An implementation of the wireless body area network of synchronized inertial sensors for balance testing

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AN IMPLEMENTATION OF THE WIRELESS BODY AREA NETWORK
OF SYNCHRONIZED INERTIAL SENSORS FOR BALANCE TESTING

by

HARSHA GANEGODA

A THESIS

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

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2020
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ABSTRACT

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Title An Implementation of the Wireless Body Area Network of Synchronized Inertial Sensors for Balance Testing

In an aging society with increased lifespans, falls represent a serious risk for older adults. Balance is a key indicator of mobility, stability, and risk of falls. Wireless body area networks (WBAN) provide opportunity for unobtrusive monitoring and assessment of balance impairments and mobility. This thesis presents an implementation of WBAN system for monitoring of balance in older adults in smart homes. The system features two wireless inertial sensor nodes, a smart watch, an always-on home server, and an Android smartphone application. The sensors are placed on the user’s lower back and forehead. We designed and implemented custom smart inertial sensors that synchronize with the connected home server running on a Raspberry Pi 3B Linux controller. We implemented a smartphone application to automate 4 stage balance test, recommended by the CDC. The application initiates the balance test, while server synchronizes sensors, acquires and processes data from the sensors, and collects all records. The user subsequently receives a test summary, while raw data is stored on the home server for additional post-processing by the smartphone application using Python scripts.
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CHAPTER 1

INTRODUCTION

The maintenance of mobility is fundamental to active aging, allowing older adults to continue to lead dynamic and independent lives [1]. Mobility is essential to participating in the activities of daily living (ADL), such as walking across a room to the bathroom or kitchen, getting out of bed or a chair, or walking through a grocery store. As life expectancy has increased, falling has increasingly become a substantial health problem among the elderly, including negative impact on their mobility. Posture balance is an important predictor of mobility within the elderly population. Balance depends on the interplay of the different functional components of the posture control system, including sensory organization, which has somatosensory, visual, and vestibular inputs; central motor planning and control, which use the brain for the integration and the formation of a motor plan; and peripheral motor execution, which uses the musculoskeletal system for the production of appropriate movements to execute the plan [2]. Common health conditions can disrupt these systems and impair posture and balance. Falls result in increased morbidity, mortality, and health care costs. An increasing age-adjusted trend in mortality from falls was observed among older U.S. adults from 2000 to 2016. Mortality rates increased with age and throughout the study period [3]. Even if there is no injury after a
fall, the chance of another fall increases [4]. Neurological conditions such as Parkinson’s
disease and strokes have a huge impact on balance. Moreover, diabetes, cancer,
cardiovascular disease, changes in vision, and other chronic conditions can cause the
balance impairments.

Falls are the leading cause of fatal and non-fatal injuries for older Americans. Falls
threatens seniors’ safety and independence and generate enormous economic and personal
costs. According to the U.S. Centers for Disease Control and Prevention (CDC), an older
adult is treated in the emergency room for a fall every 11 seconds; an older adult dies from
a fall every 19 minutes. In other words, falls result in more than 2.8 million injuries treated
in emergency departments annually, including over 800,000 hospitalizations and more than
27,000 deaths. In 2015, the total cost of fall injuries was $50 billion [5]. By the year 2050,
the older adult population in the United States will grow to an estimated 84 million, and
the financial toll for older adult falls is expected to increase as the population ages [6].

Quantitative assessment of balance is crucial for evaluation of fall risks. The CDC
has created a tool kit for healthcare providers to evaluate gait, strength, and balance. This
tool kit includes a set of rules and recommended tests for fall risk assessment and
interventions, such as Timed Up and Go, 30-Seconds Chair Stand, and 4-Stage Balance
Test [7].

Even though basic video recordings can provide both qualitative and quantitative
information about segmental postural strategies, especially when using specific advanced
software [8], only 3D motion capture systems offer the high level of accuracy and
reliability necessary to record the small motions which characterize the unperturbed upright
stance [9]. Vicon is one of the key players in optoelectronic motion capture systems based on reflective markers [10]. Initially, the Vicon system was developed for gait analysis and robotics applications. Two different technologies can be identified for using Vicon system: passive marker systems and active marker systems. Passive marker systems use reflective markers with a set of high-resolution, high-speed cameras with incorporated infrared/near infrared strobes. The cameras record the reflection from the markers placed on specific anatomical landmarks identified by software. Active marker systems use powered markers sending an infrared signal captured by a sensor unit. Each active marker has its own frequency. Active marker systems avoid the post-processing identification procedures required with passive marker systems but require small powered boxes to be attached to the subject’s body [11].

Different commercially available sensors such as inertial, environmental, and vision-based sensors can be used for balance assessment during testing or during ADL. These sensors are being used to efficiently assess the user’s balance or to make decisions about the user’s health conditions [12], [13], [14], [15].

Alternative approach introduces one or more wearable inertial sensors. Mounting single or multiple inertial sensors on different locations of the body can be used to capture body motion and recognize activities, such as sitting, standing, walking, running, and sleeping [16]. Typically, sensors are mounted on the chest, waist, lower back, or legs [17]. Mounting inertial sensors on the lower back has been demonstrated as the better location to assess standing balance [18]. The sensors can also be embedded in shoes to monitor activity throughout the day [19], [20]. With the improved quality of integrated inertial sensors, smartphones have been increasingly used for balance assessment [21], [22].
With the rapid increase of older population, support for aging in place has become an increasingly important and challenging issue. The ambient assisted living (AAL) approach provides better life conditions for the aged, as well as for people with chronic diseases and those recuperating from illness or injury, by developing innovative technologies and services. Recent advancements in mobile and wearable sensors have helped the vision of AAL to become a reality. All recent mobile devices are equipped with sensors such as accelerometers, gyroscopes, and Global Positioning System (GPS), which can be used for detecting user mobility [23] [24].

Since 2007, mobile phones like Apple’s iPhone and Google’s Android have taken over the mobile market, and 81% of American adults now own a smartphone [25]. Before the emergence of smartphones, health care services were usually provided face-to-face with patients. Now traditional face-to-face interactions between patients and doctors are changing. A recent survey indicates that there are more than 97,000 health and fitness applications available for download to mobile or tablet devices, 52% of smartphone users collect health-related information on their cell phones, 40% of doctors trust that these mobile tools can lessen the number of on-site clinical visits, and 93% of doctors say mobile apps can enhance the quality of patient health [26]. Advancements of the sensors, smartphones, smart watches, and cloud-based wireless networking platforms speed up new opportunities such as telemedicine, remote healthcare services and continuous patient monitoring in their homes.

Recent technological advancement in wireless communication networks and the trend towards miniaturization of sensor technologies have enabled the development of wireless body area networks (WBAN) as promising communication tools for continuous
remote monitoring. WBANs enable new features such as real-time monitoring, clinical diagnosis, and disease screening [27]. WBAN systems using multiple sensors attached to the body can achieve more precise monitoring of the test subject’s health conditions. Most products currently on the market use low-power wearable sensors that communicate with a smartphone to decrease power consumption, reduce size and weight of sensors, and improve user’s acceptance. Sensor intelligence facilitates low duty cycles, which extend battery life and allow continuous monitoring throughout the day.

In recent years, many projects demonstrated the development of smart assistive environments integrated into the Internet of Things (IoT) that can improve living conditions of users. The same environment can be used to monitor health conditions and improve wellness by monitoring human activities and providing feedback and guidance to the user [28]. Early detection of changes in behavior or pattern of activities allows early detection of serious conditions, such as mild cognitive impairment (MCI) [29]. Application of IoT technology is not only limited to IoT home appliances. Wearable biosensors have opened the door to new opportunities for personalized health monitoring. Biosensors embedded in everyday objects turn them into smart objects that allow measurement of physiological parameters. For example, a smart water bottle can monitor not only the user’s hydration, but also other physiological parameters, such as heart rate and activity [30]. Physiological monitoring integrated into smart objects of everyday use, also known as “smart stuff,” can be naturally integrated into IoT smart homes and provide more robust measurements and context of other measurements. Typical examples include user’s identification [31] and synergistic processing [32]. The robust home IoT system with seamless integration of sensors and always-on gateways and home servers can
Human balance is a very complex phenomenon that requires delicate coordination of the central nervous system (CNS), muscles, and the limbs. This research work describes the implementation of a system for the high-precision assessment of balance of users at home. The system consists of a wireless body sensor network, an always-on home server, and an Android smartphone application to automate the human balance assessment. To analyze two or more bio-signals simultaneously, it is necessary to synchronize signals from sensors worn on different part of the body. We developed a WBAN using two time-synchronized inertial sensors attached to the human body, a smartwatch application, an Android smartphone application, and a home server. The smartphone application controls the data collection of the wireless sensors nodes, while the home server collects synchronized records and acts as a bridge between the WBAN and the Internet. Since the home server is always on, the system is robust, reliable, and highly available. Each wireless sensor node is equipped with 9 degrees of freedom (9DOF) inertial sensors (3-axis accelerometer 3-axis gyroscope, and 3-axis magnetometer), an embedded microcontroller with WiFi interface, and a rechargeable lithium polymer battery. The home server keeps the wireless sensor nodes synchronized and stores the inertial measurements on an SD card as CSV files. After the completion of the balance test, the home server does a quick assessment and provides a summary of the results. Further processing is done on request.

In this thesis we present an implementation of the WBAN of synchronized inertial sensors for balance assessment. Chapter Two presents a survey of the existing research related to wearable monitoring technologies and systems for assessing balance. Chapter
Three describes the system architecture of our balance assessment system using a WBAN and a smartphone. Chapter Four presents the implementation of software for the wireless sensor nodes, the home server and the smartphone. Chapter Five describes the analysis of the parameters of 4SBT testing. Chapter Six concludes the thesis and describes suggestions for future enhancements.
CHAPTER 2

SURVEY OF WEARABLE MONITORING SYSTEMS FOR BALANCE ASSESSMENT

The ability to achieve and maintain balance in upright stance is a critical and complex lifelong skill [33]. The human posture balance depends on complex organizations which include sensory input from vision, somatosensory receptors (proprioceptors and mechanoreceptors), and the vestibular system [34]. The CNS gathers and processes this sensory information to assess the position and motion of the body [34]. The CNS then generates and coordinates multiple motor outputs to muscles throughout the body. The human postural control can be identified as a constantly ongoing process that loops through corrective feedforward (predictive) and feedback (reactive) regulative movement control systems as shown in Fig. 2.1 [35].
Vision provides information about the orientation of objects and movements in the visual surroundings. It provides the CNS with information that allows us to interact with a highly dynamic environment. Vision gives us a reference frame and feedback information of our own posture and movement in relationship with our surroundings. It also supports feedforward motor control, which helps us to anticipate the continuous change of the surroundings we interact with. Vision is important, but not essential, in regulation of the standing posture [36]. Balance tests with eyes closed are used to assess balance control by minimizing sensory information. Minimizing sensory information results in increased body sway, particularly in older adults [37].
The vestibular system is located in the inner ear and consists of the otoliths and the labyrinths. The labyrinth includes the anterior, posterior, and lateral semicircular canals, which detect the head’s acceleration in space in the respective canals’ sensitive direction during rotational head motion. The otoliths consist of the utricular and saccular macula organs, which continuously sense linear acceleration, e.g., gravitational force and linear accelerations or decelerations affecting the head. The gravitational information provides an orientational frame of reference in space on the basis that the direction of gravitational force is constant. Afferent information from the vestibular system to the CNS is important for maintaining balance [38].

Proprioceptors provide information about the orientation of the body during static postures and movement. It has been proposed that proprioception is the most important sensory system for postural control, responsible for maintaining balance and for setting off automatic balance responses during perturbations [39]. Mechanoreceptors are divided into two types: slowly adapting (Ruffini corpuscles and Merkel disk receptors) and rapidly adapting (Pacinian and Meissner’s corpuscles) [40]. Slowly adapting mechanoreceptors constantly and accurately signal to the CNS how the pressure is distributed on the skin. Rapidly adapting mechanoreceptors signal the amplitude and the rate changes of the pressure applied on the skin [41]. Salisbury et al. [42] performed a balance test on solid and foam surfaces to determine the role of mechanoreceptor’s sensory information in human posture balance.
2.1 Balance Assessment Tests

The CDC introduced the STEADI (Stopping Elderly Accidents, Deaths and Injuries) toolkit for healthcare providers to assess mobility and balance in older adults [7]. The CDC recommends evaluating gait, strength, and balance with three tests: Timed Up and Go (TUG) [43], 30-Second Chair Stand (30SCS) [44], and 4-Stage Balance Test (4SBT) [45]. Soldera et al. [46] compared the performance of body balance maintenance systems between more senior and younger older adults. The subjects responded to a socio-demographic and clinical questionnaire and Foam-Laser Dynamic Posturography (FLDP) to perform the Sensory Organization Test (SOT) in six different conditions to assess the three balance systems: visual, somatosensory, and vestibular.

2.1.1 The Timed Up and Go (TUG)

The TUG test is a simple, quick, and widely used clinical performance-based measure of the function of the lower extremities used for assessment of mobility and fall risk. The test is widely used in populations of older adults, patients with Parkinson’s disease, and post-stroke patients[47]. The test procedure is relatively simple. Subjects are asked to stand up from a standard chair, walk a distance of three meters (should be marked on the floor) at a normal pace, turn around an obstacle, walk back, and sit down. The typical phases of the TUG test are shown in the Fig. 2.2 [48]. TUG test output is the time to complete the task, commencing with the command ‘go’ and stopping when the subject’s back is positioned against the back of the chair after sitting down. Generally, the test is performed twice, and a shorter time indicates better performance.
Zampieri et al. implemented an instrumented Timed Up and Go (iTUG) test in 2010 [22]. In this test, subjects use portable data loggers with inertial sensors worn on their body. The inertial sensor device is typically mounted on the subject’s lower back and can record x, y, and z acceleration components during the TUG test. These acceleration signals were used to derive number of parameters that can better indicate gait and balance impairments, including anterior-posterior acceleration, sit-to-stand velocity, stand-to-sit velocity, and others. iTUG was shown to be a more sensitive tool to detect gait and posture abnormalities in early- to mid-stage Parkinson’s disease over the traditional TUG [22]. Milosevic et al. introduced the smartphone Timed Up and Go application called sTUG for Android smartphones [49]. The sTUG application fully automates the TUG test with cloud-based features that can be used for continuous mobility assessment in clinical and ambulatory settings.
2.1.2 The 30-Second Chair Stand (30SCS)

The 30SCS test is performed using a straight-back chair without arm rests and a stopwatch. The subject sits in the middle of the chair with feet flat on the floor, arms crossed at the chest, and hands placed on the opposite shoulders. On the command “go,” the subject rises to a full standing position and then sits down back while holding the arms against his/her chest. The subject repeats these steps for 30 seconds. The typical phases of 30SCS test are shown in Fig. 2.3.

![Figure 2.3 30-Second Chair Stand (30SCS) test phases](image)

The outcome of the test is the number of times the subject comes to a full standing position in 30 seconds. The 30SCS test has been shown to be a useful assessment tool to determine the leg strength and endurance [50].

The duration of sit-to-stand and stand-to-sit during the 30SCS test is one of the most straightforward parameters to characterize both posture transitions [51]. Nevertheless, other studies have suggested the use of other parameters such as peak velocity of sit-to-stand and stand-to-sit transitions [52]. Moreover, the trunk is important
in generating the momentum that carries the body during the dynamic transition of standing up [53], and changes in the management of the trunk movements have been investigated as an early indicator of aging [54]. Overall, all of this research showed that both stand-to-sit and sit-to-stand transitions should be evaluated for possible diagnostic applications.

A smart watch-based 30SCS test was introduced in 2019 [55]. In this test, the subject wears a smart watch with inertial sensors, typically a three-dimensional accelerometer and a three-dimensional gyroscope. The custom-developed Android Wear smart watch application records inertial signals during the 30SCS test. The application notifies the subject to start and stop the test using vibration on the smart watch. After the completion of each test, the total number of stand counts are shown on the smart watch display, and full records are uploaded to the personal medical health record.

### 2.1.3 The 4-Stage Balance Test (4SBT)

During the 4SBT the subject is asked to maintain four standing positions that are progressively harder to maintain. A healthcare practitioner describes and demonstrates each position to the subject and then stands next to the subject, holds the subject’s arm, and helps the subject assume the correct position. When the subject is steady, the practitioner lets go of the subject and uses a stopwatch to measure how long the subject can maintain the position, while remaining ready to assist the subject in case of the loss of balance. The four respective positions or stances of the 4SBT are shown in Fig. 2.4 and are described as follows:

1. feet together stance with feet touching and side by side;
2. semi-tandem stance with the instep of one foot touching the big toe of the other foot;
3. tandem stance with one foot placed in front of the other heel to toe (heel of one foot touching the toe of the other foot); and

4. one leg stance with the subject standing on one leg.

During this test, the subject should not use any assistive device and should keep eyes open. If the subject can hold a position for 10 seconds without moving his/her feet or needing support, the test advances to the next position. If subject loses balance before the end of the 10 second period, total time in the position is written, and the test advances to the next position. The standard test outcome is the time in seconds the subject is able to hold each of the four positions. Older adults who cannot hold the tandem stance for at least 10 seconds are at increased risk of falling [45].

![Figure 2.4 The 4-Stage Balance Test (4SBT) feet positions](image)

Postural instability is one of the most common and debilitating problems for older adults [56]. Postural instability increases with disease progression, leading to an increased risk of falling, soft tissue injuries, fractures, and psychological fear of falling, all of which
results in a significant reduction in quality of life and life expectancy [56]. In older subjects, a high frequency of falling is correlated with increased body sway during the quiet stance [57].

2.2 Systems for Balance Assessment

Balance assessment systems can be classified according to the use of sensors:

1. vision-based camera systems,
2. wearable inertial sensor-based systems,
3. force platforms

2.2.1 Vision-Based Camera Systems

Vision-based camera systems are commonly used to determine human postural balance despite being more expensive than inertial sensor-based systems. Goffredo et al. proposed a motion estimation technique that uses markers on selected body points to identify the position of body segments. The method allows estimation of the body segment in time, and calculation of the center of mass (COM) trajectory [8].

Microsoft released the Kinect for the Xbox 360 game system as a game controller a subject uses to interact with the game console or computer by means of body movements [58]. Kinect can track the contours of the human body in 3D and has been used for motion capture analysis [59]. A special software package enables the calculation of the body’s COM. The projection of the COM to the floor can be used to derive the parameters such as position, displacement, velocity, and acceleration, which are used to assess human
posture balance. Grooten et al. [58] used Qinematic, an interactive movement analysis system based on the Kinect camera, for assessing posture, balance, and side bending.

### 2.2.2 Inertial Sensor-Based Systems

In recent years, most research is based on miniaturized inertial measurement units (IMUs) or magneto inertial measurement units (MIMUs) in posturography [13], [12], [14], [15]. Subjects can easily wear these sensors on various body segments due to the small form factor. Sensor size, weight, and low power operation are the key user acceptance factors. A wearable inertial sensing unit includes accelerometers, gyroscopes, and magnetometers. A three-axis accelerometer measures the linear acceleration of movements in three-dimensional (3D) space, a three-axis gyroscope measures the angular velocity in a 3D space, and the components of the rate turn are assessed in a sensor-fixed, 3D frame. Rotations around the three orthogonal axes are commonly defined as Euler angles, and referred to as roll, pitch, and yaw. A magnetometer measures orientation of the magnetic field and therefore the orientation of the sensor in 3D space. The accelerometers in smartphones enable low-cost balance assessment.

Salisbury et al. [42] performed validation of a balance accelerometry measure (BAM) using smart glasses. Smart glasses containing an accelerometer could provide a safe and engaging platform for virtual and augmented reality-based balance assessment and rehabilitation.

Mancini et al. [60] conducted two separate studies with two groups of subjects, made up of 13 subjects with early, untreated Parkinson’s disease and 12 age-matched control subjects (CTR), to compare sway from force-plate center of pressure (COP) and
inertial sensors. The first study examined sensitivity and experimental validity, while the second study established test-retest reliability and clinical concurrent validity. A different set of 17 subjects with early-to-moderate Parkinson’s disease, who were tested and on medication treatment, and 17 age-matched CTR subjects were tested in the clinic to compare clinical balance tests with sway from inertial sensors. The first study was performed in the motion analysis laboratory to determine the sensitivity and experimental concurrent validity of acceleration (ACC)s compared to force-plate measures (Study I). The second study took place in the hospital neurology clinic to determine the test-retest reliability and clinical concurrent validity of the proposed automatic clinical system (Study II). In the first study, all participants were instructed to maintain an upright standing position on a force-plate, with arm crossed and heel-to-heel distance fixed at 10cm. Subjects wore a MTX Xsens sensor with a 3D accelerometer mounted on the posterior trunk at the level of L5, near the body COM. Sensing axes were oriented along the anatomical antero-posterior (AP), medio-lateral (ML), and vertical directions. A total of three, two-minute trials were performed with eyes open gazing straight ahead at an art poster. The COP displacement was calculated from the ground reaction forces recorded by the force-plate at a 100-Hz sampling frequency, and acceleration signals were collected with a 50-Hz sampling frequency. In the second study, subjects wore the same MTX Xsens sensor on the posterior trunk at the level of L5. Data from three 30-second trials of quiet standing were collected. The sensor was removed after completion of the three trials. The subject then rested for 30 minutes in a chair, the sensor was reapplied, and the protocol was repeated.
2.2.3 Force Platforms

Force platforms are mechanical sensing systems designed to measure the ground reaction forces and movements involved in human movements. Mechanically, balance is achieved when the external forces and torques applied to a body are in static equilibrium. During quiet standing, there are two external forces: the weight and the ground reaction force (GRF). The human body’s weight acts at the COM, while the GRF acts at the COP. If there is any difference between the vertical projection of the COM and the COP, it leads to the destabilized postural balance. To avoid postural instability, the COP regulates the COM by changing the location of the vertical projection of COM [61]. Force plates are widely used to validate the postural stability parameters obtained from other systems such as inertial systems [62], [60].

2.3 Signal Processing Methods

There are many methods for assessing balance in the literature based on different balance assessment systems. This section describes the different signal processing methods related to human posture balance.

Najafi et al. suggested an innovative, portable, and cost-effective prototype to evaluate balance control objectively. They used quaternions from two sensors with a triaxial accelerometer, a triaxial gyroscope, and a triaxial magnetometer to estimate 3D angles of the hip and ankle joints using equations 2.3, 2.4, and 2.5. After the joint angles were estimated, a two-segment model of the body was used to calculate AP and ML angles during movement as shown in Fig. 2.5. They used the variation of the COM towards both the AP and the ML angles to determine subject’s postural stability.
\[ \theta = \arctan \left( \frac{2 \times qx \times qy - 2 \times qx \times qz}{1 - (2 \times qy^2) - (2 \times qz^2)} \right) \]

\[ \phi = \arcsin(2 \times qx \times qy + 2 \times qz \times qw) \]

\[ \psi = \arctan \left( \frac{2 \times qx \times qw - 2 \times qy \times qz}{1 - (2 \times qx^2) - (2 \times qz^2)} \right) \]

Figure 2.5 Two-link biomechanical model of human body for estimating COM trajectory

Salisbury et al. [42] defined the normalized path length (NPL) of the acceleration time series from the AP postural sway during the 4SBT. The estimated NPL is used to determine the subject’s postural stability during the smart glasses-based balance accelerometry measure (BAM) test.

Adkin et al. [63] measured trunk sway in AP and ML directions in Parkinson’s disease patients and age-matched controls. Two digitally based, angular-velocity transducers were used to measure angular-velocity deviations in the roll axis and pitch axis.
The transducers were attached to the lower lumber back to provide measures of trunk sway with respect to an earth-fixed reference frame. Using this system, angles were measured directly without additional processing. Angular deviations were calculated online using trapezoid integration of the angular velocities. A lightweight, 10 meter long cable was used to transfer the angular trunk velocity in roll and pitch directly to the processing computer for storage and analysis. Eleven stance tasks were performed with eyes open and with eyes closed, first when standing on a normal support surface in the subject’s comfortable stance position and then standing on a foam support surface. Total task duration and peak-to-peak excursions in roll and pitch directions for both angular displacement and angular velocity were calculated. They observed that Parkinson’s disease patients demonstrated significantly greater trunk pitch, roll angle, and angular velocity values compared to controls.

Hsu et al. [64] developed gait- and balance-analyzing algorithms to obtain quantitative measurements and explore the essential indicators from these measurements for the diagnosis of Alzheimer’s disease based on an inertial sensor-based, wearable device. Balance was measured by the sway speed in AP and ML directions of the projection path of body’s COM. The inertial sensor-based, wearable device was mounted on the participant’s waist. Then the participant was requested to maintain body balance and perform the following eight balance ability tests:

1. side-by-side stance with eyes open;
2. side-by-side stance with eyes closed;
3. left foot tandem stance, with the heel of the left foot in front of and touching
   the toes of the right foot, with eyes open;
4. left foot tandem stance with eyes closed;
5. right foot tandem stance with eyes open;
6. right foot tandem stance with eyes closed;
7. standing on left foot with eyes open;
8. standing on right foot with eyes open.

Since the wearable device was mounted on participant’s waist, the accelerations of the
triaxial accelerometer embedded in the wearable device can be regarded as the acceleration
signals at the approximate level of the COM. The average sway speed rates in AP and ML
directions of the projection path of the body’s COM are used to determine the postural
stability of the participant. Their balance analyzing algorithms follows these steps:

![Figure 2.6 Projection path of body’s center of mass](image)
Step 1: Calculation of signal vector magnitude (SVM). Where k is the time step, \(a_x(k)\), \(a_y(k)\), and \(a_z(k)\) are the filtered acceleration.

\[
SVM_{acc}(k) = \sqrt{a_x^2(k) + a_y^2(k) + a_z^2(k) \quad 2.6}
\]

Step 2: Calculate the directional cosines of the SVM of the accelerometer signals as shown in Fig. 2.6.

\[
\cos \alpha(k) = \frac{a_x(k)}{SVM_{acc}(k)}
\]

\[
\cos \beta(k) = \frac{a_y(k)}{SVM_{acc}(k)}
\]

\[
\cos \gamma(k) = \frac{a_z(k)}{SVM_{acc}(k)}
\]

Step 3: Calculate the distance (D) between wearable device and ground at each time step (k)

\[
D(k) = \frac{S_h}{\cos \gamma(k)}
\]

Where \(S_h\) represents the partial height of the participant from waist to the floor. According to [65], \(S_h\) can be estimated as 0.618 multiplied by the height of the participant.

Step 4: Calculate the projection displacement of each time step (k) from original point in the X coordinate \((dx(k))\)

\[
d_x(k) = D(k)\cos \alpha(k)
\]

This can also be regarded as the displacement of each time step in the AP direction

Step 5: Calculate the projection displacement of each time step (k) from original point in the Y coordinate \((dy(k))\)

\[
d_y(k) = D(k)\cos \beta(k)
\]

This can also be regarded as the displacement of each time step in the ML direction.
Thirteen acceleration measures were computed from the 2D acceleration as shown in Table 1. These acceleration-based measures of sway were just as sensitive as COP measures to determine posture balance.
Table 1 Parameters for assessment of balance

<table>
<thead>
<tr>
<th>Measure abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>JERK [56] [66]</td>
<td>Sway jerkiness, time derivative of acceleration</td>
</tr>
<tr>
<td></td>
<td>[ JERK = \frac{1}{2} \int_0^t \left( \frac{dACC_{AP}}{dt} \right)^2 + \left( \frac{dACC_{ML}}{dt} \right)^2 \frac{m}{s^4} ]</td>
</tr>
<tr>
<td>DIST [67] [68] [69]</td>
<td>Mean distance from center of COP (ACC) trajectory [mm] [( \frac{m}{s^2} )]</td>
</tr>
<tr>
<td>RMS [68] [70] [71]</td>
<td>Root mean square of COP (ACC) time series [mm] [( \frac{m}{s^2} )]</td>
</tr>
<tr>
<td>PATH [67] [68]</td>
<td>Sway path total length of COP (ACC) trajectory [mm] [( \frac{m}{s^2} )]</td>
</tr>
<tr>
<td>RANGE [67] [72]</td>
<td>Range of COP displacement (acceleration) [mm] [( \frac{m}{s^2} )]</td>
</tr>
<tr>
<td>MV [72] [68]</td>
<td>Mean velocity COP: PATH/trial duration [m/s]</td>
</tr>
<tr>
<td>MF [68]</td>
<td>Mean frequency, the number, per second of loops that have to be run by the COP (ACC), to cover a total trajectory equal to PATH (MF = PATH/(2*(2\pi)<em>DIST</em>trial duration) (Hz)</td>
</tr>
<tr>
<td>AREA [73] [74] [72]</td>
<td>Sway area, computed as the area spanned from the COP (ACC) per unit of time [( \frac{mm^2}{s} )] [( \frac{m^2}{s^5} )]</td>
</tr>
<tr>
<td>PWR [75] [60]</td>
<td>Total power [( mm^2 )] [( \frac{m^2}{s^5} )]</td>
</tr>
<tr>
<td>F50 [60] [72]</td>
<td>Median frequency, frequency below which the 50% of PWR is present (Hz)</td>
</tr>
<tr>
<td>F95 [60] [72]</td>
<td>95% power frequency, frequency below which the 95% of PWR is present (Hz)</td>
</tr>
<tr>
<td>CF [60]</td>
<td>Centroidal frequency (Hz)</td>
</tr>
<tr>
<td>FD [60] [72]</td>
<td>Frequency dispersion (-)</td>
</tr>
</tbody>
</table>

Soldera et al. [46] proved that basically three sensory systems are involved in maintaining body balance: visual, somatosensory, and vestibular using Foam-Laser
Dynamic Posturography in different conditions. The researchers proved that there was a significant difference between age groups in the visual and vestibular analysis (p<0.001) and in the visual preference (p=0.007), but not in the somatosensory system (p=0.741).

Different research teams have developed many methods to assess human balance in different conditions. Table 2 shows different parameters used to assess human balance as discussed in the survey above. The specific parameters are estimated during the balance test period. 4SBT is commonly used to assess balance under different conditions such as eyes open and eyes closed. In addition, two other conditions are being tested by changing the ground surface from hard to soft.

<table>
<thead>
<tr>
<th>Method</th>
<th>Specific parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center of Mass (COM) sway</td>
<td>AP and ML displacement [62]</td>
</tr>
<tr>
<td></td>
<td>AP and ML velocity [64]</td>
</tr>
<tr>
<td></td>
<td>Trajectory, Area and Frequency measures</td>
</tr>
<tr>
<td></td>
<td>as shown in Table 1</td>
</tr>
<tr>
<td>Center of Pressure (COP) sway</td>
<td>Trajectory, Area and Frequency measures</td>
</tr>
<tr>
<td>[62],[7]</td>
<td>as shown in Table 1</td>
</tr>
<tr>
<td>Hip sway</td>
<td>AP and ML displacement [62]</td>
</tr>
<tr>
<td>Trunk sway</td>
<td>AP and ML displacement [63]</td>
</tr>
<tr>
<td>Lower leg/ Ankle sway</td>
<td>AP and ML displacement [62]</td>
</tr>
<tr>
<td>Foam-Laser Dynamic Posturography [46]</td>
<td>AP and ML displacement</td>
</tr>
</tbody>
</table>
CHAPTER 3

SYSTEM ARCHITECTURE

We developed the system to automate balance testing using multiple synchronized sensors. The system consists of smartphone with custom application, two wireless sensor nodes, smartwatch with a custom application, and a home server. End of each balance test, results are automatically sent to remote computer. The system architecture is shown as in Fig. 3.1.

Figure 3.1 The system architecture
3.1. Android application

When application opens, it allows to enter the test subject’s ID and select the test stage which belongs to the 4 Stage Balance Test. Once subject’s ID and test stage number entered, start button can initialize the collecting two sensor node data and smartwatch data into the wireless gateway. The collected data can be downloaded from the Raspberry Pi.

3.2 Wireless Inertial Sensor

We implemented wireless sensor nodes as IoT sensor integrated wirelessly with home server. The sensor consists of the single inertial measurement unit (IMU), nine-degrees-of-freedom (9DOF) IMU Adafruit BNO055 [76] and Sparkfun ESP8266 Thing embedded controller [77]. Block diagram of the implemented sensor node is shown in Fig. 3.2. Microcontroller communicates with the inertial sensor through I2C serial interface. Both modules are powered by a 400 mAh Lithium polymer battery. All system components are enclosed in the printed plastic enclosure as shown in Fig. 3.3. Wireless sensor node communicates with the home server (Raspberry Pi 3B) using MQTT protocol over Wi-Fi connection [78]. MQTT is a machine-to-machine (M2M) connectivity protocol, frequently used in IoT applications. The protocol is designed to support extremely lightweight publish/subscribe messaging. The protocol is very suitable for IoT sensors because of the small code footprint and limited network and application overhead.

IMU sensor uses inertial sensor BNO055 features 3 axis accelerometer, 3 axis gyroscope, and 3 axis magnetometer.
3.2.1 Accelerometer

The MEMS accelerometer measures the acceleration in m/s\(^2\). The maximum range of the acceleration is 16g which means it can measure from -16g to +16g where “g” represents the gravity force (9.81 m/s\(^2\)). The sensor outputs are digital signals with 14-bit sample values (16384 possible values). The maximum sampling rate of the accelerometer is 100 Hz. We implemented data acquisition with sampling frequency of 100Hz. There are set of operation mode including normal, suspend, low power as shown in Table 3. Accelerometer features motion-triggered interrupt signal generation for any-motion (slope) detection, slow or no motion recognition and high-g detection.
### Table 3 BNO055 power mode, power consumption and description

<table>
<thead>
<tr>
<th>Power Mode</th>
<th>Power Consumption [mA]</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>12.3</td>
<td>All the sensors in the operation mode</td>
</tr>
<tr>
<td>Low power</td>
<td>0.4</td>
<td>If no activity (no motion) is detected for a configurable duration, the sensor enters to the low power mode</td>
</tr>
<tr>
<td>Suspend</td>
<td>0.04</td>
<td>Sensors are put into sleep mode. No values in the register map will be updated in this mode</td>
</tr>
</tbody>
</table>

#### 3.2.2 Gyroscope

The MEMS gyroscope sensor measures rotational force to measure angular velocity when the device is rotating. Angular velocity is simply a measurement of speed of rotation. The range of gyroscope can be selected from ±125 degrees/second to ±2000 degrees/second. The sensor outputs are digital signals with 16-bit values. The maximum sampling frequency of the gyroscope sensor in selected platform is 100Hz. Gyroscope are subject to bias instabilities, in which the initial zero reading of the gyroscope will cause drift over time due to integration of noise within the device. Integrating constant bias
instability will cause angular error. These errors will accumulate as gyroscope-based rotation or angle estimates drift over the long-term.

3.2.3 Magnetometer

The magnetometer sensor measures absolute magnetic field of Earth. The sensor reports values in microtesla (µT). The range of the sensor is ±1300µT (x, y axis) ±2500µT (z-axis) with a resolution of 0.3µT. The maximum sampling rate of magnetometer is 20Hz. Magnetometer is used to assess absolute orientation of the sensor, as relative orientation of Earth’s magnetic field.

3.2.4 Euler Vector

The Euler angles are three angles introduced by Leonhard Euler to describe the orientation of a rigid body with respect to a fixed coordinate system. The fusion mode of the selected sensor provides the heading of the sensor in Euler angles (roll, pitch and yaw angle) at 100Hz maximum frequency. Three axis orientation data based on a 360º sphere. The sensor reports Euler angles values in degrees as default sensor configuration.

3.2.5 Quaternions

Quaternions are four elements vector that can be used to encode any rotation in a 3D coordinates system. Euler angles are limited by a phenomenon called gimble lock, which prevents them from measuring orientation when pitch angle approaches +/- 90 degrees. Quaternions provide an alternative measurement technique that does not suffer from gimble lock.
In mathematics, the quaternions are a number system that extends the complex numbers. They were first described by Irish mathematician William Rowan Hamilton in 1843 and applied to mechanics in three-dimensional space. Quaternions are generally represented as \( q_0 + q_1 i + q_2 j + q_3 k \) where \( q_0, q_1, q_2, \text{ and } q_3 \) are real numbers, and \( i, j, \text{ and } k \) are the fundamental quaternion units [80].

The fusion algorithm is run by the internal Cortex M0 processor outputs an orientation data in quaternions format for each DOF \( q_0, q_1, q_2, \text{ and } q_3 \). The quaternions are refreshed at 100Hz sampling rate.

### 3.2.6 ESP8266 Thing

The SparkFun ESP8266 Thing is a breakout board and development board for the ESP8266 System on Chip (SoC) a leading platform for internet of things or Wi-Fi related projects. The Thing is low-cost and easy to use, and Arduino IDE integration can be integrated in just a few steps. Onboard LiPo charger allows to charge the battery while system is running. ESP8266 Thing is used as an embedded controller which integrates low power 32–bit CPU as application processor and wireless controller that supports 802.11b/g/n Wi-Fi standards.

### 3.3 Polar M600 Smartwatch

We used the Polar M600 smartwatch shown in Fig. 3.3. It is powered by Android Wear OS by Google. It integrates dual core 1.2 GHz ARM Cortex- A7 processor and high quality sensors including accelerometer, ambient light sensor, gyroscope and GPS and Glonass location sensors [81]. The wireless connectivity including 802.11b/g/n Wi-Fi and Bluetooth 4.2 allows smartwatch to connect with other wireless devices.
3.4 Home Server

Generally, in the wearable body sensor network there should be a master node. In this work home server performs as a master node of wearable body sensor network. The main tasks of the home server are maintain timely synchronized sensors, acts as intermediate gateway to the smartphone application and cloud services, and storage device for the sensors data. Home server is powered by the Raspberry Pi 3B [82] computer which is a single-board computer with wireless LAN and Bluetooth connectivity. Raspberry Pi 3B is integrated with quad core 1.2GHz Broadcom BCM2837 64bit CPU with 1GB of RAM. Onboard BCM43438 controller enables the wireless LAN and Bluetooth Low Energy (BLE) capability. In our case we used Wi-Fi interface of the Raspberry Pi to communicate with wireless sensor nodes.
Raspberry Pi 3B has access to the internet services and other servers, such as to the mHealth server. Home server software is written by Python language, and paho MQTT client which has good support with cloud based communication. Linux environment is used to run the home server software. Wireless sensor nodes directly communicate with home server using MQTT WiFi based protocol. In order to capture the sensor data from wireless sensor nodes, mosquito MQTT broker was installed on the Raspberry Pi. The python script was developed to subscribe the sensor data and store all the sensor data in separate CSV files on Raspberry Pi SD card. Always on feature of the home server enables the higher availability of continuous monitoring. As an example, our system can be used to assess mobility of the elderly throughout the day.

### 3.5 Automatic Upload of Records

Home monitoring can be implemented by automatic upload of records to the personal medial record on cloud. In this project we used a simplified mechanism using automatic upload of data files to the File Transfer Protocol (FTP). The FTP is a standard network protocol used to transfer files between a client and a server on a computer network [83]. We implemented fully automated feature to upload sensor data to remote computer after completion of 4SBT. The home server uploads all the data to the remote FTP server, as soon as the experiment is complete and data files are generated. This feature allows automatic post processing of all records in a study.
This chapter describes the software implementation on each platform described in Chapter 3.

4.1 Sensor Software

We designed the embedded application for both wireless sensor nodes using Arduino IDE version 1.8.5. This IDE allows users to compile and debug the application. As discussed in Chapter 3, we used a Sparkfun ESP8266 Thing platform, which is a complete system on chip (SoC) solution, to develop WiFi applications. The embedded software includes six major tasks.

1. Initialization of the WiFi-based MQTT connection with Raspberry Pi:

   The first time the sensor node powers up, it initializes the WiFi client connection with the Raspberry Pi MQTT broker. We used C APIs from the PubSubClient Arduino library. The WiFi configuration allows the sensor node to connect with the MQTT broker through port 1883.
2. Sensor-initialized IMU:
   
The sensor-initialized routine uses C APIs provided by the Adafruit_BNO055 Arduino library. IMU sensor configurations are done through the I2C interface, and the accelerometer, the gyroscope, the magnetometer and the internal sensor fusion unit are configured to give 3-axis accelerations, 3-axis angular velocity, 3-axis magnetic field values, and quaternions, respectively.

3. Listen for MQTT commands from the Raspberry Pi and the smartphone:
   
   We implemented MQTT subscription routines to listen for MQTT commands sent by the Raspberry Pi and the smartphone. Two types of MQTT messages are subscribed by each sensor node: a) sensor-controlled messages from smartphone used to start and stop data collection, and b) the Raspberry Pi global time message used to maintain sensor node time as in the Raspberry Pi’s global time format.

4. Read and buffer IMU sensor:
   
   We prepared another routine to read the IMU sensor every 10 milliseconds and save the data into buffer. We maintained two ping pong-type buffers to collect the continuous data stream.

5. Transmit MQTT buffer:
   
   We published the collected data buffer as an MQTT message to the Raspberry Pi. The Arduino PubSubClient library allow us to publish the MQTT messages.

6. Time synchronization:
   
   The time synchronization routine received the time from the Raspberry Pi at
one-second intervals, and we then compensated for the sensor node’s local time using Raspberry Pi’s global time.

We created the following MQTT topics for publishing and subscribing messages in above routines:

- “esp8266/imu/sensor1” – to publish collected sensor data from sensor node 1 to Raspberry Pi
- “esp8266/imu/sensor2” – to publish collected sensor data from sensor node 2 to Raspberry Pi
- “rpi/global/time” – to subscribe sensor nodes to Raspberry Pi global time
- “android/test/start” – to start data collection
- “android/test/stop” – to stop data collection

4.2 Home Server Software

The home server software runs on the Raspberry Pi using the Raspbian Buster operating system with Kernel version 4.19. The home server application was developed using Python3. In order to use the MQTT protocol, we set up a Mosquitto broker on the Raspberry Pi. Mosquitto is an open source MQTT broker server that can be installed on Raspberry Pi and other platforms to facilitate M2M communication between connected objects.

The home server software includes five major tasks.

1. Initialize WiFi-based MQTT connection with the wireless sensor nodes:

   A WiFi-based MQTT connection on Raspberry Pi uses the Python Paho
MQTT library to allow publish and subscribe messages to and from the Mosquitto MQTT broker on Raspberry Pi.

2. Publish time beacons and commands to the wireless sensor nodes:
   This routine reads Raspberry Pi time every second, wraps that into the MQTT message, and then publishes to the sensor nodes.

3. Subscribe commands from the Android application:
   The implemented MQTT subscription routines read commands obtained from the Android application. These commands with data are then used to set up the information about test.

4. Subscribe and save IMU data from Wireless sensor nodes:
   Once Raspberry Pi receives MQTT buffer from the sensor nodes, it saves them into separate files. The developed routines first detect the sensor number and then save the IMU data into different CSV files.

5. Upload sensor data to the remote computer:
   When 4SBT is completed each CSV files are upload to the remote computer through FTP.

4.3 Android 4SBT Application

The 4SBT Android smartphone application controls data acquisition and processing of the system during an automated 4SBT balance test. When the application starts, it prompts the user to enter their test subject ID. The user selects individual phases of the 4SBT using radio buttons. The subject’s ID and the test ID identify individual tests in file with raw data. At the end of the test, three CSV files are generated on the Raspberry
Pi, one for each sensor on the test subject and one for smartwatch data. The 4SBT smartphone application has four tests to choose from using the test selector screen shown in Fig. 4.1. The application starts the test after the user presses the “Start Test” button on the display screen. The application shows the number of seconds a subject can hold the position. Each test of the 4SBT lasts a maximum of 10 seconds and can be stopped if the user loses balance or cannot maintain the position.

![4SBT Android smart phone application](image)

**Figure 4.1** 4SBT Android smart phone application


4.4 Smart Watch Application

The Android smart watch application collects 3-axis acceleration data and sends the acquired data to the home server through the MQTT connection. The Android smart watch software includes six major tasks.

1. Initialize WiFi based MQTT connection with Raspberry Pi:
   The first time the smart watch application starts, it initializes the WiFi client connection with the Raspberry Pi MQTT broker through port 1883.

2. Initialize accelerometer sensor:
   The accelerometer sensor’s initialization routine uses Google Android APIs to configure the internal 3-axis accelerometer of the smart watch device.

3. Listen for MQTT commands from Raspberry Pi and smartphone:
   The implemented MQTT subscription routines listen for MQTT commands sent by the Raspberry Pi and the smartphone. The MQTT subscription routine captures the smart watch’s data acquisition controlled message from smartphone used to start and stop data collection.

4. Read accelerometer sensor and buffer:
   This separate routine reads the accelerometer sensor every 10 milliseconds and saves the data into buffer.

5. Transmit the MQTT buffer:
   The collected data buffer publishes as an MQTT message from the smart watch to the Raspberry Pi.

6. Time synchronization:
   The time synchronization routine receives the time from the Raspberry Pi at
one-second intervals and then adds the Raspberry Pi global time to the each data sample collected using the smart watch’s accelerometer sensor.

4.5 Time Synchronization of Sensors

Multi-node wireless sensor systems have to compensate for the drift of local on-chip oscillators and variable latencies, which creates a serious obstacle for time synchronization between data streams. Environmental changes such as pressure, temperature, and power supply voltage may cause changes in clock frequency and internal clock drift. Therefore, we implement a time synchronization mechanism using Raspberry Pi’s time as a master server that synchronizes and corrects time stamps from slave sensors. The home server software maintains Unix time in milliseconds, wraps it in an MQTT payload, and then sends it to the wireless sensor network of the sensor nodes and the smartwatch as time beacon, as shown in Fig. 4.2 [84].

![Home server based time synchronization diagram](image)

**Figure 4.2** Home server based time synchronization
To initiate the synchronization, each sensor node first collects eight server time beacons, sent on one-second intervals. The sensor nodes continue to use the latest eight time beacons to update linear transformation from local to global time.

To test time desynchronization, we recorded the same signal on two sensors and analyzed time difference between signals from two sensors. As a test signal, we used dynamic 3D acceleration generated on each sensor when sensors are moved together, as shown in Fig. 4.3. Table 4 shows the analysis of timing of peaks generated during the joint motion. Mean time difference between peaks represents time jitter between synchronized data streams. Average time difference during experiment was 9.84 milliseconds, or less than one sampling period.

![Figure 4.3 Time difference between two wireless sensor nodes](image-url)
Table 4 Absolute time difference between synchronized streams

<table>
<thead>
<tr>
<th>Time [msec]</th>
<th>Absolute time difference [msec]</th>
</tr>
</thead>
<tbody>
<tr>
<td>sensor1</td>
<td>sensor2</td>
</tr>
<tr>
<td>771.9</td>
<td>767.7</td>
</tr>
<tr>
<td>2261</td>
<td>2256</td>
</tr>
<tr>
<td>6064</td>
<td>6078</td>
</tr>
<tr>
<td>6245</td>
<td>6248</td>
</tr>
<tr>
<td>7996</td>
<td>8002</td>
</tr>
<tr>
<td>11860</td>
<td>11880</td>
</tr>
<tr>
<td>12060</td>
<td>12070</td>
</tr>
<tr>
<td>14070</td>
<td>14064</td>
</tr>
<tr>
<td>17850</td>
<td>17870</td>
</tr>
<tr>
<td>19340</td>
<td>19350</td>
</tr>
<tr>
<td>24500</td>
<td>24510</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td>S.D</td>
<td></td>
</tr>
</tbody>
</table>

4.6 Sensor Calibration

To ensure the accuracy of our sensor data, we performed sensor calibration as described in the BNO055 sensor datasheet [76]. Once the sensor is calibrated, the calibration profile is written in the EEPROM of the sensor and can be reused to improve accuracy of sensor measurements.

4.6.1 Accelerometer Calibration

We placed the inertial sensor in six different stable positions for a few seconds to allow the accelerometer to calibrate. For each position we choose direction perpendicular to the x, y, or z axis for better calibration.
4.6.2 Gyroscope Calibration

Gyroscope is calibrated by keeping a single stable position for a period of few seconds to compensate for time drift of the sensor.

4.6.3 Magnetometer Calibration

Magnetometer is calibrated by creating an “8” motion of the sensor that creates uniform change of the magnetic field necessary for the calibration.

4.7 The Human Body Plane

An anatomical plane is another name for the human body plane which used to transect the body, in order to describe the location of structures or the direction of movements [85]. In human anatomy, three principal planes are used as shown in the Fig. 4.4.
Figure 4.4 The human body planes

1. The sagittal plane which divides the body into left and right side
2. The coronal plane which divides the body into back and front side
3. The transverse plane which divides the body into head and tail portions

The rotation around sagittal plane is known as ML angle and the rotation around coronal plane is known as AP angle.

4.8 Signal Processing

The raw data samples were stored and analyzed in the Raspberry Pi. The main parameters calculated were RMS values of dynamic accelerations for both sensor nodes and smart watch data. The signal processing was performed for the quaternions to estimate displacement in AP and ML directions.
4.8.1 Processing of Quaternions

Since the sensor nodes were mounted on test subject’s lower back and forehead, the change of the absolute angles in AP and ML plane with positive and negative directions are shown in Fig. 4.4. The relative angles of inertial sensors are represented as:

- $\Psi$ - rotation around the y-axis, which is same as rotation around transverse plane
- $\Theta$ - rotation around the x-axis, which is AP angle, and
- $\phi$ - rotation around the z-axis, which is ML angle

Step_1: Calculate the rotation matrix for initial condition of the test, $RM_1$ is the initial rotation matrix during the 4SBT. $RM_1$ can be express using quaternions of initial condition as follows [86].

$$RM_1 = 2 \begin{bmatrix} q_0^2 + q_1^2 - 0.5 & q_1q_2 - q_0q_3 & q_0q_2 + q_1q_3 \\ q_0q_3 + q_1q_2 & q_0^2 + q_2^2 - 0.5 & q_2q_3 - q_0q_1 \\ q_1q_3 - q_0q_2 & q_0q_1 + q_2q_3 & q_0^2 + q_3^2 - 0.5 \end{bmatrix}$$

Step_2: Calculate the rotation matrix for each time step of the test $(k)$,

$$RM_k = 2 \begin{bmatrix} q_0^2 + q_1^2 - 0.5 & q_1q_2 - q_0q_3 & q_0q_2 + q_1q_3 \\ q_0q_3 + q_1q_2 & q_0^2 + q_2^2 - 0.5 & q_2q_3 - q_0q_1 \\ q_1q_3 - q_0q_2 & q_0q_1 + q_2q_3 & q_0^2 + q_3^2 - 0.5 \end{bmatrix}$$

$RM_k$ is the rotation matrix for each k time stamp during the 4SBT

Step_3: Multiple $RM'_1$ and $RM_k$ to get $RR_k$, since the relative orientation is obtained simply by division (or inverse of $RM_1$) [80]

$$RR_k = RM'_1 \ast RM_k$$

$RR_k$ is the result matrix which is obtained multiplication by $RM'_1 and RM_k$
Step 4: Use the Step3 result $RR_k$ matrix to calculate the change of absolute angle from initial state. The angles $\psi$, $\Theta$, and $\phi$ are the Euler angles [80].

$$RR_k = \begin{bmatrix}
\cos \Theta \cos \phi & \sin \psi \sin \Theta \cos \phi - \cos \psi \sin \phi & \cos \psi \sin \Theta \cos \phi + \sin \psi \sin \phi \\
\cos \Theta \sin \phi & \sin \psi \sin \Theta \sin \phi + \cos \psi \cos \phi & \cos \psi \sin \Theta \sin \phi + \sin \psi \cos \phi \\
-\sin \Theta & \sin \psi \cos \Theta & \cos \psi \cos \Theta
\end{bmatrix}$$

Step 5: Since we know the $RR_k$ from Step 3 and Step 5, the angles $\psi$, $\Theta$, and $\phi$ can be calculated. The angle $\Theta$ is equal to the change of absolute angle in AP direction, the angle $\phi$ is equal to the change of absolute angle in ML direction.

Figure 4.5 Sensor orientation, medial-lateral and anterior-posterior angle change during 4SBT
CHAPTER 5

EXPERIMENTAL VALIDATION

This chapter represents the experimental validation of the balance assessment system during 4SBT using healthy control subjects.

5.1. Validation of the balance assessment system

To validate the angle calculations which is described in the chapter 4, we attached the both sensors to the rigid cardboard stick and then give the rotation between -30 degrees and +30 degrees and -90 degrees to +90 degrees as shown in the Fig. 5.1. The sequence of changes of angle \{-30, 0, 30\} and \{-90, 0, +90\} are shown in Fig. 5.2 and Fig. 5.3 respectively.
**Figure 5.1** The rigid cardboard sensor attachment for angles validations

**Figure 5.2** The validation of orientation measurement for angles \{-30, 0, 30\}
Figure 5.3 The validation of orientation measurement for angles \{-90, 0, 90\}

Table 5 shows the analysis of accuracy of angle measurements. Mean absolute error during the test is 0.24 degrees. Maximum error at 30 degrees is 2.1% for sensor 1 and 3.9% for sensor 2. More precise validation would require a more sophisticated setup, but the accuracy of orientation measurement is sufficient for the balance assessment applications that is primary objective of our system.
### Table 5 Validation of angle measurement

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>sensor 1</td>
<td>sensor 2</td>
<td>sensor 1 &amp; 2</td>
</tr>
<tr>
<td>29.37</td>
<td>28.83</td>
<td>30</td>
</tr>
<tr>
<td>29.5</td>
<td>29.04</td>
<td>30</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.03</td>
<td>-0.2</td>
<td>0</td>
</tr>
<tr>
<td>-0.01</td>
<td>-0.25</td>
<td>0</td>
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<tr>
<td>-0.14</td>
<td>-0.44</td>
<td>0</td>
</tr>
<tr>
<td>-0.06</td>
<td>-0.06</td>
<td>0</td>
</tr>
<tr>
<td>-30.04</td>
<td>-29.96</td>
<td>-30</td>
</tr>
<tr>
<td>-30.05</td>
<td>-29.92</td>
<td>-30</td>
</tr>
<tr>
<td>89.95</td>
<td>89.39</td>
<td>90</td>
</tr>
<tr>
<td>89.87</td>
<td>89.69</td>
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</tr>
<tr>
<td>89.52</td>
<td>89.81</td>
<td>90</td>
</tr>
<tr>
<td>-89.52</td>
<td>-89.24</td>
<td>-90</td>
</tr>
<tr>
<td>-89.48</td>
<td>-89.33</td>
<td>-90</td>
</tr>
<tr>
<td>-89.56</td>
<td>-89.33</td>
<td>-90</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S.D</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.2. Human subjects testing

The system was tested by five healthy participants, ages of 24-32 years, mean 28.8 years and standard deviation 2.95 years, as shown in the Table 6. All subjects had normal hearing and normal or corrected-to-normal vision. All participants were free of any preexisting condition that may have altered their ability to balance, such as Parkinson’s disease or physical mobility issues.
5.3. Experimental setup and protocol

Subjects were outfitted with two inertial sensor nodes, one at a lower back (LBIS), one on forehead (FHS), and a smartwatch, as shown in Fig. 5.4.

![Figure 5.4 The balance assessment system setup.](image)

We prepared a balance test to assess subject’s balance. The protocol uses CDC recommended 4 stage balance Test (4SBT) [87], but repeating every stance with eyes closed, that is much more challenging than eyes open. Each test requires subject to keep balance for 10 seconds in the sequence of 8 standing conditions: (1) Feet together with eyes open, and (2) Feet together with eyes closed; (3) Semi tandem stand with eyes open; (4) Semi tandem stand with eyes closed; (5) Tandem stand with eyes open, and (6) Tandem stand with eyes closed; (7) One leg stand with eyes open, and (8) One leg stand with eyes closed.
**Table 6** Test subjects information

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age [years]</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>29</td>
<td>Female</td>
</tr>
<tr>
<td>2</td>
<td>29</td>
<td>Male</td>
</tr>
<tr>
<td>3</td>
<td>24</td>
<td>Female</td>
</tr>
<tr>
<td>4</td>
<td>32</td>
<td>Male</td>
</tr>
<tr>
<td>5</td>
<td>30</td>
<td>Female</td>
</tr>
<tr>
<td>Mean</td>
<td>28.8</td>
<td></td>
</tr>
<tr>
<td>S.D</td>
<td>2.95</td>
<td></td>
</tr>
</tbody>
</table>

We calculated the changes of angles in AP and ML planes using quaternions as described in above steps for each five subjects. The Figure 5.5 shows the changes of AP angle and ML angle during 4SBT for a 24 old healthy female subject (subject 3) using lower back mounted sensor during open eyes condition.
Figure 5.5 Comparison of AP and ML angle changes during open eyes (a) two leg stance, (b) semi tandem stance (c) tandem stance (d) one leg stance for subject 3
Figure 5.6 Changes of AP and ML angles during four phases of the 4SBT

Fig. 5.6 demonstrates significant variation of angle in both AP and ML plane as subject is trying to maintain her balance. CDC describes four phases of the test as “progressively harder balance tests”.
Figure 5.7 Comparison of AP and ML angle speed changes during open eyes (a) two leg stance, (b) semi tandem stance (c) tandem stance (d) one leg stance for subject 3
Figure 5.8 Changes of AP and ML angle speeds during four phases of the 4SBT

5.4. The Results of the 4SBT Balance Test

Summary of analysis of the balance biomarkers is represented in Tables 7-10. RMS values of AP and ML angles are represented in Tables 7 and 8, while angular velocity of AP and ML is represented in Tables 8 and 9. We represented the results for each test in eyes open and eyes closed conditions.
Table 7 RMS values of AP and ML for FHIS during 4SBT

<table>
<thead>
<tr>
<th>Subject</th>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.42/0.46</td>
<td>0.17/0.46</td>
<td>0.38/0.39</td>
<td>0.32/0.38</td>
</tr>
<tr>
<td>2</td>
<td>0.89/1.50</td>
<td>0.83/0.81</td>
<td>1.74/2.08</td>
<td>1.21/1.01</td>
</tr>
<tr>
<td>3</td>
<td>0.44/0.98</td>
<td>0.83/0.27</td>
<td>1.16/0.72</td>
<td>0.81/0.98</td>
</tr>
<tr>
<td>4</td>
<td>0.90/1.04</td>
<td>0.19/0.30</td>
<td>0.49/0.99</td>
<td>0.59/0.52</td>
</tr>
<tr>
<td>5</td>
<td>0.52/0.35</td>
<td>0.60/0.36</td>
<td>0.49/0.93</td>
<td>0.18/0.26</td>
</tr>
<tr>
<td>Mean</td>
<td>0.63/0.87</td>
<td>0.52/0.44</td>
<td>0.85/1.02</td>
<td>0.62/0.63</td>
</tr>
<tr>
<td>S.D</td>
<td>0.24/0.47</td>
<td>0.29/0.22</td>
<td>0.58/0.64</td>
<td>0.41/0.35</td>
</tr>
</tbody>
</table>

Table 8 RMS values of AP and ML for LBIS during 4SBT

<table>
<thead>
<tr>
<th>Subject</th>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.73/0.68</td>
<td>0.25/0.18</td>
<td>0.22/0.38</td>
<td>0.08/0.33</td>
</tr>
<tr>
<td>2</td>
<td>0.41/0.91</td>
<td>0.21/0.19</td>
<td>1.05/0.98</td>
<td>1.22/0.87</td>
</tr>
<tr>
<td>3</td>
<td>0.73/0.69</td>
<td>0.22/0.08</td>
<td>1.08/0.63</td>
<td>0.24/0.96</td>
</tr>
<tr>
<td>4</td>
<td>0.49/0.30</td>
<td>0.01/0.05</td>
<td>0.33/0.76</td>
<td>0.20/0.66</td>
</tr>
<tr>
<td>5</td>
<td>0.82/0.51</td>
<td>0.10/0.07</td>
<td>0.34/0.82</td>
<td>0.06/0.73</td>
</tr>
<tr>
<td>Mean</td>
<td>0.64/0.62</td>
<td>0.16/0.11</td>
<td>0.60/0.71</td>
<td>0.36/0.71</td>
</tr>
<tr>
<td>S.D</td>
<td>0.18/0.23</td>
<td>0.10/0.07</td>
<td>0.42/0.23</td>
<td>0.49/0.24</td>
</tr>
</tbody>
</table>
Our system introduces new measure of user balance – information about compensatory efforts using inertial sensors on the smartwatch (SWIS). Fig. 5.9 represents AP and ML angles during eyes closed one leg stand test, and dynamic acceleration on the
smartwatch. It can be seen that dynamic acceleration follows the change of angle as user is trying to maintain the balance.

**Figure 5.9** AP and ML angles during eyes closed one leg stand test, and dynamic acceleration on the smartwatch (a). AP and ML angle of FHIS (b). AP and ML angle of LBIS (c). dynamic acceleration of SWIS
Table 11 Absolute value of dynamic acceleration on SWIS during 4SBT

<table>
<thead>
<tr>
<th>Subject</th>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EO [m/s²]</td>
<td>EC [m/s²]</td>
<td>EO [m/s²]</td>
<td>EC [m/s²]</td>
</tr>
<tr>
<td>1</td>
<td>0.06</td>
<td>0.05</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>0.16</td>
<td>0.08</td>
<td>0.21</td>
<td>0.15</td>
</tr>
<tr>
<td>3</td>
<td>0.06</td>
<td>0.17</td>
<td>0.12</td>
<td>0.15</td>
</tr>
<tr>
<td>4</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.1</td>
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<tr>
<td>5</td>
<td>0.05</td>
<td>0.08</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td>Mean</td>
<td>0.07</td>
<td>0.08</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>S.D</td>
<td>0.05</td>
<td>0.05</td>
<td>0.06</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Figures 5.10 – 5.11 show box plots for AP and ML speed for FHIS during eyes open and eyes closed conditions. Figures 5.12-5.13 show box plots for AP and ML speed for LBIS during eyes open and eyes closed conditions.
Figure 5.10 Mean absolute values of AP and ML speed for FHIS during eyes open

Figure 5.11 Mean absolute values of AP and ML speed for FHIS during eyes closed
Figure 5.12 Mean absolute values of AP and ML speed for LBIS during eyes open

Figure 5.13 Mean absolute values of AP and ML speed for LBIS during eyes closed
Fig. 5.14 and Fig. 5.15 were generated based on the results for subject 4’s LBIS during open eyes and closed eyes conditions of one leg stance of 4SBT. It’s clearly shows there is higher variation of speed for both AP and ML direction when subject is tested closed eyes condition.

**Figure 5.14** AP angle vs ML angle for subject 4 a) open eyes condition b) closed eyes condition results of one leg stance of 4SBT
Figure 5.15 AP speed vs ML speed for subject 4 a) open eyes condition b) closed eyes condition results of one leg stance of 4SBT
CHAPTER 6

DISCUSSION

This chapter discusses the results in Chapter 5 which we validated using five healthy subjects during 4SBT in eyes open and eyes closed conditions.

6.1 Difference between each test of 4SBT

CDC introduced 4SBT which has four different stages of stances progressively harder balance test incremental order. As shown in the Fig. 5.6, there is a significant variation of both AP and ML angle as subject is trying to maintain her balance. One leg stance shows highest variation for both AP and ML angles amount four tests stages. When we look at the Figures 5.10 – 5.13, it clearly shows the increment of AP and ML speed towards the higher order test stages. One leg stance shows significant high value of AP and ML speed since the all five subjects were facing difficult to maintain balance.

6.2 Difference between sensors and sensor positions

There is a higher variations of the angle speed in both AP and ML directions for FHIS. Fig. 5.10 – Fig. 5.12 and Fig. 6.1 clearly shows there are higher median value and
Standard deviation of AP and ML speed for each four stages using FHIS than LBIS. So FHIS shows more sensitivity than LBIS.

Figure 6.1 Standard deviation of AP and ML speed for FHIS and LBIS

Tables 12 and 13 represent the summary of RMS value of AP and ML speed between FHIS and LBIS during eyes open condition. Every test stage shows higher RMS value for FHIS than LBIS. Fig. 6.2 is generated based on the Table 12 data and it proves FHIS is more sensitive than LBIS.

Table 12 Statistics for RMS value of AP speed between FHIS and LBIS during eyes open condition

<table>
<thead>
<tr>
<th></th>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td>APEO</td>
<td>1.04</td>
<td>0.59</td>
<td>1.04</td>
<td>0.65</td>
</tr>
<tr>
<td>Mean</td>
<td>1.04</td>
<td>0.59</td>
<td>1.27</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Two leg stance</td>
<td>One leg stance</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>FHIS [deg/s]</td>
<td>LBIS [deg/s]</td>
</tr>
<tr>
<td>APEO</td>
<td>1.76</td>
<td>2.10</td>
<td>2.10</td>
<td>1.76</td>
</tr>
<tr>
<td>Mean</td>
<td>2.10</td>
<td>1.76</td>
<td>2.10</td>
<td>1.76</td>
</tr>
</tbody>
</table>
Table 13 Statistics for RMS value of ML speed between FHIS and LBIS during eyes open condition

<table>
<thead>
<tr>
<th></th>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FHIS</td>
<td>LBIS</td>
<td>FHIS</td>
<td>LBIS</td>
</tr>
<tr>
<td>MLEO [deg/s]</td>
<td>0.98</td>
<td>0.26</td>
<td>1.05</td>
<td>0.49</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 6.2 Variation of RMS value of AP and ML speed between FHIS and LBIS during eyes open condition
6.3 Difference between eyes open and eyes closed conditions

Vision gives a great help to maintain posture balance. Even health subjects are facing difficulties in keep their balance when minimize the sensory information from their eyes. We performed 4SBT for each five subjects with eyes open and eyes closed conditions. Our statistics shows each five subjects has significant high values for angle variation and speed. As an reference Fig. 5.14 was based on the results for subject 4’s LBIS during eyes open and eyes closed conditions of one leg stance of 4SBT. It’s clearly shows there is higher variation of speed for both AP and ML direction when subject is tested closed eyes condition.

We defined APEC/APEO and MLEC/MLEO ratios based on the RMS values from Table 9 and calculated the ratio as shown in the Table 14.

**Table 14** RMS value of speed for FHIS during eyes open and eyes closed condition

<table>
<thead>
<tr>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td>APEC/APEO</td>
<td>MLEC/MLEO</td>
<td>APEC/APEO</td>
<td>MLEC/MLEO</td>
</tr>
<tr>
<td>0.98</td>
<td>0.68</td>
<td>1.36</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.58</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1.62</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2.18</td>
</tr>
</tbody>
</table>
Our EC/EO ratio has a value greater than 1 except test stage one in 4SBT. That means during eyes closed condition there is higher variation of speed for both AP and ML direction. When test stage is going up, the ratio is dramatically increased since subject has to do significant effort to maintain his/her balance.

### 6.4 Measuring compensatory efforts using SWIS

Since our balance system has SWIS, we are able to capture the compensatory efforts during the 4SBT. Statistics from Table 1 proves that all five subject show increment of dynamic accelerations when test stage going up during open eyes and closed eyes conditions.
**Figure 6.4** Variation of absolute dynamic acceleration for SWIS (a) eyes open (b) eyes closed condition

Fig. 6.4 demonstrates that all subjects show higher variation of dynamic acceleration during one leg stand eyes closed condition.

To get a better picture of compensatory effort we defined a EC/EO (eyes closed to eyes open) ratio using RMS value of acceleration for the smartwatch. Table 15 show the calculated ratios.

**Table 15** EC/EO ratio for RMS of acceleration data on smartwatch

<table>
<thead>
<tr>
<th>Two leg stance</th>
<th>Semi-tandem stance</th>
<th>Tandem stance</th>
<th>One leg stance</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC/EO</td>
<td>EC/EO</td>
<td>EC/EO</td>
<td>EC/EO</td>
</tr>
<tr>
<td>1.14</td>
<td>1</td>
<td>2.45</td>
<td>2.52</td>
</tr>
</tbody>
</table>

When test stage is going up subject has to do more effort to compensate his/ her balance. Our new smartwatch sensor proves that since EC/EO ratio is dramatically increased as shown in the Fig. 6.5.
Figure 6.5 EC/EO ratio for RMS of acceleration on smartwatch
CHAPTER 7

CONCLUSIONS

Falls are the leading cause of fatal and non-fatal injuries for older population throughout the world. Falls very often lead to rapid decline of overall user’s health. The treatment costs and resources required for rehabilitation after the fall have significant impact on economy. According to the U.S Centers for Disease Control and Prevention (CDC), an older adult is treated in the emergency room for a fall every 11 seconds; every 19 minutes, an older adult die from a fall. Moreover, falls result in more than 2.8 million injuries treated in emergency departments annually, including over 800,000 hospitalizations and more than 27,000 deaths [88]. We designed a system for accurate balance testing at home and physician’s offices, as a tool for automated assessment of balance. The system can enhance the quality of life and facilitate better screening procedures, and improved balance assessment for remote healthcare and aging in place applications.

We implemented the Wireless Body Area Network for balance assessment with two inertial sensors and a smartwatch, smartphone application to control the setup, and a home server to synchronize all devices and collect the records. Android smartphone
application is developed to automate the 4 Stage Balance Test. Moreover, the “always on” home server enables anytime connectivity between individual devices.

This thesis presents an implementation of the system, testing of accuracy of inertial measurements and time synchronization between wireless sensor, and validation of system functionality in a pilot study with five subjects using 4SBT test with eyes open and eyes closed. The system can be used to accurately generate digital biomarkers of balance in a variety of settings.

The main contributions of this thesis are as follows:

- The development of wireless IMU sensor node
- The development of always on home server that is always ready to accept data from sensors and synchronizes on-body sensors
- Android smartphone application that initiates and controls the 4 Stage Balance Test
- Android smartwatch application using smartwatch as another IMU
- Time synchronization of sensors
- Real-time extraction of parameters associated with balance tests
- Automatic upload of sensor data files to a remote FTP server

Future work includes:

- implementation of the cloud based medical server for automatic upload and processing of patient records, and
- implementation of additional signal processing methods for balance assessment in real-time on home server and off-line on cloud.
REFERENCES


[79] H. Ganegoda and E. Jovanov, “IoT Based Longitudinal Monitoring of Activity and Posture Transitions in Smart Homes.”


