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UNIVERSITY OF CALIFORNIA, SAN DIEGO

Objective Metrics for Fall Risk Assessment

A Thesis submitted in partial satisfaction of the requirements
for the degree Master of Science

in

Bioengineering

by

Sneha Priya Bhattaram

Committee in charge:

Ramesh Rao, Chair
Todd P. Coleman, Co-Chair
Pedro J. Cabrales
Harinath Garudadri

2017

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The Thesis of Sneha Priya Bhattaram is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

Chair

University of California, San Diego

2017

DEDICATION

To Amma, for I am nothing without you

To Naanna, for reminding me time and again that the best of all the most beautiful creations in the world is a kind, educated person

To Akka, for being the perfect soul sister

To Ammamma, Thaathayya, Naannamma, Thaathayya, for being the most wonderful grandparents

To Almighty, for Your two words of wisdom: Faith and Perseverance

To self, for sincerely adhering to the wishes of your dear ones

EPIGRAPH

“And so we beat on, boats against the current, borne back ceaselessly into the past.”

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LIST OF ABBREVIATIONS

SPPB……………………………………………… Short Physical Performance Battery

EPESE...………………………………………..….. Epidemiologic Studies of the Elderly

LTC……………………………... Long Term Care

ADL……………………………………………………….... Activities of Daily Living

DVS……………………………………………………………Dynamic Vision Sensor

IR……………………………………………………………………………….Infra-red

MART …………………………..………………Multiple Additive Regression Trees

5STS ……………………………………………………...........Five Times Sit to Stand

FISP …………………………………………Frontiers of Innovation Scholars Program

HOG …………………………………………………...Histogram of Oriented Gradient

SVM ……………………………………………………..Support Vector Machine

COP..……………...…………………………………………………....Center of Pressure

TUG ……………………………………………………………….Timed Up and Go

PPT………………………………………………………..Physical Performance Test

EPARC…………………………………..Exercise and Physical Activity Resource Center

RadLab………………………………..Research on Autism and Development Laboratory

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ACKNOWLEDGMENTS

This research study would not have been possible without the support of many people. First and foremost, I would like to express my deep sense of gratitude to Dr. Harinath Garudadri, my advisor, for helping me get started in the field of data analytics, believing in me, guiding me meticulously, opening up doors to present my research at Symposiums, always being a constant source of encouragement, urging me to think big and out of the box throughout and outside of this research study. I would like to thank Dr. Todd P. Coleman, my co-advisor, for paving ways to foray into the field of statistical learning and for instilling in me an enthusiasm for machine learning and teaching.

I am grateful to Dr. Job Godino for helping and providing mentorship during the early stages of this research study. I am also extremely thankful to Dr. Leanne Chukoskie and Sarah Hacker from RadLab for helping with the design of data collection protocol and equipment setup.

I worked on this project in close collaboration with Vaibhav Gandhi, who helped me tremendously and without whom, gait algorithm would not have been possible. I would like to thank him for his valuable and continuous support throughout. I would like to thank Kevin, Alex, Esther, Sewon, Kuanlin, Allison and Ishan for making the data collection process an enjoyable one and for helping in their own individual ways.

I would like to thank my committee members, Dr. Ramesh Rao and Dr. Pedro Cabrales, for their time, consideration and motivation.

I am forever grateful to my dear parents and sister and grandparents, without whom I wouldn’t have even dreamt of coming this far in my life.

I would like to express my deepest sense of respect and gratitude to my friends at UCSD for their acts of kindness, support and inspiration.

Finally, I am forever grateful to the Department of Bioengineering at UC San Diego for helping me in immeasurable ways and making me an eligible and a capable graduate student.

ABSTRACT OF THE THESIS

Objective Metrics for Fall Risk Assessment

by

Sneha Priya Bhattaram

Master of Science in Bioengineering

University of California, San Diego, 2017

Dr. Ramesh Rao, Chair
Dr. Todd P. Coleman, Co-Chair

Traditional Physical Performance Tests (PPT) are subjective, labor-intensive and involve on-body sensors for assessing gait and balance disturbances of an individual. Therefore, we developed an unobtrusive, off-body camera based approach to derive objective metrics for gait and balance monitoring. The outcome of our research demonstrates the capability of a computer vision based SPPB assessment tool that can be used as a promising alternative to conventional SPPB protocol to assess and score physical performance objectively and unobtrusively.

Chapter 1 – Introduction

1.1 Motivation

In the United States, the annual rate of falls among adults aged 65 years and older is commonly reported to be 33%, but may be as high as 48%. Balance stability and gait variability are correlated with fall risk among adults over the age 65. The consequences of falls include decline in functional status, nursing home placement, increased use of medical devices and reduced quality of life. Centers for Disease Control estimate annual cost of falls as $23.3 billion in 2013 and $55 billion in 2020 [1-1, 1-2, 1-3]. Consequently, there is a critical need for the development of cost-effective and easily deployed tools and interventions that can be scaled to aid in the prevention of falls and promote healthy aging. These estimates clearly show the magnanimity of the problem and why we should be moving towards tackling it. If left unsolved, the problem of movement disorders can adversely affect the productive lives of the active, working population of the world in addition to a host of other problems that come along. However, in order to take any preventive measures, we should first analyze the risk associated with a fall. Although there are many tools available to assess fall risk, they are mostly done manually resulting in subjective metrics and hence we will develop objective metrics for fall risk assessment, which are repeatable, easy to administer and will readily integrate with current workflows. The "gold standards" such as clinical grade force plates, accelerometers and other sensors do provide objective metrics. However, due to cost and time constraints, they are not frequently used. Our approach is based on off-body (visual) sensors and computer vision algorithms to supplement current best practices with objective metrics for fall risk assessment. Such a system is of extreme value to caregivers for early detection of fall risk and to intervene appropriately for fall prevention.

For assessing physical performance, the principal diagnostic tool in clinical practice is Short Physical Performance Battery (SPPB). The SPPB was developed by Jack Guralnik and colleagues as part of a National Institute on Aging project, the Established Populations for Epidemiologic Studies of the Elderly (EPESE). Ever since then, it has been used in large-scale epidemiological studies, and as such has an excellent normative basis [1-4].

People typically visit clinics/labs that have been designed for the purpose of conducting an SPPB test. Every year, a large number of such gait and balance related studies are conducted and some of these studies involve on-body sensors which inevitably disrupt the normal movement pattern of an individual. Tests assessing physical performance routinely require multiple trials and usually the first trial is not scored or recorded with the notion that the first trial is for the subjects to understand and get used to performing tasks with the sensor equipment. Balance and gait are most frequently evaluated through direct observation, wherein an older adult is scored on completing a series of challenging physical tasks on criteria such as the successful completion of a task, time taken to complete a task, or even observed difficulty during a task. These methods are very subjective and require face-to-face time with a specialist. This makes it virtually impossible to have the frequency of evaluation necessary to detect small yet clinically meaningful changes over time, which is necessary for more accurate fall risk assessment and early intervention. On-body sensor equipment is expensive and conventional SPPB is time-consuming, labor-intensive and gait labs might even have long waiting lists. Apart from this, the scoring schematic for SPPB is mostly manual. An expert clinician manually looks at the various tasks performed by the individual and assigns a score (usually pass/fail or 1-5 scale) to each task according to rules framed by the specific clinic. This technique, in addition to the disadvantages mentioned above, is subjective and in the presence of multiple experts is prone to significant inter-rater variability.

Hence, there is a persisting need for an off-body sensor, portable system that can perform gait and balance monitoring unobtrusively. The system must also give a read-out of objective scoring that can been used by healthy human population in addition to those with chronic gait disorders.

And so, the overarching goal of this research project is to create a comprehensive fall risk assessment system that is valid, reliable, can easily be incorporated into both homes and various clinical settings. We envision a near future in which clinically meaningful changes in metrics equating to a significant increase in fall risk would trigger notification of the individual using the system, their clinician, or their caregiver, thus facilitating early intervention. This will in turn help older adults maintain an independent lifestyle and high quality of life.

The specific aims of the proposed work are (i) to collect training and testing data during simulated activities of daily living (ii) to develop computer vision based algorithms to derive SPPB specific metrics. (iii) to validate results with gold standards used in clinical settings.

Like mentioned earlier, even though some objective methods exist like force plates and computerized walkways, they are time consuming and cost prohibitive. We believe that this barrier could be overcome via our novel approach to objective fall risk assessment that uses an affordable, off-body camera and computer vision algorithms to passively assess balance and gait disturbances. We also believe that continuous monitoring in the home helps detect early health changes which would otherwise remain unnoticed. This inspired us to develop algorithms to measure objective metrics using a camera system in an automated manner.

Briefly, we have developed a sophisticated camera system that is responsive only to pixel changes. Consequently, the camera system has the advantage of obscuring an individual’s identity (i.e., images of individuals are indistinguishable to the human eye), while resolving subtle movements in the visual field.

In this thesis, the capabilities of novel, flexible computer vision algorithms are developed for monitoring gait and balance ability. Data collected from 20 subjects is analyzed and hypothesis testing is performed on the data. The results of modeling and hypothesis testing indicate that a computer vision based SPPB assessment tool could be a promising alternative to conventional SPPB protocol as an acquisition cum assessment tool for monitoring movement disorders.

1.2 Organization of the Thesis

Chapter 2 gives an overview of the background of clinical aspects of falls and relevant literature review of previous experimental studies related to gait and balance assessment. Chapter 3 deals with the description of the materials and protocols used in this project. The algorithmic framework of the thesis along with the results of statistical analysis is covered in chapter 4. Discussion, conclusion and future directions are part of chapter 5.

Chapter 2 – Background

2.1 Clinical Aspects of Falls

The maintenance of mobility, broadly defined as movement within one's environment, is an essential component of healthy aging, because it underlies many of the functions necessary for independence [2-2]. Ability to maintain balance and walk are the primary components of mobility [2-3]. Decrease in balance and gait speed that accompany aging is a universal phenomenon [2-4].

The human body is made up of a complex system of interconnected functionalities that adapt to a variety of external stressors. Despite this, aging or illness can still reduce these inherent adaptive mechanisms exposing the human body to a host of diseases or disorders. Frailty is the phenotypic manifestation of this process [2-4].

A significant cause of injury is falling and it can lead to death especially in older adults because of frailty. Adults residing in long-term care (LTC) facilities may fall for a plethora of reasons. They are more likely to endure and sustain injuries after a fall than those who live in the community. Decrease in body weight and osteoporosis may also result in serious injuries or fracture as a consequence of a fall [2-1].

Many factors can facilitate the occurrence of falls in the daily lives of the elderly. These factors can be categorized into two: intrinsic factors are those that are inherent to the person and are related to the biological and psychosocial changes associated with aging and extrinsic factors are those that result from external factors such as, for example, quality of flooring and lighting in the residences, access to public transportation and recreational areas, among others. However, occurrence of falls is attributed to multitude of events both intrinsic and extrinsic and can be thought of as the ability to maintain the skills needed to perform the basic activities of daily living and so it is often difficult to report them separately. [2-5, 2-6, 2-7].

Such high prevalence of falls can have serious consequences on the quality of life of the older adults. Consequences of falls include prolonged hospitalization, institutionalization, restriction of activities and mobility, changes in balance and postural control, social isolation, anxiety and depression [2-8]. Therefore, it is important to know and identify the potentiating and protective factors, to adopt preventive measures for these events of falls.

In addition to aging, there have been numerous publications in the field of gait analysis about how motor skills are affected in different types of disorders. Tremor, rigidity, bradykinesia (slow movement), postural instability (balance problems), and walking/gait problems are the primary motor related symptoms for Parkinson's disease and are extensively used to diagnose [2-9].

2.2 Fall Risk Assessment Tools

There is a high need to assess the risk associated with falling to be able to prevent falls. There have been numerous techniques and protocols mentioned in the literature designed for preventing falls. However, the first step for all of these protocols is to identify persons at highest risk upon whom to target specific interventions. Unfortunately, fall risk assessment is not standardized within or across settings. Traditionally, three types of assessments relevant to falls and mobility have been done, usually on the basis of setting or specific discipline factors. These include (i) comprehensive medical assessments performed by geriatricians or nurse practitioners in the outpatient or nursing home setting, (ii) nursing fall risk assessments completed in hospital and nursing home settings, and (iii) functional mobility assessments completed by physical therapists or physicians in an outpatient setting [2-10].

The first approach is used by geriatricians and nurse practitioners to evaluate and treat patients at risk for falls or who have recently fallen [2-11]. This type of assessment takes into account an in-depth medical evaluation of previous falls, cognition, balance, gait, strength, chronic diseases, mobility, nutrition, and medications [2-12], resulting in a very time-consuming approach [2-13] and often involves a team of clinicians [2-14].

The nursing assessment of a patient's risk of falling has been widely performed in hospital and nursing home settings and employs specific screening instruments or forms. Based on the intrinsic or medical conditions of the patient (e.g., psychological status, mobility dysfunction, fall history, elimination frequency/dependence, acute/chronic illnesses, and sensory deficits), these instruments [e.g., Morse Fall Scale [2-15] , STRATIFY [2-16], Resident Assessment Instrument (RAI; 23), Fall Risk Assessment Tool [2-17], Hendrich Fall Risk Model [2-18], High Risk for Falls Assessment Form [2-19], or Royal Melbourne Hospital Risk Assessment Tool [2-20]] identify who is likely to fall.

For our study, we use the Short Physical Performance Battery (SPPB) protocol that is widely employed in various clinical settings. It is described in detail below.

2.2.1 Short Physical Performance Battery

Amongst various interventions, the Short Physical Performance Battery is a widely used fall risk assessment tool in clinical settings. SPPB is a performance based test that assesses the ability of a subject to maintain balance and move through various tasks carried as part of the protocol. It is specifically designed for elderly participants and consists of three parts: The Balance Test, the Gait Speed Test, and the Chair Stand Test. In the Balance Test, the participant holds his/her balance for 20 s in three standing positions with eyes open: feet side by side, feet in semi-tandem stance (big toe of one foot touching heel of other foot), and feet in tandem stance (heel to toe). Before the subject performs, each stance is demonstrated by a tester present so that the subject understands the protocol before he/she attempts it. In addition, clear instructions are given regarding what the participant can and cannot do to maintain his/her balance (i.e., can bend knees or put arms out, but should not move his/her feet or use another aid), and the examiner remains close to the participant to assist in the event that he/she cannot maintain his/her balance. If the subject fails to perform a particular task, subsequent tasks are not to be performed to avoid any complications that would result. Only one attempt is permitted for each stance. In the Gait Speed Test, subjects walk along a pathway of length 4 m at their usual walking pace while the examiner times their walk with a stopwatch. Usually, two attempts are allowed for gait analysis and the fastest recorded score is used for factoring into the overall score. If at any point, the subjects find the need to use an assisted device, he/she may feel free to use. However, it is recommended not to. The Chair Stand Test or the sit stand test examines a person's ability to rise from a sitting to a standing position from an armless chair. Even for this test, the tester demonstrates the entire protocol before the subject can perform. The subject is asked to rise and sit back on the chair with his/her arms folded across their chest.

They can use their arms to assist them in case they are not able to rise from the chair, however the test is then discontinued. If the subject performs one sit stand cycle without any hassle, then he/she would be asked to perform the entire SPPB protocol which involves five consecutive sit-stand cycles with the arms folded across the chest. While he/she carries out the task, the total duration taken to complete is recorded by the expert using a stopwatch. The SPPB provides a comprehensive evaluation of an individual's lower extremity and helps in identifying ADLs (Activities of Daily Living) that the participant may have problems with, and consequently the degree of support that is needed. It can also be used for identifying people at risk of disability, and hence those who may benefit from intervention strategies or programs [2-21].

Since SPPB is widely used, the assessment as such is shorter and does not require assessing the subject intensively. A poor score generally triggers either further assessment or anticipatory nursing interventions depending on the physician's take of the assessment.

2.3 Literature Survey

2.3.1 Sit-To-Stand Test

Among the studies involving visual sensors, Allin et al. [2-30] focused on using hands/arms and position of feet as a measure of physical capability. 3 dimensional features such as distance between feet, head and body were constructed using 3 cameras. These features were tracked using ellipsoid tracking of the individual positions of the head, torso and feet using the Weka Machine Toolkit for classification [2-31], and strong correlations were achieved for five participants between the measured rise time and the Berg Balance score. However, this approach required labelling the body parts for each subject manually for at least one image for the system to learn the color information for the individual. Goffredo et al. [2-32] implemented a method to extract the silhouette of the human body using the snake algorithm in order to get postural information. Pehlivan et al. [2-33] constructed pose descriptors by extracting circular features such as the number of circles, area of outer circles, etc. from each layer from volumetric image data and classified them according to different activities by employing Nearest neighbor method. In [2-34], activities including sit-to-stand in Alzheimer's patients were studied by incorporating a priori information such as the location of furniture and objects in the room the participant resides to identify the possible 3D locations (position, height, width) of silhouettes to track activities. Measurements from accelerometers placed on the body were also used in the pipeline. In [2-35], an array of 132 embedded fiber optic pressure sensors was placed under a hospital bed mattress. These pressure sensors were used to form pressure images which were then used to measure the total pressure measurement over time and used it to compute sit to stand time. The above approaches involve the use of wearable sensors which indicate the need for patients to constantly wear the devices for monitoring, thus disrupting their normal movement. Among the visual detection techniques, usage of a 3-camera system increases the complexity and makes it computationally expensive as well.

2.3.2 Balance Test

Dynamic Vision Sensor (DVS) Camera has been successfully used for Balance stability analysis. Nalci et al. (2015) [2-36] propose a system that uses the Total variation metric on a window of DVS event stream to compute a metric that quantifies the instability of a subject while maintaining a given pose. This metric has been shown to correlate with a pearson correlation coefficient of 0.99 with center of pressure measurement from a BTrackS Balance plate.

A paper comparing two-dimensional video analysis to three-dimensional motion capture in lower extremity movement suggests that there is no statistically significant difference between the two methods, providing further evidence about using an inexpensive camera system to assess movement instead of a costly complex system [2-22]. However, this paper uses data gathered from retroreflective markers placed all over the body.

In [2-23], a real-time 3D computer vision system for balance assessment based on the Kinect sensor is presented. Although there are multiple advantages of using Kinect technology to assess movement, it is still an expensive system and Kinect is sensitive to Infrared source (sunlight) and cannot detect crystalline or highly reflective objects.

2.3.3 Gait Speed Test

Human gait has been shown to be an important indicator of health with many medical applications. Human gait has four different phases. Each leg has a swing phase when it is not touching the ground and the stance phase when it is in contact with the ground. Gait can be characterized by different durations of these swing and stance phases. These together also determine the speed of walking. A variety of sensors like the Microsoft Kinect, Pressure sensors, Accelerometers and Gyroscopes have been used to perform gait analysis in the literature. Below is a summary of various approaches that have been used.

Marker based systems use Infra-red (IR) cameras and markers placed at specific locations on subjects. They are typically only suited for supervised laboratory setting and are very expensive. Force plates can also be used for gait analysis but they too suffer from similar problems.

Gabel et al. (2012) [2-24] propose a method based on regression trees to predict the different parameters mentioned above using Microsoft Kinect to capture gait data. They use the Multiple Additive Regression Trees (MART) algorithm to learn the ensemble of regression trees. They use virtual skeleton which consists of 3D positions of 20 joints of the human body and convert that into a feature vector which is independent of the position of the sensor relative to the subject. To validate their approach and to train their supervised regression model, they use data collected from pressure sensors placed inside the shoes of subjects as ground truth data. They use a state machine to calculate the duration of each phase of gait from the pressure sensor data. To demonstrate the robustness of their system to placement of sensor relative to subject, they train the model using data collected by placing sensor in one orientation and test the model placing the sensor in a different orientation. The fact that their system performs well suggests that the features they use are invariant to such variations which are common in real life deployments of gait analysis systems. Therefore, it is very important to use features which are invariant to variations such as placement of sensor relative to the subject.

Banerjee et al. (2012) [2-25] use data from a single depth camera (Microsoft Kinect) to identify older residents based on their gait characteristics at a senior housing facility. To reduce the privacy concerns associated with continuous monitoring of daily activities, they use anonymized imaging features - 2D silhouettes from depth images. They propose two kinds of features 1. Bounding box (width & height) 2. Image Moments. Fuzzy K means clustering is used for resident identification. Seven features from data with average duration of 4 seconds - Get 2D silhouettes from 3D depth images (from Kinect). From Bounding box, they use width, height and their ratio as features. One feature from average of difference between distance profile captures change in shape of silhouette over time or gait signature.

Ejupi et al. (2014a) [2-26] propose a game designed with Microsoft Kinect to distinguish between fallers and non-fallers. Clinical fall risk assessment is often described as subjective and qualitative. Whether a subject was a faller or non-faller was determined from a face-to-face interview that collected self-reported history of falls. This can be very unreliable in distinguishing fallers from non-fallers. Skeletal data from Kinect and Accelerometers are used. A two-sided students t-test for independent measures was used to evaluate differences between faller and non-faller groups. P values less than 5% are considered significant. They have observed slower trunk reaction time for fallers compared to non-fallers.

Ejupi et al. (2015) [2-27] propose a Kinect based Five Times Sit to Stand (5STS) test. Objectives were 1) determining feasibility of this test to discriminate between fallers and non-fallers. 2) test for supervised and unsupervised in-home fall risk assessments. The mean velocity of the sit-to-stand transitions discriminated well between the fallers and non-fallers based on 12-month retrospective fall data. Falls are associated with 1. slow reaction time 2. poor balance 3. weak muscle strength.

Iluz et al. (2014) [2-28] propose a system for automated detection of missteps in patients suffering from Parkinson's disease. They use accelerometers and gyroscopes placed on the lower backs of patients to collect data which is fed to a custom misstep detection tree based on their clinical data they collected.

Chapter 3 – Materials & Protocol

The conventional SPPB practice is unwieldy, subjective and time consuming. The novel computer vision based fall risk assessment tool developed in our lab has features that indicate to be a promising alternative to the existing SPPB system. In this study, we recorded data from about 30 individuals for each sub-task. The reason behind performing the study is to test our hypothesis of whether a 2D camera based system and conventional manual SPPB recording practices give similar scores for fall risk.

3.1 Data Collection and Recording Equipment

For our research, we collected our own data by conducting multiple trials. Having the setup ready and suitable for recording purposes and collecting good and usable data is challenging but is a must to get good, meaningful results. With each round of data collection, we listed down important points to consider and execute while collecting data and prepared a protocol for data collection for future drives. We collected data from about 30 young adults and 8 older adults overall. However, for our analysis and after pre-processing, we were left with data from about 10 individuals for each of the three tasks in SPPB. The sources of error in data are mentioned in Section 3.4. For our ground truth purposes, we used GAITRite mat to generate ground truth for gait assessment, BTrackS balance board to generate ground truth for balance assessment and expert-measured metrics as ground truth for sit-to-stand movement assessment. In the following sections, a list of do's and not's of the data collection protocol along with a brief description about each of the equipment is given.

3.1.1 Data Collection Protocol

3.1.1.1 Camera Setup:

Do’s:

1. The camera is fixed either on mounts or on walls. Cameras should be set up in such a way that the entire body of the participant from head to toe is captured.
2. For balance and sit-stand tasks, participants should perform the tasks facing the camera.
3. For walking task, there should be two cameras on either side of the walking stretch on a straight line. The line joining the cameras should be along the direction of the walking stretch.

Don’ts:

1. Don’t have any other object in the field of view of the camera. More particularly, people and laptops/cellphones as the screen brightness can add to a lot of noise.

3.1.1.2 Balance Test

Do’s:

1. Concentrate only on maintaining balance on the BTrackS Balance board from the time the stopwatch starts and till it ends without any distractions.
2. Stand still and look straight during the test.

3. Can have hands on hips to help with balance. If hands on hips, they should be in the same posture throughout the task.

Don’ts:

1. Don’t talk to the research assistant or anyone else while the test is still on.
2. Don’t look here and there during the test, as it can add a lot of noise.

3.1.1.3 Sit-to-stand Test

Do’s:

1. Have your arms folded across your chest while performing the task.
2. Complete all the five sit-stand cycles. Start the test by making the sit-stand transition and end the test with stand-sit transition. Make sure you sit at the end because that marks the end of the test.

3.1.1.4 Gait Test

Do’s:

1. Walk at your normal pace along the stretch on the GAITRite mat.
2. At the end of the stretch turn around, walk back to where you started.

Don’ts:

1. Do not talk with the research assistant during the duration of the test.

3.1.2 Recording Equipment

3.1.2.1 GAITRite mat:

The GAITRite measures how a person walks. It measures gait patterns for both time and space through pressure sensors in the mat based on foot placement patterns and overall gait patterns [3-1]. It gives useful information of a subject's walking pattern such as step time, step length, cadence, cycle time, stride length, stride time among other measurements. We used GAITRite Classic manufactured by CIR Systems, Inc.

We use the GAITRite to provide valid and reliable walking measurements. For our research purposes, we used stride time from the ground truth to compare to our results derived from the algorithms.

Figure 3.1 GAITRite Mat

3.1.2.2 BTrackS Balance Board:

BTrackS Balance Board is manufactured by Balance Tracking Systems, Inc. It is a practical force plate for balance testing purposes [3-2]. We collected data using their Assess software. The balance data sheet consists of Center of Pressure (COP) measurements for all of the tasks the subject performs. We use the COP path length from the data sheet as our ground truth.

Figure 3.2: BTrackS Assess Balance Board

3.1.2.3 RGB Camera:

For our video recording purposes, we used an inexpensive RGB camera manufactured by Canon [3-3]. We recorded all of the video data using this camera mounted on mounts in UCSD Research on Autism and Development Laboratory (RadLab).

Figure 3.3: Canon VIXIA HF R600 Black

3.2 Subject Recruitment

The subjects were recruited through word-of-mouth description of the fall risk assessment research that was going to be conducted. We set inclusion and exclusion criteria to select participants for our research study. Self-reporting of the subjects was relied upon for the inclusion/ exclusion criteria.

Inclusion criteria

- Age group 15-30
- Any ethnic background
- Healthy adults; Smokers and caffeine-drinkers will be permitted

Exclusion criteria

- Current movement related disorders

For our research study, we recruited about 30 subjects and conducted about 3 data collection rounds. One of the data collection rounds took place in Exercise and Physical Activity Resource Center (EPARC) at Qualcomm Institute at UC San Diego. The rest of the collection happened in RadLab at UC San Diego. Before the experiments began, the subjects were given a detailed explanation of the procedures. We also obtained the subjects' consent for taking a video recording of them performing various tasks in addition to obtaining consent to use the data in paper publications and research presentations eventually. Based on the above outlined procedures, we had recruited 30 subjects for our study, of which only a few subject recordings were used for making inference (See Section 3.4).

3.3 Overall setup

3.3.1 Assumptions

There has been a lot of research in computer vision techniques for object recognition, object tracking and scene interpretation to support various applications including self-driving vehicles, autonomous flying objects (drones), industrial robotics, etc. But the analysis of movements in small spaces, such as those identified in the problem statement afford us to make some assumptions and simplify the image processing tasks for problem at hand. Hence, we make the following assumptions:

1. The camera is stationary; the background is stationary and only the subject is moving during the tasks associated with SPPB.

2. There are no reflections of the subject in the visual field of the camera.

3. The typical speed of subject movements is much smaller than sampling speed of the camera. We observe that web cameras of 30 fps or 60 fps are adequate for typical SPPB maneuvers in this context.

4. There are no foreign moving objects, including the expert administering SPPB, in the visual field during SPPB maneuvers. First, we will analyze the performance under these assumptions and then address the task of eliminating outliers resulting from subject maneuvers that do not comply with the assumptions.

3.3.2 Recording protocol

We conducted three different data collection drives at RadLab and one at EPARC and had the participants come in and give their data. During each of those trials, we maintained a list of names of the participants along with the list of tasks to be performed. Each participant followed the data collection protocol that is aforementioned and with all the camera and the sensors set up, we recorded video data of the different tasks performed by each subject. Our labeling system enabled us to match our video data with the ground truth data generated from BTrackS balance board and GAITRite mat. The total duration of the subject's involvement in the study was about 3 minutes for each recording. The subjects were compensated for participating in the study using funding provided by Frontiers of Innovation Scholars Program (FISP) award.

3.4 Sources of Error

During the initial few data collection drives, some of the videos recorded were not included for inference purposes. This was due to the following reasons:

1. Field of view of the camera didn't enclose the entire body of the subject.
2. Subjects were distracted despite proper instructions.
3. There were lighting issues resulting in poorer resolution and noise.

We carefully considered all these outliers for future data collection drives. It is for these reasons that a good number of subjects' video recordings were omitted in making inferences.

Chapter 4 – Methodology

4.1 Overview of Statistical Techniques Sued

4.1.1 Bland Altman plot

Bland Altman plots are extensively used to evaluate how well in agreement two sets of measurements that measure the same component are. It is a plot of difference between the two sets of measurements versus their average. They give us a good picture of how much the difference between the two sets of measurements is as well as if these differences fall well within the confidence intervals [4-2].

4.1.2 Hypothesis Testing

Generally, in hypothesis testing, we have two hypotheses. One is the null hypothesis (H_0), which usually corresponds to statistical models that happen by chance. The other is the alternate hypothesis (H_A), corresponding to a different set of statistical models which exhibit a hypothesized structure in the statistical properties of the data [4-3]. When we perform hypothesis testing, we usually compute a test-statistic and a p-value associated with it. This p-value tells us the probability of observing a test-statistic as extreme as what we computed due to random chance under the assumption that the null hypothesis is true. If the p-value is sufficiently small (e.g. below 0.05), then we "reject" the null hypothesis and can confidently declare that what we have observed is indeed statistically significant. If, on the flipside, the p-value is not sufficiently small, then we fail to reject the null hypothesis. For instance, in our study, the null hypothesis represented no difference between the true value and the estimated value and the alternate hypothesis represented that there was a significant difference. For our algorithms to deliver the expected results, we needed a p-value greater than 0.05 to go in favor of the null hypothesis.

4.2 Sit Stand Analysis

The sit stand task consists of the subject performing five continuous sit-stand cycles with their arms folded across the chest. The actual SPPB protocol is outlined below.

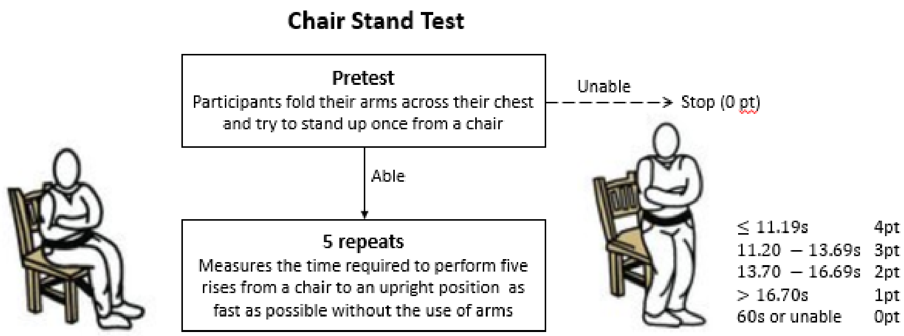


Figure 4.1 SPPB Sit-to-stand protocol

For sit stand analysis, we recruited about 30 individuals to collect data from. After cleaning the data for outliers, we were left with data from 14 young adults and 7 older adults (See Section 3.4). Data from young adults was collected in RadLab and data from older adults was collected in EPARC as part of MEDEX data collection at UC San Diego.

The ground truth for sit-stand analysis is the total duration of the task for each participant measured by an expert using a stop watch. And so, the goal is to develop an algorithm to measure the total duration of the sit-stand task and compare it with the ground truth as measured by an expert. We propose an approach to solving the above problem with its pros and cons. The subject carries out the task facing an RGB camera fixed in a closed environment.

The method consists of the following steps:

-Background subtraction

-Estimation of pixel activity

-Smoothing and peak detection

Each of the steps is described in detail below.

4.2.1 Background Subtraction

The key preprocessing step for all of our approaches is background subtraction using frame differencing. We extract frames (F) from raw input RGB video. We convert each frame f to YUV space and pick just the Y-channel (y) followed by normalizing the frame to 0-1 range using the following equation.

$$y_N = \frac{y}{\max(y) - \min(y)}$$

We then perform frame differencing $d^{(t)}$

$$d^{(t)} = \text{abs}\left(y_N^{(t)} - y_N^{(t-1)}\right)$$

to subtract background followed by applying a median filter of order 6 to remove any noise in the frame differenced images. This helps also in obscuring the identity of the subject thus respecting privacy.

$$d_f[m,n] = \text{median}\{d[i,j], (i,j) \in w\}$$

We then binarize the pixel values by thresholding. The value of the threshold is empirically set to 0.2 for sit stand algorithm to get the binary image.

$$i[m,n] = \begin{cases} 1, & d_f[m,n] \geq \tau \\ 0, & d_f[m,n] < \tau \end{cases}$$

Following figure shows YUV video along with the preprocessed video.

Figure 4.2 Figure displaying YUV video of a subject performing sit-to-stand test on the left and preprocessed video of the same subject on the right

4.2.2 Estimation of Pixel Activity

After we do background subtraction using frame differencing, we now have a set of preprocessed pixel differenced frames. For each background subtracted frame, we estimate the total number of active pixels by taking the sum of all the active pixels in each frame, (s). We will now have a list containing the total pixel activity for every frame.

$$s = \frac{1}{MN} \sum_{m=1,n=1}^{m=M,n=N} i[m,n]$$

For every sit-stand cycle, there is very little pixel activity when a person completely sits or stands and there is a high pixel activity when the subject makes a transition from sit to stand and vice-versa. This should result in a sinusoidal like graph with troughs representing the sit and stand phases and peaks representing the transitions between sit and stand phases. This simple realization enables us to use the total pixel activity as a measure of estimating the total duration of the sit-stand cycle. The following graph shows how the pixel activity varies across different frames for the same subject shown above.

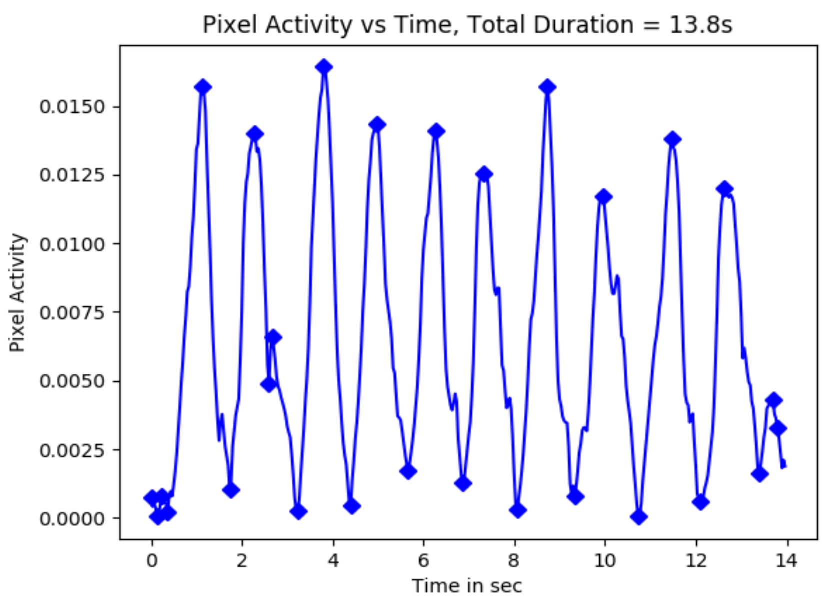


Figure 4.3: Figure showing pixel activity versus time for a single subject during sit-to-stand test

4.2.3 Smoothing and Peak Detection

In order to remove the spurious peaks and troughs, we smooth the list s containing the total pixel activity of all frames by applying moving average of 6 frames. Smoothing results in elimination of noisy activity.

$$s_m[n] = \frac{1}{W} \sum_{k=0}^{W-1} s[n-k]$$

From s_m, we get the total duration of the sit-stand task by detecting peaks and troughs. The time taken from the first trough to the last trough gives the total duration of the task. Time difference between successive troughs gives the duration for every transition.

We use peak detection to detect the peaks and troughs which would further enable us in computing the necessary metrics from the data. Unlike the conventional peak detection methodology which employs the zero-derivative method, we use a modified version of the same that looks for the highest point, around which there are points lower by some quantity on both sides. In this technique, we require a peak threshold which indicates a difference of at least 0.5 between a peak and its surrounding to declare it as a peak. Same goes with valleys. In essence, we followed "peakdet" function methodology as described in [4-1].

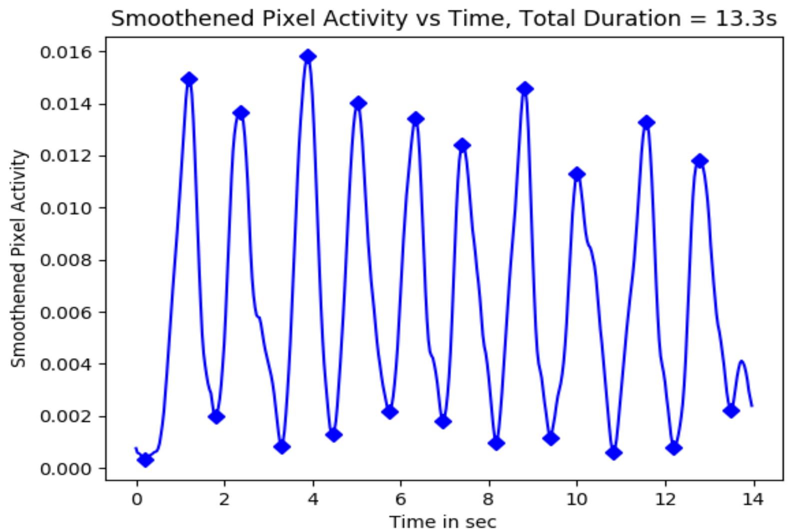


Figure 4.4: Figure showing smoothed pixel activity versus time for a single subject during sit-to-stand test

4.2.4 Sit Stand Algorithm

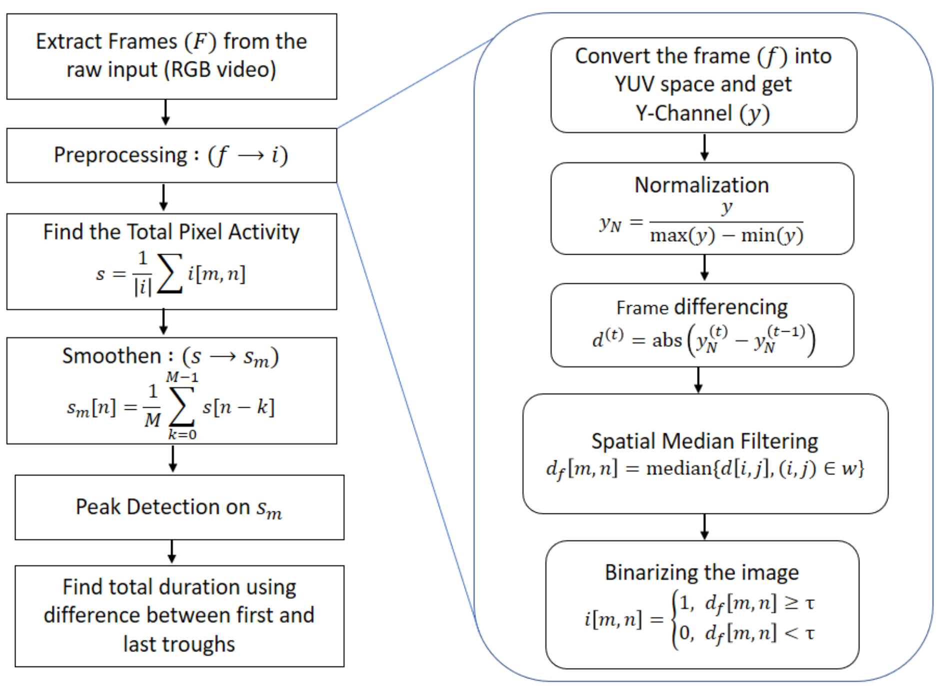


Figure 4.5 Flowchart describing the algorithm we developed for sit-to-stand test

4.2.5 Results

Below is a table showing both the ground truth and the estimated time for all the participants along with a graph describing the same

Table 4.1: Table displays the ground truth along with the algorithm – derived total duration for all participants along with their IDs

Participant	True total duration (s)	Predicted total duration(s)
LMN001	8.44	10.767
LMN002	9.15	10.367
LMN003	8.93	9.833
LMN004	8.63	9.867
LMN005	6.22	6.233
LMN007	6.91	7.6
LMN008	14.59	16.3
LMN009	7.75	7.367
LMN010	11.68	13.3
LMN011	6.03	7.33
LMN013	12.47	14.167
LMN015	5.7	6.4
LMN016	9.47	10.567
LMN017	7.62	9.1
10018	16.72	15.9
10028	10.03	9.9
10035	10.25	11.233
10041	6.32	6.9
10076	10.16	10.9
10134	9.97	11
10138	15.31	17.167

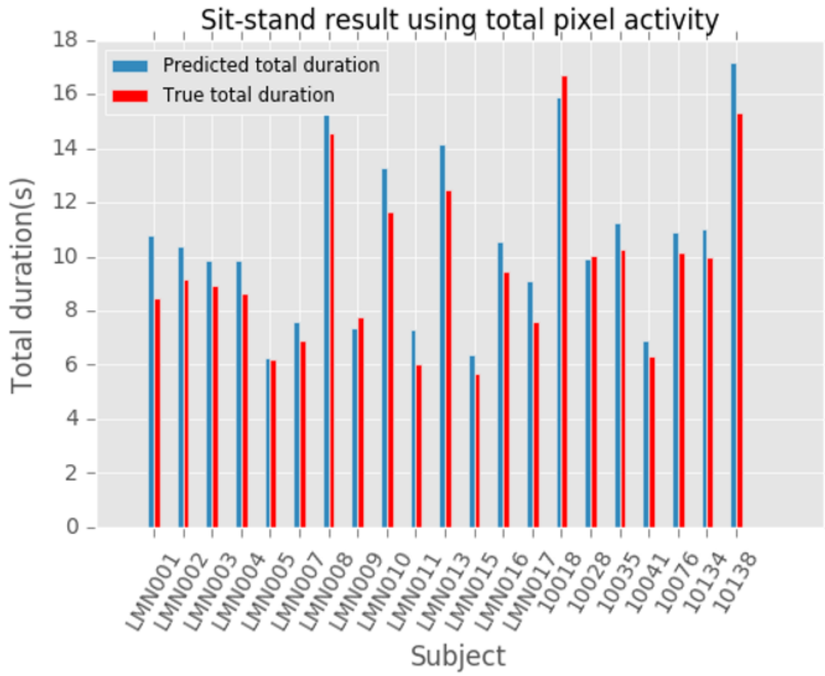


Figure 4.6: Figure showing true and predicted total duration for all participants for sit-to-stand test

4.2.6 Statistical Analysis

To assess how well the sit-stand algorithm is performing, Pearson correlation coefficient between the ground truth and the estimated time was calculated. We report a correlation coefficient of 0.971 with a p-value of 4.1e-9 indicating a very good correlation between the ground truth and the estimated time results.

In addition, we also used Bland Altman plots to assess how closely the estimated time is in agreement with the ground truth.

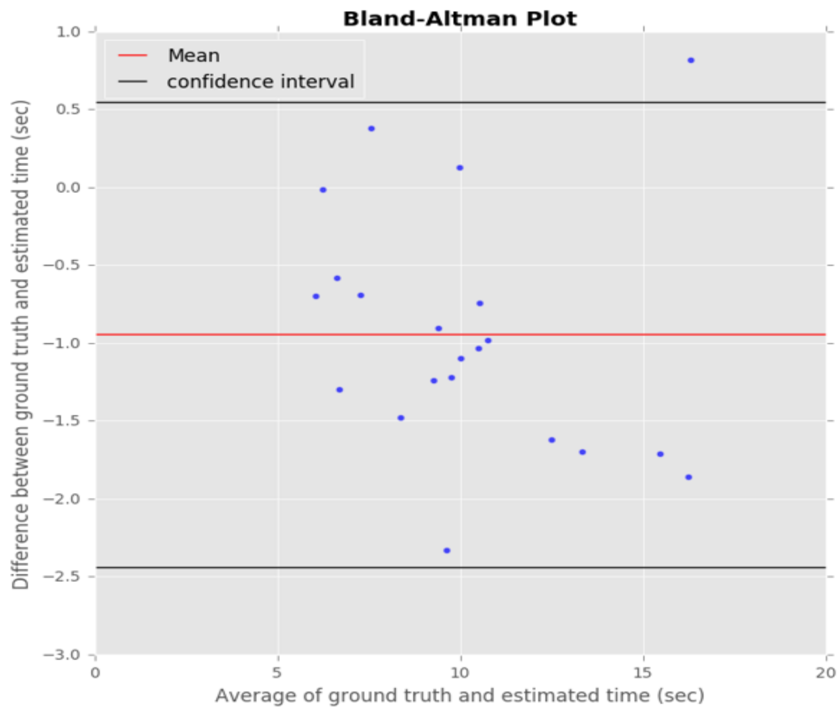


Figure 4.7: Bland Altman Plot for sit-to-stand test

From the Bland Altman plot, we can see that although there are a very few outliers, for the most part, the two sets of measurements are very well in agreement with a confidence interval of (-2.436, 0.546).

Finally, we carried out hypothesis testing to ensure that the estimated time and the ground truth are statistically similar to each other.

We define the null and the alternate hypothesis as the following

- Null hypothesis H_0: Ground truth and estimated time are similar
- Alternate hypothesis H_A: Ground truth $\neq$ Estimated time

After carrying out a t-test, we report a t-statistic: -0.97, p-value: 0.337. Since the p-value is greater than 0.05 which is our significance level, we fail to reject the null hypothesis which states that the ground truth is similar to estimated time. From all of the above statistical analysis, we conclude that the sit stand algorithm determines total duration that is very close to the ground truth.

4.3 Gait Analysis

The gait video consists of the subject walking in a straight line along a short stretch of 4 m. We need to measure the gait speed and the gait speed variability of the subject from only the video. Two cameras are placed facing the rear and the front of the subject as he/she performs the test. The objective is to obtain the average stride-times for the left and the right feet. The ground truth step and stride times of the left and the right feet are obtained by GAITRite. We develop a model-based approach to measuring the step and stride times from the videos. The actual SPPB protocol is outlined below.

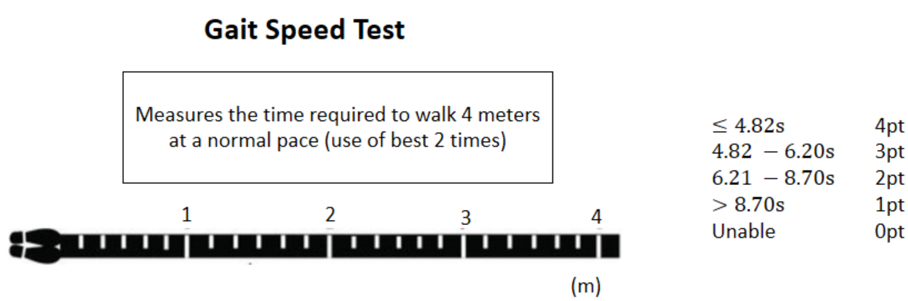


Figure 4.8: SPPB protocol for gait test

For gait analysis, we recruited about 20 individuals to collect data from. After cleaning the data for outliers, we were left with data from 8 young adults (See section 3.4). Data from young adults was collected in RadLab.

The ground truth for gait analysis is generated by GAITRite mat. It consists of a long list of different attributes like stride time, step time etc. that are generated as the subject walks over the mat. The goal is to develop an algorithm to measure the stride-time of each participant and compare it with the ground truth as measured by GAITRite. We propose an approach to solving the above problem with its pros and cons.

Our approach consists of the following steps:

-Bounding Box estimation for the legs and feet using HOG+SVM pedestrian detection algorithm

- Background subtraction

-Construction of a time series of pixel activity in the region of interest.

-Extraction of the stride time from the time series

Each of the steps is described in detail below.

4.3.1 Bounding Box Estimation

For gait analysis, we find the overall bounding box BB of the subject using SVM+HOG pedestrian detection routine in OpenCV. Consequently, we consider only the bounding box with the highest weight discarding all other boxes returned by the routine.

The basic idea behind the SVM+HOG approach is that the distribution of local intensity gradients or edge directions characterize the local object appearance and shape.

The image window is first divided into small spatial regions and for each region, we accumulate a local 1-D histogram of gradient directions or edge orientations over the pixels of the cell. The combined histogram entries form the representation. We then contrast-normalize the local responses to make the detection invariant to illumination etc. by accumulating a measure of local histogram “energy” over larger spatial regions (“blocks”) followed by normalizing all the cells in the block. These are referred to as Histogram of Oriented Gradient (HOG) descriptors. We then apply machine learning based Support Vector Machine (SVM) classifier to train the data on object/no object classes and use it on test data. SVM is a popular classifier used because it reduces the misclassification rate and works well in a high dimensional setting [4-4].

After finding the overall bounding box BB, we then find the bounding box BB' of the leg region. We do this by considering only the lower 3/5$^{\text{th}}$ of the overall box BB. Divide BB' into left and right halves BB'_L and BB'_R respectively.

After finding the bounding box in this way, we do background subtraction by differencing the frames.

4.3.2 Background Subtraction

The key preprocessing step for our approach to gait test, just like for the previous tests, is background subtraction using frame differencing. For each frame (f), we first extract the Luma or the Y-component (y),. We then increase the contrast of this frame by Histogram Equalization y_{heq}.

Next, we scale the pixel values to lie in the range [0,1]

$$y_N = \frac{y_{heq}}{\max(y_{heq}) - \min(y_{heq})}$$

We subtract the background by finding the absolute difference between the frames.

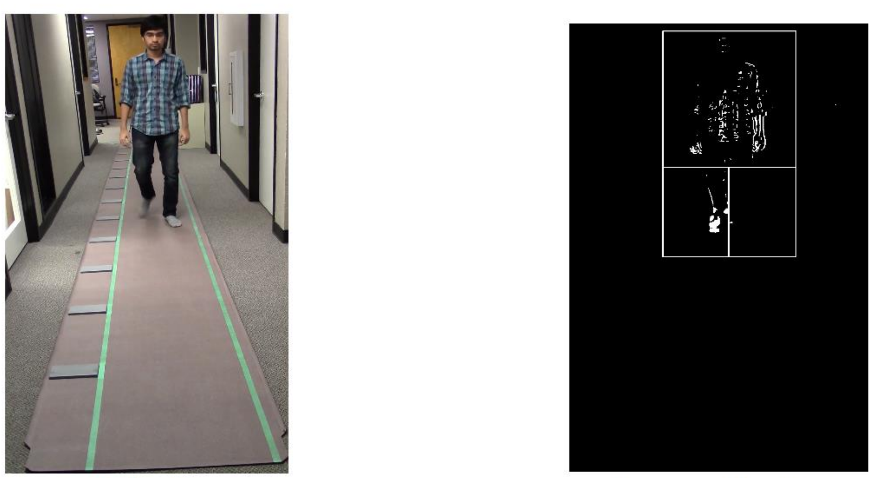
$$d^{(t)} = \text{abs}\left(y_N^{(t)} - y_N^{(t-1)}\right)$$

To reduce the noise in the pixel-differenced frame we use a spatio-temporal median filter of order 6.

$$d_f[m,n] = \text{median}\{d[i,j], (i,j) \in w\}$$

and further binarize them by thresholding. The value of the threshold is empirically set to 0.15.

$$i[m,n] = \begin{cases} 1, & d_f[m,n] \geq \tau \\ 0, & d_f[m,n] < \tau \end{cases}$$



RGB video　　　　Preprocessed video

Figure 4.9: Figure showing raw RGB video on the left and preprocessed video on the right for gait test

4.3.3 Estimation of Pixel Activity

After we do all the above steps, we count the number of active pixels in the left and right leg boxes and we store them as time series s_L and s_R.

After running all the above steps on all the frames in the video, extract the dominant frequencies in the DFT of the time series. Call these f_L, f_R. Return the average stride time as the reciprocals of f_L, f_R.

$$\text{Avg. Stride Time} = \frac{\frac{1}{f_L} + \frac{1}{f_R}}{2}$$

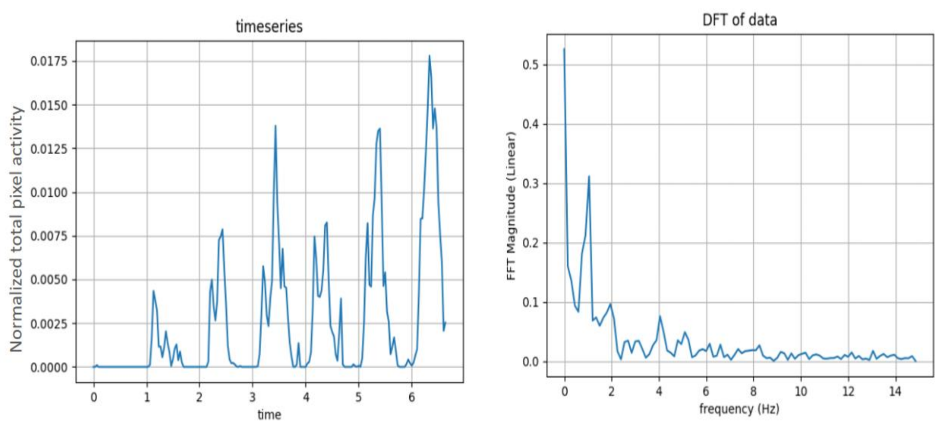


Figure 4.10: Figure showing timeseries plot of normalized total pixel activity on the left and DFT of the timeseries on the right for gait test

4.3.4 Gait Stride Algorithm

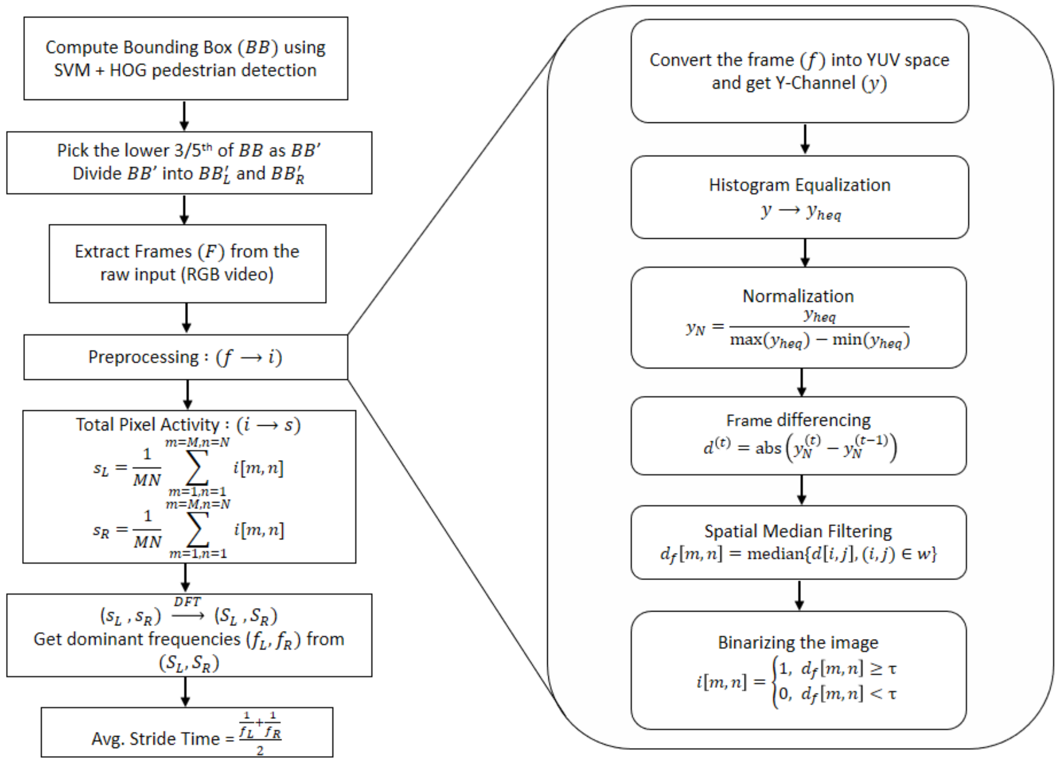


Figure 4.11: Flowchart describing the algorithm we developed for gait test

4.3.5 Results

Table 4.2: Table showing the true versus predicted stride times for all the participants for gait test

Participant	True stride time (s)	Predicted stride time (s)
1	1.381	1.295
3	0.995	0.943
4	1.296	1.298
6	0.949	1.02
7	1.099	1
8	1.608	1.667
9	1.315	1.299
10	1.177	1.111

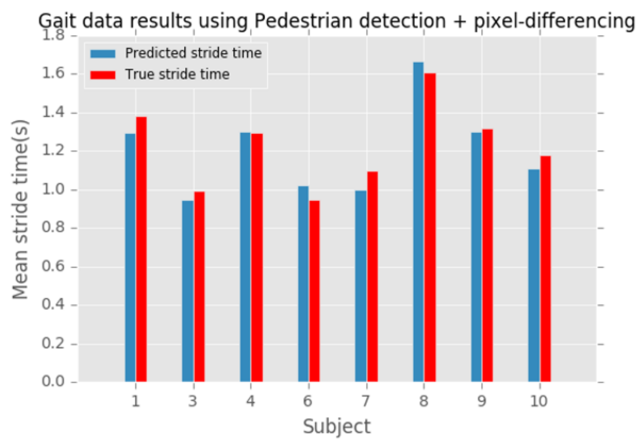


Figure 4.12: Figure showing the true versus the predicted stride times for gait test

4.3.6 Statistical Analysis

To assess how well the gait algorithm is performing, Pearson correlation coefficient between the ground truth and the estimated time was calculated. We report a correlation coefficient of 0.963 with a p-value of 0.0003 indicating a very good correlation between the ground truth and the estimated stride time results. In addition, we also used Bland

Altman plots to assess how closely the estimated stride time is in agreement with the ground truth.

Figure 4.13: Bland Altman plot for gait test

From the Bland Altman plot, we can see that the two sets of measurements are very well in agreement with a confidence interval of (-0.09, 0.14).

Finally, we carried out hypothesis testing to ensure that the estimated stride time and the ground truth are statistically similar to each other.

We define the null and the alternate hypothesis as the following

- Null hypothesis H_0: Ground truth and estimated time are similar
- Alternate hypothesis H_A: Ground truth $\neq$ Estimated time

After carrying out a t-test, we report a t-statistic: 0.205, p-value: 0.84. Since the p-value is greater than 0.05 which is our significance level, we fail to reject the null hypothesis which states that the ground truth is similar to estimated time. From all of the above statistical analysis, we conclude that the gait algorithm estimates stride time that is very close to the ground truth.

4.4 Balance Analysis

The balance video consists of the subject trying to maintain balance on BTrackS balance board which simultaneously records the ground truth for 20s. Subjects for our study performed six different tasks in balance. They are as follows: 1. Eyes open with both feet on the balance board. 2. Eyes closed with both feet on the balance board. 3. Eyes open with only left foot on the balance board. 4. Eyes closed with only left foot on the balance board. 5. Eyes open with only right foot on the balance board. 6. Eyes closed with only right foot on the balance board. Each of the aforementioned tasks is performed for 20 seconds. A camera is placed facing the front of the subject while he/she carries out the task. Each subject performs each of the six tasks three times. For our study, we picked the trial 1 videos of all the subjects along with the ground truth generated for trial 1. The actual SPPB protocol is outlined below.

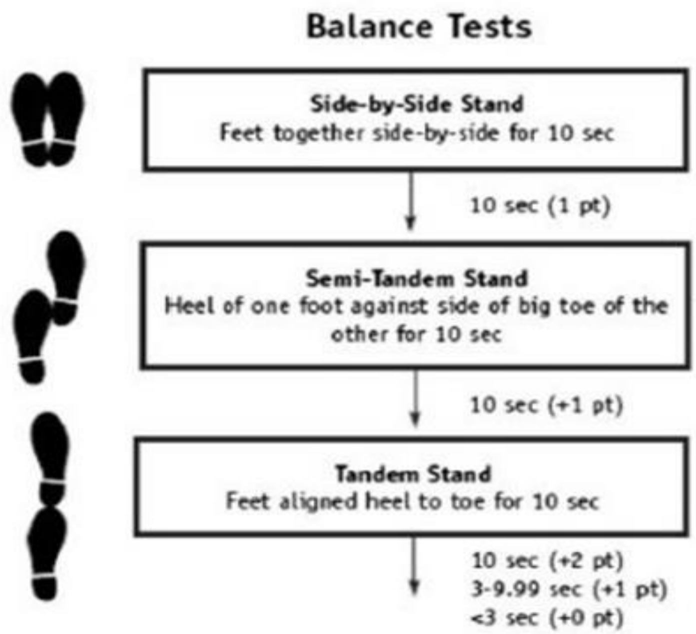


Figure 4.14: SPPB Protocol for Balance test

For balance analysis, we recruited about 10 individuals to collect data from. After cleaning the data for outliers, we were left with data from 4 young adults (See Section 3.4). Data was collected in RadLab at UC San Diego.

The ground truth generated from the BTrackS balance board consists of a data sheet detailing on the Center of Pressure (COP) path length along with COP measurements given in terms of COP_x and COP_y. We develop a simple approach to measuring the total variation from the videos. And so, the objective is to obtain the total variation, or in other words, the total sway, subject experiences, while trying to maintain balance on the balance board. We propose an approach to solving the above problem with its pros and cons. The subject carries out the task facing an RGB camera fixed in a closed environment.

The method consists of the following steps:

-Background subtraction

-Estimation of pixel activity

-Computing Total Variation and Normalized Total Variation

Each of the steps is described in detail below.

4.4.1 Background subtraction

The key preprocessing step for all of our approaches is background subtraction using frame differencing. We extract frames (F) from raw input RGB video. We convert each frame (f) to YUV space and pick just the Y-channel (y) followed by normalizing the frame y_N to 0-1 range.

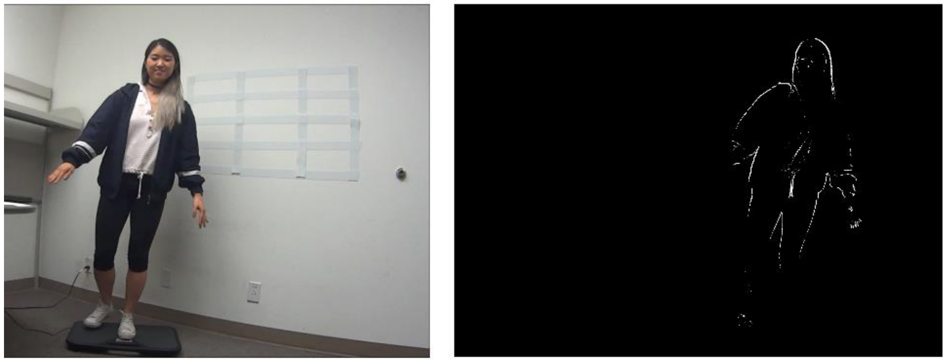
$$y_N = \frac{y}{\max(y) - \min(y)}$$

We then perform frame differencing

$$d^{(t)} = \text{abs}\left(y_N^{(t)} - y_N^{(t-1)}\right)$$

to subtract background followed by applying a median filter of order 6 to remove any noise in the frame differenced images.

$$d_f[m,n] = \text{median}\{d[i,j],(i,j) \in w\}$$



YUV video Preprocessed video

Figure 4.15: Figure displaying the raw RGB balance video for right foot up eyes closed on the left and preprocessed video on the right

4.4.2 Estimation of pixel activity

After we do background subtraction using frame differencing, we now have a set of preprocessed pixel differenced frames. For each background subtracted frame, we estimate the total number of active pixels by taking the sum of all the active pixels in each frame, (s). We will now have a list containing the total pixel activity for every frame.

$$s = \frac{1}{MN} \sum_{m=1,n=1}^{m=M,n=N} i[m,n]$$

For every balance video, there is very little pixel activity when a person maintains balance extremely well and does not sway or experience even the slightest of movement. On the other hand, when he tends to sway a lot and move his arms or his body in order to stabilize his balance, it will result in a lot of pixel activity in differenced frames. We call this pixel activity variation and sum it up across all the frames.

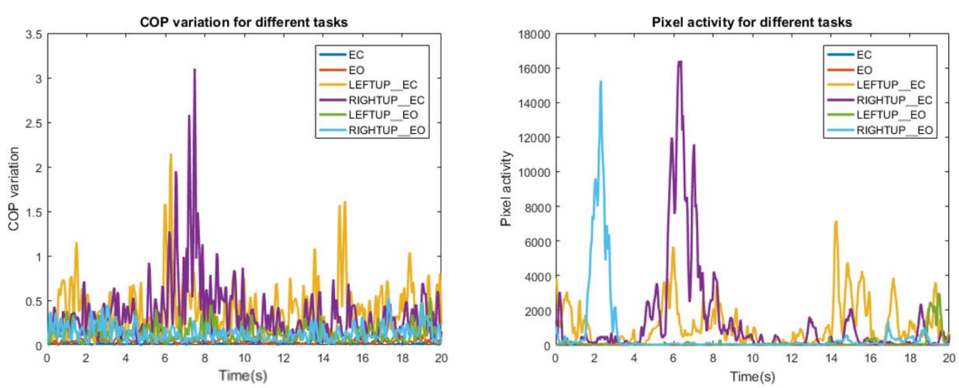
4.4.3 Computing Total Variation and Normalized Total Variation

Summing up pixel activity across all frames produces Total Variation, a metric we use to determine how well a person can balance. More specifically, we use Normalized Total Variation (TV) to assess the balance ability of an individual. The normalization factor is the number of frames present in the video.

$$TV = \frac{1}{|F|}\sum_{k=1}^{|F|} s(k)$$

The following graph shows how the pixel activity varies across different frames for the same subject performing all six different tasks of balance analysis on the right and COP variation for the same on the left. From the balance data sheet, we compute COP variation which we define as the following:

$$cop_t = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$$



LMN005

Figure 4.16: Figure displaying the COP variation across time for all the six balance tasks for a subject on the left and pixel activity across time on the right for the same subject

4.4.4 Balance Algorithm

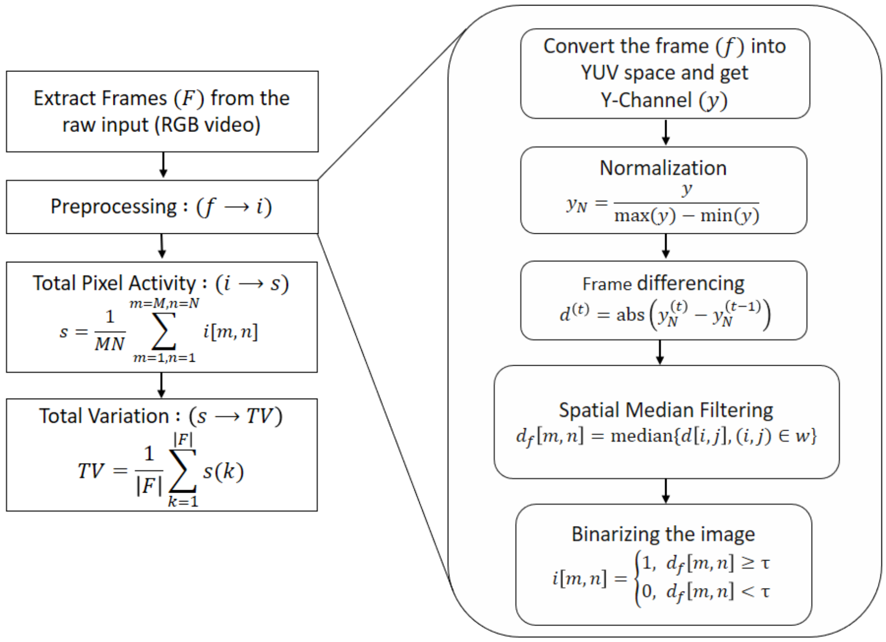


Figure 4.17: Flowchart describing the algorithm we developed for balance test

4.4.5 Results

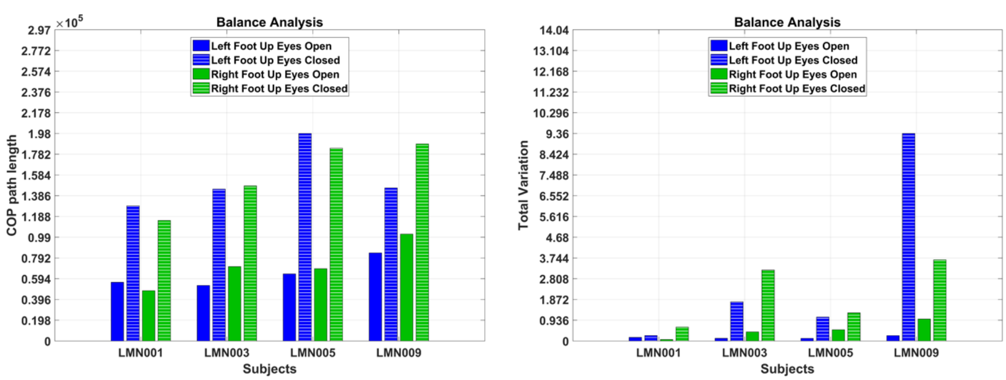


Figure 4.18: Figure displaying the COP path length for all subjects for the four major balance tasks on the left and total variation for all subjects for the same four balance tasks on the right

Table 4.3: Table displaying the Total Variation for all subjects for the four major balance tasks

Subject	Left Foot Up Eyes Open	Left Foot Up Eyes Closed	Right Foot Up Eyes Open	Right Foot Up Eyes Closed
LMN001	0.0001628	0.000245	6.70E-05	0.0006254
LMN003	0.00012	0.00177	0.00041	0.0032
LMN005	0.000119	0.00108	0.000508	0.00127
LMN009	0.000243	0.00936	0.00099	0.00366

4.4.6 Statistical Analysis

To assess how well the balance algorithm is performing, Pearson correlation coefficient between the ground truth COP path length and the estimated total variation was calculated. We report a correlation coefficient of 0.658 with a p-value of 0.0001 indicating a very good correlation between the ground truth and the estimated total variation results.

Chapter 5 – Discussion and Future Directions

5.1 Sit Stand Analysis

5.1.1 Discussion

Estimating the total duration of the sit stand task for all adults is very easily and simply done using the total pixel activity algorithm developed for sit stand analysis. Although we conjectured that the total pixel activity detects cycle-cycle variation of the sit stand task for all the subjects in addition to the total duration, we came across an issue while trying to estimate the cycle-cycle variation for an old adult whose data we collected from MEDEX study happening at EPARC at UC San Diego. Our intuition behind believing this algorithm would give us a cycle-cycle variation is that for any subject, the total pixel activity for sit and stand phases is much smaller (troughs) than the total pixel activity during the sit-stand or stand-sit transition phases (peaks). Hence, ideally, it should result in two peaks and three troughs in one sit-stand-sit cycle. However, we realized this might not be the case with older adults as they sometimes pause a lot while carrying out the task. These pauses cause no or very less pixel activity resulting in more troughs than the usual. The graph below shows how total pixel activity could fail in determining cycle-cycle variation of older adults.

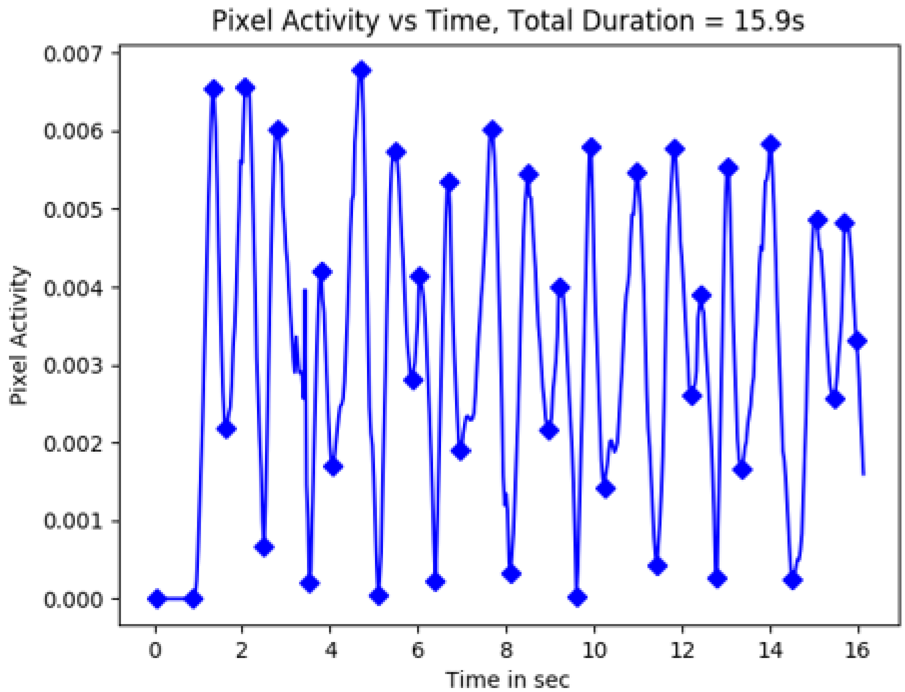


Figure 5.1: Figure displaying the pixel activity across time for an older adult for sit-to-stand test

Hence, using troughs to determine the cycle-cycle variation is quite inefficient when dealing with subjects who are either older or have movement disorders.

5.1.2 Future Directions

1. One approach to this problem could be to use a bounding box around the subject and plot its y-coordinate across the frames in order to get the peaks and troughs. In this case, we can be more confident about estimating cycle-cycle variation of any subject. However, ensuring that the bounding box is stable across successive frames is an area needing more attention.

2. The sit-to-stand test algorithm can be extended to incorporate Timed Up and Go (TUG) which is one of the commonly used physical performance tests in movement related disorders like Parkinson's Disease etc.

5.2 Gait Analysis

5.2.1 Discussion

We initially started off gait analysis by making strong assumptions of the underlying data and we were modeling the coordinates of the active pixels of a moving human as Mixture of Gaussians. This enabled us to estimate a bounding box for the leg region, which is our area of interest for gait analysis. However, this box was very sensitive to noise and the results we got were not very promising. We then went on to use SVM+HOG based pedestrian detection routine available in OpenCV to estimate the bounding box. The results we got were promising with a very high correlation. As much as we tried to simulate a controlled environment, the lab where we collected data from had lighting issues which we were not able to account for. In real world, it is not possible to have an extremely controlled environment. To account for all the irregularities the real world presents, there should be a lot of focus on our pre-processing steps.

5.2.2 Future Directions

1. Since, we are looking at total pixel activity for each leg, the bounding box estimated using SVM+HOG approach sometimes might not bound each leg perfectly, especially when the subject walks with both his feet much closer together, and could result in unwanted activity in either of the boxes. Hence, a more robust approach to bounding box is needed.

2. Our assumptions enabled us to use a much simpler SVM+HOG model to identify the subject. In future, we can explore deep learning techniques to identify subjects in a more complex environment where these assumptions fail to meet.

5.3 Balance Analysis

5.3.1 Discussion

For balance analysis, currently, we are looking at correlations between the total variation and the COP path length. Although sit-to-stand and gait tests gave very promising results, balance test algorithm gave a good correlation.

5.3.2 Future Directions

1. Since we are essentially relying on the pixel activity in differenced frames and since we make a strong assumption that there is no to little pixel activity when a person maintains balance perfectly, the focus should primarily be on pre-processing steps. Although, we do median filtering to remove unwanted noise, we are still left with some noise in the background in the preprocessed videos contributing to total variation.

2. [2-36] is a study conducted previously for balance analysis in our lab using Dynamic Vision Sensor (DVS) Camera. DVS encodes the local pixel-level changes caused by movement at the time they occur with extremely high resolution capturing even the slightest of movements more accurately than a conventional RGB camera. The results they got were promising. In our research study, we extended the same and used an RGB camera instead. As we can see, we gain pixel activity when there is noise. We lose pixel activity sometimes due to the very low frame rates of the RGB camera thus failing to capture the

subtle variations. In the future, research needs to be done in the areas of signal acquisition and pre-processing as it would enhance the performance of the algorithm.

Overall, our study indicates need for research in the following areas: 1. Violation of every assumption we made for this study to make it more suitable as a real-world application. We know that the real world is messy and it is nearly impossible to simulate a controlled environment. Hence, in the future, we should concentrate on developing algorithms which are invariant to different environments. 2. Ultimately, we would like to deliver a fully automated fall risk assessment tool that can be deployed in home-settings or clinics for continuous monitoring of an individual, and hence research focus should be on building a product at large scale.

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