2015 IEEE 29th International Conference on Advanced Information Networking and Applications

Evaluation of Human Activity Recognition and Fall Detection Using Android Phone

Muhammad Babar Rasheed[1], Nadeem Javaid[1,*], Turki Ali Alghamdi[2],
Sana Mukhtar[3], Umar Qasim[4], Zahoor Ali Khan[5], M. Haris Baidar Raja[1]

[1]COMSATS Institute of Information Technology, Islamabad, Pakistan
[2]CS Dept, College of CIS, Umm AlQura University, Makkah, Saudi Arabia
[3]Hamdard University, Islamabad, Pakistan
[4]University of Alberta, Alberta, Canada
[5]CIS, Higher Colleges of Technology, Fujairah Campus, UAE
[*]www.njavaid.com, nadeemjavaid@comsats.edu.pk, nadeem.javaid@univ-paris12.fr

***Abstract*—Human Activity Recognition (AR) using kinematic sensors is one of the widely used researched area based on smartphone. Development in sensor networks technology provided birth to the applications that can give intelligent and amicable services based on the AR of people. Although, this technology supports analyzing different activities pattern, empowering applications to identify the activities performed user independently is still a fundamental concern. For improvement quality of life and personal safety, caregiving process can be enhanced by introducing the AR, automatic fall detection, and prevention systems. Modern smartphones have different built in sensors like accelerometer, magnetometer, proximity, and gyroscope which can be used for AR as well as fall detection. In this paper, we present an AR and fall detection system which used built in sensors with alarm notification service. We use Signal Magnitude Vector (SMV) algorithm to analyze the fall like events. To overcome the false alarm activation problem, system uses different threshold values to determine the daily life activities like walking, standing, and siting, that could be wrongly detected as a fall. For assessment, a trial setup is done to acquire sensor's information of diverse positions.**

I. Introduction

Smartphone has become an important technology and incorporated with powerful and diverse sensors used in activity monitoring for modern health care systems. Due to small size and powerful processing capabilities of the smartphone, they can use to monitor a patient's activity in real time. Fall related injuries, including, body damages, fractures, connective tissue damages can result in genuine problems regarding health and monetary particularly for elderly individuals. An abnormal walking pattern and fall have great psychological effects and it can also reduce the independence and confidence of the people. This may lead to the health decline or future fall, which is dangerous for life. Impacts of fall depends on the long time period during which patient remains on the ground after the occurrence of fall. So, it is a basic and fundamental need to provide quick assistance to the affected people.

Basic solution during fall consists of simplest personal emergency response system with a small and battery operated device embedded on a belt with a push button on a wrist watch, belt, or in the pocket. This kind of device also embeds a wireless transmitter which is connected with the emergency help center. These devices are widely used in different countries without any configuration [1]. However, these devices suffer a serious problem during sudden falls. A person must press the push button to get immediate assistance which might be unable to press at that time due to serious condition. Body sensors are used to collect medical data during patients daily life activity for a long span of time [1], [2]. Other techniques including; video mechanism [3], [4] laboratory analysis system [5], which are used under the circumstances of free living having limited functionality and reliability [6].

Now a days, smartphone with different built-in sensors like; accelerometer, gyroscope, orientation, Global Positioning System (GPS), bluetooth, Wi-Fi, camera, and microphone, is a growing device which people can carry and take away at any time. Built in accelerometer, gyroscope, and orientation sensors are used to recognize different activities of people which reduces the extra hardware cost as well as exploit current communication technologies for ubiquitous monitoring. The effectiveness of the android based technologies has been demonstrated by the current and previous studies [7]. Acceleration due to patients movement or fall can be measured by using two devices; smart phone with built in sensors and external device with inertial measurement units. AR measurement using smart phone is more attractive and feasible due to massive storage, enhanced processing capabilities, size, weight, power consumption, portability and ease of use. Different approaches have been used for AR and fall detection by using inertial measurement unit or accelerometer method. An accelerometer can be used for detecting different activities based on different statistical techniques. Inertial measurement based sensors, accelerometer and gyroscope provide values of different parameters related to these sensors for the characterization and analyzing different activities such as, sitting, standing, walking, running, etc.

Although, ratio of fall is very high in elderly people due to abnormal walking pattern and it is very difficult to analyze

1550-445X/15 $31.00 © 2015 IEEE
DOI 10.1109/AINA.2015.181

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.

and capture daily life activities and real world falls. This is due to short interval time period in which commercial sensors transmit sensed data to end device. During the measurement of long interval periods, accuracy may also be affected. Previous studies show that [8], only the accelerometer sensor is used for fall detection, AR and notification for emergency assistance. Accelerometer sensor only provides the linear acceleration data in three axis whereas, to evaluate and measure the correct activity of the patient, we need orientation data as well for accuracy. To address the aforementioned problems, we use Samsung Galaxy Nexus mobile to capture real world activities of different people and analyze data to determine different activities and falls. During abnormal activities, alarms are generated to aware the doctor as well as patient for possible fall.

II. Related Work

Different android based AR systems have been used so far. It is evidence that idea of using an android phone for AR and fall detection is solid. Previously developed systems using kinematic sensors embedded in smartphone are used for AR due to its availability, massive storage, and great processing capabilities. Each system used some algorithms to measure an activity. These algorithm ranges from simple threshold based AR to machine learning and wavelet analyser. In [9], authors describe the implementation of Discrete Wavelet Transform (DWT) algorithm to detect different activities of athletes. Smartphone technology is used for activity detection and data transmission. Extracted features are analyzed and are made less complex through DWT algorithm. Major drawback of using DWT is that there is no mother wavelet found which is suitable for particular activity. Authors use Biorthagonal wavelet which is less suitable for AR application due to aforementioned drawback.

In this paper [10], authors identify and measure accuracy of different activities of players by using location independent android phone. Position activity model, behaviour model, and activity model are used to compare activity and accuracy of human movement. Moreover, authors use built-in accelerometer which is attached with different positions to test the activities such as; running, walking, still, downstairs, and upstairs. After classifications, activity model gives the highest accuracy which is 80.29%. Different patients exhibit different activities and even same activity can be performed in a different way by the different people.

To analyse and identify accurate physical behaviour of people is still a challenging task. In order to investigate activities with great accuracy, authors in [11], use neural network and three stage genetic algorithm techniques. Experimental results are compared with that of some well known algorithms for validation. Single smartphone based accelerometer is used for Human Activity Recognition (HAR) in which smartphone is attached with different positions [12]. Data fusion model is used for feature selection and classification to authenticate the accuracy. Placing smartphone at different position can create different variances which are reduced by using nonlinear Support Vector Machine (SVM) classifiers. Moreover, to save the battery and quick response time, only time domain analyses are performed. To analyze human activities, Baye's algorithm is another attracting technique as compared to other algorithms (Machine Learning) due to low computation overheads and faster modeling time. However, this algorithm has some limitations such as, slow processing and incompatibility with mobile environment.

In order to overcome above mentioned problems, authors in [13], propose an adaptive Native Baye's approach and HAR model to measure the human activities and requirements using different built in kinematic sensors. If, activity of any user is matched with the predefined activity selected by Baye's algorithm, it will be considered as an activity.

A. Motivation

There are different techniques and algorithms discussed in related work which are used for AR and fall detection. Authors use external as well as built-in sensors for monitoring daily life activities by attaching them with human body. In this situation, sensing device must have some physical contact with body and this approach is not suitable for long term AR due to improper device placement and adjustment. Moreover, in case of emergency due to abnormal activity or fall, there needs a quick assistance. For proper and accurate recognition of falls and activities, we use accelerometer and magnetometer's data. While, using only accelerometer, results might be false. Therefore, both accelerometer and magnetometer are used for precise and more accurate results.

III. System Design and Requirements

AR and fall detection systems can be useful for people who are working and performing recreational activities in some places where there is a high risk of falls. However, elderly people can take benefits of system like AR or fall detection. In last few years, life expectancy has increased to make a more astronomically immense fraction of the older population more prone to falls. Injuries due to walking disorders of elderly people are major cause of falls, disabilities and hospitalization. Thus, our proposed framework is particularly for the individuals having age over 60 years who are going outside for an extended period of time. For the most influenced and distinguished frameworks for such individuals must address the problems such as automation, reliability, promptness, communications, and ease of use. In order to design system which fulfills aforementioned requirements, AR system must be designed on the following guidelines.

- AR and fall detection framework must utilize the information obtained from accelerometer as well as other sensors for validation and authentication.
- Position of different sensors on human body impacted and influenced the usability strongly. Single sensor can give accurate information to investigate action. However, information obtained from different sensors might be used for precision and authentication.

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.

- Posture information is also important for AR and precision. Posture information can be calculated by knowing accelerometer position with respect to the body.
- AR and fall detection algorithm must be automated and may adjust the parameters according to the body and environment.

To allow the system to work outdoors, a smartphone is a good choice due to powerful processing capabilities and extensive memory along with different sensors. Also, due to availability of the smart phones, AR and fall detection system can be adopted by many people without the need of any other device. We propose an AR and fall recognition system which uses the smartphone attached to different body parts of the patients. The system has self-learning mechanism to detect an abnormal activity of the patient and send the caution and alerts to the patient and to the caretakers in case of emergency.

IV. Hardware and Software

We use Samsung Galaxy Nexus smartphone for proposed AR application. This smartphone is embeded with tri-axes accelerometer, gyroscope, proximity, orientation, compass, and barometer sensors. This device also includes a powerful Dual-core 1.2 GHz Cortex-A9 processor. Operating System (OS) used in this device is Android OS v4.0 (Ice Cream Sandwich) which supports API level-18. However, OS runs on an external sensors is TinyOS with nesC programming language. Figure 1 shows different phases of the proposed application. Phase 1 is used for data sensing and collection. While, phase 2 and 3 are used for data processing and transmission to monitoring station using different communication technologies like; Internet, GPRS, ZigBee, Bluetooth, etc. Working of proposed application is discussed in the following subsections.

A. Data Collection

Smartphones come with different built in sensors and this is one of the major reasons for the selection of smart phone as an alternative to that of conventional AR and fall detection system. Another vital reason to use smartphone is that people can easily carry smartphone whenever they go outside. Normally, smartphone based accelerometer sensors are widely used for AR. However, combination of different smart phone based sensors can also be used during sensing phase [14]. AR systems based on smartphone and external sensors are also used for health monitoring systems. Moreover, in some applications, smartphone is only used for processing and communication purpose, whereas, external sensors for detection of the falls. In first phase, sensed data is collected through built in kinematic sensors and stored in the main memory. Android based application is developed and executed on smartphone to control data collection process. A simple graphical user Interface permitted the user to begin and stop an activity and save the data in the memory using the SQLite database framework. This application also provides facility and controls what kind of data is required and how frequently it will be collected. During all data collection phases, we use 100 samples per second.

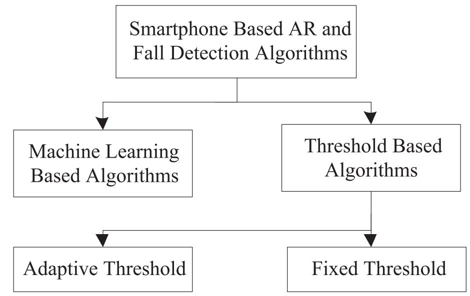


Fig. 2. Smartphone based algorithms

B. Feature Extraction and Data Classification

Data obtained from different sensors must be analysed. Decisions are made by analysing and classifying sensed data after feature selection and classification. Normally, threshold based algorithms are widely used for feature extraction due to their less complexity and low computational power to reduce battery consumption of mobile. They make a decision about activity or fall by comparing predefined threshold value with that of obtained output. Threshold values can be fixed or adopted according to the requirements of application. In the proposed work, threshold based algorithm use tri-accelerometer data for calculating the Signal Magnitude Vector (SMV). Figure 2 shows the classification of algorithms.

$$SMV = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

Where, A_x, A_y, and A_z represent the tri-axes accelerometer data. If, value of SMV at any instant exceeds threshold value, then the system indicates that a fall or a walking disorder. To make a correct decision, algorithm checks all the expected values by comparing with threshold.

C. Data Transmission

After features extraction, decision is made by using decision algorithm on the basis of threshold value. Whenever a smartphone detects abnormal event, it informs the patient as well as caregivers. First alert is sent to patient to obtain response. If in the next cycle, system receives a normal user activity, no alerts are transmitted to the concerned authorities. Otherwise, alarms and SMS alerts are transmitted to the doctors as well as family members for assistance. There are different types of smartphone based alerts such as; alarms, SMS, vibration, Multimedia Message Service (MMS), and automatic voice call used to take help from doctors or family members. We use, vibration, SMS, and alarm based alerts in our system.

D. Alarm Notifications

Fall alarm system is also incorporated in the AR system to facilitates the caregivers or caretaking institutes to find and help the patients in case of serious conditions. Alarm system empowers the doctors for quick emergency aid and can reduce the chances of harm risks during fall. To determine the exact falls, there needs a compact and accurate system.

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.

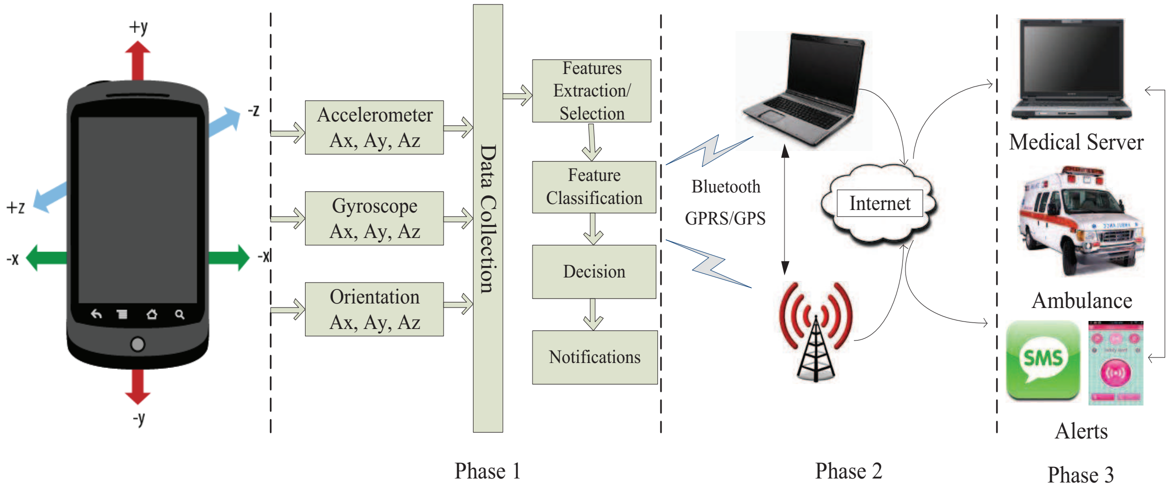


Fig. 1. Block diagram of proposed scheme

To accomplish these objectives, following are some system guidelines, which can be helpful while designing this system.

- Daily life activities other than fall must be distinguished.
- There is a strong need to determine exact location of person which is affected from a fall.
- There must be a mechanism to send an alert notification to doctors as well as caretakers for assistance.

Fall alarm system is installed on android phone along with all the sensors, Wi-Fi and GPS module. AR and fall detection system is always on whenever a person wants to go outside. Application continuously senses accelerometer data along with other sensors while, classifier algorithm extracts the features and analyse data for classification. If, current value of the sample is normal as compared with the previous one, patient is in normal position and there is no need to activate the alarm system. However, if the current value does not match with threshold value or gives greater difference, an alarm will be activated and send notifications to the consultants along with coordinates value. Moreover, during fall conditions, current values of the accelerometer and the upcoming value is analysed. Moreover, if algorithm shows constant value after comparing with the first value, algorithm considers it an abnormal activity or fall.

V. Daily Living Activities

In our proposed scenario, we consider four activities; walking, sitting, standing and taking turns. These activities are selected because they are regularly performed by different people during daily life. Motion related activities are also taking into account on different time stamps. Mostly, all activities repeat their pattern by making the user easier to diagnose. We always record data of different sensors like, accelerometer, and gyroscope, in three axes where, y-axis records upward/downward, z-axis forward or backward, and x-axis side (horizontal) movement.

Figure 3 and 4 show body movement of the patient and the resultant data of the accelerometer in three axes. It is clear from the figure 4 that during normal walking, x and z-axes show periodic behavior with little variations whereas, y-axis shows more variations. This is due to the normal walking activities of the patient. Figure 4 shows standing, sitting and walking behavior of patient. During walking, sitting or standing positions, accelerometer shows constant value because, patient is performing single activity. Peaks or different values are generated while patient is moving form one activity to other. There are some minor variations when patient is taking sudden turn during walking.

Figure 5 shows different activities and their pattern based on orientation data. It is clear from figure that during activity monitoring, all axes show greater variations in magnitude values. This is due to the consequences of earth's gravitational pull which affects the accelerometer to measure value of 9.8 m/s^2 towards the earth's centre. Activity patterns of all scenarios; sitting, walking, still, and during turn can be visualized in terms of x, y, and z-axes magnitude values relative to the time between different peaks. Figure 5 shows series of different high and low peaks for x and y-axes during different time intervals. During sitting and standing, one can visualize that, peaks do not show regular change and values are comparatively constant. While, walking and standing peaks also show the continuous and constant behavior. In case of any turn during walking, there is a small change in the behavior

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.

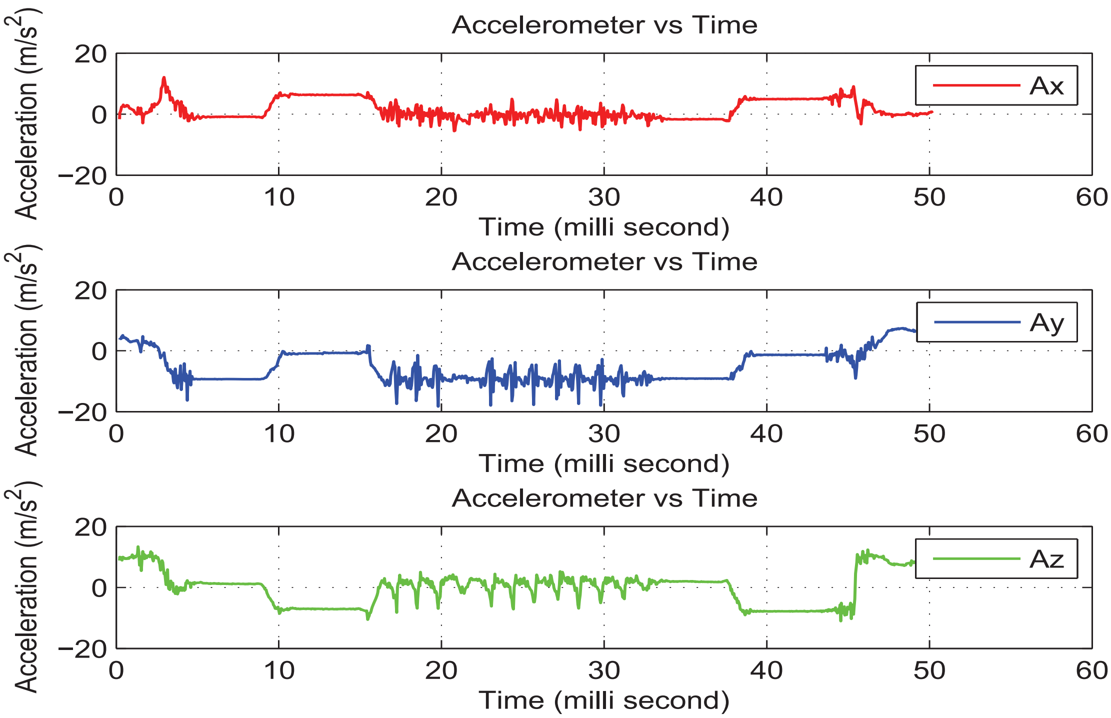


Fig. 3. Accelerometer data (three-axes)

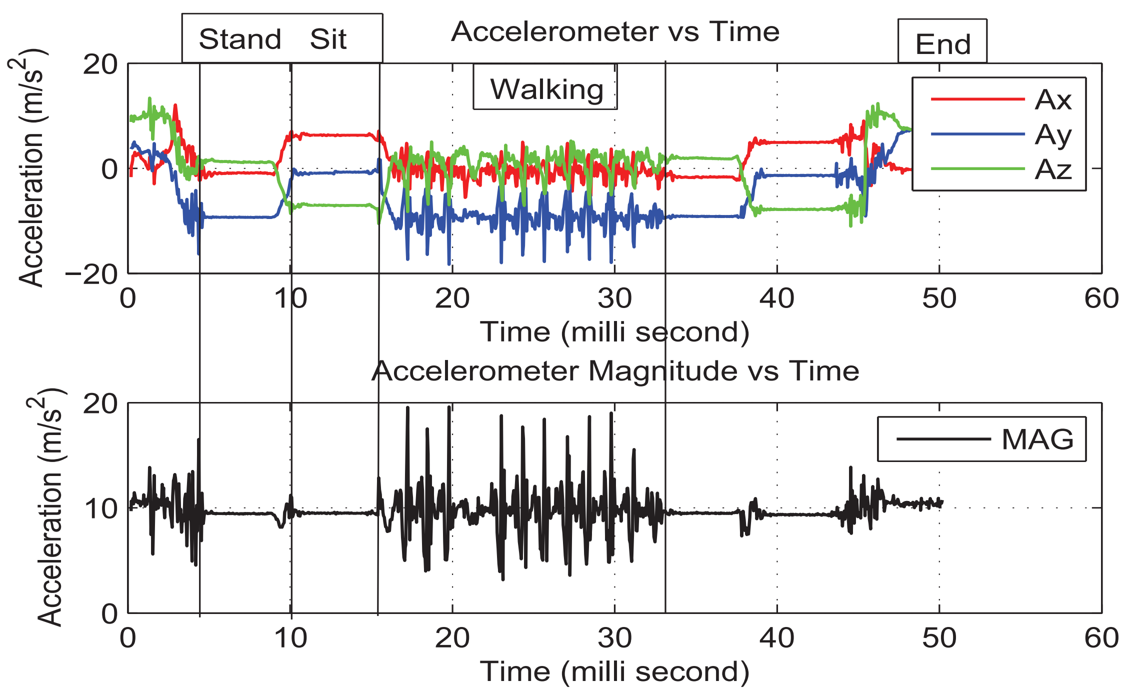


Fig. 4. Accelerometer data during standing, sitting, and walking positions

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.

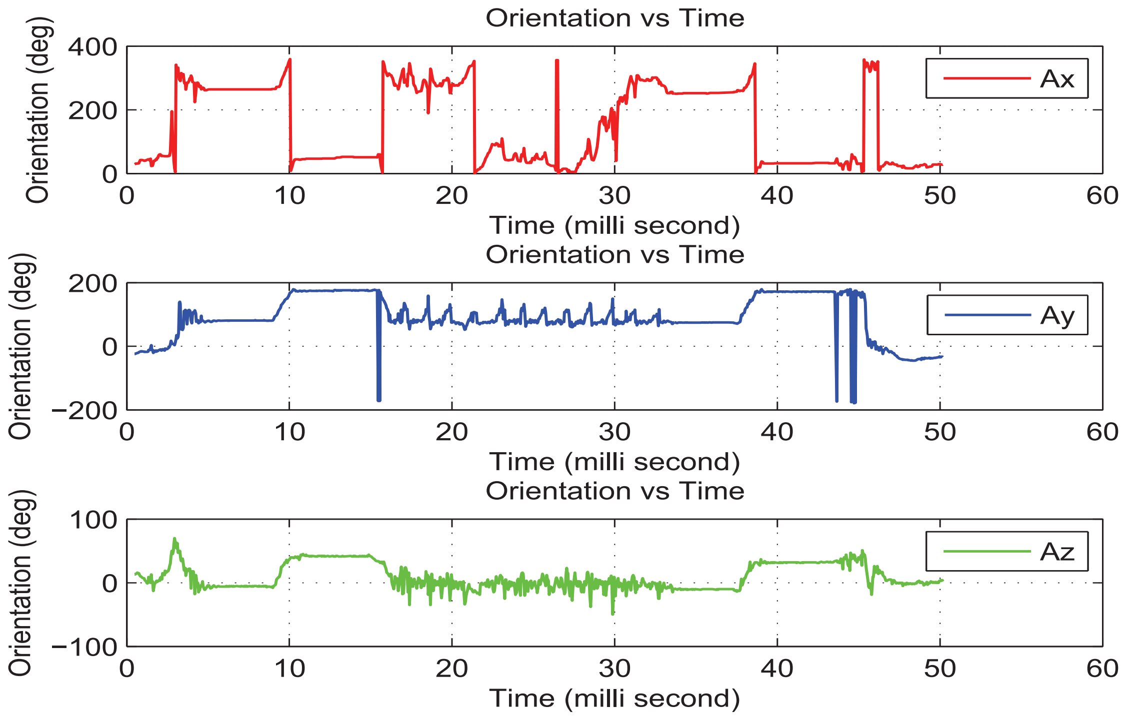


Fig. 5. Orientation data (three-axes)

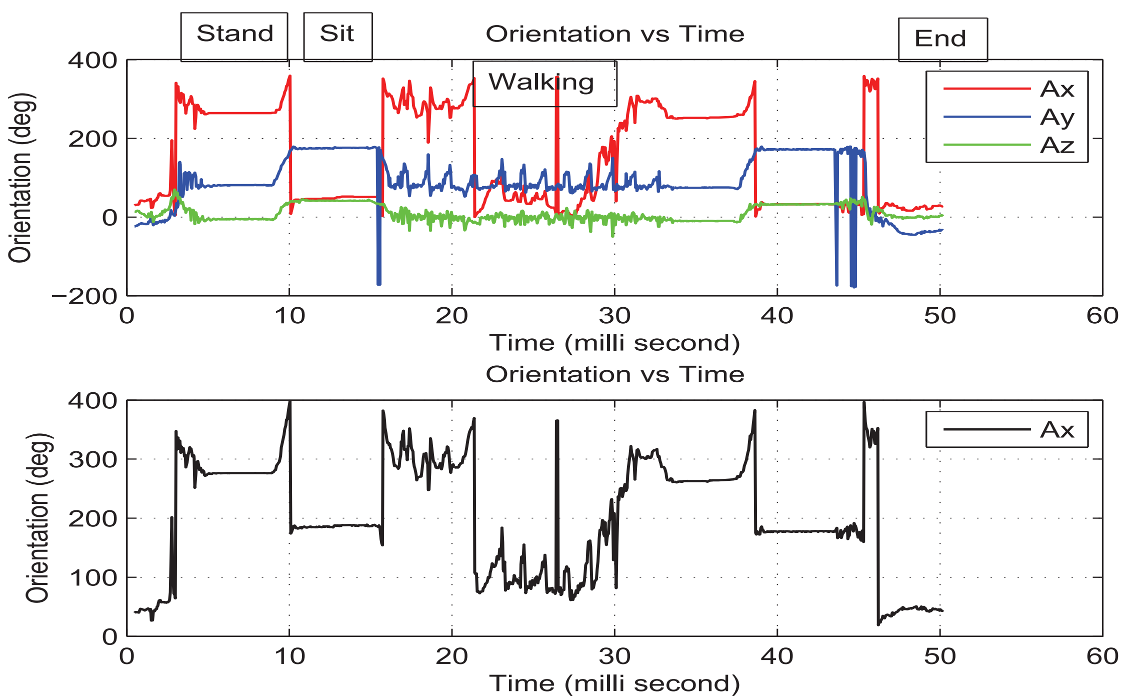
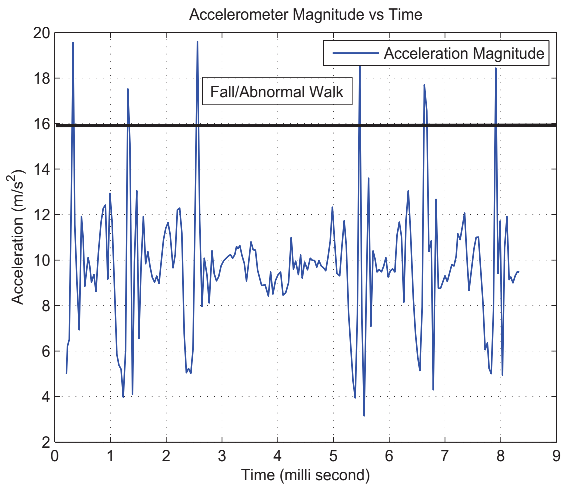
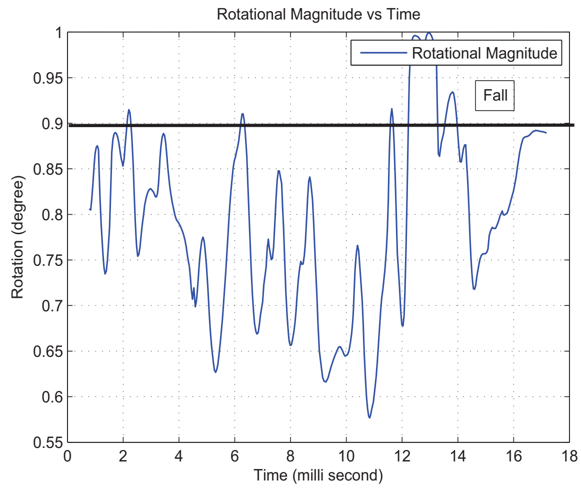


Fig. 6. Orientation data during standing, sitting, and walking positions

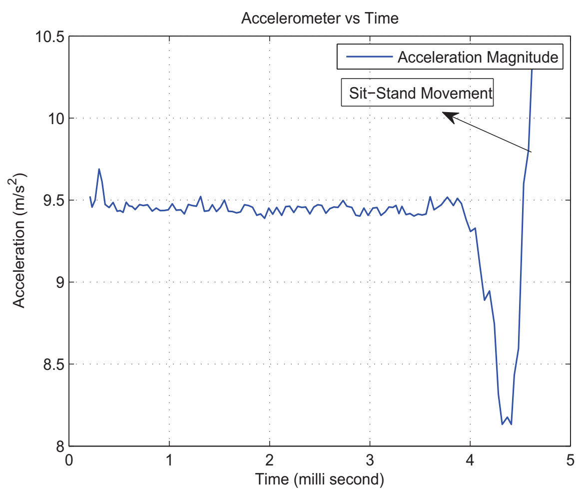
Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.



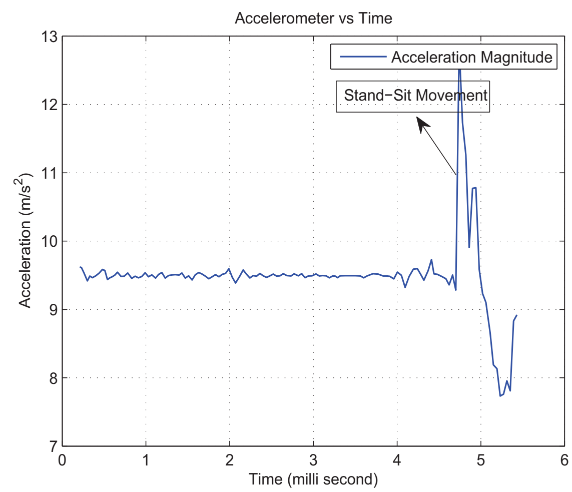
(a) Acceleration magnitude during walking



(b) Rotation magnitude during walking



(c) Acceleration magnitude during sitting



(d) Acceleration magnitude during standing

Fig. 7. Magnitude variation of different fall

of the peak at 22 ms time interval. Each quick peak shows the one step forward during walking. Negative z-axis values describe the regular walking pattern of a person. It is clear from the results that to visualize the difference between these activities is based on the difference between the magnitude values of the accelerometer as well as an orientation sensor during body movement.

A. Walking Activity

AR mechanism greatly reduces the false alarm notifications during activities which have sufficient duration like, walking, sitting, and standing. Even a fall related events can still be occurred whenever patient stops walking. Walking phenomenon consists of smooth set of steps which generates a sequence of acceleration magnitude patterns as compared to that of sitting and standing which produce a constant set of peaks followed by a set of sharp peaks. During the walk, relatively a high set of peaks may lead to the fall like events when the patient stops walking.

B. Sitting Activity

Sitting on hard or soft surface can produce fall related events when a patient due to tiredness or muscular problem, moves in an abnormal way and hits the surface very quickly. Different peaks are generated after hitting the ground by hard, soft, and elastic surfaces. When sitting or lying on elastic or hard surface

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.

like sofa or bed, fall related events are unlikely generated. In some cases, acceleration peaks could be produced due to high kinetic energy of human body. Acceleration peaks show smooth behavior after hitting the body on the ground. This is due to fact that, body dissipates energy slowly after a fall has occurred. As shown in figure 7 (a), there are some peaks which are greater than threshold value followed by regular oscillations during sitting position.

C. Acceleration Threshold Limits

The proposed algorithm detects fall based events by using SMV thresholds, and time intervals during which fall occurred. High and low threshold values are used to detect and analyze fall and its impact on the surface. A lower time-out is selected to check the impact which happened not later than threshold time, after that time fall has been considered. After the fall, there is a bouncing time interval during which samples are not analyzed until stabilizing the acceleration peaks. In order to make a comprehensive analysis of our proposed algorithm for AR, we implemented it with real time data set. In order to achieve full accuracy, we choose parameters within realistic ranges.

VI. Conclusion and Future Work

In this paper, we proposed an AR framework for analyzing different behaviors and activities of a patient based on built in kinematics sensors. To analyze and characterize features, SMV algorithm is used. In order to obtain data from different sensors, we attached smartphone with different body parts of patient. Data from different activities such as, sitting, walking, and standing, is collected. After feature extractions, if the obtained value is within the threshold range, person is in normal position. Otherwise, the abnormal activity is detected and alerts will be displayed on the patient's as well as the caretaker's smartphone. For classification and AR using smartphone empowers the technology available for everyone without having extra hardware and installation cost. Usually, all the processing and analyzing tasks are performed off-line after data collection. We implemented SMV algorithms for data processing and feature classifications after obtaining the real time data during different daily life activities. Results also show that, during different activities, there might be some abnormal activities. Alarm mechanism is used to aware the patients for any harmful situation. Moreover, our proposed framework can be used by any person for real time AR and classifications. In the future, we will investigate some additional activities like bicycling, car driving, and playing for collecting real time data which helps for accurate analysis. We will investigate other algorithms for feature selection and classification based on machine learning and neural networks. Furthermore, we will also investigate activity recognition by using external sensors which are gaining attraction now a days [15] due to accuracy.

References

[1] L. Philips, "the trusted medical alert service provider, http://www.lifelinesys.com," 2009.

[2] B. Caby, S. Kieffer, M. de Saint Hubert, G. Cremer, and B. Macq, "Feature extraction and selection for objective gait analysis and fall risk assessment by accelerometry," *Biomedical engineering online*, vol. 10, no. 1, p. 1, 2011.

[3] Z. A. Khan and W. Sohn, "Abnormal human activity recognition system based on r-transform and kernel discriminant technique for elderly home care," *Consumer Electronics, IEEE Transactions on*, vol. 57, no. 4, pp. 1843–1850, 2011.

[4] W. Lao, J. Han, and P. H. de With, "Automatic video-based human motion analyzer for consumer surveillance system," *Consumer Electronics, IEEE Transactions on*, vol. 55, no. 2, pp. 591–598, 2009.

[5] A. Sixsmith and N. Johnson, "A smart sensor to detect the falls of the elderly," *Pervasive Computing, IEEE*, vol. 3, no. 2, pp. 42–47, 2004.

[6] S. J. Preece, J. Y. Goulermas, L. P. Kenney, D. Howard, K. Meijer, and R. Crompton, "Activity identification using body-mounted sensorsa review of classification techniques," *Physiological measurement*, vol. 30, no. 4, p. R1, 2009.

[7] R. Y. Lee and A. J. Carlisle, "Detection of falls using accelerometers and mobile phone technology," *Age and ageing*, p. afr050, 2011.

[8] G. A. Koshmak, M. Linden, and A. Loutfi, "Evaluation of the android-based fall detection system with physiological data monitoring," in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pp. 1164–1168, IEEE, 2013.

[9] E. Mitchell, D. Monaghan, and N. E. O'Connor, "Classification of sporting activities using smartphone accelerometers," *Sensors*, vol. 13, no. 4, pp. 5317–5337, 2013.

[10] L. FAN, J. WANG, and H. WANG, "Activity recognition based on position-independent smartphone," *Journal of Computational Information Systems*, vol. 10, no. 11, pp. 4921–4928, 2014.

[11] T. R. D. Saputri, A. M. Khan, and S.-W. Lee, "User-independent activity recognition via three-stage ga-based feature selection," *International Journal of Distributed Sensor Networks*, vol. 2014, 2014.

[12] A. M. Khan, A. Tufail, A. M. Khattak, and T. H. Laine, "Activity recognition on smartphones via sensor-fusion and kda-based svms," *International Journal of Distributed Sensor Networks*, vol. 2014, 2014.

[13] M. Han, J. H. Bang, C. Nugent, S. McClean, and S. Lee, "A lightweight hierarchical activity recognition framework using smartphone sensors," *Sensors*, vol. 14, no. 9, pp. 16181–16195, 2014.

[14] A. J. A. Majumder, F. Rahman, I. Zerin, W. Ebel Jr, and S. I. Ahamed, "iprevention: Towards a novel real-time smartphone-based fall prevention system," in *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, pp. 513–518, ACM, 2013.

[15] J. P. Porta, D. J. Acosta, A. N. Lehker, S. T. Miller, J. Tomaka, and G. A. King, "Validating the adidas micoach for estimating pace, distance, and energy expenditure during outdoor over-ground exercise accelerometer," in *International Journal of Exercise Science: Conference Proceedings*, vol. 2, p. 23, 2012.

Authorized licensed use limited to: UNIVERSITAETSBIBL STUTTGART. Downloaded on December 11,2022 at 14:02:46 UTC from IEEE Xplore. Restrictions apply.