This full text paper was peer-reviewed at the direction of IEEE Instrumentation and Measurement Society prior to the acceptance and publication

Fall Detection Using Kinematic Features from a Wrist-Worn Inertial Sensor

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***Abstract*— The threats and injuries caused by falling are significant and pose risks to life among the elderly population. Detecting falls and providing prompt care helps in reducing the risks associated with falling. Technology solutions are being employed for the detection of falls and to enable provisions to access immediate assistance. These solutions require the user to wear specialized equipment continuously that are inconvenient for prolonged usage, especially among the elderly population. To address this concern, numerous research works have focused on developing solutions that are minimally intrusive to the user. Insufficiency of clinical fall dataset limits the investigation of diverse approaches to improve the accuracy using devices that offer user comfort. Algorithms developed through research fall short of extensive datasets to offer reliable detection of falls through a wrist-worn device. However, such algorithms cannot generalize falls using data collected from a specific population. This research discusses an approach for the generalization of falls by the inclusion of kinematic parameters associated with falls. A hybrid detection model comprising of threshold parameters and a machine learning based classifier is proposed. The detection model ignored all the activities of daily living. An accuracy of 92% was observed in the detection of actual falls among non-falling actions with kinematics similar to those of falling action.**

Keywords—Fall detection, inertial sensors, wrist-worn sensor, kinematic parameters

I. Introduction

The World Health Organisation imputes falls as the second leading cause of accidental or unintentional injury deaths worldwide [1]. The largest demographic afflicted with fall-related injury are the elderly [2]. A fall is defined as an event which results in a person coming to rest inadvertently on the ground or floor or a lower surface [1]. The most common cause of falls in healthy adults is tripping or slipping in undulating surfaces. Elderly people who have a history of stroke are prone to falling due to improper gait, reduced muscle tone, weakness and side effects of drugs. More than one-third of people over the age of 65 fall each year [3]. Falls are considered the main cause for loss of independence among the elderly [4].

By 2050, the number of people availing long term care will likely double from 13 million to 27 million due to the rise in the population of older people requiring care. The growing populace of the elderly poses a need for automated tools that detect falls and empower caregivers to attend to them at the earliest. Fall detection has been explored in the past two decades and its popularity has grown drastically since 2014. Fall detection can be broadly classified into wearable based and Context-Aware Systems (CAS) [5]. CAS perform fall detection using Wi-Fi, Kinect, and Radar for unobtrusive monitoring of elderly people. Kinect has a range of less than 4m that limits the monitoring range. The video-based system is the gold standard for kinematic analysis as well as Fall Detection Systems (FDS). However, these systems are constrained to a capture volume and require extensive infrastructure for practical applications.

The general population is accustomed to wearing watches on the wrist. This location is considered the least intrusive for placing a wearable. In recent years, wrist-worn wearables with inertial sensors have become popular for activity tracking. Despite substantial research being carried out to develop algorithms for fall detection using inertial sensors, the lack of reliable fall datasets is one of the hurdles in the development of algorithms to address wide age range. FARSEEING has the largest dataset for real-world falls recorded with inertial sensors but the sensor locations are confined to thigh and hip [6]. SisFall is a similar repository containing fall data collected using a sensor on the waist [7]. UMAFall, a publicly available dataset for falls, comprises of inertial sensor data collected from the wrist. The data is sampled at 20 Hz that limits the amount of contained information pertaining to falls [8].

Current research on wrist-worn FDS focuses on statistical features of falls to build machine learning models [9]. These features obtained directly from the inertial sensor data include the mean, variance, kurtosis, etc., of the signals corresponding to a fall event that does not capture the actual dynamics of a fall. Existing algorithms were primarily based on tracking the change in orientation of the faller, detection of impacts, monitoring the posture of the individual and velocity during a falling event. This approach naturally demands a large amount of fall data to capture ample instances of falling action. Access to high-quality inertial sensor data and practical limitations in the availability of a large dataset calls for an efficient approach to reliably detect falls.

The proposed research involves the extraction of kinematic parameters associated with a fall to consider its dynamics and improve the reliability of detection. With data from the gyroscope, local frame acceleration output by the accelerometer is converted to earth frame to represent the dynamics of a fall with consistency. The algorithm extracts key parameters from these dynamics of the earth frame data and analyses it to detect falls. It is optimised to be immune to other activities that closely resemble falls.

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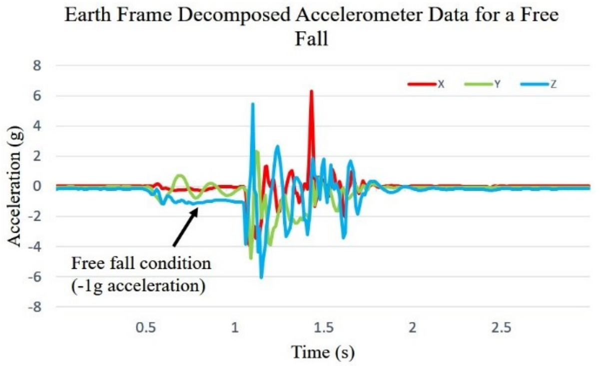

Fig. 1. Tri-axial accelerometer output showing free fall condition characterized by -1g along the z-axis (downward direction) for a freely falling object.

The underlying physics of a fall and techniques to extract kinematic features from it are discussed in the following section. Further sections explain the hardware, data collection protocol and methods to build a computationally efficient hybrid classification model that combines both threshold based and machine learning models for fall detection. Simulated fall data collected through controlled setup and real fall data have been used to capture generalized parameters for algorithm design.

II. Physics of Fall

A. Fall Dynamics

Free falling is the state where gravity is the only force acting on the falling object. Ideally, any freely falling object, irrespective of the physical parameters, experiences a constant acceleration that is governed by the equation,

$$s = \frac{1}{2} g t^2 \tag{1}$$

Where, s is the distance moved by the object in the downward direction over time t and g being the acceleration due to gravity.

An object under free fall experiences a constant acceleration with a magnitude of 9.8 m/s^2 (measured as 1g in the downward direction) and a linearly increasing velocity profile. An accelerometer instrument attached to a freely falling object experiences this constant acceleration of -1g before hitting the ground (However, the local acceleration experienced by the sensor is 0g since it is a sum of freely falling acceleration, -1g and the acceleration due to gravity, +1g). This phenomenon, termed as the free fall condition, is illustrated in Fig. 1.

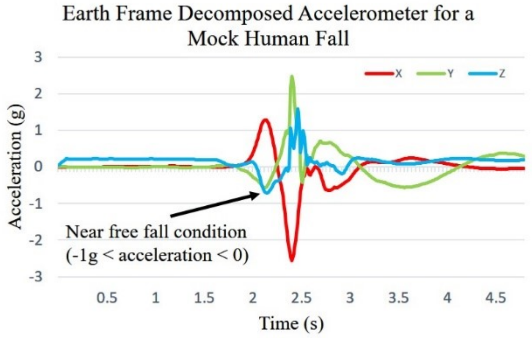

Fig. 2. Tri-axial accelerometer output showing near free fall condition characterized by an acceleration between 0 and 1g along the z-axis (downward direction) for an emulated human fall.

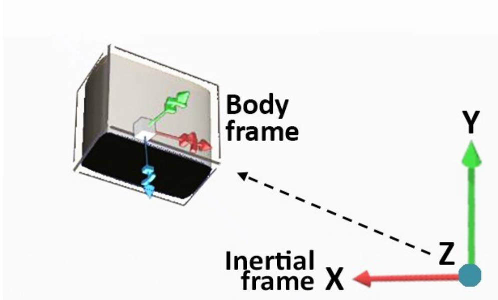

Fig. 3. Representation of local or body frame with respect to the inertial or earth frame. The earth frame or the inertial frame measures the acceleration of the object consistently along a co-ordinate axes irrespective of the object's orientation.

The body of a falling person loses its balance and is subject to experience a free fall condition momentarily. However, the foot being in contact with the ground restricts the person from accelerating downward at the rate of 9.8 m/s^2 and moving swiftly towards the ground. In addition, attachment of sensors to the wrist measures the acceleration imparted by the counter-movement of the arms while falling. This acceleration and the acceleration associated with the fall together contribute to a vertical acceleration closer to -1g and this is termed as the Near Free Fall condition (NFF). Fig. 2 illustrates the acceleration measured at the wrist of a person during an emulated fall and the near free fall condition. This condition is a characteristic signature of a free fall event, although its observability is largely masked by motion artefacts during a fall.

The motion associated with a fall comprises two components, vertical component acting along the downward direction and the horizontal component acting along the horizontal plane parallel to the surface of the earth. The wrist is the point of observation of motion associated with a fall. The kinematics experienced by the arm is posed as a superposition of the kinematics of the waist and that of the arm. The horizontal component of the arm motion experiences rapid variations during a fall. This is characterised by variations of acceleration along the horizontal plane and is termed as Rapid Motion along the Horizontal Plane (RMHP).

The signature of the artefacts-prone NFF condition can be characterized since it is an uncontrolled event. Upon experiencing this condition, the body lands on the ground surface with an impact that imparts a significant mechanical shock. The impact causes rapid changes in the velocity, causing the body to decelerate and come to rest abruptly. The Impact characteristic (IC) of the fall, that predominantly marks a falling event, is dependent on the type of fall and the weight of the person [10].

Observation of the aforementioned characteristics requires measurement of kinematic parameters against a consistent reference. The acceleration of the wrist obtained with reference to the earth frame can be used for extraction of features pertaining to a fall.

B. Earth Frame Motion Decomposition (EFD)

The earth frame acceleration is defined as the acceleration of an object with respect to a reference frame attached to the earth. The acceleration of an object with respect to a coordinate frame attached to the sensor is referred to as its local frame acceleration. Fig. 3 illustrates the local frame of an object placed with reference to the earth frame. In order to characterize the acceleration consistently along fixed axes, the local frame acceleration is converted to earth frame acceleration using a technique called Earth Frame Motion Decomposition (EFD). This method primarily takes into account the orientation changes undergone by the object experiencing acceleration. By continually measuring the effect of a change in orientation through a gyroscope and an accelerometer, the sensor data in the local frame is mapped to a fixed earth frame [11]. Irrespective of the orientation of the object, the earth frame decomposed acceleration gives motion data with respect to a rest frame attached to the earth.

EFD enables separation of the vertical acceleration from the acceleration along the horizontal plane throughout the falling action. The vertical component of the acceleration helps in investigating the dynamics of a near free fall event and the impact whereas the horizontal plane acceleration faithfully captures the counter movements of the arm during a fall, denoted by RMHP.

C. *Timing aspects of a fall*

A fall constitutes of three distinct phases: the NFF phase, the impact phase, and the post-fall phase. Identifying the impact and the NFF event enables detection of fall without depending on the uncertainties in the post-fall phase. The timing parameters for variations caused by arm movements characterize a falling event and distinguish a fall from other motion with similar kinematics of a fall.

III. Data Preparation

Public meta datasets available online either have low sampling rates or are acquired with the sensor placed away from the wrist. Owing to the lack of clinically validated datasets from wrist-worn inertial sensors at high sampling rates, an in-house data collection was carried out. The lack of quantified error parameters of the sensor used for fall data collection further increases the need for a dataset with known sensor error parameters [7].

The data acquisition is focused on obtaining both simulated falls and actual falls. The simulated fall pattern is different from actual falls since the subject is already aware of the act of fall. During the collection of simulated falls, the impact acceleration threshold and the damping nature of the signal post impact are compromised since the mattress absorbs the shock during impact. The mattress shown in Fig. 4 is made of sheets of memory foam to provide enough cushioning for the subject and therefore it absorbs significant impacts during a fall.

Fig. 4. Setup for acquiring emulated fall data (left), soap football arena to collect actual fall data (right).

Data required for actual falling cases is obtained from slip falls in a safe and controlled environment. Slip happens when the friction between the substrate is too less to keep the foot on the ground. Slips occur due to a liquid or material that reduces the friction coefficient of the surface. Actual slip falls differ from the vertical falls, as the body tries to compensate for the imbalance by imparting a counter moment with the arm which is a trait in slip falls. A soap football arena was opted as the closest environment meeting the conditions to obtain slip falls in a safe and reliable fashion. The captured falls are primarily due to the slippage of both feet. Fig. 4 depicts the arena for simulated and actual data collection.

A. *Hardware*

The kinematic data for the fall study was obtained using a wrist-worn device with an embedded Inertial Measurement Unit (IMU) measuring tri-axial acceleration and tri-axial angular velocity. For the data collection exercise, the wearable device acquired accelerometer and gyroscope data at 100 Hz and stored on its onboard flash memory. The accelerometer range was set to ±16g and the gyroscope was set to ±2000 °/s. The splash-proof device is worn on the left hand and its orientation is maintained consistently across all subjects.

B. *Protocol*

The proposed methodology attempts to develop an algorithm that uses an optimal combination of simulated and uncontrolled falls as well as considering Activities of Daily Living (ADL) for benchmarking. Data corresponding to various types of falls was acquired from 22 subjects upon obtaining prior informed consent.

Uncontrolled falls: 12 subjects (10 male, 2 female) aged between 20 and 30 years were asked to perform a set of predefined activities on a soap football arena. The arena is a miniaturized football turf with a soft-bedded polyester floor covered with soapy water, making it slippery to induce falls. The participants were equipped with protective pads and helmets for safety. For the data collection, the subjects were asked to take brisk paces while performing activities such as kicking a football, intercepting a football in motion and goalkeeping.

The device worn by the participants continuously stored the data for the entire duration of the exercise. Two video cameras were placed at diagonally opposite corners of the arena to record instances of fall. Slip falls corresponding to the instructed activities were recorded over a period of approximately 60 minutes. 138 fall signals were acquired from the collected data and the data was annotated using the video as the reference. This method is novel in its conception as it generates real-world fall data with very minimal risk of injury to the subjects.

Simulated falls: 10 subjects aged between 20 and 30 years were asked to perform 3 categories of falls over a cushioned mattress: forward fall, backward fall and lateral fall (Left and Right). An average of three instances of fall in each category were recorded amounting to 99 falls in total. Subjects were asked to perform the 3 instances of a category interspersed with an arbitrary gap of 1-3 seconds. The recording of falls was in the same sequence spanning approximately 10 seconds for each fall. Video recording was done spanning the arena for validation of inertial fall signals.

Activities of Daily Living (ADLs): 22 subjects (14 Male, 8 Female) aged between 20 and 35 years were asked to perform a set of pre-defined ADLs such as walking on a flat surface, walking upstairs, walking downstairs, jogging and random activities that included clapping, stretching, bending and lifting objects. ADL involving kinematics similar to that of a fall, like easing the arm on a table and random impacts on various substrates were included in the data set along with necessary labels.

The walking exercise was conducted in an open space to ensure no constraint on trajectories. The random activities were performed with a stationary stance with feet on the ground. Each subject performed the aforementioned activities for a duration of 1 minute each, under supervision. An arbitrary break of 1-2 minutes was ensured for relaxation between each of the activities.

IV. Methods

A fall is an imbalance where the victim experiences NFF kinematics. This is followed by an impact and its nature of damping is specific to the human body. Based on these mechanics, a hypothesis was formulated to detect fall. To make these features observable the local frame accelerometer and gyroscope data is converted to earth frame data which provides a better understanding of the trajectory of fall rather than the magnitude of acceleration.

A. Calibration and Preprocessing

The Micro Electro Mechanical Systems (MEMS) based inertial sensor has intrinsic error parameters that are corrected for both systematic and random errors. Consumer grade IMU sensors have large drift errors and a drift range in the order of 50 - 100 degrees/h in gyroscopes [12]. Both accelerometer and the gyroscope need bias compensation to avoid considerable errors in the measured angular rate and acceleration. The calibration procedure carried out involves finding the constant bias in both accelerometer and the gyroscope. A generic calibration procedure is followed to correct the constant bias in angular velocity across the three axes of the gyroscope [13]. The accelerometer bias compensation is done by placing the sensor on a horizontal surface and any bias along the three axes except the 1g measured along the vertical axis is negated and zeroed.

To convert raw data corresponding to local frame motion into the earth frame, the orientation of the sensor with respect to a fixed reference frame (earth frame) is obtained. This is achieved through a sensor fusion algorithm that minimises the error between sensors with complementary error patterns to better estimate parameters. The orientation computation problem is formulated as a stochastic model where the angular rate from the gyroscope acts as the input to the state space transition model [14]. The output of the filter is the 3D orientation denoted by a four-dimensional vector known as quaternions and is represented by equation 2.

$$q = [q_0 \quad q_1 \quad q_2 \quad q_3] \tag{2}$$

The rate of change of orientation is computed in terms quaternions from gyroscope readings as shown in equation 3 and the state transition model of the filter is given by equation 4.

$$\dot{q} = \frac{1}{2} q \begin{bmatrix} 0 \\ \omega \end{bmatrix} \tag{3}$$

$$q_{i+1} = q_i + \dot{q}\Delta t \tag{4}$$

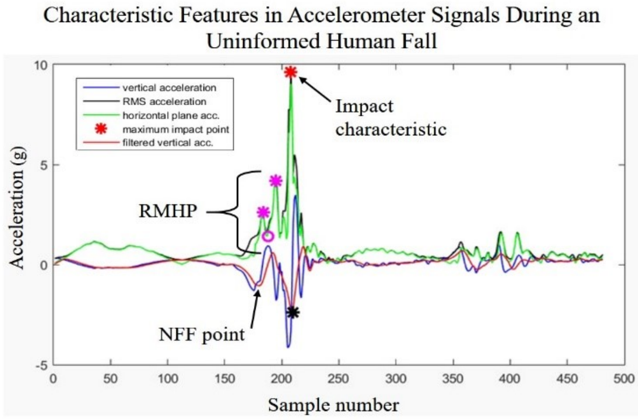

Fig. 5. Characteristic features of an uninformed fall indicating impact, near free fall event and rapid movement along the horizontal plane.

$\dot{q}$ is the rate of change of orientation and ω is the angular velocity. Δt represents the time between two sample points. q_{i+1} represents the predicted orientation of the system.

In the proposed method, Madgwick's algorithm, being computationally efficient, is used to calculate orientation [15]. The proposed fall detection system is implemented only using parameters derived from the acceleration signals. Therefore, to obtain the absolute acceleration (acceleration with reference to earth frame) of the system, the acceleration due to gravity present in the absolute acceleration has to be removed. This is achieved by subtracting 1g from the vertical component of the earth frame acceleration.

B. Feature Extraction

Features based on both kinematics and statistical metrics on key events of a fall are chosen to faithfully represent a fall. These features are listed as follows.

a) *The magnitude of Impact Characteristic (IC):* Impact is directly related to the momentary changes in the acceleration when the body comes in contact with the ground. The magnitude of these changes in acceleration is higher when the wrist comes in direct contact with the surface.

b) *Minimum acceleration during Near Free Fall (NFF) event:* The occurrence of a near free fall condition signifies a falling action or motion having similar kinematics of a free fall. The minimum acceleration (ideally, expected to be -1g) is a metric to characterize a fall.

c) *Mean magnitude of RMHP:* Movement of the variations caused along the horizontal plane indicate a counter motion associated with a typical fall. The magnitude of these observed variations confirms the likeliness of the captured action being a fall.

d) *Variance in time of local maxima in RMHP:* The rapid movements associated with hand movements correspond to a smooth timing pattern in the local maxima and minima points. The variance of these points capture the regularity of these patterns and enable isolation of non-falling actions.

e) *Variance in the amplitude of local maxima in RMHP:* A natural fall is characterised by significant hand movements that stand out from other intentional non-falling actions. The inclusion of the variability in the

RMHP patterns along with other RMHP associated features aid in the detection of uninformed falls.

Fig. 5 illustrates the features in processed earth frame accelerometer data corresponding to an actual fall. Impact during fall is characterized by high magnitude in the total acceleration and the vertical component of acceleration experiences near free fall condition before impact.

C. Fall Detection Algorithm

Acceleration signals obtained using the EFD technique is used for the extraction of kinematic features of a fall and detection of fall associated events. These tri-axial acceleration signals are continuously acquired by the processor at a rate of 100 frames per second where a frame consists of one sample of acceleration along each of the axis viz. X, Y, and Z. The data is buffered as windows comprising of 300 frames (corresponding to 3s) in a sliding buffer with an overlap of 100 frames. The overlap ensures that the features of the signal corresponding to a fall are completely captured irrespective of their occurrence between two adjacent windows. Fig. 6 depicts a simplified version of the flow of operations implemented in the algorithm.

The proposed hybrid algorithm is designed to observe potential events containing parameters relevant to a fall. These events include the Impact Characteristic (IC) and the occurrence of the Near Free Fall (NFF). Root Mean Squared (RMS) value of the acceleration signals captures the total acceleration experienced by the sensor and the impacts during a fall. Presence of IC is confirmed if this RMS value exceeds a predefined threshold. The threshold is based on the magnitude of the acceleration corresponding to the impact and is obtained by empirical methods based on fall and non-fall activities data. These methods are based on binary tree classifiers that identify an acceleration magnitude value to separate falls and non-falls.

Upon confirmation of the presence of IC, the occurrence of NFF is verified. The verification logic compares the amplitude characteristic of a typical NFF with that of buffered acceleration signal fed to the algorithm. The comparison is based on checking if this characteristic parameter exceeding a specified threshold. The mean of the minimum vertical acceleration during the NFF event for all the falls in the dataset is set as the threshold for comparison.

These primary steps based on comparison with predefined threshold rejects the majority of ADL reliably without having to invoke the rest of the algorithm. This, being the advantage of the hybrid algorithm, reduces the computational complexity and power consumption of the wearable device. Upon detection of an activity that resembles a fall, a classifier model is invoked to extract all five features from the buffered acceleration signal and reliably confirm a fall.

Elaborate feature extraction is carried out on the vertical and horizontal acceleration signals to extract the aforementioned features. These features, apart from capturing the actual magnitude of acceleration during IC and NFF events, correspond to the signature contained in hand movements during a fall. The classifier is based on bagged trees model and its output is the final output of the fall detection algorithm.

V. Results and Discussion

The performance of the model to reject common activities was tested using a dataset containing 43 minutes of ADL data. The dataset comprised of outdoor activities such as playing sports, running, jogging and walking in addition to indoor activities such as eating and writing. The data was processed to perform EFD and acceleration signal outputs were windowed to 300 frames with an overlap of 100 frames. These windows were fed to the hybrid model which rejected 96.4% of the windows at the threshold phase. The bagged trees

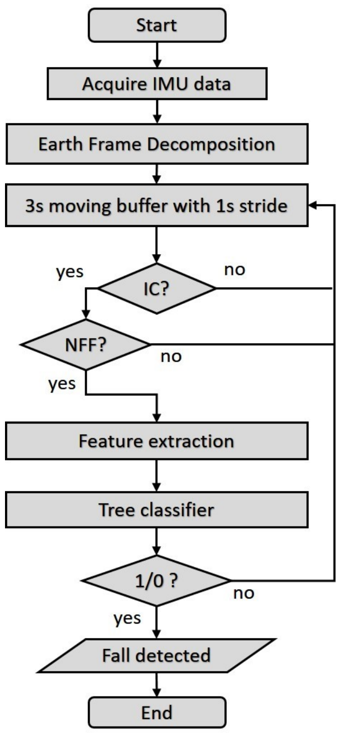

Fig. 6. Hybrid model consisting of threshold based methods followed by bagged trees classifier for the detection of actual falls among ADL and other actions resembling the kinematics of a fall.

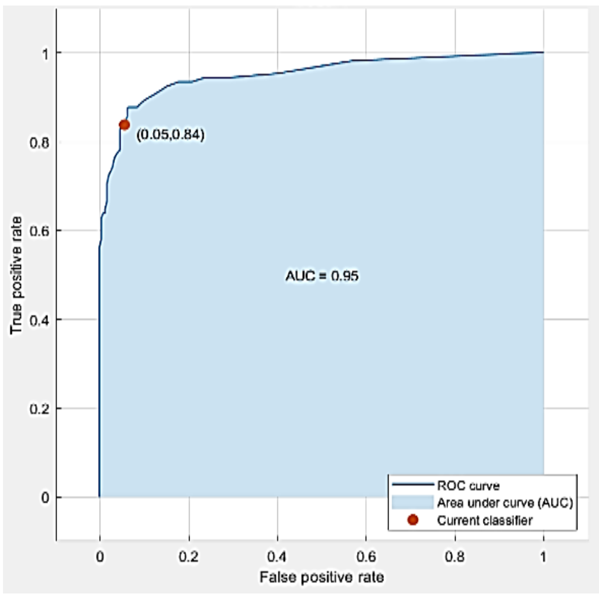

Fig. 7. ROC plot showing the sensitivity and specificity of the bagged trees classifier for detection of falls among other actions with kinematics resembling a fall.

classifier rejected 3.4% of the data thereby resulting in an overall rejection accuracy of 99.8% for ADL data.

Non-falling actions having kinematics similar to that of a fall were recorded to build a robust fall detection algorithm. These activities included knocking the desk and easing an extended arm against a table. A dataset containing 342 instances of both fall (138 falls on the soapy arena and 99 emulated falls) and non-fall data (105 actions that have similar kinematics of a fall) was used to train the bagged trees classifier model. An accuracy of 92.7% was obtained with 5-fold cross-validation on the dataset. The Region of Convergence plot for the bagged trees classifier is illustrated in Fig. 7. The model showed a sensitivity of 0.93 and a relatively lower specificity of 0.85.

Higher specificity of the model enables reliability in detection that is crucial for clinical applications. This effected in a lower specificity that allowed more false positives. However, the shortcoming can be overcome by deploying the algorithm for real-world usage along with assistive modalities to augment care delivery. Such modalities include automated calls to the caregiver after a specified duration of inactivity post-fall. This augmentation significantly reduces the false positives without compromising on the sensitivity of the model. In overall, from an implementation standpoint, the proposed model comprising of conditional statements and a random forest classifier consume fewer operations in comparison with the existing algorithms.

VI. Conclusion

This work focuses on understanding the nature of falls for detecting them reliably in real-world scenarios. The similarity between the falls captured in the dataset and the real-life falls has to be further investigated. However, the techniques proposed and the features discussed have potential in enhancing the performance of wearable devices targeted for fall detection. The algorithm is built with the premise to reduce computational cost and to be ported to a wearable device for real-time detection of fall. Both simulated and actual falls were used to understand the nature of falls and the hybrid model hence developed is to be ported on to a wearable device for testing on the field.

Integration of assistive methods during deployment, in addition to improving the reliability of detection, can be used to fine tune the model over time. Further work is being carried out to develop a real-time learning model that trains on the field taking input from usage scenarios and user responses.

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