Reliable and Secure Body Fall Detection Algorithm in a Wireless Mesh Network

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ABSTRACT

Falls in elderly is one of the most serious causes of severe injury and lack in immediate medical help makes these injuries life threatening. An automatic fall detection system, presented in this research, will help reduce the arrival time of medical attention, reduce the mortality rate and in turn promote independent living. This research finds its primary application in the nursing homes and hospitals which account for highest elderly fall as compared to homes. In this research, body falls are detected with the help of a small wearable embedded device. The proposed design aims at distinguishing between a real fall and Activities of Daily Life (ADL). The device is a programmable wrist watch with an in-built accelerometer sensor and microcontroller circuitry. On detection of fall, the watch sends a signal to the neighboring receptor node watch, worn by nurses and alerts them of a fallen patient. The display on these watches notifies as to which patient fell. Signal transmission and reception between these devices is via wireless communication, where every patient watch acts as a sensor node forwarding the signal to the nearest neighboring node.

Keywords—Accelerometer, fall detection, ADL, wireless

1 INTRODUCTION

A fall is defined as “unintentionally coming to ground, or some lower level not as a consequence of sustaining a violent blow, loss of consciousness, sudden onset of paralysis as in stroke or an epileptic seizure” [1]. Approximately 3% of all fallers lie for more than 20 minutes without external support [2]. The need of assistance in the case of unconsciousness or extreme injury is the main reasons why elders leave the comfort and have to depend on their family for assistance. Thirty-two percent of elderly people aged over 75 years have ever fallen at least once a year, and among them, 24% have seriously injured [3]. In the recent years the number of fall detection systems has increased but very little work has been done for the same in the wireless domain. Body attached accelerometers and gyroscopes are used for detecting human motions and falls.

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This design uses body mounted embedded System on Chip (SoC) device with in-built accelerometer and micro-controller circuitry to distinguish between day-to-day activity or (ADL) and a genuine fall so as to avoid triggering false alarms. The fall detection algorithm takes into account the acceleration due to gravity and the co-ordinate reference points. The detected fall triggers a mechanism to generate an alert signal which transmits via other sensor nodes, reaches the destination node in minimum number of hops and notifies the authority to send help. Texas Instruments' device uses wireless transmission to communicate with neighboring nodes. The background of similar work and different approaches is described in section II. Detailed explanation of the algorithm, methodology and technique is described in Section III. Section IV presents the observed results of the implemented system and its future scope.

2 RELATED WORK

Several research and computing projects have successfully detected and distinguished daily activities by attaching accelerometers in known positions [4]. The work proposed in [4] uses the accelerometer to determine various movements of body without knowing the orientation. It makes use of the co-ordinate system which acts as the axes of the accelerometer. In the work presented, gravity component on each axis is averaged over a specific sampling frequency. From these acceleration values, vertical acceleration is calculated and the final difference between the corresponding acceleration and the vertical acceleration values gives the accurate reading. Fall detection mechanism and methodology is presented in [5], [3] [6] and [7] make use of body mounted accelerometer sensors to detect motion.

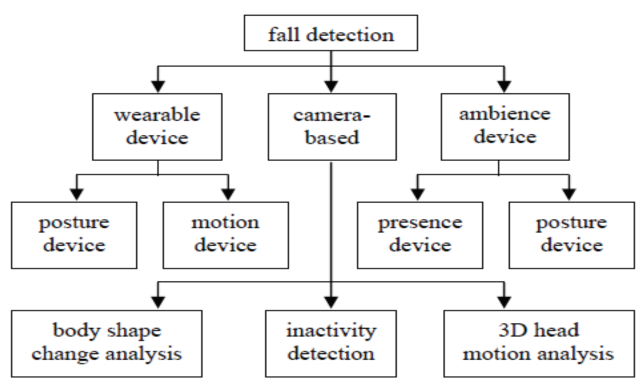

Figure 1. The hierarchy of approaches and classes of fall detection methods. **[8]**

Fall detections system can be categorized into three types. Figure 1 shows three different categories of prevalent systems on fall detection. This research is motivated from the first type of system i.e. wearable device. The first is using a wearable sensor device which triggers an alarm. The second approach is by constant monitoring using a live camera and third is using an ambience device which uses multiple sensors and collects relevant data. The ubiquitous fall detection systems lack automatic recognition and hence, the patient is left in fallen state until help reaches him. Ubiquitous systems also make use of Gyroscopes for angle and tilt determination for accuracy purpose. Many devices also take into consideration the altitude along with the change in acceleration for accuracy. Bluetooth and Zigbee is a common mode of communication for these devices.

3 METHODOLOGY

3.1 TI Chronos eZ430 watch setup

Texas Instruments' eZ430 development kit is used for the study and implementation of the body fall detection algorithm. The eZ430-Chronos software development tool is a highly integrated, wearable, wireless and embedded development system that is based on the CC430F6137 microcontroller. It is a sub-1 GHz RF System on Chip which has a 96 segment LCD display. The display makes the system highly user interactive. Along with the display and the micro-controller, it comes with a pressure sensor and a 3 axis accelerometer sensor for motion sensitive control. The algorithm is implemented in a wireless sensor network. The integrated wireless interface allows the eZ430-Chronos to act as a central hub for nearby wireless sensors. [47] This feature is utilized in implementing the application of fall detection by sending the signal over to the neighboring nodes/watches worn by the nurses. The eZ430-Chronos watch may be disassembled to be reprogrammed with custom applications and includes an eZ430 USB programming interface. Integrated development environment used for this research is the Code Composer Studio and the programming language used is "C". The watch is programmed with the help of an additional USB emulator which connects to the PC/laptop for real time and In-System Programming.

Figure 2 eZ430 Chronos watch with USB emulator

3.2 Approach

The algorithm for body fall detection takes into account the values obtained from the accelerometer and the changes in the co-ordinate axes. The tri-axial accelerometer in the watch measures linear acceleration due to gravity in the x, y and z axes. It is observed that whenever the watch is dropped in the vertical direction, maximum change occurs in the acceleration in the z axis. This single axis change in acceleration works significantly in determining a real fall. The formula mentioned below makes use of this phenomenon to distinguish between a genuine body fall and ADL. The data obtained from the accelerometer is processed at real time to avoid time lapses. Also, The accelerometr in the SoC has been programmed to automatically adjust the relative and the actual reference co-ordinates when the watch is powered on. For establishing the connection between the relative and the real reference coordinates, the previous values of x, y and z axis is saved and when powered on the correct real reference points is calculated. After the watch is programmed, the side buttons on the watch are used for navigating through the menu and selecting the desired option from it. The Menu consists of 5 options:

i) Idle: This is similar to reset condition. If the watch is not transmitting or receiving any data, it stays in the idle state.
ii) Node Address: This option allows the user to set patient's node to a unique single digit node address.
iii) Transmit start: The patient's watch needs to be in the transmit mode for fall to be detected. This option also activates the accelerometer.
iv) View node: "View node" menu option is for the nurse's watch. The selected node number is continuously monitored for fall.
v) Battery Voltage: Shows the battery life and notifies if the battery needs to be replaced.

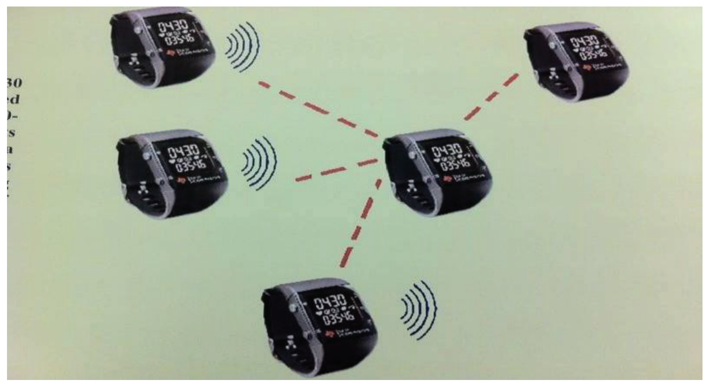

Figure 3 Watches in the transmit/receive mode

1) -

3.3 Fall detection algorithm

The in-built accelerometer plays the most significant role in the accomplishment of the body fall detection algorithm. The entire algorithm revolves around the readings measured by the accelerometer and the threshold values. Accelerometer is a motion sensitive electro-mechanical device which measures the acceleration due to gravity. The algorithm follows the following two important steps:

1) Calculation of the acceleration values in x, y and z co-ordinate axes, calculating the overall acceleration value and comparing it with the threshold value.
2) If the value of the calculated acceleration is found to be greater than the threshold value of 2g, fall flag is raised and alert signal transmitted across the wireless network, if not, the accelerometer continues its normal mode of operation until a genuine fall is detected.

The following formulas give an exact idea about the implementation of the fall detection algorithm.

$$A_{total} = \sqrt{(Ax^2) + (Ay^2) + (Az^2)} \quad (1)$$

$$\omega_{Tot} = \sqrt{(\omega x)^2 + (\omega y)^2 + (\omega z)^2} \quad (2)$$

In equation (1), A_{total} is the total sum vector magnitude for the 3-D acceleration data and ω_{Tot} is the angular movement where Ax, Ay, and Az denote accelerations along x, y and z-axis [9] [10].As a triaxial accelerometer is used, there are three components of acceleration, each for an axis.

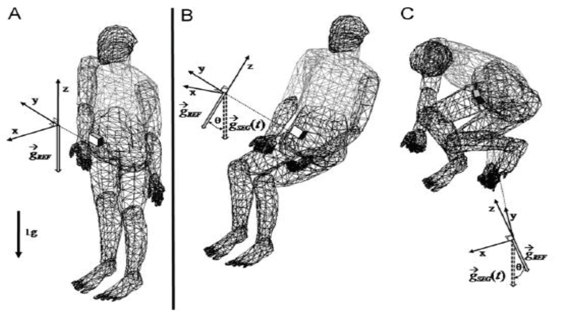

Figure 4 The figure shows the orientation and calculation of angle of inclination **[6]**

The second aspect of the algorithm is the determination of the angular velocity and angle of orientation. TI Chronos watch is not used for this purpose due to the absence of gyroscope in it. The measurement of angle of orientation is an essential component in determining a fall. It helps in determining the exact position of the patient before fall and also how severe or amenable the fall was. The angle of orientation is calculated as follows:

$$\Theta\text{orientation} = \arccos\left(z / (\sqrt{x^2 + y^2 + z^2}) \right) \quad (3)$$

Where x, y, z are the accelerometer values in 3D space co-ordinates [1] [11]. The Tilt Angle TA describes the body's posture, when the body is static. Its value was defined as indicated in Eq. 5, 6 and 7 below:

$$\text{TAx} = \arccos\left(\frac{Ax}{G}\right) . \left(\frac{180}{\Pi}\right) \quad (4)$$

$$\text{TAy} = \arccos\left(\frac{Ay}{G}\right) . \left(\frac{180}{\Pi}\right) \quad (5)$$

$$\text{TAz} = \arccos\left(\frac{Az}{G}\right) . \left(\frac{180}{\Pi}\right) \quad (6)$$

Where Ax, Ay, Az, is the acceleration in the x, y, and z axes, respectively. G is gravity acceleration (=1g). As the sensor position described above, the value of TAx, TAy, and TAz are 90°, 90°, and 0°, respectively, when the user is standing. [1] [12]. In the figure below, 60 degrees is the threshold value for fall detection.

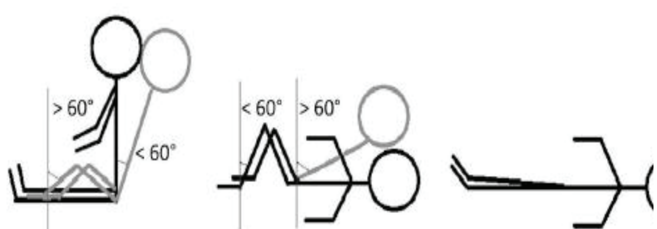

Figure 5 Fall positions and angles **[1]**

Post-fall posture is determined by taking the dot product of the reference gravity vector, gREF or the threshold value of acceleration due to gravity, and the current gravity vector estimate relative to the body segment, gSEG, as shown in figure 5, and by using the angle between the vertical accelerometer axis, z-axis, and gravity. These produce the inclination angle of the waist segment from vertical

$$\Theta(t) = \cos^{-1}\left(\frac{gSEG(t) * gREF}{(|gSEG(t)|.|gREF|)}\right) . \frac{180}{\Pi} \text{ degrees} \quad (7)$$

gREF is the reference of threshold gravity value. [11] [6]

This algorithm extracts features of falls by wireless communication by discriminating between genuine falls and sudden movements or ADL events. The change in acceleration describes the activity level of the body, which contains both the dynamic acceleration and the gravity acceleration. The time between the changes in the values of the parameters to be measured also plays significant part in detecting a fall and differentiating it from fall like movement. Generally, a fall lasts for 1-2 seconds [8]. So the difference in the values at the start and a few seconds after the fall determines if a fall has been detected or not. For reliable operation of the fall detection system, genuine fall events should not be missed while sudden body activity and jerks should be minimized. This is taken care by the algorithm as the magnitudes of acceleration in falling are generally greater than those in normal activity [1] . Setting thresholds for each of the three axes of measurement does not work well, because it does not cover all the possible directions of impact in a uniform way [10]. To consider the acceleration uniformly, the norm of the three axes can be taken, which is the magnitude of acceleration in three-dimensional space when the three acceleration values are for the same point in time. Normal activity usually does not exceed 3G, but occasionally may during some rigorous movements, for instance in jumping, running or sitting down abruptly. Since there is some overlap in the ranges of the acceleration norm between safe activities and falling, we need another way to distinguish falling from normal activity for a more robust algorithm [10].

3.4 Working

Figure 6 shows "safe" mode on the display of the watch. This watch is programmed to be node one and is in the transmit mode. When the patient is in a stationery position or when body fall is not detected the watch will always display "Safe".

Figure 6 Patient Watch in "Safe" mode

Figure 7 Nurse watch waiting for data

Figure 7 shows the display of the watch worn by the nursing home/hospital authorities. This watch constantly monitors the patients' watches. As it constantly monitors other watches, it awaits data from the neighboring patient watch. Until a genuine fall is detected, it will always display "data wait". After a patient falls, the display on the watch changes from "safe" to "fall". This is shown in figure 8. This signal is immediately transmitted to the nearest receptor node sensor. Thus, the display on the receiver watches changes from "data wait" to "data rx 01", as shown in figure 9. 01 is the node number representing the fallen patient. This helps in identifying the fallen patient and sending him timely help. When the patient is reached, the watch needs to set back to idle/reset state to save battery. Setting the watch back to idle condition also stops the transmission and de-activates the accelerometer. The battery of the watch can be checked by navigating the menu using the up/down buttons on the side of the watch.

Figure 8 "Fall" signal on the patient's watch -programmed as node1

Figure 9 Data received on the nurse's watch notifying the fallen node number - node 1

4 ENERGY AND POWER ANALYSIS

TI Chronos eZ430 development kit is a low power SoC. In the CPU active mode, the current consumption is 160uA/MHz. In the radio RF reception/transmission mode at a frequency of 915MHz, the figure goes up to 15mA at a data rate of 250kbps.

The kit uses a Lithium battery of 3Volt for functioning. The estimated battery life for continuous acceleration measurement is one and a half months with average current of 166 uA. When in transmission mode, the battery life reduces to 2 days with current of 3.7 mA. Due to the very high current consumption during the transmission and reception of RF signals, the buzzer of the watch cannot be made to function on reception of the alert signal. This drains the battery completely and the display of the watch goes blank. Therefore, the watch needs frequent human monitoring.

$$\text{Power} = \text{Current} * \text{Voltage} \quad (8)$$

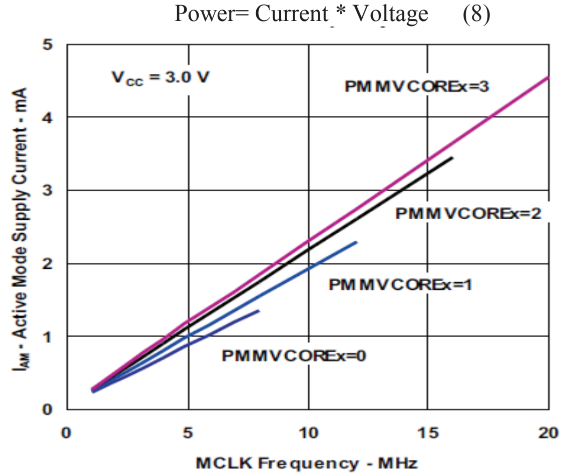

Figure 10 Current versus frequency values for the micro-controller in the watch

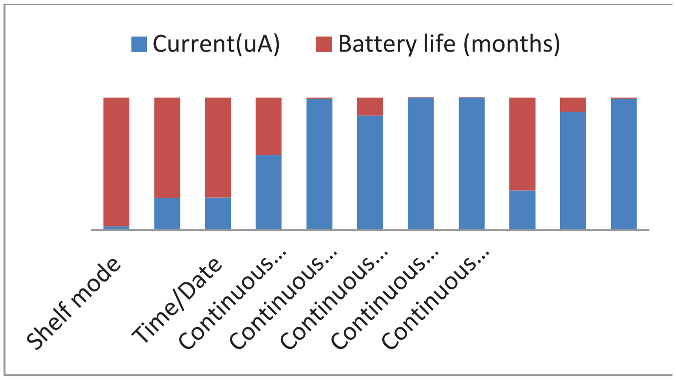

Figure 11 Current consumption and battery life for different modes of eZ430 Chronos watch

Figure 11 shows the current consumption and battery life for different mode of operation. eZ430 Chronos watch may be programmed for all the above modes, however, in this research only 3 modes are used. Comparison between the current consumption and battery life for these modes is shown in figure 12.

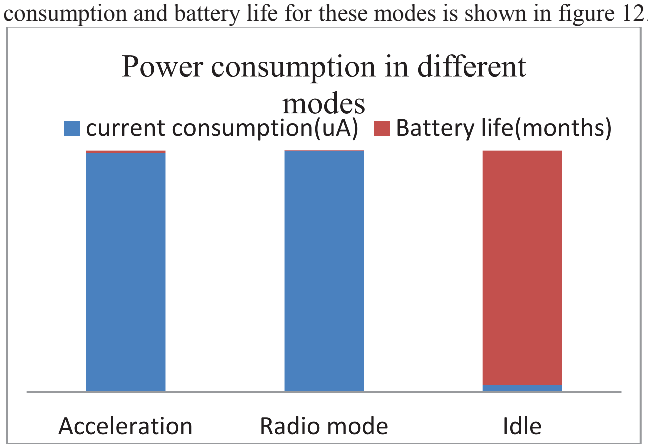

Figure 12 Current consumption and battery life for 3 modes in the programmed watch

5 Results

The entire setup is capable of monitoring up to 9 sensors simultaneously. The number of patient nodes may be increased if required. This helps in forming a mesh network. Other factors like tilt, tap and free fall may also be measured using the accelerometer, sensor and the transceiver module. The sensor measures the x, y, and z co-ordinates and measures the change in acceleration due to gravity. The device software tool is also capable of plotting the change in co-ordinates on a scope window. The graphs and figures presented in this section mentions about the overall results in terms of correct detection of body fall, false alarm triggering and relation body fall and total acceleration. As mentioned earlier, acceleration plays the most important role in determining and distinguishing between a real fall and fall like activity. Figure 13 shows the difference in the acceleration values in 3 axes for fall and different ADL. Different positions and directions have been considered for fall. It is clearly seen that the bars on the left which represent fall activities are taller than the bars for fall like activities.

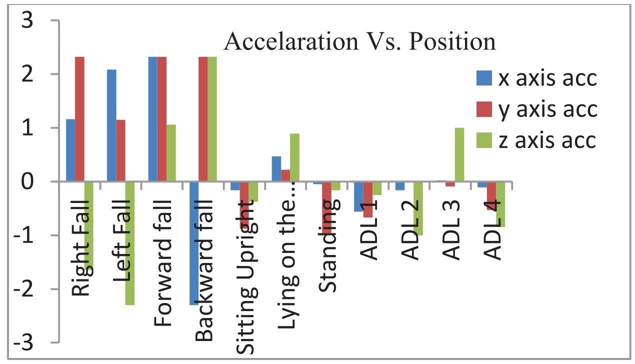

Figure 13 Changes in acceleration values for ADL and fall positions

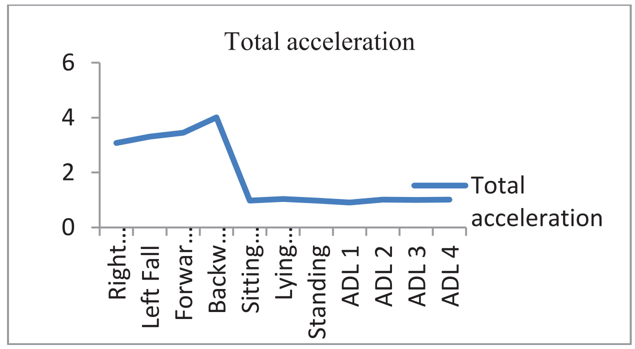

Figure 14 Total acceleration for fall positions and ADL

Figure 14 is the graph which show the total acceleration for body fall and ADL. It is observed that the acceleration values for fall, especially backward fall is higher than the daily activities.

5.1 Sensitivity and Specificity

The algorithm needed statistical analysis and result activity base on series of tests performed. There are 4 possible situations:

- True positive (TP): a fall occurs and the device detects it.
- False positive (FP): the device announces a fall, but it did not occur.
- True negative (TN): a normal (no fall) movement is performed, the device does not declare a fall.
- False Negative (FN): a fall occurs but the device does not detect it.

In 2, it was also proposed a classification and evaluation of fall detectors. Two criteria were proposed to evaluate the response to these four situations. Sensitivity is the capacity to detect a fall, Eq. 9 and specificity is the ability to detect only a fall, Eq. 10 [16]

$$\text{Sensitivity} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \qquad (9)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \qquad (10)$$

Results show that the sensitivity of algorithm to distinguish between a real and false fall is 78% and specificity was found to be 69.2%. The rate of detecting false alarms was higher when the person moved wrist from higher to lower level with a free-fall like motion. Series of tests performed gave the following results in terms of success, failure percentage and the false alarm rate. The failure percentage represents the false alarm rate.

Scenario	Wrist		Waist/trunk	
	Success %	Failure %	Success %	Failure %
Falls	86	14	94	6
Non-Falls	73	27	88	12

Figure 15 Success and failure rate for fall detection.

In the table above, when the device is worn on wrist, for ten genuine falls, approximately nine falls were correctly detected whereas around three out of ten ADL activities were detected as falls. Similarly, when the device is placed on waist the fall detection success rate is 94% and the false alarm rate is 6%. For ADL, the false alarm rate is reduced.

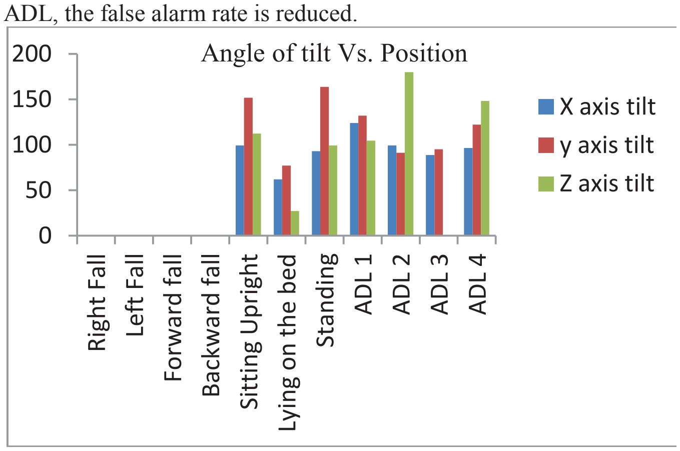

Figure 16 Angle of tilt in different axes for fall positions and ADL

Figure 16 gives a comparison between the position and the angle of tilt. It is observed that the angle of tilt is null for all the fall positions as the angle exceeds the threshold, whereas for ADL the angle remains within the threshold value and the angle of tilt remains between forty to two hundred degrees.

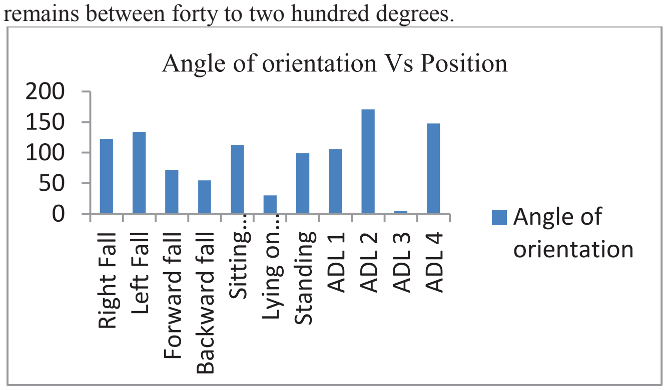

Figure 17 Angle of orientation for fall positions and ADL

Figure 17 shows angle of orientation for different body positions. This graph helps in knowing the position of the patient before the fall and assists in determining the severity of fall. These calculations are for future improvement of the algorithm.

6 Conclusion and Future Scope

The research is in its completion stage but has plenty scope of further development. The setup successfully detects body fall. It distinguishes between fall like movements and real falls. The wireless sensor networks helps in adding the feature of automatic, hand free assistance calling. It is also observed that the algorithm is 86% efficient in detecting true falls when the watch is worn on the wrist. However, if the SoC is placed on waist or trunk of the patient, the efficiency increases to 94%. This means, the false rate alarm triggered is higher when the SoC is placed on wrist as compared to when placed on waist. Since the TI Chronos kit is low power SoC, it consumes very little power and has an option of setting the watch in idle mode to save power.

There are plenty features which can be included to improve the current setup. Altitude is an important criterion which may be considered to enhance the accuracy of the overall algorithm. Also, utilizing a higher voltage battery may clear away the constant human monitoring by implementing application to trigger a buzzer or call an emergency phone. Further research and implementation of the above features will result in a fully function product for nursing homes and hospitals of fall detection system which will be reliable and transmit secure data over the wireless mesh network.

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