angelo Bos from Pontifical Catholic University of Rio Grande, Brazil, ran the smartwatch applications in elderly care ran smartwatch application on patients and provided us with videos and sensor data.

We also recorded each of the tests on individual subjects(S2&S3) using an iPhone camera with 30fps and smartwatch application running at 100 Hz. Videos are annotated for manual steps and compared with the results generated by the algorithm running in the smartwatch application.

5.2. STUG Analysis and Algorithm

5.2.1 Raw Signal Data Analysis

We used the Right Heel and Left Heel sensor data from MAL and identified the steps as shown in **Figure 5.2**.

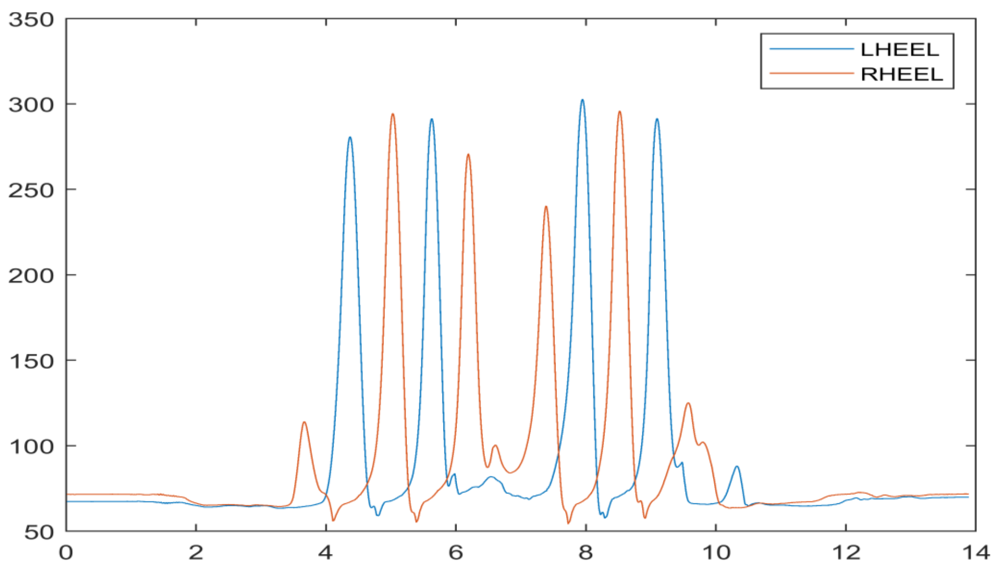

Figure 5.2 TUG step detection using absolute position of heel markers from Vicon data.

Annotations from the Vicon data allowed precise time stamps for each step. We were able to confirm that the peaks of accelerometer magnitude and gyroscope component *Gz* zero crossing, could be used to find the absolute steps as shown **Figure 5.3**.

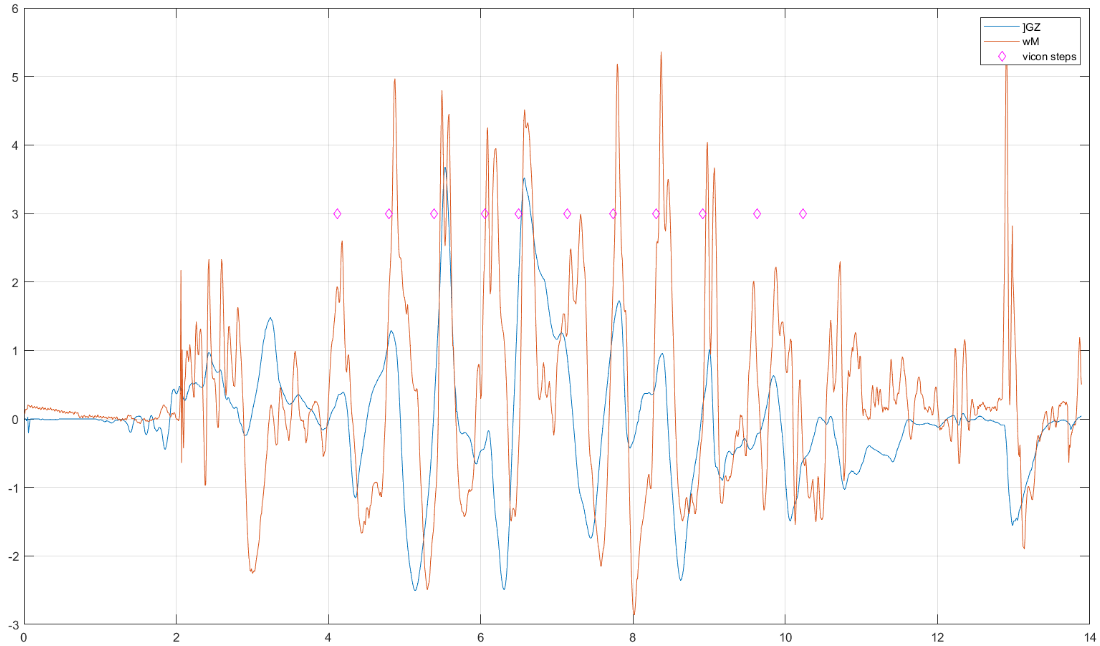

Figure 5.3 STUG Manual annotations from Vicon video recording.

Making annotations from the iPhone at 30fps and using the Accelerometer magnitude and Gyroscope Gz zero crossing, we could find the absolute steps on two trials is shown **Figure 5.4** and **Figure 5.5**.

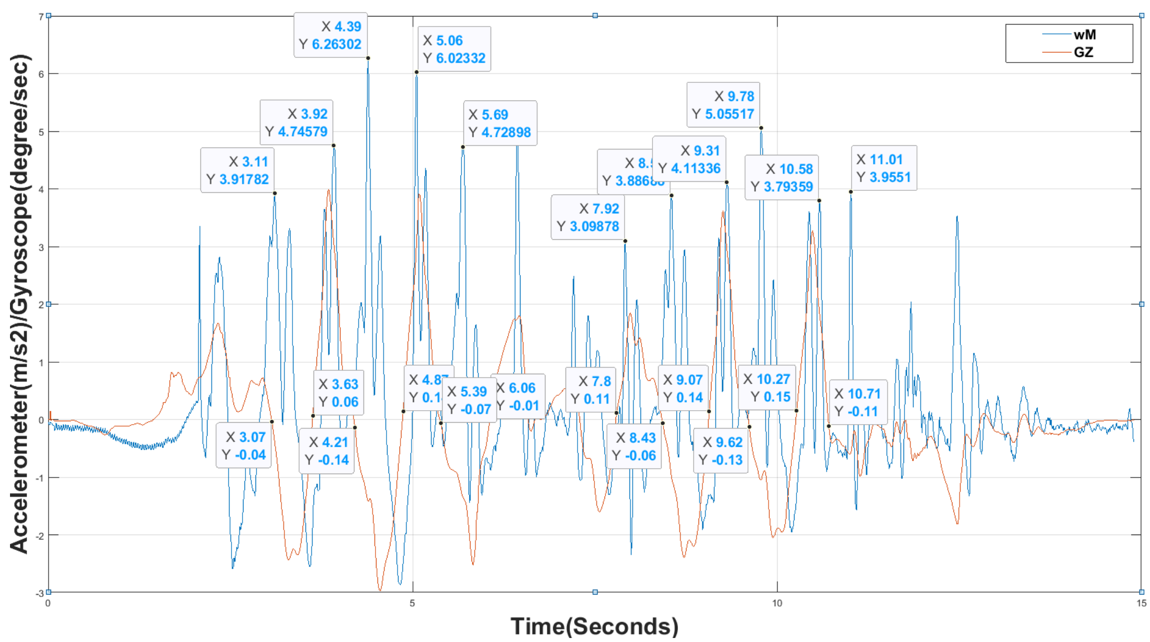

Figure 5.4 STUG Manual steps annotations from iPhone video recording -Trial1.

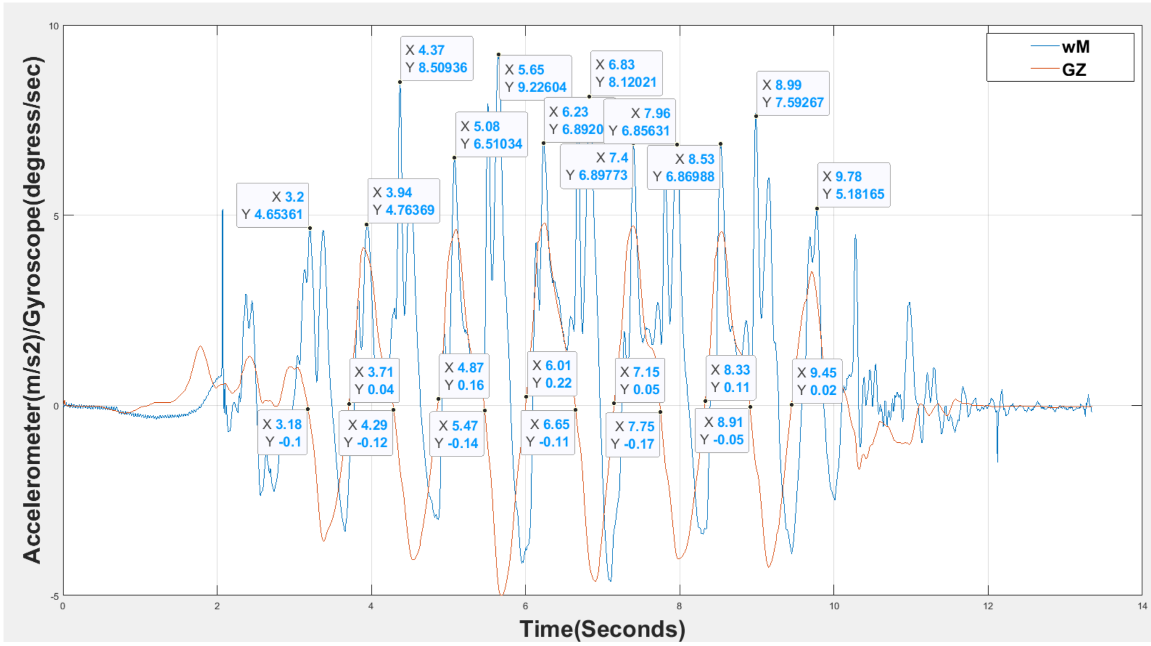

Figure 5.5 STUG Manual steps annotations from iPhone video recording -Trial2.

5.2.2 Algorithm Based on IMU Sensors

Based on the manual annotations above, we developed an algorithm to calculate steps based on sensor values from Accelerometer and Gyroscope. as shown in **Figure 5.6.**

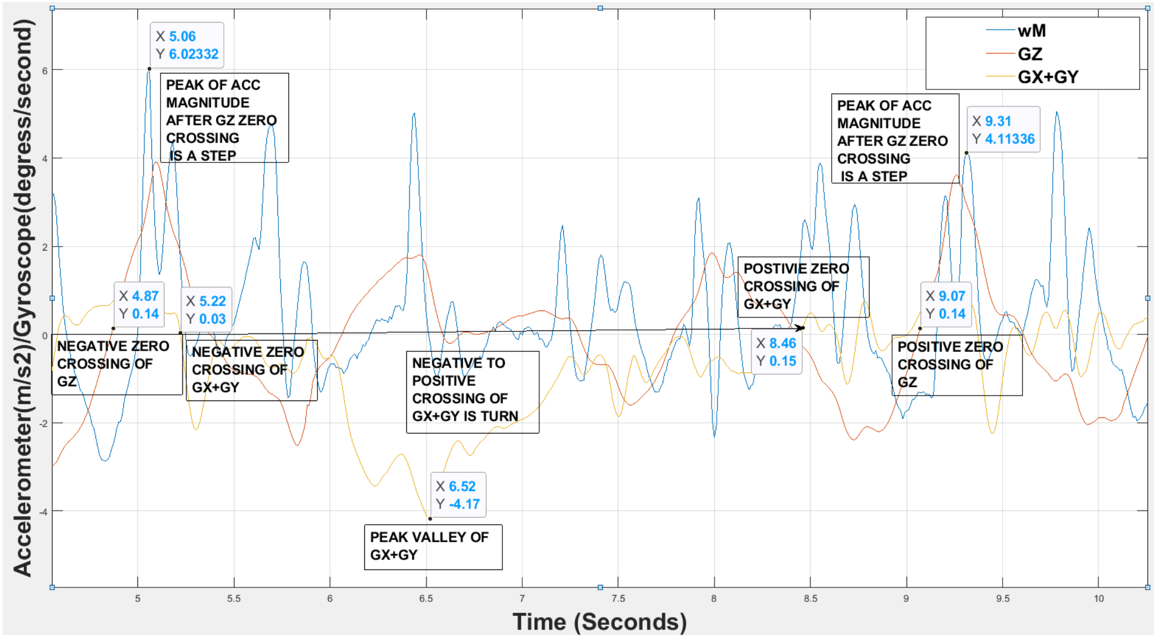

Figure 5.6 STUG Algorithm Annotations.

- Calculate magnitude of the dynamic 3D acceleration with gravity subtracted (wM) and find peaks.
- Store GyroZ and annotate indices of the zero crossing samples.
- Store and calculate peak valley for combined angular velocity (GyroX+GyroY).
- Find the first peak of wM after every zero crossing, which gives us the individual steps.
- Ignore the steps that fall in peak valley of GyroX+GyroY as they account for turns.
- Total time of the test is the timestamp of the last sample in the IMU vector.

5.2.2 Results

Results of validation of STUG application using Vicon and video data analysis is shown in Table 5.1. We present results from three subjects, one using Vicon (S1) and two (S2&S3) using video analysis [53]. Primary focus in this analysis was possible use for assessment of stroke rehabilitation patients. Therefore, we tried to assess timing of individual steps on each side and symmetry of left and right steps. During recovery and rehabilitation from stroke it is important to quantify recovery, and we implemented symmetry of left and right steps as a quantitative measure of their recovery. We can use only full steps before and after the turn, shown as Left and Right steps in the table. Average duration of Left/Right steps is presented as TsL/Tsr, together with the standard deviation of step duration on each side. Symmetry of step duration is presented and calculated as shown in equations (1) and (2).

$$LRratio = TsL/TsR \quad (1)$$

$$Symm = (TsL-TsR)/(TsL+TsR) \quad (2)$$

Table 5.1 STUG Results.

	S1	S2	S3
Vicon/video			
No. of steps (L/R)	5/4	5/6	3/4
TsL (step time Left)	0.653	0.578	0.569
TsR (step time Right)	0.605	0.607	0.687
stdev(TsL)	0.076	0.023	0.061
stdev(TsR)	0.018	0.054	0.042
ratio TsL/TsR	1.08	0.95	0.83
symmetry(TsL/TsR)	0.04	0.02	-0.09
Smartwatch app			
No. of steps (L/R)	3/2	3/5	3/4
TsL (step time Left)	0.656	0.553	0.55
TsR (step time Right)	0.567	0.626	0.71
stdev(TsL)	0.085	0.012	0.062
stdev(TsR)	0.109	0.05	0.042
ratio TsL/TsR	1.16	0.88	0.77
symmetry(TsL/TsR)	0.07	-0.06	-0.13
Errors			
TsL (mean/std)	0.003/0.01	0.025/0.017	0.019/0.049
TsR (mean/std)	0.038/0.089	0.019/0.017	0.02/0.035

$$\frac{TsL - TsR}{TsL + TsR}$$

Average error in the assessment of individual steps was 27ms, maximum error was 89ms, and error in the assessment of symmetry of left and right steps for each subject is shown below.

5.3. 30SCST Analysis and Algorithm

5.3.1 Signal Data Analysis

We used the Right Wrist and Left Wrist sensor data from MAL and identified individual stands, as shown in **Figure 5.7**. Inertial signals from the smartwatch are shown in **Figure 5.8**.

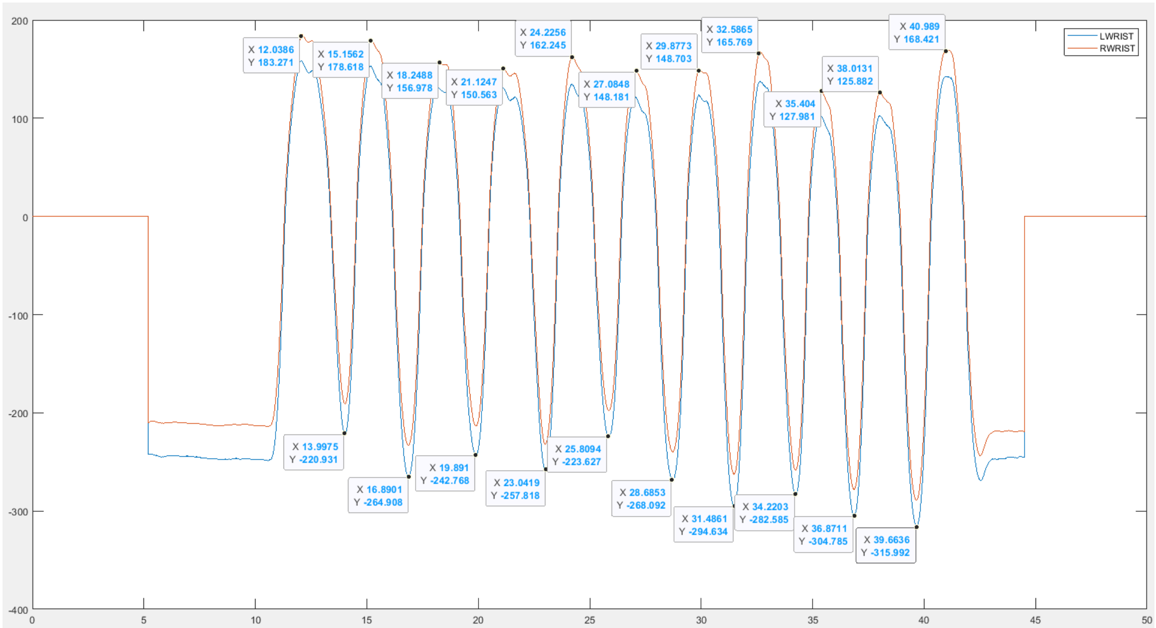

Figure 5.7 30SCST Manual annotations and stand detection from Vicon Data.

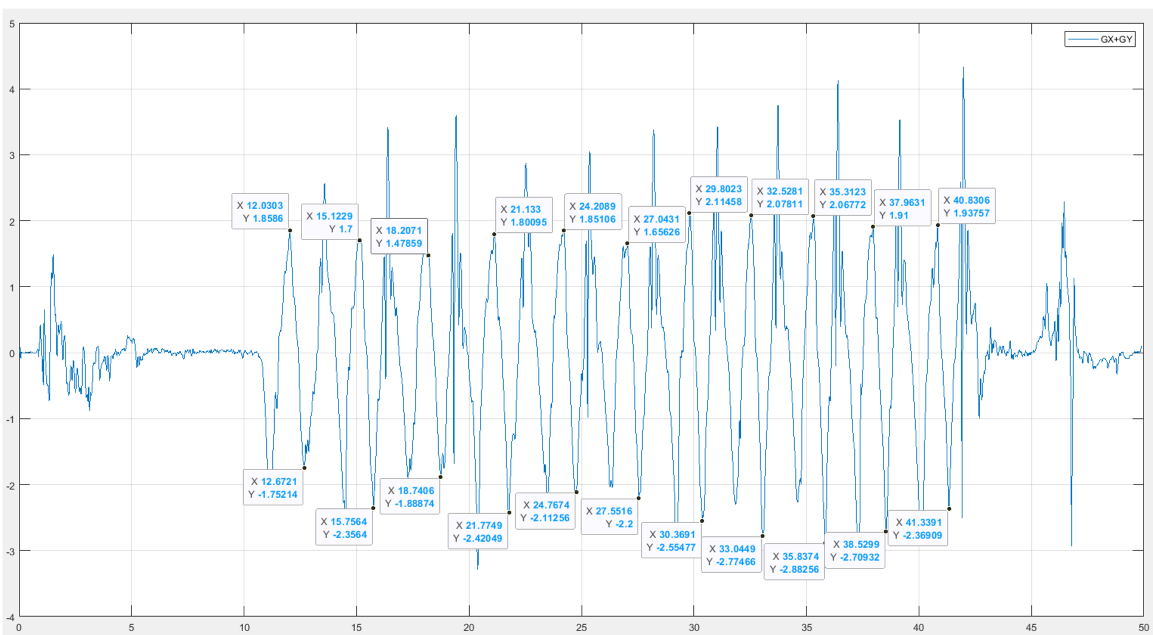

Figure 5.8 30SCST Manual stand annotations from Vicon Trial.

Making annotations from the video at 30fps and using zero crossing of the combined angular velocities (Gyroscope Gx + Gy), we could find the absolute steps on two trials is as shown in **Figure 5.9** and **Figure 5.10**.

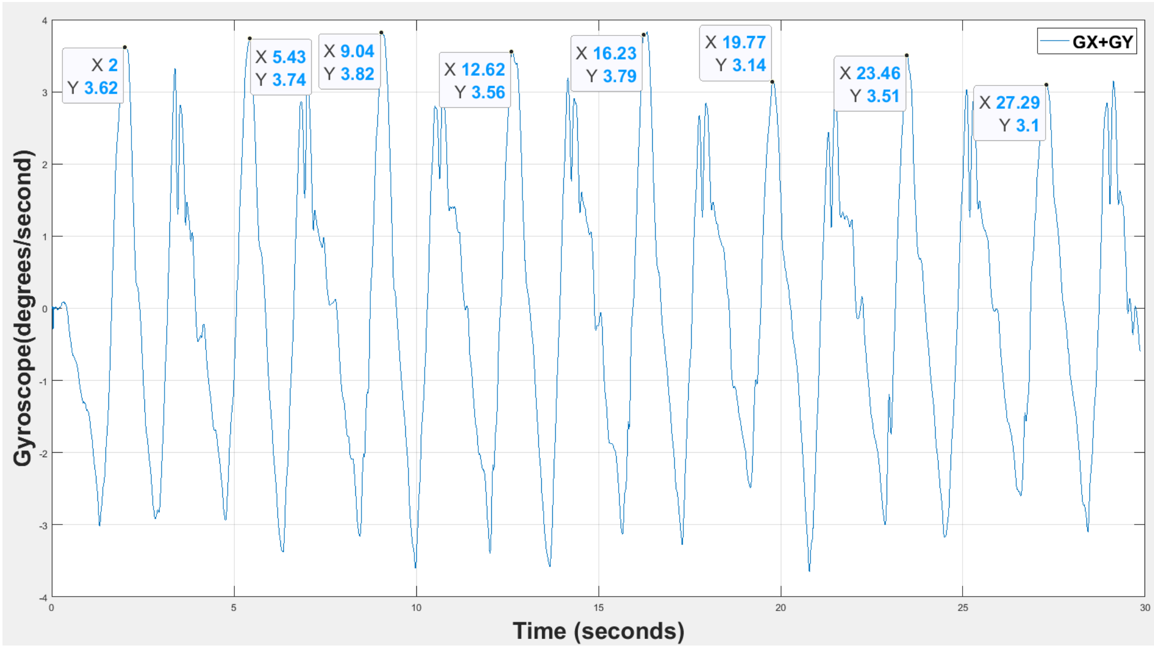

Figure 5.9 30SCST Manual stands annotations from video recording -Trial1.

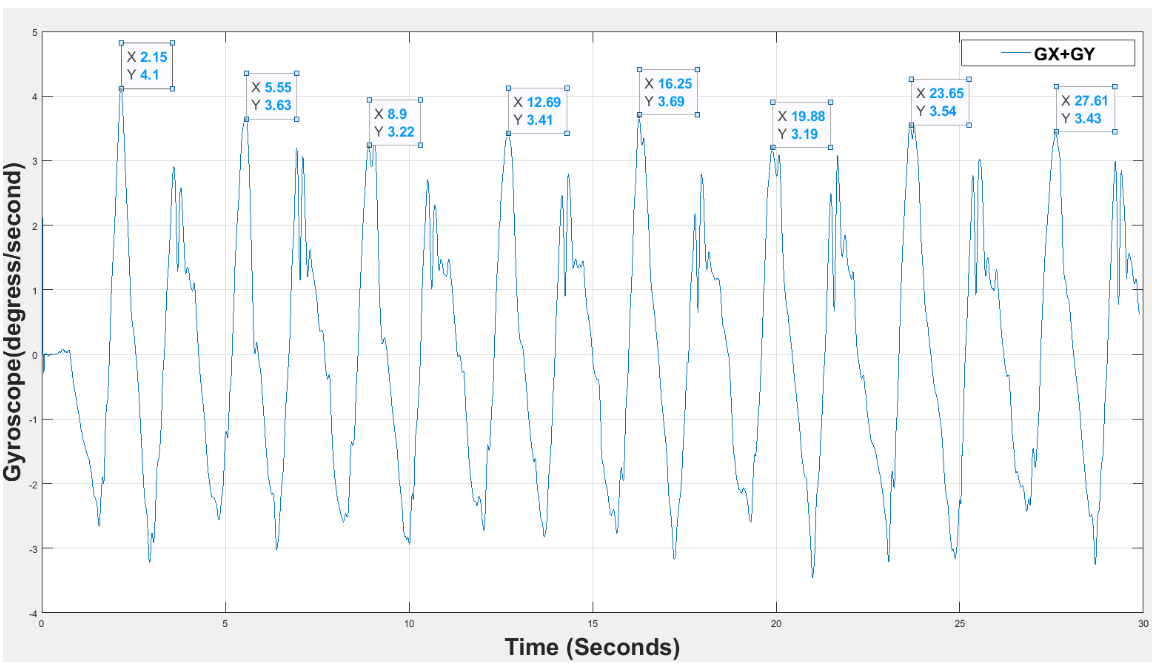

Figure 5.10 30SCST Manual stands annotations from video recording -Trial2.

5.3.2 Algorithm Based on IMU Sensors

Based on the manual annotations above, we came up with an algorithm to calculate steps based on sensor values from Accelerometer and Gyroscope as shown in **Figure 5.11**.

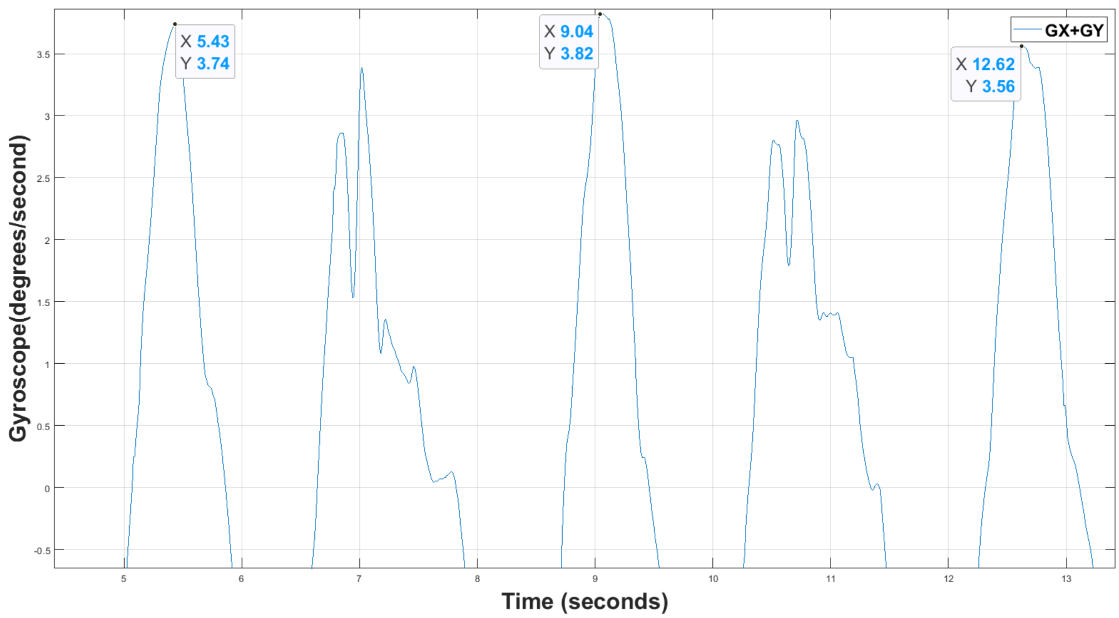

Figure 5.11 30SCS Algorithm Annotations.

- Store combined angular velocity (GX+GY) and find zero crossings.
- Find peaks of GX+GY.
- find the first peak of (GX+GY) after every zero crossing which gives us the potential stands.
- Use every other peak to mark stands since two peaks are generated per each cycle (standup).
- Count all completed stands in 30 seconds.

5.3.2 STUG Results

We used 3 subjects to validate the algorithm. Subject S1 was monitoring in MAL (Vicon lab) with high precision. The average stand duration error is 13ms. Next two subjects are video recorded using iPhone at 30fps and the average stand duration errors were 26ms and 21ms. We believe that the reason for the increased error ratio can be because of the manual annotation of the video.

Table 5.2 30SCS Results.

Vicon/video	**S1**	**S2**	**S3**
No. of stands	9	7	7
Average stand Duration	2.893	3.636	3.656
smartwatch app			
No. of stands	9	7	7
Average Stand Duration	2.88	3.61	3.634
errors			
errors	0.013	0.026	0.021

5.4. 2MWT Analysis and Algorithm

5.4.1 Raw Signal Data Analysis

The 2MWT is used to assess mobility. Traditionally, only total distance traveled is used to assess mobility of subjects. We decided to use measurement of individual steps and support evaluation of symmetry of steps to support assessment of stroke patients. Step recognition algorithm implemented in 2MWT is the same as algorithm used for STUG. We used the algorithm to assess the duration of steps and annotate them as left or right steps.

Since the distance traveled in 2MWT is much longer than typically used in Vicon labs, we used videos to validate algorithms. Making annotations from the iPhone at 30fps and using the Accelerometer magnitude and Gyroscope GZ zero crossing, we could find the absolute steps on two trials is as shown in **Figure 5.12**.

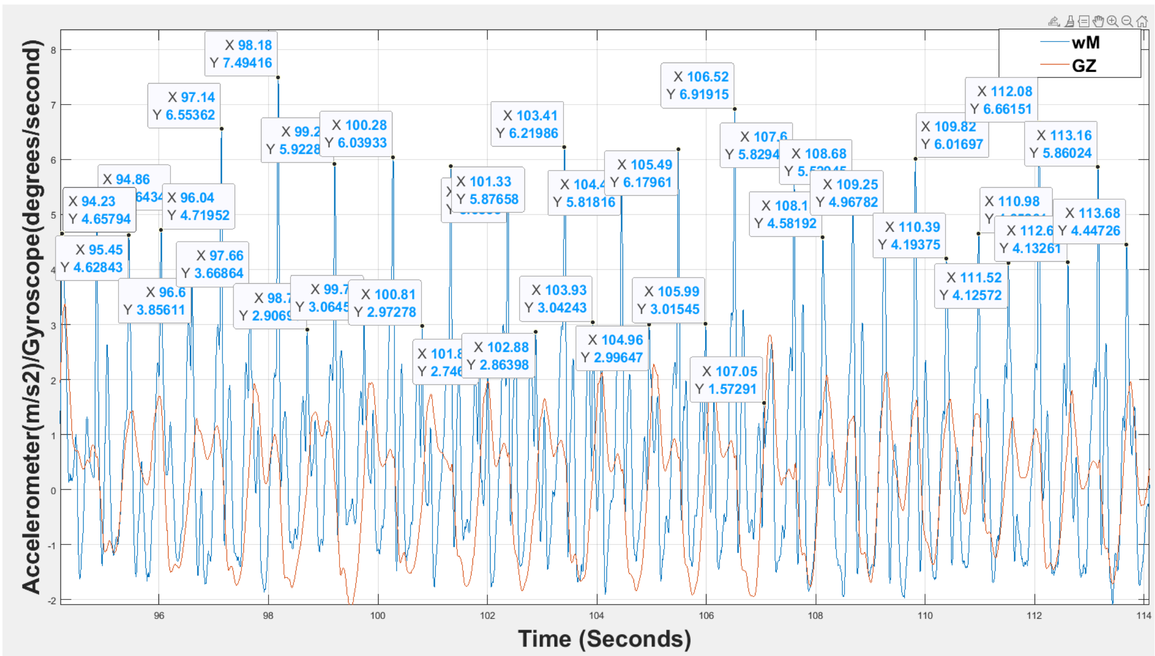

Figure 5.12 2MWT Manual steps annotations from iPhone video recording -Trial1.

5.4.2 Algorithm Based on IMU Sensors

Based on the manual annotations above, we developed an algorithm to calculate steps based on sensor values from Accelerometer and Gyroscope. The algorithm is the same as the step processing algorithm used in STUG application.

- Calculate magnitude of the dynamic 3D acceleration with gravity subtracted (wM) and find peaks.
- Store GyroZ and annotate indices of the zero crossing samples.
- Store and calculate peak valley for combined angular velocity (GyroX+GyroY).

- Find the first peak of wM after every zero crossing, which gives us the individual steps.
- Ignore the steps that fall in peak valley of GyroX+GyroY as they account for turns.
- Total time of the test is 120 seconds (2 minutes) which is controlled by the software in the application.

5.4.2 Results

We collected results from only one subject for this application. The subject walked in a room for 2 minutes and had to turn multiple times due to the limitation in the length of the room. We could detect those turns as regular steps with sufficiently wide turns (~>0.5m) if they satisfy the algorithm constraints. We are working on collecting more data so that we can compare the results and identify the turns more accurately. A test run with one subject (S3), indicates the error in Average step duration of about 56ms as shown the **Table 5.3**.

Table 5.3 2MWT Results.

video	**S3**
No. of steps Average step Duration [s] **smartwatch app**	218 0.537
No. of steps Average Step Duration [s] **errors**	217 0.536
Average step error [ms]	5.6

Chapter 6. Conclusions

Smartwatches represent powerful sensing and processing platforms that provide new opportunities for diagnostic and monitoring healthcare procedures. Since the smartwatch is conveniently located on the body and used most of the time throughout the day, it could be used for health care applications without attaching new sensors.

This thesis demonstrated that smartwatch devices can be successfully used to automate the execution of the standardized mobility tests, paving the way for less intrusive and prolonged monitoring for both clinical and wellness practices. We demonstrated that the application could perform all the data processing in real time on the smartwatch, without depending on other computing devices like smartphones. Collected signals are also uploaded to the server for possible postprocessing, longitudinal monitoring, and data mining.

The main original contributions of this thesis include:

- Development of an expanded suite of the smartwatch mobility assessment applications to include modified 30SCST, and new applications STUG and 2MWT.
- Validation of algorithms using Vicon monitoring and video annotations.

Future work would include improvement of the algorithms:

- Fine tuning of algorithms for older subjects with slower and uneven motion.
- STUG: Improve Algorithm to identify sit-to-stand at the start and stand-to-sit at the end.
- 30SCST: Improve Algorithm to identify each sit along with stand and get data on average time on sit-to-stand and stand-to-sit.

The algorithm used in these applications should be robust and independent of the arm used. The application can be ported on other compatible smartwatches.

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Appendix A. Sensors

Table A.1 Comprehensive List of Sensors.

Sensor	**Reporting Mode**	**Description**
TYPE_ACCELEROMETER	Continuous	Measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity.
TYPE_GYROSCOPE	Continuous	Measures the angular velocity in all three physical axes (x, y, z), in degrees/sec
TYPE_HEART_RATE	On-Change	The reported value is the heart rate in beats per minutes.
TYPE_MAGNETIC_FIELD	Continuous	Measures the ambient geomagnetic field for all three physical axes (x, y, z) in microTesla.
TYPE_GRAVITY	Continuous	Measures the force of gravity in m/s2 that is

		applied to a device on all three physical axes (x, y, z).
TYPE_AMBIENT_TEMPERATURE	On-Change	Provides the ambient (room) temperature in degrees Celsius
TYPE_LIGHT	On-Change	Reports the current illumination in SI lux units
TYPE_PROXIMITY	On-Change	Reports the distance from the sensor to the closest visible surface
TYPE_PRESSURE	Continuous	Reports the atmospheric pressure in hectopascal (hPa)
TYPE_RELATIVE_HUMIDITY	On-Change	Measures relative ambient air humidity and returns a value in percent

Examples of composite sensors that rely on data from one or several physical sensors are shown below.

Table A.2 Composite Sensors.

Sensor	**Category**	**Underlying physical sensors**	**Reporting Mode**
Game rotation vector	Attitude	Accelerometer, gyroscope	Continuous
Gravity	Attitude	Accelerometer, gyroscope	Continuous
Linear Acceleration	Activity	Accelerometer, gyroscope	Continuous
Rotation Vector	Attitude	Accelerometer, gyroscope, magnetometer	Continuous
Step Counter	Activity	Accelerometer	On-Change
Tilt Detector	Activity	Accelerometer	Special
Wake up Gesture	Interaction	Undefined	One-shot

Appendix B. Setting up Applications on the Samsung Galaxy Watch 4

To set up the Samsung Galaxy Watch 4, we used the "Galaxy Wearable" app from the Samsung Galaxy android phone. It can be done from an iOS-based phone too with a Samsung wearable app.

https://www.samsung.com/us/support/answer/ANS00078020/

Turn off all the notifications on the watch so that they will not interrupt during the test.

https://developer.android.com/training/wearables/get-started/debugging

Install adb and fastboot by following this page.

https://nerdschalk.com/how-to-install-adb-and-fastboot/

Enable developer options, adb debugging, debug over wi-fi on the watch and connect debugger to it.

https://www.samsung.com/us/support/answer/ANS00061433/

Download the applications over wi-fi using android studio or install the apk file of each application using adb commands as shown.

- adb push app-debug.apk /sdcard/
- adb -e install app-debug.apk

The applications STUG, 30SCST and 2MWT will be seen on the watch.

Appendix C. TUG Instructions

ASSESSMENT

Timed Up & Go (TUG)

Patient ______________________

Date ______________________

Time ______________ ☐ AM ☐ PM

Purpose: To assess mobility

Equipment: A stopwatch

Directions: Patients wear their regular footwear and can use a walking aid, if needed. Begin by having the patient sit back in a standard arm chair and identify a line 3 meters, or 10 feet away, on the floor.

NOTE: Always stay by the patient for safety.

① Instruct the patient:

When I say "Go," I want you to:

1. Stand up from the chair.
2. Walk to the line on the floor at your normal pace.
3. Turn.
4. Walk back to the chair at your normal pace.
5. Sit down again.

② On the word "Go," begin timing.

③ Stop timing after patient sits back down.

④ Record time.

Time in Seconds: ______________________

An older adult who takes ≥12 seconds to complete the TUG is at risk for falling.

OBSERVATIONS

Observe the patient's postural stability, gait, stride length, and sway.

Check all that apply:

- ☐ Slow tentative pace
- ☐ Loss of balance
- ☐ Short strides
- ☐ Little or no arm swing
- ☐ Steadying self on walls
- ☐ Shuffling
- ☐ En bloc turning
- ☐ Not using assistive device properly

These changes may signify neurological problems that require further evaluation.

CDC's STEADI tools and resources can help you screen, assess, and intervene to reduce your patient's fall risk. For more information, visit www.cdc.gov/steadi

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National Center for Injury Prevention and Control

2017

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Appendix D. 30SCST Instructions

ASSESSMENT

30-Second Chair Stand

Purpose: To test leg strength and endurance

Equipment: A chair with a straight back without arm rests (seat 17" high), and a stopwatch.

NOTE: Stand next to the patient for safety.

① **Instruct the patient:**

1. Sit in the middle of the chair.
2. Place your hands on the opposite shoulder crossed, at the wrists.
3. Keep your feet flat on the floor.
4. Keep your back straight, and keep your arms against your chest.
5. On "Go," rise to a full standing position, then sit back down again.
6. Repeat this for 30 seconds.

② **On the word "Go," begin timing.**

If the patient must use his/her arms to stand, stop the test. Record "0" for the number and score.

③ **Count the number of times the patient comes to a full standing position in 30 seconds.**

If the patient is over halfway to a standing position when 30 seconds have elapsed, count it as a stand.

④ **Record the number of times the patient stands in 30 seconds.**

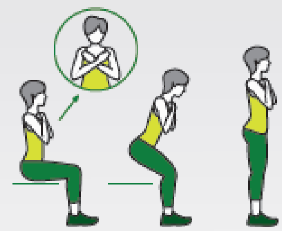
Number: ____________ Score: ____________

CDC's STEADI tools and resources can help you screen, assess, and intervene to reduce your patient's fall risk. For more information, visit www.cdc.gov/steadi

Patient ____________

Date ____________

Time ____________ ☐ AM ☐ PM



SCORING

Chair Stand
Below Average Scores

AGE	MEN	WOMEN
60-64	< 14	< 12
65-69	< 12	< 11
70-74	< 12	< 10
75-79	< 11	< 10
80-84	< 10	< 9
85-89	< 8	< 8
90-94	< 7	< 4

A below average score indicates a risk for falls.

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Appendix E. 2MWT Instructions

General Information:

Individual walks without assistance for 2 minutes and the distance is measured.

- Start timing when the individual is instructed to “Go.”
- Stop timing at 2 minutes.
- Assistive devices can be used but should be kept consistent and documented from test to test.
- If physical assistance is required to walk, this should not be performed.
- A measuring wheel is helpful to determine the distance walked.
- Should be performed at the fastest speed possible.

Set-up and equipment:

- Ensure the hallway is free of obstacles.
- Stopwatch.

Patient Instructions:

Cover as much ground as possible for over 2 minutes. Walk continuously, if possible, but do not be concerned if you need to slow down or stop to rest. The goal is to feel at the end of the test that more ground could not have been covered in the 2 minutes.

Appendix F. Abbreviations and Acronyms

Table F.1 Abbreviations and Acronyms.

TUG	Timed Up and Go
STUG	Smart Timed Up and Go
30SCST	30 Second Chair Stand Test
2MWT	2 Minute Walk Test
BAC	Body Alcohol Content
IMU	Inertial Measurement Units
iOS	iPhone Operating System
CAGR	Compound Annual Growth Rate
RAM	Random Access Memory
AMOLED	Active-Matrix Organic Light-Emitting Diode
LTE	Long Term Evolution
XML	Extensible Markup Language
RTOS	Real Time Operating System
HR	Heart Rate
ML	Machine Learning
STEADI	Stopping Elderly Accidents, Deaths & Injuries
CDC	Centers for Disease Control and Prevention
MQTT	Message Queue Telemetry Transport