PERSON IDENTIFICATION AND TINETTI SCORE ASSESSMENT USING BALANCE PARAMETERS TO DETERMINE FALL RISK

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ABSTRACT

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This thesis is aimed at a substantial health problem among the elderly population that is “Fall”, a major cause of accidental home deaths. Studies show approximately one-third of community-dwelling people over 65 years of age will experience one or more falls each year. The balance and walking pattern are useful to determine the risk of fall in an individual and is highly influenced by several parameters and conditions. The deterioration in the balance and walking stability of an individual can occur because of the natural processes related to aging or as a result of various underlying health conditions, fatigue, muscle tone, or impaired balance.

The Tinetti-test is widely used to assess the gait and balance in elder adults to determine the perception of balance and stability during daily activities and fear of falling. It is considered a good indicator of the fall risk of an individual. In this research, we aimed to provide a new way for non-intrusive balance assessment and Tinetti score prediction by creating a Machine Learning model for predicting fall risk and early detection of the onset of chronic health conditions. This will help to improve eldercare by facilitating constant

monitoring and by reducing the white-coat syndrome that inhibits clinical examinations.

This thesis mainly focuses on designing algorithms to extract the balance parameters for the quiet standing instances capable of differentiating normal or abnormal patterns for an individual from the pressure readings obtained from a smart floor. A variety of time and frequency domain features are build based on the center of pressure (COP) values. These COP values were obtained from time-series data from a pressure monitoring smart floor. A classification model is build using a support vector machine for distinguishing 30 individuals based solely on these balance parameters. Further, using these parameters, a regression model is built to predict the balance component as well as the compete Tinetti score of an individual which is used to predict the fall risk. This is a novel approach for Tinetti score prediction using balance analysis.

1. INTRODUCTION

1.1 Problem Statement Introduction

Falls are one of the most common problems and the leading causes of fatal and non-fatal injuries for elderly individuals around the world [40]. Falls not only threaten an individual’s safety and independence but also generate enormous economic and personal cost. A fall is defined as an event which results in a person coming to rest inadvertently on the ground or floor or at another lower level. Research shows that in the United States, falls are a leading cause of morbidity and mortality among elder adults [40]. It is the second leading cause of accidental or unintentional injury or death after road traffic injuries. The rates were higher in hospitalized patients and nursing home residents.

There are a number of factors that are involved in fall risks, such as weak muscles, dizziness, loss of consciousness, foot problems, memory loss, confusion or difficulties with thinking or problem solving, vision and hearing problems, taking medication that makes you dizzy or drowsy. All these factors may contribute to poor balance, causing unsteadiness on your feet and result in a fall. Various underlying health conditions like Parkinson’s disease, Alzheimer’s disease (AD) and Frontotemporal dementia (FTD), sensory abnormalities, cardiovascular diseases, and musculoskeletal disorders also contribute to poor postural stability and might result in falls [50].

1.2 Postural Stability

Gait and balance are some of the major factors that determine a person's postural stability. Also, disorders in gait and balance are among the most common causes of falls in older adults. They are usually multifactorial in origin and require a comprehensive assessment to determine contributing factors and targeted interventions [40].

Older persons with cognitive dysfunction are especially vulnerable for gait and balance problems, resulting in repeated falls because of the associated multiaxial dysfunction involving not only cognition but also, joints, ligaments, tendons, vision, and hearing. Patients with attention and cognitive disorders are at risk of disequilibrium in this automatic, unconscious act of walking due to the inability to concentrate in dual tasking. There is evidence for abnormal equilibrium in AD and motor dysfunction in FTD. This can increase morbidity significantly in these patients. Neurological disorders at any level can compromise the biomechanics of the gait and balance as it involves several complex mechanisms. Posture control needs to maintain the center of mass over the Base of Support (BOS) all through the gait cycle. A dynamic balance needs cerebellum, vestibular system, and unconscious reactive reflexes such as long loop reflexes. Early identification of gait and balance disorders and appropriate intervention may prevent dysfunction and falls.

1.3 Gait

A human's gait refers to an individual style of walking. According to the Oxford Dictionary, it is defined as a person’s manner of walking. As clear and simple as these definitions are, they do not fully provide us the information about the fundamental facts about the human gait. Fundamentally, it is a particular characteristic of a person that is influenced by a list of an individual’s body feature, among which are: an individual’s weight, foot length, height, waist angle, limb length, an individual’s posture combined with characteristic motion and external factors such as floor and foot wear among others[3]. Gait analysis involves the investigation of an individual pattern of walking. Based on studies in Psychophysics. It has been shown that the human gait contains unique information that is useful in a clinical environment as well as in athletics, for the evaluation of foot and gait pathologies. The measurement of the pressure distribution during gait is useful for the clinical evaluation of foot and gait pathologies. Similarly, changes in gait such as slower walking or a more variable stride and rhythm, may be early signs of mental impairments [3] that can develop into Alzheimer's before such changes can be seen on neuropsychological tests

Studies show at least 30 percent of persons 65 and older report difficulty walking three city blocks or climbing one flight of stairs, and approximately 20 percent require the use of a mobility aid to ambulate. In a sample of noninstitutionalized older adults, 35 percent were found to have an abnormal gait. The prevalence of abnormal gait increases with age and is higher in persons in the acute hospital setting and in those living in long-term care facilities. In one study, gait disorders were detected in approximately 25 percent of persons 70 to 74 years of age, and nearly 60 percent of those 80 to 84 years of age [40].

1.4 Balance

In biomechanics, balance is an ability to maintain the line of gravity, that is a vertical line from the center of mass of a body, within the base of support with minimal postural sway. Sway is the horizontal movement of the center of gravity even when a person is standing still. In the case of an individual standing quietly upright, the limit of stability is defined as the amount of postural sway at which balance is lost and corrective action is required.[6]

Balance, postural steadiness, or static posturography, characterizes the performance of the postural control system in a static position and environment during quiet standing.[21] Maintaining balance requires coordination of input from multiple sensory systems, including the vestibular, somatosensory, and visual systems. There are environmental factors that can affect balance such as light conditions, floor surface changes, alcohol, drugs, and ear infection.

There are balance impairments associated with aging. Age-related decline in the ability of the above systems to receive and integrate sensory information contributes to poor balance in older adults.[4] As a result, the elderly are at an increased risk of falls. In fact, one in three adults aged 65 and over will fall each year.[5]

Body sway can occur in all planes of motion, which makes it an increasingly difficult ability to rehabilitate. There is strong evidence in research showing that deficits in postural balance are related to the control of medial-lateral stability and an increased risk of falling. To remain balanced, a person standing must be able to keep the vertical projection of their center of mass within their base of support, resulting in little medial-lateral or anterior-posterior sway.

Ankle sprains are one of the most frequently occurring injuries among athletes and physically active people. The most common residual disability post ankle sprain is instability along with body sway. Mechanical instability includes insufficient stabilizing structures and mobility that exceed physiological limits. Functional instability involves recurrent sprains or a feeling of giving way of the ankle.[7] Nearly 40% of patients with ankle sprains suffer from instability and an increase in body sway.[8] Injury to the ankle causes a proprioceptive deficit and impaired postural control. Individuals with muscular weakness, occult instability, and decreased postural control are more susceptible to ankle injury than those with better postural control.

Balance can be severely affected in individuals with neurological conditions. People who suffer a stroke or spinal cord injury, for example, can struggle with this ability. Impaired balance is strongly associated with future function and recovery after a stroke, and is the strongest predictor of falls.[9]

Another population where balance is severely affected are Parkinson's disease patients. A study done by Nardone and Schieppati (2006) showed that individuals with Parkinson's disease problems in balance have been related to a reduced limit of stability and impaired production of anticipatory motor strategies and abnormal calibration.

Balance can also be negatively affected in a normal population through fatigue in the musculature surrounding the ankles, knees, and hips. Studies have found, however, that muscle fatigue around the hips (gluteal and lumbar extensors) and knees have a greater effect on postural stability (sway).[10] It is thought that muscle fatigue leads to a decreased ability to contract the muscles with the correct amount of force or accuracy. As a result, proprioception and kinesthetic feedback from joints are altered so that conscious joint awareness may be negatively affected.[3]

1.5 Tinetti Test

The Tinetti-test was published by Mary Tinetti (Yale University) to assess the gait and balance in older adults and to assess the perception of balance and stability during activities of daily living and fear of falling. It is also called the Performance-Oriented Mobility Assessment (POMA). It is a very good indicator of the fall risk of an individual. It has better test-retest, discriminative and predictive validities concerning fall risk than other tests including, Timed Up and Go test (TUG), one-leg stand and functional reach test. [44]

It is used in various settings, for example for those diagnosed with Multiple Sclerosis, Parkinson's Disease, acquired brain injury, spinal cord injury, stroke and the elderly population. The Tinetti test has a gait score and a balance score. It uses a 3-point ordinal scale of 0, 1 and 2. Gait is scored over 12 and balance is scored over 16, totaling 28 for the complete Tinetti test. The lower the score on the Tinetti test, the higher the risk of falling. The test requires a hard-armless chair, a stopwatch and also 15 feet even and uniform walkway. It has 2 sections: one assesses balance abilities in a chair and also in standing; the other assesses dynamic balance during gait on a 15 feet even walkway. Fig 1.1 shows the Tinetti score range and the level of risk associate based the range of scores.

Tinneti tool score	Risk of fall
≤ 18	High
19-23	Moderate
≥ 24	Low

Table 1.1 Tinetti score range

1.6 Motivation

The causes for falls do not generally appear in one day unless the fall is due to some environmental factors or unexpected accidents. The balance and gait deterioration usually occur over a period of time. Falling is not an inevitable result of aging. If we are able to monitor the gait and balance characterizes of the individual over a certain period of time to analyze and capture the abnormality in walking in the early stage itself, then it will help in planning preventive strategies to prevent falls.

Hence, the main motivation of the entire research project is to prevent falls among elder individuals by providing a smart care health facility which is an intelligent sensor-driven living environment for the elderly. The research presented in this thesis is a part of this smart care system where the person's gait and balance characteristics are studied on the sensor-based smart floor. This research in particular focuses mainly on the balance characteristics of an individual and to create a machine learning-based, automated system that helps to early detect the abnormal patterns in the balance that could suggest early signs of a physical or cognitive issue.

2. APPROACHES

2.1 Existing Approaches

Existing approaches for gait and balance analysis generally make use of devices worn on the body, video surveillance cameras, electrodes mounted on the skin, needles pierced into the muscle, or kinematic systems to name a few, to obtain data for detection of abnormality in gait and balance. Traditionally, clinical analysis is carried out to determine neurological or musculoskeletal disorders using the measurements obtained from these approaches. Here we try to briefly describe the different existing approaches for gait analysis. The approaches listed here are not exhaustive but aim to cover most of the popular approaches. Gait analysis can be done with and without having technological aids. Simple techniques can be used to manage clinical problems.[4]

One of the approaches mentioned by Yu-Liang Hsu [45] uses an Inertial-Sensor-Based Wearable Instrument for Gait and Balance Analysis for Patients with Alzheimer's Disease (AD). An Inertial-sensor-based wearable device composed of a triaxial accelerometer and two gyroscopes is mounted on each participant's waist. Then the participants are requested to maintain body balance and perform tasks to test balance ability. These devices are embedded with automatic gait and balance analyzing algorithms to analyze gait patterns and balance ability for AD patients. The automatic gait analyzing algorithm consists of stride detection followed by gait cycle decomposition to decompose a gait cycle into stance and swing periods and acquire several sophisticated gait parameters. On the other hand, the automatic balance analyzing algorithm applies the center of mass (COM) analysis to acquire the sway speed of the body in anterior-posterior (AP) and medial-lateral (ML) directions. The experiments suggest the high possibility of using solely inertial sensors for AD patient gait and balance analysis and therefore, a truly wearable device used for clinics and AD daily evaluation should be further developed.

Despite the fact that gait and balance analysis have already commonly adopted in the diagnosis of AD patients, there is a lack of reliable wearable devices that can be used for measuring the gait and balance parameters. Traditional methods with a camera, footswitches, or electronic mats are constrained to a laboratory environment [45]

Another approach discussed in [46] uses force platforms. They are steel blocks equipped with strain gauges or piezoelectric transducers to measure ground reaction forces (GRF) and can be embedded in a walkway or treadmills for continuous recordings of multiple gait cycles. The gait cycle results in a repetitive and unique GRF pattern with precisely timed events such as heel-contact and toe-off that can be quantitatively assessed. Additionally, the center of pressure (CoP) can be measured continuously between the body and ground as an indicator of balance. Force platforms are generally expensive and require dedicated laboratory environments and skilled technical personnel to operate.

In-floor force platforms display high test-retest reliability for gait and balance variables. The reliability of treadmill-based force platforms for simple gait variables is generally also good. However, for more complex measures such as gait variability, the reliability it is only low to moderate. Significant differences also exist in the GRF patterns during treadmill walking compared to over the ground walking, so it is unclear whether treadmills are optimal for identifying pathological gait function in neurological diseases [46].

Similar approaches were also discussed in another research paper 'Evaluation of balance in fallers and non-fallers elderly' [30]. This study was designed to identify balance impairments associated with falling in elderly subjects. The purpose of this study was mentioned to evaluate the balance between fallers and non-fallers amongst the elderly. This study reports comparative results of Computerized Dynamic Posturography (CDP) and Berg Balance Scale (BBS) tests carried out on either group among which Group I consist of 15 elderly subjects who are reported to have experienced two or more unexpected falls during the past 12 months and Group II which includes elderly people that are non-fallers (n = 15). A simple predictive model was reported using logistic regressions that combined the Berg Balance Scale (BBS) scores with a self-reported history of imbalance to predict the risk of falls.

Over the past two decades, many clinical balance examinations have been developed for evaluating human balance ability. For example, the Berg Balance Scale (BBS), the Timed Up and GO Test (TUGT) and the Short Physical Performance Battery (SPPB). Recently, the abovementioned examines were further used to probe into the relationship between balance ability and cognitive function. Pettersson et al. utilized the Frenchay activities index (FAI), BBS, TUGT, TUG manual (diffTUGT), Talking While Walking (TWW), and Tinetti balance tests for the evaluation of the activity level and motor function of the subjects with no cognition impairment, Alzheimer's Disease and other dementia. The results suggested that the motor function seems to be affected in very mild AD but not in MCI subjects, and the AD subjects had difficulties in performing a cognitive task during walking. Alexander et al used an optoelectronic camera system to compare body motion and force output at the feet in AD subjects with those in healthy elderly while they were asked to stand on a forced plane. The literature concluded that AD subjects had poor balance ability [45]

The Timed Up and Go test is a fast and reliable diagnostic tool. Persons who have difficulty or demonstrate unsteadiness performing the Timed Up and Go test require further assessment, usually with a physical therapist, to help elucidate gait impairments and related functional limitations. The most effective strategy for falls prevention involves a multifactorial evaluation followed by targeted interventions for identified contributing factors. Evidence on the effectiveness of interventions for gait and balance disorders is limited because of the lack of standardized outcome measures determining gait and balance abilities.

Rehabilitation and health monitoring technologies today often suffer from an inability to provide indoor monitoring in cases where the users have to have some device attached to their body or have to wear them on their clothes or in the form of gait monitoring shoes [3]. In a few studies, a shoe or body attached monitoring system is used. These systems however have no way to provide constant and consistent unobtrusive monitoring since the user will have to remove this device, take off this shoe from time to time and will have to remember to recharge them in some cases. In the time period in which, the user has to take off the devices to fulfill other duties or to change them; some significant information might be lost.

Due to recent technological advances, a growing trend in balance assessments has become the monitoring of the center of pressure (CoP), the reaction vector of the center of mass on the ground, and the path length for a specified duration.[24] With quantitative assessments, the minimal CoP path length is suggestive of a good balance. Laboratory-grade force plates are considered the "gold-standard" of measuring CoP to determine the balance characteristics. The Neuro Com Balance Manager (Neuro Com, Clackamas, OR, United States) is a commercially available dynamic posturography system that uses computerized software to track CoP during different tasks. These different assessments range from the sensory organization test looking at the different systems that contribute through sensory receptor input to the limits of stability test observing a participant's ankle range of motion, velocity, and reaction time. While the Neuro Com is considered the industry standard for balance assessments, it does come at a steep price (about $250,000).

Apart from this, the most traditional approach used for gait and balance assessment is physical examination [40]. Patients are evaluated for orthostatic hypotension, vision and hearing problems, and cardiovascular and pulmonary conditions. They are also evaluated for joint deformity, swelling, instability, and limitations in range of motion involving the hips, knees, ankles, back, neck, arms, and feet. Postures are examined, and footwear is assessed for comfort, support, and stability. Physicians look for focal neurologic deficits and assess for muscle strength and tone, reflexes, sensation, proprioception, tremor, coordination, and cerebellar and vestibular function. Also, patients have a cognitive status evaluation and depression screening. Fear of falling can be assessed directly or using a validated questionnaire [22].

2.2 Our Approach

User convenience is an integral part of any design and, many of the devices currently in use require a significant amount of effort and involvement from the user and rely heavily on the willingness of the user at any specific time to use the device. This, however, can lead to biased sensor results where data is obtained only in specific situations and is thus not representative. For example, an individual might get the urge to check their temperature if they feel different, overemphasizing unusual temperature readings, or in the case where users have to put on some specially designed shoes, they might be reluctant to do so when they feel weaker or ill, thus removing the ability of the device to detect changes in health and hence limiting its utility in the detection of the health incidents and trends. Also, there is another lingering problem called the white coat syndrome (WCS) which inhibits clinical examination. For example, existing technologies that offer excellent tools have no way to change the users' perspective that they are undergoing an examination when they are about to use their device. This knowledge of being examined by a medical device can produce a psychological effect similar to that observed during a doctor's examination (WCS). This impairs the ability of the devices to obtain an accurate result.

Also, one important point to consider here apart from user convenience and WCS is that not all illness provides a noticeable signal to the user in order for them to take an appropriate measure and thus a more regular means of obtaining measurements without the need for the user initiation would be preferable. [3]

To address this, the Smart-Floor, a new way for health monitoring and abnormality detection aims to be used for a wide range of health applications for monitoring without inhibiting the user's convenience and without the need for active user intervention to provide measurements [3]. The method used in this project is unique since most systems that perform similar functions are "on-body" systems using leg attached sensors, body tags, or "off-body" systems using vision. Our approach uses floor-mounted pressure sensors which are designed to collect data unobtrusively, over long periods of time, and without interfering with gait or inconveniencing the user [1].

3. RELATED WORK

3.1 Balance Parameter Extraction

A significant amount of work has been done in this area to determine and extract the balance parameters to evaluate the postural stability of an individual for assessing the risk of fall.

3.2 Factors Determining Balance:

Center of Gravity (COG): The center of gravity is the point at which the combined mass of the body appears to be concentrated. Because it is a hypothetical point, the COG need not lie within the physical bounds of an object or person, it lies approximately anterior to the second sacral vertebra. However, since human beings do not remain fixed in the anatomical position, the precise location of the COG changes constantly with every new position of the body and limbs. The bodily proportions of the individual will also affect the location of the COG.

Center of Pressure (COP): In biomechanics, COP is the term given to the point of application of the ground reaction force vector. The ground reaction force vector represents the sum of all forces acting between a physical object and its supporting surface. Analysis of the center of pressure is common in studies on human postural control and gait. COP and COG are both related to balance in that they are dependent on the position of the body with respect to the supporting surface. The center of gravity is subject to change based on posture. Center of pressure is the location on the supporting surface where the resultant vertical force vector would act if it could be considered to have a single point of application. A shift of CoP is an indirect measure of postural sway and thus a measure of a person's ability to maintain balance.[47]

The Base of Support (BOS) refers to the area beneath an object or person that includes every point of contact that the object or person makes with the supporting surface. These points of contact may be body parts, e.g. feet or hands, or they may include things like crutches or the chair a person is sitting in. The BOS is an important concept to understand an individual's ability to Balance, as the balance is defined as the ability to maintain the line of gravity (passing through the Centre of Gravity) within the BOS. A wide base of support (BOS) has long been believed to be a hallmark of unsteady gait. [2]

Body Sway: Body sway is defined as the slight postural movements made by an individual to maintain a balanced position and can be measured by the total displacement of the center of mass relative to the base of support over time. Balance is often assessed as the amount of postural sway of the human body and it has been assessed for static balance and dynamic balance conditions, depending on whether the base is stationary or moving such as standing or walking. The cause of sway is attributed to many factors such as inherent noise within the human neuromotor system, as reflective of an active anticipatory search process, or as an output of a control process to maintain postural control [47]. Studies have suggested falls in the elderly are attributed to difficulties adapting one's balance in response to changes in sensory information, as well as increased sway in the anterior-posterior (AP) and medio-lateral (ML) directions compared to young adults.

Anterior-posterior is concerned with or extending along a direction or axis from front to back or from anterior to posterior. While medio-lateral is relating to, extending along a direction or axis from side to side or from the median to lateral. Figure 3.1 shows Anterior-posterior and Medio-Lateral Sway.

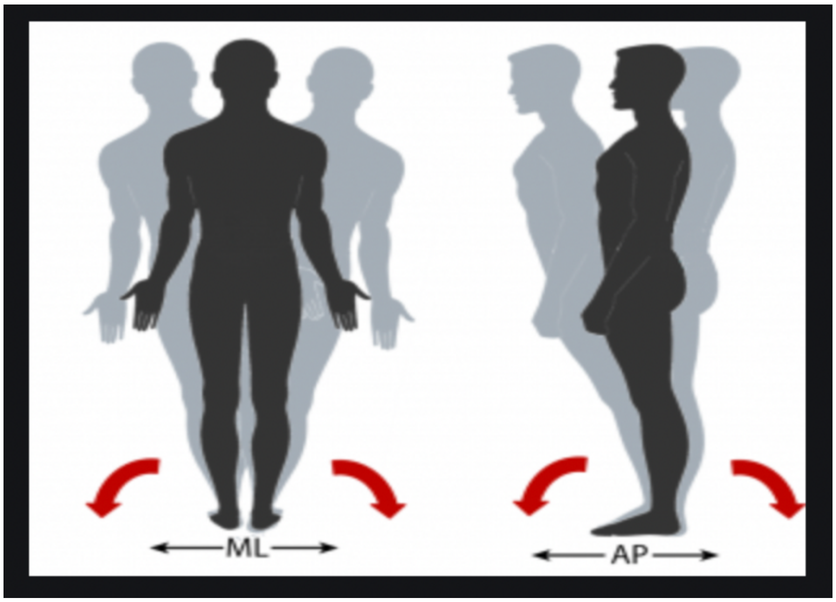


Figure 3.1 Anterior-Posterior (AP) and Medio-Lateral (ML) Sway

While balance is mostly an automatic process, voluntary control is common. Active control usually takes place when a person is in a situation where balance is compromised. This can have the counter-intuitive effect of increasing postural sway during basic activities such as standing.

Age, gender, and height have all been shown to impact an individual's ability to balance and the assessment of that balance. Typically, older adults have more body sway with all testing conditions. Tests have shown that older adults demonstrate the shorter functional reach and larger body sway path lengths. Height also influences body sway in that as height increases, functional reach typically decreases

3.3 Related Work in Extracting Balance Parameters:

Now that we have discussed the factors that define the quiet balance characteristic of an individual, this section will discuss some of the work that has already been done to extract these parameters. Most of the work which is discussed here is based on the balance parameters extracted out of the COP.

The Research paper on 'Measures on Postural Steadiness to characterize the dynamics of the postural control system' associated with maintaining balance during quiet standing [21] discusses various balance parameters that are extracted from COP. The objective that was mentioned in this study was to evaluate the relative sensitivity of center-of-pressure (COP)-based measures to changes in postural steadiness related to age. A variety of time and frequency domain measures of postural steadiness were compared between a group of twenty healthy young adults (21-35 years) and a group of twenty healthy elderly adults (66-70 years) under both eyes-open and eyes-closed conditions. The COP coordinate time series, AP and ML, are commonly used to compute measures of postural steadiness in this paper. Other parameters that were discussed in this paper are: The resultant distance (RD) time series which is the vector distance from the mean COP to each pair of points in the AP and ML time series; The root mean squared distance (RDIST) from the mean COP; The total excursions (TOTEX) which is the total length of the COP path; The mean velocity (MVELO) is the average velocity of the COP All features used are time domain area measures.

Another paper, 'The contribution of postural balance analysis in older adult fallers' [27] also uses similar balance parameters. The main objective of this research was the identification of postural characteristics of older adults at risk of falling using both static and dynamic postural balance assessments. The research claims that Centre of pressure (CoP) path length, CoP velocity and sway in medial lateral and anterior- posterior are the variables that distinguish older adult fallers from non-fallers.

The research published in the paper ‘A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population’ [24] conducted a study of postural balance and risk of falling in an ambulatory and independent elderly population. These balance tests were performed on 100 volunteers (aged 62-96) and falling was then monitored prospectively over a one-year period. The balance testing comprised measurements of: (a) spontaneous postural sway, (b) induced anterior-posterior sway, (c) induced medial-lateral sway, (d) anticipatory adjustments preceding volitional arm movements, (e) timed one-leg stance, and (f) performance on a clinical balance assessment scale. Small pseudorandom platform motions were used to perturb balance in the induced-sway tests. Using force plates, the spontaneous- and induced-sway responses were quantified in terms of the amplitude, speed, and mean frequency of the center-of-pressure displacement; input-output models were also used to parameterize the induced-sway performance. The results explained in this paper suggest that control of lateral stability may be an important area for fall-preventative intervention.

The paper “Time-to-boundary measures of postural control during single leg quiet standing” details an approach to quantifying postural stability in single-leg standing. Stance is an assessment of time-to-boundary (TTB) for center of pressure (COP) excursions. TTB estimates the time required for the COP to reach the boundary of the base of support if it were to continue with its instantaneous trajectory and velocity, thus quantifying the spatiotemporal characteristics of postural stability.

In five studies conducted in the paper 'Force platform measurements as predictors of falls among older people '[29], fall-related outcomes were associated with some force platform measures. For the various parameters derived on the basis of the force platform data, the mean speed of the medio-lateral (ML) movement of the center of pressure (COP) during normal standing with the eyes open and closed, the mean amplitude of the ML movement of the COP with the eyes open and closed, and the root-mean-square value of the ML displacement of COP were the indicators that showed significant associations with future falls.

There are a few other papers that performed the experimentation using similar balance features but using different approaches. In our research we have used a number of similar methods mentioned in these papers to extract the balance parameters from COP coordinates. The detailed explanation of the features and the algorithms are explained in Chapter 5.

3.4 Person Identification Related Work

Although, there is a significant amount of research on person identification based on gait parameters, when it comes to the person identification task using balance parameters, there are no such significant research experiments.

Most of the approaches for person identification are based on video data.[4] 'Person Identification and Anomaly Detection using Gait Parameters Extracted from Time Series Data', [4], a research paper from Suhas Mandikal in 2007, explains a variety of existing experimentation related to Person Identification and also introduces a contrasting approach based on pressure data. His experimentation is performed using time series data from pressure monitoring floor sensors and presents an approach to real-time segment walking data and separate it from data representing other activities like standing and turning by using unsupervised and supervised learning. He then extracts spatial-temporal gait parameters from relevant walking segments. A model of walking of individuals is then learned based on these parameters to predict deviation in a walking pattern using the Support Vector Data Descriptor (SVDD) method and the One-Class Support Vector Machine (OCSVM) for anomaly detection. He applied these models to real walking data from 30 individuals to attempt person identification to demonstrate the feasibility of building personalized models.

Taking motivation from this research project, the work in this thesis tries to provide a novel approach for person identification based on the balance parameters extracted from COP coordinates. The experimentation is performed on the same smart floor on the same 30 subjects, but instead of gait, this research mainly focuses on corresponding standing segments of the 30 individuals to extract the features corresponding to balance stability. Subsequently, a person identification model is built using one vs rest multi-class Support vector machines based purely on the balance parameters.

3.5 TINETTI Score Prediction Related Work

As discussed in Section 2.1 and the previous sections of this chapter, there are various approaches to assess the risk of the fall in elder individuals, including the Tinetti Score. Especially for the latter, these approaches mostly require human in the loop for the analysis and manual experimentation and computation of the score. Currently, there are not many significant experiments where this process of the Tinetti score prediction is automated using Machine learning based techniques.

In this research, we tried to provide a novel approach for Tinetti score predictions by using machine learning based models predicting these scores based on balanced parameters extracted for Individuals. In particular we used two approaches:

1. To predict the balance score and Tinetti score for 30 individuals based purely on balance parameters. We compared the results with the Tinetti and balance scores provided by trained evaluators for these 30 subjects.

2. We also tried to predict the Tinetti scores purely based on gait parameters available from previous research.

4. APPROACH AND IMPLEMENTATION

This chapter covers the entire experimental setup and procedure starting from the Data Collection to Person Identification and Tinetti Score Prediction.

4.1 End to End Experimentation Overview

The experimentation is performed on 30 subjects on a sensors-based pressure sensitive smart floor. The data in the form of the raw pressure values are collected from the smart floor sensors. The data is then calibrated to cancel the offsets in pressure values, which are due to the additional default pressure values contributed by the sensor floor. Offset cancellation is achieved using Machine Learning (ML) based simple Linear Regression model based on the ground truth that the total pressure values of a subject should be equal to the weight of the subject. Center of pressure (COP) coordinates are then computed from the calibrated pressure values and they form one of the key features which help to differentiate the standing segments from walking segments. Using COP coordinates and average COP value, an unsupervised Hierarchical Agglomerative clustering algorithm is used to segment the entire data corresponding to each subject into various clusters at different hierarchy levels. For this experimentation, we used data segmented into 3 clusters, namely Walking, Standing and Other. All results of calibration, segmentation, and clustering are available from the previous experiments.[1][2][3][4]

Using the above details, for this research we extracted the data corresponding to standing segments alone. This data set consists of COP x, COP y, and COP combined pressure values. On this data, Principal Component Analysis (PCA) is applied to transform the data in Major and Minor axis which serves as AP-

ML axis, respectively. Balance parameters (features) are then extracted from these PCA transformed data and also from raw COP coordinates using the algorithms explained in detail in Chapter 5. With the help of these hand-crafted features, an SVM model is trained to classify 30 subjects in a person identification process. Subsequently these balance related features are used to build a regression model to predict the balance component and total value of the Tinetti score. Similarly, the gait features available from the previous experiment are used to predict Tinetti score from Walking segments alone. The idea is to combine the balance score from balance parameters and gait score from gait parameters to combinedly predict the Tinetti Score. However, in this research no combination is performed and Tinetti scores are individually predicted based on the balance and gait parameters, respectively. Fig 4.1 shows the high-level diagram for the entire experimental setup

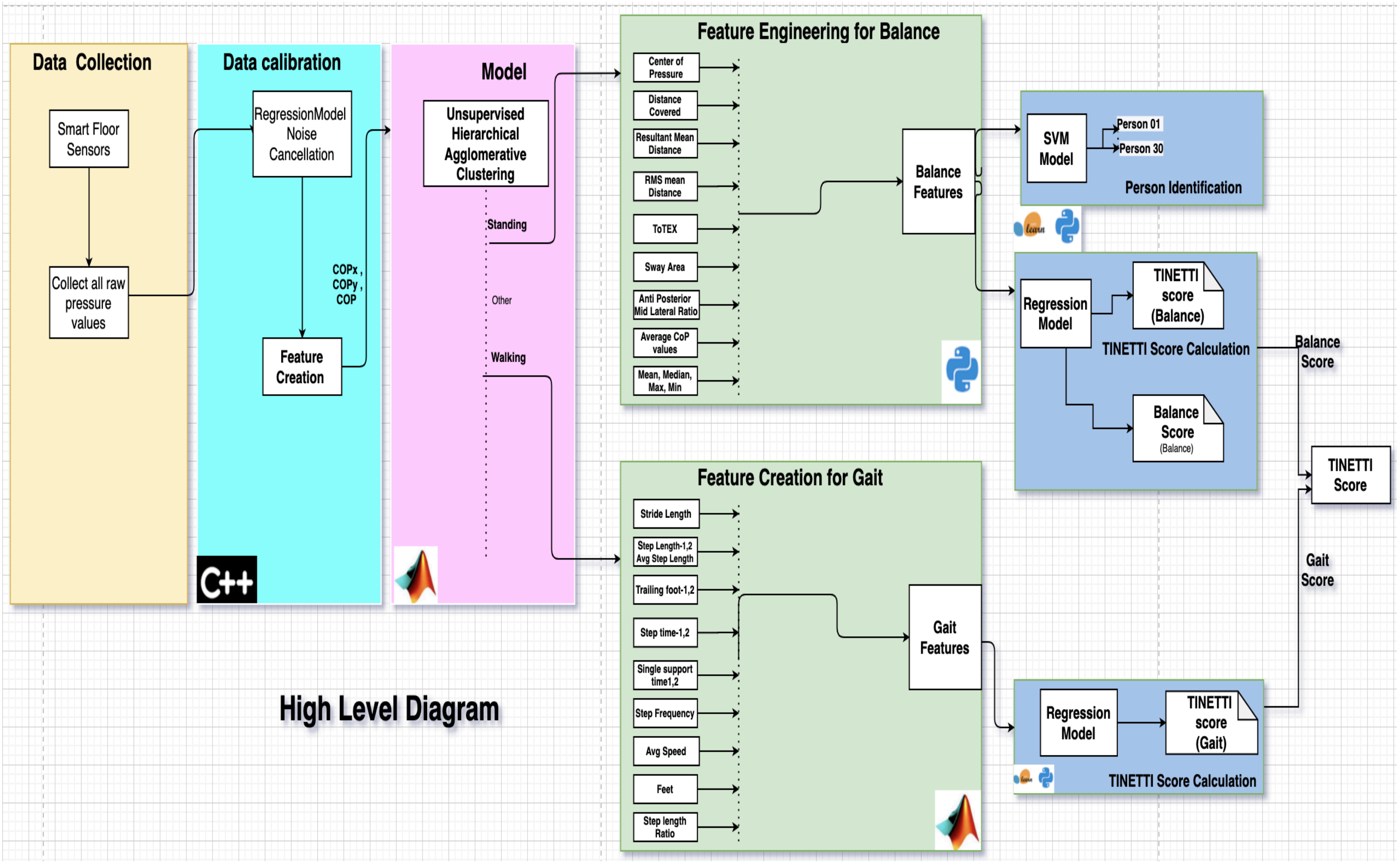
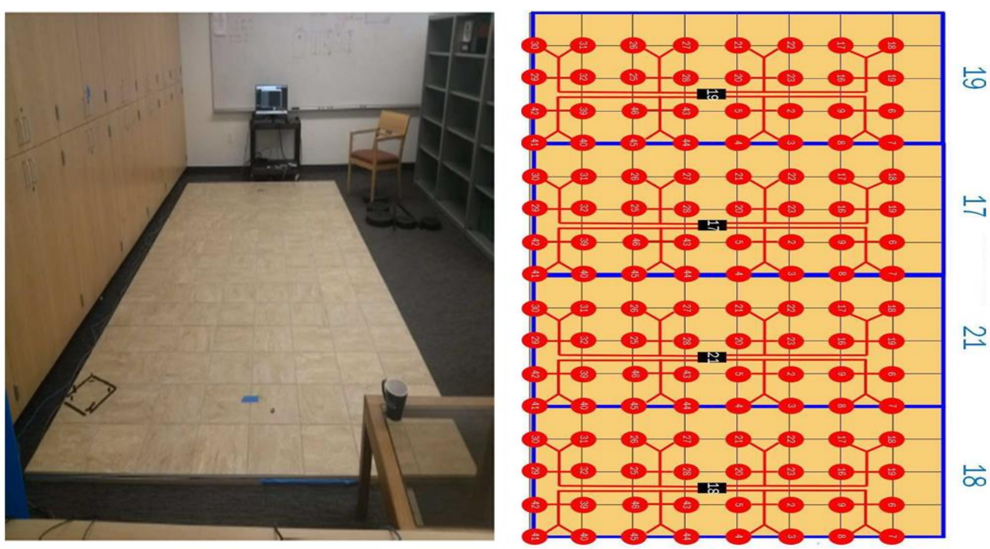


Figure 4.1 High level diagram: ***End-to-End experiment pipeline***

4.2 Smart Floor Setup and Data

Data Collection

For data collection we use a pressure-sensitive smart floor and experimental data obtained in previous work [10]. A series of pressure monitoring sensors are here placed underneath the floor tiles to record pressure data. The Pressure exerted by a subject while performing activities like standing and walking are collected at a rate of 25Hz. Data is transmitted continuously from the floor containing 128 sensors placed under 128 tiles to a nearby computer. The size of each tile is 30 cm x 30 cm. The laid-out tiles form a grid of 8 x 16 tiles. Data were collected from 30 participants consisting of 11 males and 19 females. Balance and walking data were collected from each of the participants. Figure 4.2 shows the floor that generates the data and the layout of sensors underneath the floor. [10].



(i) (ii)

Figure 4.2 (i) is the floor that generates the data and (ii) is the layout of sensors underneath the floor [4].

4.3 Trial Description

All the participants were volunteers and they were first asked to acknowledge and sign a consent form before taking part in the study. After this, each participant performed multiple scripted activities that were designed to generate representative balancing and walking gait data for the subject. In this, one activity was specifically designed to obtain static balancing data while another was performed to obtain several continuous gait cycles during a multi-directional walking path. As part of these activities, a Tinetti balance and gait assessment score was also elicited and a corresponding form was filled out by 3 trained investigators to assign appropriate gait and balance scores to each participant. These can later be used to compare automatic gait and balance assessments with the obtained Tinetti scores, which represents the current method of assessment. [3]

4.4 Experimental Protocol

Each subject was asked to perform a series of tasks on the floor. These started with the standard Tinetti assessment activities and then continued through another set of scripted activities.

Tinetti gait and balance assessment

For the balance Trial and gait assessment, each subject was asked to perform a series of tasks following the Tinetti Assessment Tool. These activities were as follows:

- Subject sits down on a chair
- Subject stands up
- Subject is requested to turn 360 degrees

- Subject is nudged while standing.
- Subject walks for a set of steps, turns around, and returns.

4.5 Data Calibration and Preprocessing

The data obtained from the floor was obtained with approximately pre-calibrated. sensors to ensure that sensor values in different floor regions are providing pressure information in terms of a uniform measurement unit. There are a total of 128 sensors on the experimental floor. Each sensor can output a value from 0-1023. Since the Tekscan FlexiForce A401 Sensors behave linearly, we can represent each sensor in the standard slope-intercept form of a linear equation:

$$w = ax + b$$

where w is the weight in pounds we want to calculate, x is the "raw" output from the sensor (0 – 1023), a is the x's coefficient, and b is a constant (offset).

Calibration of the slope and intercept was performed using a set of standard weights that were placed on the sensor locations. A linear least square fit was then applied to obtain the calibration parameters for each sensor. [3]

After calibration of the data, we obtain the pressure being exerted by the subject while standing or walking on the floor along with the weight of the tile. The weight of the tile is subtracted from the data after finding the mode for each sensor. This allows us to extract the pressure exerted by the subject on the floor [10].

4.6 The Preprocessed Data

The data comprises the location coordinates x and y and the associated pressure value. The pressure value is determined by averaging the pressure over the region of activated sensors. Data is generated at 25Hz. One second of data contains 25 data points. 25 data points form a data segment. The data segment is a matrix of 25 X 3 values. [3][4].

4.7 Data Segmentation

The preprocessed data which is COP coordinates in the X and Y axis and average COP value, has a mixture of Standing, slow walking, walking and various segments. The segments are converted from the time domain to the frequency domain using multidimensional Fourier Transform to obtain the frequency spectrum along each dimension. Then similar segments were grouped together by using unsupervised Agglomerative Hierarchical clustering using spectral coherence as a similarity metric on data segments of 30 subjects.

The purity of the cluster was assessed by visualizing the plot showing the movement of the center of pressure. The labels of the clusters were assigned by visualizing the segments of the cluster. Fig 4.3 shows the plot of standing segments, Fig 4.4 shows a visualization of walking segments, and Fig 4.5 shows turning COP trial segments.

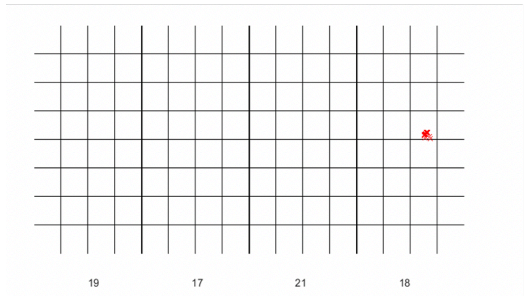


Fig 4.3 Standing COP trial segments. [4]

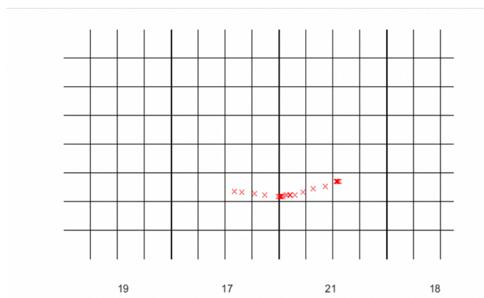


Fig 4.4 walking COP trial Segments [4]

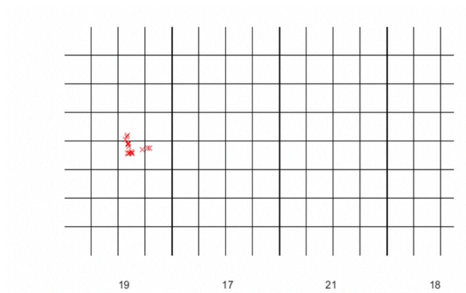


Fig 4.5 Turning COP trial Segments [4]

4.8 GAIT Features Extraction

The features related to gait are extracted from the strides; detailed information is given in the research "Gait analysis on a smart floor for health monitoring" [3]. The following gait features were extracted from the walking segments:

1. Stride length
2. Step length - 1
3. Step length – 2
4. Distance between heel strike of the leading foot and toe-off of the trailing foot - 1
5. Distance between heel strike of the leading foot and toe-off of the trailing foot – 2
6. Average step length
7. Step time - 1
8. Step time - 2
9. Single support time - 1
10. Single support time -2
11. Step frequency
12. Average speed
13. Feet
14. And 15. Step length ratios

All the details explained above are available from the documentation of the previous research [3][4]. Based on this data, the main components of this research are presented next.

4.9 Data Transformation and Datasets

In this work, we focus mainly on the standing segment data. We have extracted the standing segments for 30 subjects (subject 4 to subject 34, excluding subject 15) from the MATLAB code available from the previous research project [4]. The standing segment data has COP coordinates in X and Y direction, average COP value, and, for each segment 25 records corresponding to 1 sec of data. Some of the subjects' information related to the Tinetti test is listed in the Table 4.1 in Section 4.11.

For extraction of balance parameters, we considered 5 seconds of data segments since, as opposed to gait characteristics where 1s of data is usually sufficient to extract most gait parameters, balance features such as sway area tend to be lower frequency events, thus requiring longer segments to extract and filter. The resulting new standing segments have 5 seconds of data each with 125 records. The new segments are formed by combining for each 1 second segment the data with the following 4 standing segments sequentially, leading to segments with overlapping data. For instance, subject 1 has 20 consecutive original segments, each representing 1 sec of data (that makes 20 seconds of data), then new data segments are formed in this way:

New segment 1 = old segments 1 to 5
New segment 2 = old segments 2 to 6

Similarly, all data is re-segmented for all the 30 subjects.

This new dataset from here onwards will be referred to as Raw COP data which is one of the datasets that we used for features extraction.

4.10 Data Transformation Using Principal Components

Now the dataset that we have is 5 seconds of data with CoP coordinates in X and Y directions. One of the major attributes or parameters to analyze the postural balance is sway. So, to be able to do ante-posterior and mid-lateral sway analysis, it is necessary to know the orientation of the subject. In our scenario, we have the X and Y axis of COP coordinates, but we do not have the information which direction (axis) the standing subject is facing. Hence to overcome this problem we used Principal Component Analysis (PCA) to transform the X and Y axis into Major and Minor axis. In this process, we applied PCA on the newly segmented 5 seconds of data, and the resulting eigenvector with maximum eigenvalue is considered the Major axis and the other value the minor axis. This data set will be referred as the PCA Transformed dataset. Figure 4.6 shows the transformation of COP X and Y coordinates into Major and Minor axis

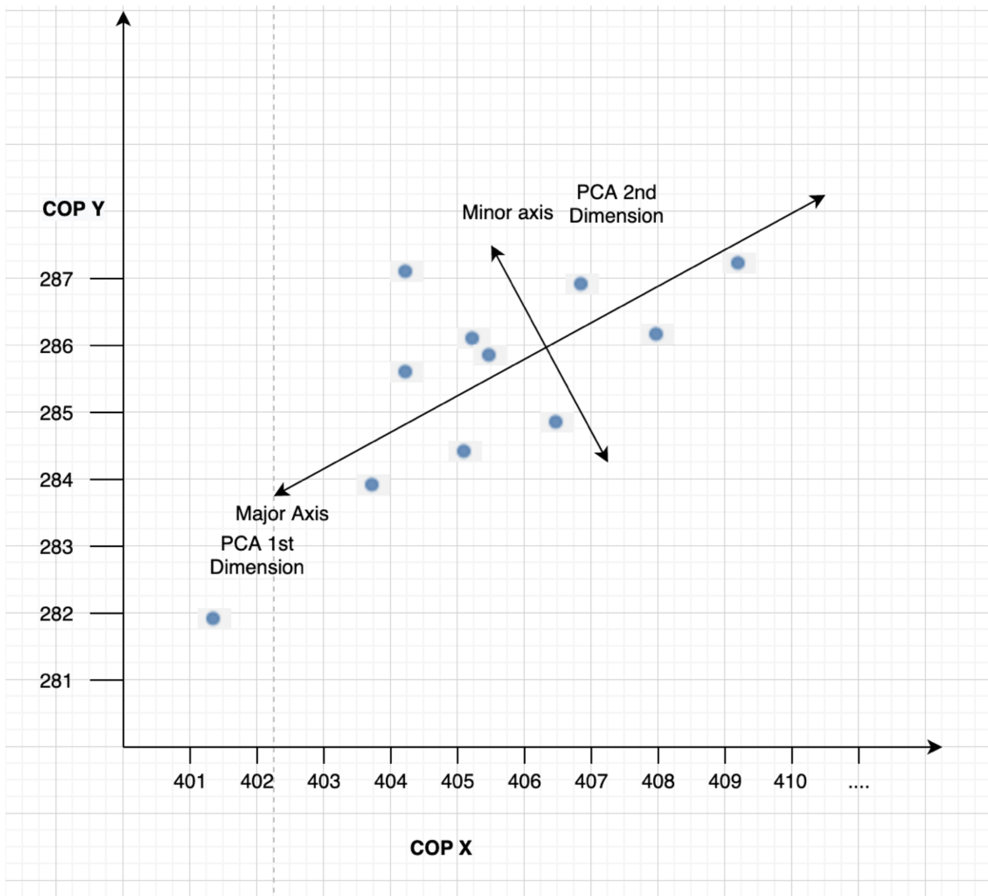


Figure 4.6 Transformation of COP X and Y co-ordinates into Major and Minor axis

4.11 Frequency Domain Transformation

The raw COP data or the PCA Transformed data may not be feasible to be used as direct input data for Deep Learning or Machine Learning algorithms for feature extraction or classification purposes. The Cop X, Y coordinates or PCA Transformed X, Y coordinates representing the location parameters are constantly varying and themselves carry limited meaning. We, therefore, transform the data from the time domain to the frequency domain, where each data point represents amplitude at a specific frequency. We used Fast Fourier Transformation for this purpose and the PCA Transformed data and the Raw COP data are transformed to the corresponding frequency domain representation. The datasets so formed are referred to as the Frequency Domain dataset. Also, for easy reference, X, Y coordinates in Raw COP data and Major and Minor axis in PCA Transformed Data will be referred to as AP and ML coordinate, respectively, and they all mean the same.

4.12 Feature Engineering for Balance Parameters

From the data segments we need to extract features that can be used to perform person identification of to predict the Tinetti scores. To do this, we can either form manually pre-defined balance features or try to learn features using machine learning approaches. The main advantage of the former is that they have specific meaning and thus lead to interpretable, explainable parameters. In addition, feature engineering tends to require significantly less data to be successful. On the other hand, learned features would require less engineering and could potentially find features that we did not consider relevant beforehand. We will briefly discuss our feature learning approach below. However, due to the very limited availability of standing data, the results of learning yielded limited results and most follow up work was performed with the engineered features. The main reason to discuss feature learning here is that it could be useful in situations where significantly more data is available.

4.13 Algorithm Based Balance Parameters Extraction

Now that we have data, we wanted to extract the parameters that define the postural stability. As discussed in Chapter 1, Chapter 2, and Chapter 3, there are a variety of factors that determine balance during quiet standing, but not every parameter can be extracted from the pressure-based data that we have. Also, a number of parameters, for instance, height, weight, age of subjects also contribute to the balance of a person, but we did not use these factors for our experimentation as these values are specific for each subject in our pool, and this would make the model overfit these values. We rather wanted to create a more generalized ML model for Person Identification and Tinetti Score prediction. Hence, considering all these factors and also taking reference from the existing work, we have created mathematics-based algorithms to extract the balance parameters out of AP ML (COP coordinates) and pressure values. Details about the algorithm are explained in Chapter 5.

Parameters extracted from each subject's balance dataset include:

1. COP Speed
2. Distance covered- Total Sway Path
3. Resultant Mean Distance
4. RMS Mean Distance
5. TOTEX
6. Sway Area
7. AP ML Ratio
8. Average COP values
9. Descriptive Statistics -Mean, Median, Maximum, Minimum

4.14 Deep Learning Based Feature Extraction

Although we have extracted a number of handcrafted parameters as mentioned in Section 4.10.1, we also wanted to experiment with feature learning from Raw COP data and PCA Transformed data. The initial idea was to learn the features from the deep learning network and combining these features with the handcrafted features and use these sets of features for the person identification and Tinetti score prediction tasks.

A variety of feature learning algorithms are available but automatic feature-based approaches using deep learning models have recently been successfully applied to time series classification problems, especially Convolutional Neural Networks (CNNs) performing temporal convolution which are regarded as the most successful and commonly used deep learning model. There are also a few research papers [43] that explain various CNN approaches that can be used for feature learning. In our experimentation, we have used a 1D convolutional neural network on the Raw COP time series data and PCA transformed time-series data for 5 second intervals. The classification experiment is performed on 30 subjects with different levels of convolution and Kernel size and filter size. But as the size of the training set was very small with regards to the number of the o/p classes, the resulting models generally overfitted and performance was very poor. So as of now, we have not proceeded further with this approach and continued the person identification and Tinetti score prediction tasks with the hand-crafted features that are extracted using the above-mentioned algorithms. However, given the availability of significantly more data, there could be a performance boost using CNN based feature learning that could extract more accurate and potentially previously not considered relevant features.

4.15 Person Identification

This research, we used a novel approach for person identification solely based on balance parameters. Person identification is basically a classification technique used to classify the different subjects based on the balance parameters (features) derived from the COP based data. For this, the data corresponding to standing instances of 30 subjects are considered and meaningful features or balance parameters are extracted for each individual as explained in Section 4.10.1. The subjects' data considered for this experiment are subject 4 to subject 34 except subject 15.

The main motivation for this experimentation is to analyze how well the balance parameters that are extracted represent the balance characteristics of the subject and how well it helps to distinguish one subject from the other. While we are ultimately interested in predicting fall risks and detecting anomalies that might indicate a health change or deterioration, person identification can be seen as a test example where we can determine whether balance features for a different person can be identified as anomalies for an individual. These features will subsequently also be used to build a model for balance score prediction which is discussed in the next section.

Given that we have multiple classes (30 classes) to classify, we have used a multi-class classifier and will here use various one vs rest Supervised Classification models for Person Identification due to their high robustness especially in the context of limited amounts of data for each class. Hyperparameter tuning is performed to achieve the best performance accuracy. The experimental results are compared in Chapter 6.

Algorithms used here are:

1. One vs Rest Support vector classifiers with polynomial kernel
2. One vs Rest Support vector classifiers with RBF kernel
3. Logistic regression with various regularization techniques

4.16 Tinetti Score prediction

This research also tries to implement a novel approach for the Tinetti score prediction using a machine learning based model. This is basically a regression process wherein the input data is the balance features extracted from the algorithms on various sets of datasets, and the output is the balance score values and Tinetti score values. For balance score prediction, the regression model is trained on the balance score values for 30 subjects, these scores are provided by the trained evaluators which are obtained from the experimentation process performed on the smart floor in our laboratory. Similarly, the model for Tinetti score prediction is trained on Tinetti scores obtained in a similar fashion as explained above. We also tried to predict the Tinetti scores using gait parameters alone. These gait parameters are available from previous research work [4]. We have not performed gait score prediction since the 30 subjects do not exhibit sufficiently high variance in the gait score, causing the model to overfit. The experimental results are shown in Chapter 6. Table 4.1 shows Tinetti, Balance, and Gait score with details of the 30 subjects in the study. The machine learning models used are:

1. Linear Regression
2. Lasso Regression

3. Ridge regression

4. Support vector regression

Subject	Balance Score	Gait Score	Tinetti Score
4	15	12	27
5	15	13	28
6	15	12	27
7	15	12	27
8	15	12	27
9	15	12	27
10	15	12	27
11	14	12	26
12	13	12	25
13	16	12	28
14	15	12	27
16	13	12	25
17	13	12	25
18	12	12	24
19	16	12	28
20	14	10	24
21	15	12	27
22	12	12	24
23	15	12	27
24	14	12	26
25	14	12	26
26	13	12	25
27	13	12	25
28	13	12	25
29	14	12	26
30	14	12	26
31	14	12	26
32	14	12	26
33	14	12	26
34	16	12	28

Table 4.1 Tinetti, Balance and Gait score with details of 30 subjects

5. FEATURE ENGINEERING FOR BALANCE

5.1 Balance Parameter Extraction and Algorithms

The spatial and temporal parameters of balance for each individual have been extracted from the AP and ML (COP X, Y coordinates, major and Minor axis in PCA Transformed data) coordinates and COP value obtained from the 3 datasets. Hence parameters are built and analyzed on frequency domain data and PCA Transformed data as well as on Raw COP data in the time domain to determine the balance characteristics of individuals. Parameters extracted from each subject's balance dataset include:

1. COP Speed
2. Distance covered- Total Sway Path
3. Resultant Mean Distance
4. TOTEX
5. RMS Mean Distance
6. TOTEX
7. Sway Area
8. AP ML Ratio
9. Average COP values
10. Descriptive Statistics -Mean, Median, Maximum, Minimum

5.2 Center of Pressure Speed (COP Speed)

The COP speed is the rate of change of the COP over time. It is directly proportional to the coordinates of the COP. Hence, if the displacement of the

COP from its initial position is high, there is an increase in the COP speed and vice versa when there is a low displacement. [3] Mean velocity of the COP has been suggested to be one of the measures that identified age-related changes in both eye conditions and differences between eye conditions in both age groups [21]

Let *t* be the time of the last COP point for a subject in their data set, t_i be the i[th] time step, and $d(x_i, y_i)$ be the corresponding COP coordinate. Using these, the COP speed can be extracted using the algorithm shown below.

We also computed Mean, Median, Maximum and Minimum values for COP Speed.

COP Speed Algorithm

$\boldsymbol{for}\ t = 0\ to\ N$

$\quad Obtain\ the\ COP\ coordinate\ (X_{t+1}, Y_{t+1})\ at\ Time\ t+1$

$\quad Obtain\ the\ COP\ coordinate\ (X_t, Y_t)\ at\ Time\ t$

$\quad Distance: D = \sqrt{(X_{t+1} - Y_{t+1})^2 + (X_t - Y_t)^2}$

$\quad Compute\ change\ in\ time(T) = dt = (T_t, T_{t+1})$

$\quad COP_{speed} = \dfrac{D}{dt}$

$\boldsymbol{end\ for}$

Algorithm 5.1 COP Speed

5.3 Center of Pressure Distance (Total Sway path)

COP Distance is the total length of the path covered by a subject over the period of time. It is directly proportional to the coordinates of the COP. This also represents the total sway path. Let *t* be the time of the last COP point for a subject in their data set, t_i be the i^th time step, and $d(x_i, y_i)$ be the corresponding COP coordinate. Using these, the COP Distance can be extracted using the algorithm shown in Algorithm 5.2.

We also computed Mean, Median, Maximum and Minimum values for COP Speed

---

COP Distance Euclidean

$\boldsymbol{for}\ t = 0\ to\ N$
  $Obtain\ the\ COP\ coordinate\ (X_{t+1}, Y_{t+1})\ at\ Time\ t+1$
  $Obtain\ the\ COP\ coordinate\ (X_t, Y_t)\ at\ Time\ t$
  $Distance: D = \sqrt{(X_{t+1} - X_t)^2 + (Y_{t+1} - Y_t)^2}$
$\boldsymbol{end\ for}$

Algorithm 5.2 (i) Euclidean

5.4 Mean Resultant Distance:

The parameters described in this section are the most commonly used measures of postural steadiness [32].

The mean distance-AP (MDISTAP) is the mean absolute value of the AP time series and represents the average AP distance from the mean COP. Algorithm

5.3 shows the computation of Mean AP. Here N = 0 to 125 in our experiment for 5 secs of a data segment.

Figure 5.1(i) and 5.1(ii) shows the corresponding body sway in Ante-Posterior (AP) and Mid-Lateral (ML) direction for one of the subjects.

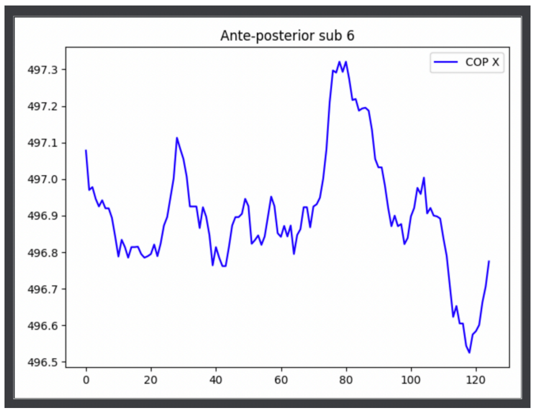


Figure 5.1(i): Ante-Posterior Sway

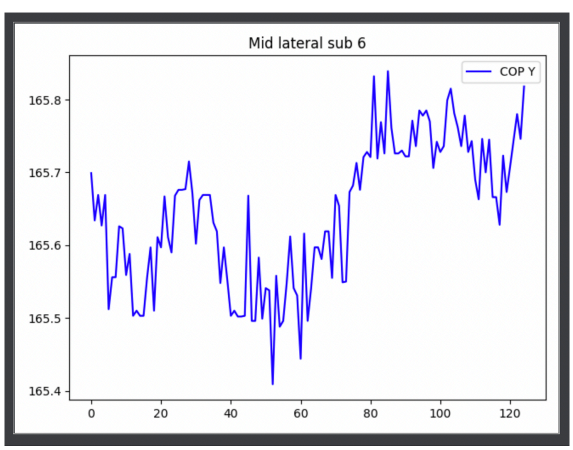


Figure 5.1(i): Mid-Lateral Sway

Mean AP (anterior- posterior)

$$AP_{mean} = \frac{1}{N}\sum_{i=0}^{N-1} X[i]$$

Algorithm 5.3 Mean AP

Similarly, mean distance-ML(MDISTML) is the mean absolute value of the ML time series and represents the average ML distance from the mean COP. Algorithm 5.4 shows the computation of Mean ML. Here N = 0 to 125 in our experiment for 5 seconds of a data segment.

Mean ML (mid lateral)

$$ML_{mean} = \frac{1}{N}\sum_{i=0}^{N-1} Y\,[i]$$

Algorithm 5.4 Mean ML

The resultant distance (RD) time series is the vector distance from the mean COP to each pair of points in the AP and ML time series. Algorithm 5.5 shows the computation of Resultant distance RD.

$\boldsymbol{for}\ i = 0\ to\ N - 1$

$AP[i] = X[i] - AP_{mean}$

$ML[i] = Y[i] - ML_{mean}$

$RD[i] = \sqrt{AP[i]^2 + ML[i]^2}$

$\boldsymbol{end\ for}$

Algorithm 5.5 Resultant distance

The mean distance (MRDIST) is the mean of the RD and represents the average distance from the mean COP. Algorithm 5.6 shows computation of MRDIST, MDIST in AP and ML direction

$$MRDIST = \frac{1}{N}\sum_{i=1}^{N} RD\ [i]$$

$$MDIST_{AP} = \frac{1}{N}\sum_{i=1}^{N} |AP[i]|$$

$$MDIST_{ML} = \frac{1}{N}\sum\nolimits_{i=1}^{N} |ML[i]|$$

Algorithm 5.6 MRDIST, MDIST in AP and ML direction

5.5 RMS Distance:

The RMS distance (RDIST) is the root mean squared distance from the mean COP. Algorithm 5.7 shows computation for RMS Resultant distance, RMS distance in AP and ML

$$RDIST_{RD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RD[i])^2}$$

$$RDIST_{AP} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(AP[i])^2}$$

$$RDIST_{ML} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(ML[i])^2}$$

Algorithm 5.7 RMS Resultant distance, RMS distance in AP and ML

5.6 Total Excursions

The total excursions (TOTEX) is the total length of the COP path and is approximated by the sum of the distances between consecutive points on the COP path. The total excursions-AP (TOTEXAP) the total length of the COP path in the AP direction, and is approximated by the sum of the distances between consecutive points in the AP time series. Algorithm 5.8 shows computation for TOTEX, TOTEX in AP and ML.

$$TOTEX =. \sum_{i=0}^{N-1} \sqrt{(AP[i+1] - AP[i])^2 + (ML[i+1] - ML[i])^2}$$

$$\mathrm{T}OTEX_{AP} = \sum_{i=0}^{N-1} |AP[i+1] - AP[i]|$$

$$\mathrm{T}OTEX_{ML} = \sum_{i=0}^{N-1} |ML[i+1] - ML[i]|$$

Algorithm 5.8 TOTEX, TOTEX in AP and ML

5.7 Sway Area:

An increase in sway alone is not necessarily an indicator of dysfunctional balance, but typically older adults have more body sway within all testing conditions. Earlier experimentation tests have shown that older adults demonstrate shorter functional reach and larger body sway path lengths.

The sway area describes the enclosed area covered by the CoP as it oscillates within the base of support. Multiple studies suggest that high Sway Area could be related to a distorted balance condition [27].

There are a number of methods explained in previous research that use sway area measures [34]. In this experimentation two methods are used to calculate the sway Area.

<u>**Area of Stabilogram:**</u>

Sway area (AREA-SW) estimates the area enclosed by the COP path per unit of time. This measure is approximated by summing the area of the triangles formed by two consecutive points on the COP path and the mean COP [13]. Sway area is dependent on the distance from the mean COP and the distance traveled by the COP and can be conceptualized as proportional to the product of mean distance and mean velocity.[27] Algorithm 5.9 shows computation for Sway area of Stabilogram. Figure 5.3(iii) and Figure 5.3(iv) shows the sway path in 3D and 2D respectively for one of the subjects.

$$Sway\ Area = \frac{1}{2T}\sum_{i=0}^{N-1}\left|(AP[i+1]ML[i]) - (AP[i]ML[i+1])\right|$$

Algorithm 5.9 Sway area of Stabilogram

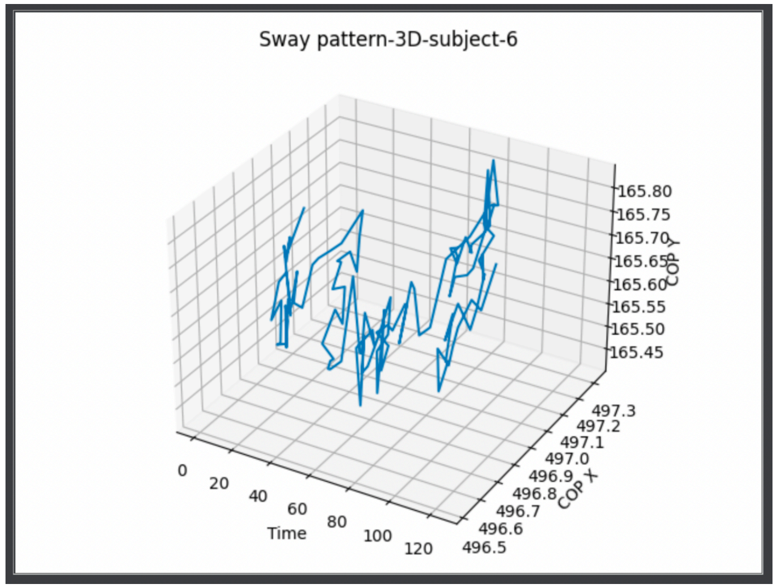


Figure 5.3(iii): Sway path in 3D Space

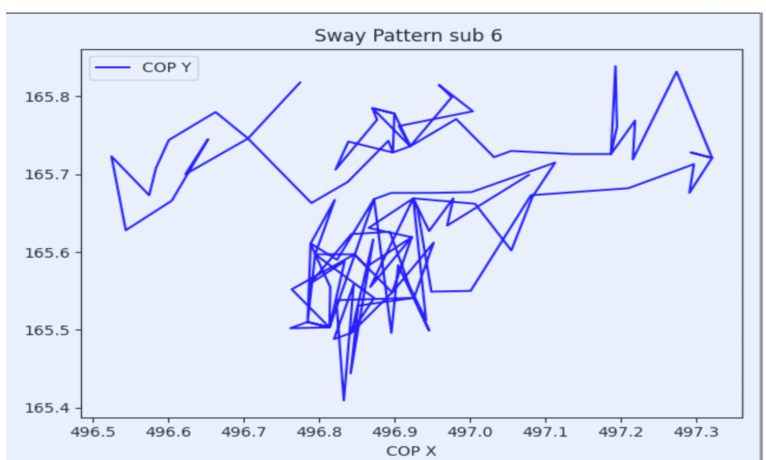


Figure 5.3(iv): Sway Path in 2D space

Gauss-Green:

A numerical approximation of the Gauss-Green formula is used to calculate the sway area.[27] Algorithm 5.10 shows computation for Sway area using Gauss Green method.

$$Guass\ Sway\ Area\ =\ \frac{1}{4}\sum_{i=1}^{N-1}\Big|\ \big((AP[i+1]+AP[i])(ML[i+1]-\ ML[i])\big) - (\ (AP[i+1]-AP[i])(ML(i+1)+ML(i)))\Big|$$

Algorithm 5.10 Sway area using Gauss Green method.

5.8 AP ML Ratio

The AP -ML ratio is the mean of the ratio of AP to ML. Algorithm 5.11 shows computation for AP ML Ratio

$$\begin{aligned}&\boldsymbol{for}\ i=0\ to\ N-1\\&\qquad ratio=\frac{AP[i]}{ML[i]}\\&\boldsymbol{end\ for}\end{aligned}$$

$$Mean\ Ratio=\frac{1}{N}\sum_{i=1}^{N-1} ratio\ [i]$$

Algorithm 5.11 AP ML Ratio

5.9 Descriptive Statistics:

Descriptive statistics help to describe and understand the features of a specific data set by giving short summaries about the sample and measures of the data. The most recognized types of descriptive statistics are measures of center: the mean, median, and mode. Measures of central tendency, or averages, are used in a variety of contexts and form the basis of statistics.

In this experimentation Mean, Median, Maximum and the Minimum, respectively, are extracted from the above-mentioned parameters.

Mean:

The Arithmetic Mean is the average of the numbers: a calculated "central" value of a set of numbers.

For instance, consider the distance from Algorithm 5.2. The mean distance is the average distance covered by a subject over the given period of time.:

Mean COP distance

$$Mean\ Distance = \frac{1}{N}\sum_{i=0}^{N-1} Distance[i]$$

Median:

In statistics and probability theory, a median is a value separating the higher half from the lower half of a data sample, a population or a probability distribution. For a data set, it may be thought of as "the middle" value. For example, the basic advantage of the median in describing data compared to the mean is that it is not skewed so much by a small proportion of extremely large or small values, and so it may give a better idea of a "typical" value.

Maximum and Minimum:

The Maximum and the Minimum of distance for instance is the Maximum and the Minimum distance covered by subject in the given time interval.

5.10 Average Center of Pressure

Average Center of Pressure (COP) is the average value of COP for each user on the floor. With the center of pressure, a subject's balance as a measure of postural sway while a person is standing can be measured.

Considering the center of pressure's x coordinate, COP(x,), it can be calculated using the formula:

$$COP(x) = \frac{\sum_i x_i . F_i}{\sum_i F_i}$$

where F_i is the pressure at a sensor location x_i relative to a reference point in the x-direction. Computation of the y position of the COP is performed in the same way. And the average is computed by considering the number of tiles where is pressure value is above a threshold. This value is used from previous research, details are explained in [3].

6. EXPERIMENTATION AND ANALYSIS

All the experiments are performed on balance parameters extracted using the algorithms mentioned in Chapter 5 from 4 categories of datasets, and results are analyzed:

1.Features extracted from PCA Transformed Time series data
2.Features extracted from PCA Transformed Frequency domain data
3. Features combined from 1 and 2
4. Features extracted from Raw COP data

Input data to both Person Identification and Tinetti Score prediction is feature vectors extracted from above mentioned 4 datasets representing the same underlying movement sequences. Output data are subject 4 to subject 34 modelled as output classes 0-29 in the case of the classification task in the Person Identification problem. The classification model is trained using the subjects' data corresponding to these classes. In case of the regression task for balance score prediction, the output data is the balance score and the Tinetti score of the corresponding individual. This model is trained on the balance and Tinetti score differently and output results are compared with the experimental test results which were manually determined by trained experimenters. Both the Person Identification and the Tinetti and Balance score prediction experiments are conducted using all 30, the first 20 and the first 10 subjects, respectively, to observe how the model behaves with different variance in the datasets.

Also, experiments are performed on all 30, the first 20 and the first 10 subjects, respectively, considering only a selected subset of the features to identify the significance of certain features. The train and test data are shuffled and split according to a 80 - 20 ratio using a seed to reproduce the results.

Here the test data is the data not seen in training in both Person Identification as well as in balance and Tinetti score prediction problems. In the case of the Balance and Tinetti score prediction experiments, two different test conditions are used, the first corresponds to the above-mentioned test set containing data not used for training from individuals that were present in the training set. The second condition, referred to as Unseen data in the below experiment refers to test data consisting of 20% of the subjects that were not included in the training. This case is only applicable for Balance and Tinetti score experiments since Person Identification cannot be performed on individuals that were not part of the training set.

6.1 Person Identification Experiment Results:

In Person Identification, the classifier used for this task is a one vs rest classifier and the initial training algorithm used was logistic Regression. Though the Logistic regression model performed well on the training dataset, it was prone to overfitting and performed poorly on the test dataset. Experiments were performed by tuning the regularization parameter but still the result did not improve.

Another training algorithm used in this experiment is the one-versus-rest classifiers with Linear SVM, and SVM with various kernel functions and hyperparameters. These hyperparameters are selected after performing grid search and randomized grid search over a wide range of degree, regularization and gamma values.

Experiment 1: All Features on all 30 subjects:

Table 6.1: Shows the best performing SVM model considering all the features with hyperparameters, C=100, gamma=3, kernel=poly, degree=7.

SVM All features **Best C=100, gamma=3, kernel=poly, degree=7									
Datasets	30 Subjects			20 Subjects			10 Subjects		
	Train	Test	Train Test (avg)	Train	Test	Train Test (avg)	Train	Test	Train Test (avg)
Time Series	93.45	45.02	69	94.12	52.94	74	98.19	68.47	83
Frequency Domain	83.03	45.39	64	84.26	46.47	65	92.29	65.77	79
Raw COP	89.21	**74.17**	82	91.91	**68.82**	80	98.19	**81.98**	90
Frequency+Time	95.85	46.49	71	96.03	51.18	74	97.73	60.36	79

Table 6.1: The best performing model SVM considering all the features

With this model the best accuracy is achieved on the Raw COP dataset with 74.17 % on Test Data. On the entire dataset that is both Training and Test dataset combined the accuracy is 82%. If we compare the results of Raw COP test data across the number of subjects, we can see that the percentage of correctly identified individuals is 81.98% for the first 10 individuals, 62.82 % for the first 20 individuals and 74.17 for the first 30 individuals. This is most probably due to the increase in the number subjects causing an increase in the probability of wrong prediction. In case of 30 subjects there will be a probability ratio of 1 vs 29 and there is a high possibility that there is a similarity among data points of different subjects. As the number of subjects decreases, the prediction ratio goes to 1vs 9 and the chances of wrong predictions decrease. Tables 6.2 and 6.3 show the per-class accuracy of each class for 10 and 30 subjects, respectively

SVM: Hyperparameters [**C=100, gamma=3, kernel=poly, degree=7**] Overall Accuracy:		
Subjects	**Train**	**Test**
4	72.22	40.0
5	94.0	65.0
6	78.26	25.0
7	100.0	50.0
8	97.44	84.62
9	94.0	66.67
10	86.89	76.92
11	100.0	94.44
12	93.33	75.0
13	95.65	60.0
14	66.67	50.0
16	100.0	62.5
17	93.18	100.0
18	53.33	75.0
19	82.14	42.86
20	77.55	54.55
21	84.62	100.0
22	100.0	100.0
23	80.56	50.0
24	69.23	25.0
25	100.0	100.0
26	71.43	75.0
27	86.27	80.0
28	100.0	90.91
29	96.15	100.0
30	95.0	77.78
31	90.48	62.5
32	97.73	100.0
33	55.88	20.0
34	85	80

Table 6.2: Train and Test per class accuracy for 30 subjects

SVM: Hyperparameters [C=100, gamma=3, kernel=poly, degree=7] Overall Accuracy:		
Subjects	Train	Test
4	100.0	60.0
5	98.33	90.0
6	95.65	75.0
7	100.0	80.0
8	95.35	88.89
9	98.18	69.23
10	98.15	90.0
11	100.0	91.18
12	100.0	42.86
13	91.67	75
14	100.0	60.0

Table 6.3: Train and Test per class accuracy for 10 subjects

train metrics	precision	recall	f1-score	support
0.0	0.68	0.72	0.70	18
1.0	0.96	0.94	0.95	50
2.0	0.90	0.78	0.84	23
3.0	0.93	1.00	0.96	13
4.0	1.00	0.97	0.99	39
5.0	1.00	0.94	0.97	50
6.0	0.60	0.87	0.71	61
7.0	1.00	1.00	1.00	125
8.0	0.88	0.93	0.90	30
9.0	0.96	0.96	0.96	23
10.0	0.67	0.67	0.67	9
11.0	0.77	1.00	0.87	23
12.0	0.98	0.93	0.95	44
13.0	1.00	0.53	0.70	15
14.0	0.96	0.82	0.88	28
15.0	0.86	0.78	0.82	49
16.0	0.85	0.85	0.85	13
17.0	1.00	1.00	1.00	4
18.0	0.88	0.81	0.84	36
19.0	0.90	0.69	0.78	26
20.0	0.99	1.00	0.99	72
21.0	0.96	0.71	0.82	35
22.0	0.79	0.86	0.82	51
23.0	0.95	1.00	0.98	41
24.0	0.83	0.96	0.89	26
25.0	0.86	0.95	0.90	40
26.0	0.97	0.90	0.94	42
27.0	0.93	0.98	0.96	44
28.0	0.83	0.56	0.67	34
29.0	0.77	0.85	0.81	20
accuracy			0.89	1084
macro avg	0.89	0.87	0.87	1084
weighted avg	0.90	0.89	0.89	1084

	precision	recall	f1-score	support
0.0	0.33	0.40	0.36	5
1.0	0.87	0.65	0.74	20
2.0	0.25	0.25	0.25	4
3.0	0.25	0.50	0.33	2
4.0	0.79	0.85	0.81	13
5.0	0.80	0.67	0.73	18
6.0	0.59	0.77	0.67	13
7.0	0.92	0.94	0.93	36
8.0	1.00	0.75	0.86	4
9.0	0.43	0.60	0.50	5
10.0	0.50	0.50	0.50	2
11.0	0.50	0.62	0.56	8
12.0	0.60	1.00	0.75	3
13.0	1.00	0.75	0.86	4
14.0	0.60	0.43	0.50	7
15.0	0.75	0.55	0.63	11
16.0	0.50	1.00	0.67	2
17.0	1.00	1.00	1.00	2
18.0	1.00	0.50	0.67	8
19.0	0.20	0.25	0.22	4
20.0	1.00	1.00	1.00	15
21.0	0.86	0.75	0.80	8
22.0	0.86	0.80	0.83	15
23.0	0.77	0.91	0.83	11
24.0	0.67	1.00	0.80	2
25.0	0.64	0.78	0.70	9
26.0	0.91	0.62	0.74	16
27.0	0.93	1.00	0.97	14
28.0	0.25	0.20	0.22	5
29.0	0.50	0.80	0.62	5
accuracy			0.74	271
macro avg	0.68	0.69	0.67	271
weighted avg	0.77	0.74	0.74	271

Table 6.4: Evaluation Metrics for 30 subjects

Table 6.4 shows the Precision, Recall add F1 score metrics. The model performance looks better as for most of the subjects the precision and recall are above 0.6.

Similar experiments were performed on selected features for first 30, 20 and 10 subjects, respectively, and the results are displayed in Table 6.5. Here the AP-ML ratio feature is not used and Mean, Max, Min of AP and ML coordinates are also dropped. This improved the accuracy by reducing overfitting. However, the raw dataset still performs best in this scenario as well with a training accuracy of 87.08%, a test accuracy of 71.9%, and an overall accuracy of 80%

SVM Selected features **Best C=100, gamma=3, kernel=poly, degree=7									
Datasets	**30 Subjects**			**20 Subjects**			**10 Subjects**		
	Train	Test	Train Test (avg)	Train	Test	Train Test (avg)	Train	Test	Train Test (avg)
Time Series	90.68	**57.93**	74	91.76	61.18	76	97.96	**73.87**	86
Frequency Domain	80.54	**47.6**	64	81.76	45.29	64	90.48	**64.86**	78
Raw COP	87.08	**71.96**	80	90.59	67.06	79	97.73	**81.08**	89
Frequency+Time	93.73	**57.93**	76	94.26	54.12	74	97.28	**69.37**	83

Table 6.5 with selected features on 30 subjects

We also performed PCA on the feature space to reduce the dimensions of input features to analyze the model performance. Table 6.6 shows the result on 30 subjects using the best hyperparameters on SVM. The results for the case of 15 and 5 PCA components are shown, respectively. From the data it can be observed that accuracy on the dimension reduced feature set is significantly lower and thus the original feature sets were used for the remaining experiments.

SVM All features 30 Subjects (PCA) C=100, gamma=3, kernel=poly, degree=7						
Datasets	**15 Components**			**5 Components**		
	Train	Test	Train &Test (avg)	Train	Test	Train &Test (avg)
Time Series	80.26	44.65	62	68.27	34.32	51
Frequency Domain	67.16	47.6	56.99	49.54	39.85	45
Raw COP	43.82	36.16	40	41.14	32.1	37
Frequency+Time	88.28	38.75	64	63.84	33.95	49

Table 6.6: PCA Transformed features

The remaining experiments are performed similarly with various hypermeters.

Tables 6.8 and 6.9 show the results of various experimentations performed with different SVM hyperparameters as well as with the logistic regression model for 30 ,20 and 10 subjects considering all features and selected features respectively.

All 30 Subjects with ALL Features for Person Identification						
Algorithm	Experiments	Accuracy	Time Based	Frequency	Raw	Frequency and Time
SVC One-Vs-Rest	EXP1 C=100,kernel='poly',gamma=2,degree=7	Train	86.53	76.84	80.99	90.86
		Test	44.28	47.23	**70.47**	44.64
	EXP2 C=1000,kernel='rbf',gamma=2,degree=3	Train	70.87	65.40	67.52	84.40
		Test	47.60	50.18	**60.14**	47.23
Logistic Regression One-Vs-Rest	EXP1 multi_class='ovr',penalty='l1',solver='saga	Train	86.53	76.84	80.99	90.86
		Test	28.04	24.72	17.34	29.88

All 10 Subjects with ALL Features for Person Identification						
Algorithm	Experiments	Accuracy	Time Based	Frequency	Raw	Frequency and Time
SVC One-Vs-Rest	EXP1 C=1,kernel='poly',gamma=2,degree=7	Train	84.35	79.13	76.64	87.07
		Test	**71.17**	62.16	62.16	60.36
	EXP2 C=1000,kernel='rbf',gamma=2,degree=3	Train	86.21	81.85	81.40	89.34
		Test	67.56	63.96	**68.46**	62.16
Logistic Regression One-Vs-Rest	EXP1 multi_class='ovr',penalty='l1',solver='saga	Train	93.42	86.62	92.74	93.87
		Test	55.85	40.54	34.23	51.35

Table 6.8: Experimentation with various hyper parameters all features

All 30 Subjects with Selected Features for Person Identification							
Algorithm	Experiments	Accuracy	Time Based	Frequency	Raw	Frequency and Time
SVC One-Vs-Rest	EXP1 C=100,kernel='poly',gamma=2,degree=7	Train	81.91	71.77	80.07	89.39
		Test	**59.77**	**48.70**	**68.26**	**56.82**
	EXP2 C=100,kernel='rbf',gamma=2,degree=3	Train	60.79	56.27	55.71	66.97
		Test	52.39	48.70	52.39	51.66
Logistic Regression OVR	EXP1 multi_class='ovr',penalty='l1',solver='saga	Train	81.91	71.77	80.07	89.39
		Test	28.78	23.61	17.34	30.62

All 20 Subjects with Selected Features for Person Identification						
Algorithm	Experiments	Accuracy	Time Based	Frequency	Raw	Frequency and Time
SVC One-Vs-Rest	EXP1 C=100,kernel='poly',gamma=2,degree=7	Train	85.29	74.26	80.00	88.52
		Test	**60.00**	**48.82**	**60.00**	**54.74**
	EXP2 C=100,kernel='rbf',gamma=2,degree=3	Train	67.50	59.58	62.35	72.20
		Test	52.35	47.64	51.76	51.17
Logistic Regression OVR	EXP1 multi_class='ovr',penalty='l1',solver='saga	Train	85.29	74.26	80.00	88.52
		Test	41.76	35.88	27.05	40.00

All 10 Subjects with Selected Features for Person Identification						
Algorithm	Experiments	Accuracy	Time Based	Frequency	Raw	Frequency and Time
SVC One-Vs-Rest	EXP1 C=1,kernel='poly',gamma=2,degree=7	Train	80.04	75.96	76.64	85.26
		Test	**70.27**	**64.86**	**62.16**	**66.66**
	EXP2 C=1,kernel='rbf',gamma=2,degree=3	Train	77.55	72.33	73.24	83.67
		Test	71.17	62.16	63.06	67.56
Logistic Regression One-Vs-Rest	EXP1 multi_class='ovr',penalty='l1',solver='saga	Train	80.04	75.96	76.64	83.67
		Test	54.95	39.63	34.23	51.35

Table 6.9: Experimentation with various hyper parameters selected features

SVM performance is better for Raw COP data whereas Logistic regression model is too much overfitted to the training data and hence performs poorly on test data.

Also, we observe that the data set containing the combination of both frequency domain features and Time domain features is performing well on Training data, but not on the test data, likely overfitting given that it has twice the number of features compared to the other data sets.

SVM with Polynomial kernels performed better when compared to the rest of the classifiers. Also, the features extracted from Raw COP values were able to classify all 30 persons with better accuracy when compared to other classifiers.

Also, the models using only selected features seem to perform slightly better, likely as a result of decreased overfitting.

Overall, the models in most of the experiments suffer from some degree of overfitting. This could be because we are highly penalizing model while training, so it is learning perfectly during and failed to generalize the data points. Another reason is that Person Identification has a significant number of classes and the available data corresponding to each class on average is only about 50 datapoints.

6.2 Tinetti score prediction

Tinetti score and balance score prediction experimentation is performed using various regression models: Linear, Lasso, Ridge, and Support vector regression. The regression model performance was almost the same on Training and Test data. A number of experiments are also performed on completely Unseen data, where in few subject's data was not included in training.

The experimentations were again performed on the 4 datasets on 30 subjects and on first 10 subjects, respectively. As before, evaluation experiments were also performed considering all features as well as using only selected features.

Tables 6.10, 6.11, 6.12, and 6.13 show the balance and Tinetti score predictions for 30 subjects considering all features for Linear Regression, Lasso Regression, Ridge Regression, and Support Vector Regression (SVR), respectively.

All 30 Subjects with ALL Features							
Algorithm	Experiments	Scores	RMSE	Time Based	Frequency	Raw	Frequency and Time
Linear Regression	**EXP1** Polynomial Degree=1	Balance	Train	0.829	0.844	0.823	0.809
			Test	0.833	0.850	**0.801**	0.858
		TINETTI	Train	1.005	1.012	0.985	0.979
			Test	1.026	1.017	**0.986**	1.049
	EXP2 Polynomial Degree=2	Balance	Train	0.715	0.693	0.610	0.00006
			Test	1.025	2.387	2.287	22797.70
		TINETTI	Train	1.005	1.012	0.985	0.979
			Test	1.026	1.017	0.986	1.049
	EXP3_Unseen Polynomial Degree=1	Balance	Train	0.863	0.886	0.848	0.851
			Test	**0.702**	**0.656**	**0.752**	**0.684**
		TINETTI	Train	1.069	1.075	1.039	1.046
			Test	**0.758**	**0.719**	**0.780**	**0.772**

Table 6.10 Linear Regression

Algorithm	**Experiments**	**Scores**	**RMSE**	**Time Based**	**Frequency**	**Raw**	**Frequency and Time**
Lasso	EXP1 alpha=2	Balance	Train	0.898	0.898	0.898	0.898
			Test	0.863	0.863	0.863	0.863
		TINETTI	Train	1.071	1.071	1.071	1.071
			Test	1.051	1.051	1.051	1.051
	EXP2 alpha=10	Balance	Train	0.898	0.898	0.898	0.896
			Test	0.863	0.863	0.863	0863
		TINETTI	Train	1.071	1.071	1.071	1.071
			Test	1.051	1.051	1.051	1.051
	EXP3_Unseen alpha=10	Balance	Train	0.944	0.944	0.944	0.944
			Test	0.638	0.638	0.638	0.638
		TINETTI	Train	1.150	1.150	1.150	1.150
			Test	**0.635**	**0.635**	**0.635**	**0.635**

Table 6.11 Lasso Regression

Algorithm	Experiments	Scores	RMSE	Time Based	Frequency	Raw	Frequency and Time
Ridge	**EXP1** alpha=2	Balance	Train	0.869	0.864	0.881	0.862
			Test	0.836	0.833	0.835	**0.832**
		TINETTI	Train	1.038	1.028	1.052	1.029
			Test	1.010	**1.001**	1.016	1.004
	EXP2 alpha=10	Balance	Train	0.876	0.869	0.886	0.867
			Test	0.839	0.837	0.844	0.832
		TINETTI	Train	1.038	1.028	1.052	1.029
			Test	1.010	1.001	1.016	1.004
	EXP3_Unseen alpha=10	Balance	Train	0.919	0.911	0.923	0.909
			Test	0.622	0.621	0.655	0.625
		TINETTI	Train	1.106	1.094	1.117	1.096
			Test	0.654	0.652	0.680	0.651

Table 6.12 Ridge Regression

Algorithm	Experiments	Scores	RMSE	Time Based	Frequency	Raw	Frequency and Time
Support Vector Regression	**EXP1** C=100 degree=3 kernel='rbf'	Balance	Train	0.797	0.821	0.826	0.799
			Test	0.832	0.863	**0.791**	0.878
		TINETTI	Train	0.948	0.967	1.010	0.950
			Test	1.045	1.026	**0.977**	1.071
	EXP2 C=100 degree=6 kernel='rbf' gamma=2	Balance	Train	0.768	0.805	0.820	0.739
			Test	0.834	0.883	**0.793**	0.860
		TINETTI	Train	0.910	0.949	1.002	0.875
			Test	1.051	1.042	**0.980**	1.053
	EXP3_Unseen C=100 degree=6 kernel='rbf' gamma=2	Balance	Train	0.814	0.895	0.848	0.793
			Test	0.936	0.810	0.845	0.867
		TINETTI	Train	0.990	1.052	1.064	0.954
			Test	1.094	0.982	0.862	1.032

Table 6.13 SVR

The Overall Root Mean Square (RMS) error for the balance score is 0.791 and for the Tinetti score it is 0.977 for SVR model for the subjects present in training data but test data that is not seen during training.

For the Unseen data where the subjects are not present in training, SVR yields an average RMS error of 0.845 for the balance and 0.862 for the Tinetti score.

Tables 6.14 and 6.15 show the experimental results using only the first 10 subjects. It is no surprise that model is performing better with RMS error for the balance score of 0.527 and for the Tinetti score of 0.578. This is because there is very low variation /variance in the expected output values. That is the reason that the model is performing bad on the Unseen data. Training with this few individuals leads to significant overfitting and customization to these individuals and thus other individuals scores can no longer be predicted well.

All 10 Subjects with ALL Features							
Algorithm	Experiments	Scores	RMSE	Time Based	Frequency	Raw	Frequency and Time
Linear Regression	**EXP1** Polynomial Degree=1	Balance	Train	0.522	0.535	0.500	0.514
			Test	**0.540**	**0.527**	**0.557**	**0.545**
		TINETTI	Train	0.620	0.606	0.598	0.597
			Test	**0.642**	**0.578**	**0.641**	**0.640**
	EXP3_Unseen Polynomial Degree=1	Balance	Train	0.173	0.160	0.130	0.213
			Test	1.236	1.259	1.274	1.277
		TINETTI	Train	0.365	0.3353	0.331	0.360
			Test	1.325	1.273	1.366	1.365

Table 6.14 Linear Regression 10 Subjects

Algorithm	**Experiments**	**Scores**	**RMSE**	**Time Based**	**Frequency**	**Raw**	**Frequency and Time**
Support Vector Regression	**EXP1** C=100 degree=3 kernel='rbf'	Balance	Train	0.461	0.522	0.437	0.464
			Test	**0.462**	**0.572**	**0.440**	**0.551**
		TINETTI	Train	0.516	0.586	0.556	0.520
			Test	**0.535**	**0.592**	**0.551**	**0.610**
	EXP2_Unseen C=100 degree=6 kernel='rbf' gamma=2	Balance	Train	0.081	0.093	0.112	0.080
			Test	1.237	1.316	1.278	1.225
		TINETTI	Train	0.234	0.286	0.390	0.221
			Test	1.299	1.274	1.295	1.267

Table 6.15 SVR 10 subjects

Similar experiments are performed with selected features and Tables 6.16 and 6.17 show the experimental results.

All 30 Subjects with Selected Features							
Algorithm	Experiments	Scores	RMSE	Time Based	Frequency	Raw	Frequency and Time
Linear Regression	**EXP1** Polynomial Degree=1	Balance	Train	0.840	0.846991064	0.823334565	0.826664047
			Test	0.830	0.853086244	0.**801031017**	0.846412664
		TINETTI	Train	1.012	1.016367511	0.985835152	0.995333539
			Test	1.013	1.021370563	0.**984099633**	1.016084387
	EXP2_Unseen Polynomial Degree=1	Balance	Train	0.874	0.889343918	0.848821817	0.865454561
			Test	0.688	0.657065456	0.750871486	0.674528227
		TINETTI	Train	1.075	1.08205307	1.039040398	1.058979784
			Test	0.727	0.706790384	0.780459768	0.717205137

Table 6.16 Linear Regression 30 Subject Selected Features

Algorithm	**Experiments**	**Scores**	**RMSE**	**Time Based**	**Frequency**	**Raw**	**Frequency and Time**
Support Vector Regression	**EXP1** C=100 degree=3 kernel='rbf'	Balance	Train	0.803821337	0.820389786	0.820620384	0.776289959
			Test	**0.817343213**	**0.857248886**	**0.79313122**	**0.838519608**
		TINETTI	Train	0.95738499	0.964392015	1.002729014	0.926172428
			Test	**1.003562265**	**1.024302116**	**0.980500334**	**1.027972975**
	EXP2_Unseen C=100 degree=6 kernel='rbf' gamma=2	Balance	Train	0.849352433	0.911368484	0.84867176	0.851895386
			Test	0.929073721	0.795347691	0.845019272	0.819818845
		TINETTI	Train	1.023040902	1.070451811	1.064794531	1.02463797
			Test	1.08751079	0.922851217	0.862517585	0.98736885

Table 6.17 SVR 30 subjects Selected features

We see that there is no significant difference in the results. Here, Support Vector regressors with RBF kernel and c=100, gamma=2 and degree=6, performs best for 30 subjects' data with an average RMS error for Balance score of 0.791 and for the Tinetti score of 0.977

Tinetti Score prediction based on Gait parameters.

Tinetti scores are calculated based on the Gait parameters alone obtained from the previous experiments [4]. This experimentation is performed on 15 subjects (subject 19 to subject 34) and the results are compared with the Tinetti scores available from the professionals. Table 6.18 shows the Tinetti scores for Gait parameters.

The Ridge Regression model gives better results with Root mean squared error of 0.53 when compared to Linear and Support vector Regressors.

Tinetti Scores For Gait		
	Train RM	Test RMSE
Linear Regression	0.354	0.536
Ridge Regression	0.36	0.535
Support Vector Regression	0.4	0.591

Table 6.18 Tinetti Scores for Gait Parameters

7. CONCLUSION AND FUTURE WORK

7.1 Findings

As the number of prediction classes in the person identification task increases, the performance decreases because of insufficient data examples for each class so as to learn patterns for each class and differentiate among 30 classes. The highest performance achieved with all 30 individuals was 71.9%.

The model performance is better when there are fewer classes to predict, i.e. when fewer individuals are used. For instance, the model performs better with 12 classes with less overfitting when considering individuals with balanced data with on average 60 data points for each class.

In case of Tinetti score prediction, we trained the model with the available subjects who has balance scores in the range of 12-16 and Tinetti scores in the range of 24-28. We do not have data samples for other possible values for Balance and Tinetti scores. The resulting model was able to predict the balance and overall Tinetti scores for trained individuals with a RMS error of 0.791 and 0.977, respectively, and for unseen individuals with a RMS error of 0.845 and 0.862. The model could be made more robust by training it with individuals' data that includes a wider range possible values of balance and Tinetti score. However, such data was not available from the previous study.

In the future we are planning to train the system on a wider range of data obtained from the actual Smart care home data with a wider range of possible outcome values.

7.2 Conclusion

Falls are a major contributor to hospitalizations and loss of quality of life especially in older individuals. The goal of this research was to use balance characteristics recorded from a pressure sensing smart floor to detect variations in balance patterns and to predict balance characteristics that could be indicative of fall risks. For this, pressure-based balance features were extracted from the data and a person identification model as well as a model to predict the balance component and the complete Tinetti score were developed.

With this research we are successfully able to extract the Balance parameters and were able to build the baseline models for Person Identification and Balance and Tinetti score prediction based on balance parameters alone.

When considered all the features the SVM model is giving a good performance with hyperparameters c=100, gamma=3, and polynomial kernel function of degree 7. For raw data we were able to achieve overall accuracy of 82 % for 30 subjects and 90% for the first 10 subjects.

We are also able to build regression models. Support Vector regressors with RBF kernels and c=100, gamma=2 and degree=6 here performed best for 30 subjects with average RMS error for Balance score of 0.791 and for Tinetti score of 0.977.

7.3 Future work

As discussed in the conclusion, there is the potential for improvements in both the classification and regression models. Effective techniques can be developed to combat the overfitting problem.

The Tinetti model can be trained on a broader range of data from the Smart care home facility on a wider range of Tinetti scores to make it more robust and hence to make it more applicable to real time Tinetti score prediction.

Person Identification could also be enhanced using Unsupervised Clustering Algorithms by leveraging Balance parameters build in this model.

Deep Learning based models can also be used for feature learning by creating more training data.

Currently in this research we used balance parameters alone to predict the balance scores and Tinetti scores. And gait parameters are used separately to find the Tinetti score. In future research we can use both gait and parameter together to generate Tinetti score collectively.

L I S T O F F I G U R E S

L I S T   O F   T A B L E S

LIST OF ALGORITHMS

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