Design and Implementation of a Smartphone Based Multisensory Dynamic Fall Detection System

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Abstract

A dynamic fall detection system is a key issue in ensuring sound daily life, reducing fall related injuries and reducing post fall affects. Based on only smartphone's in-built sensors we have designed and developed an effective dynamic fall detection system. The system will detect fall for any smartphone position and will place an instant communication with the care-giver with the victim's location. We estimated fall by monitoring user's movement in terms of total acceleration and surrounding environment in terms of sound level with the help of smartphone's inbuilt sensors like- accelerometer sensor and microphone sensor. We have detected fall, based on these sensors real time data. Each of the parameter dictates relevant information about the user's present condition. These parameters information then merged to get the accuracy of the fall decision. Depending on the values the system detects human fall and tries to get the user's attention by generating an alarm. Upon failing to get the user's attention the system will automatically and instantly notify the care-giver with the user's location for quick medical aid. And statistics show that the majority of serious consequences are not direct result of fall rather it is due to delay in aid, treatment or in worst case detection. The system is evaluated using a mannequin and two human shaped scarecrow dummy of different height. Testing objects were used to mimic the human fall. The test results were promising. More than 70 falls were mimicked placing smartphone either in shirt's pocket and pants pocket. The test results showed us that the developed system is functioning well and attaining high accuracy in detecting fall. And the rate of false negativity is also low with sensitivity of 89.04% and specificity of 75%. Our proposed system with smartphone's in-built multiple sensor fusion and their classified results can be an exquisite candidate in adaptive, user-oriented health-care system.

Keywords: dynamic fall detection; smartphone; multisensory; ubiquitous computing; elderly

1. Introduction

Falls are considered as the second leading cause of accidental or unintentional injury deaths worldwide. A fall is defined as an event which results in a person coming to rest inadvertently on the ground or floor or other lower level [1]. Fall-related injuries can be fatal or non-fatal. For example, in People's Republic of China, for every death due to fall, there are 4 cases of permanent disability, 13 cases requiring hospitalization for more than 10 days, 24 cases requiring hospitalized for 1-9 days and 690 cases seeking medical care or missing work/school [1]. The largest morbidity occurs in people aged 65 years of older, young adults, aged 15-29 years and children aged 15 years of younger.

Each year around 6, 46,000 individuals [1] die globally from falls. Regions of Western Pacific and South East Asia are accounting for 60% of these deaths. Aside from death, falls are also responsible for over 17 million DALYs (disability-adjusted life yeas) lost [1]. While, nearly 40% of the total DALYs lost due to falls worldwide occurs among children. Around 37.3 million falls are severe enough to require medical attention. One out of five falls causes a serious injury like broken bones or head injury [2, 3]. More than 95% of hip fractures are caused by falling [4]. Falls are also most common cause of traumatic brain injuries [5] and 80% of this occurs in low and middle-income countries. Individuals from all age group are prone to fall, starting from children to old. And this fall rate is high especially among children, pregnant-women and old men. Though, the risk of fall increases below 6 years and above 60 years gradually.

According to WHO, in Brazil, for children under 15 years of age, more than half of all non-fatal injuries are the results of fall [6]. In America, fall is 1.1% of total DALY's, in South-east Asia Regions, it is 1.7%. In European regions it is 2.2%. In Bangladesh also the lead cause of child-injury is fall. The fatal fall injury rate was 2.8/100 000 for children of all ages. The percentage of mortality by fall for boys of age less than 1 year is 8.4. While among girls of less than 1 year it is 36%. Around 770 children are injured each day. Among them 10 are cursed with permanently disability each day [7]. In case of pregnant-women, due to their ongoing physical transformation, they are very prone to sudden seizure and loosing sense. Failure of immediate assistance can affect both mother and child. Old peoples are much more prone to falls. Each year 2.8 million older people are treated in emergency departments for fall injuries [8]. In United States of America, 20-30% of older people who fall suffer moderate to severe injuries such as bruises, hip fractures or head traumas. It has been observed that males are more likely to die from a fall, while female suffers more non-fatal falls. Worldwide males consistently sustain higher death rates and DALYs lost. Additionally, many people who fell, even not being injured, become afraid of falling. This fear may cause a person to shrink their everyday activities. When a person is less active they became weaker and this increases their chances of falling [9].

Financial costs from fall-related injuries are substantial. For people aged 65 years or older, the average health system cost per fall injury in the Republic of Finland and Australia are US$ 3611 and US $ 1049 respectively [1]. Direct medical costs for fall in uries are $ 31 billion annually [10]. Hospital costs account for two-thirds of the total.

So, the considerable risks of falls and the substantial increase in population have stimulated both commercial product and academic research on fall detection and prevention. A typical fall detection system complies of two major parts: the detection component which detects fall and the communication component which communicates with the given contact persons. Evidence from Canada suggests that the implementation of effective fall prevention would create a net savings over US $ 120 million each year [1].

2. Literature Review

Due to different adverse effects in social, physical, psychological and economical, falls have been an attractive issue to the researchers for the last decade. Though first fall detection system was introduced by Hormann in early 1970s [11] but Hansen et al. [12] used the smartphone's camera for the first time in 2005 for fall detection. Fall detection techniques can be generalized into four categories: external sensor-based detection, database-based motion type classification, visual-based detection and smartphone based detection.

In external sensor-based detection process, in general external sensor's value like, accelerometer sensor's value is used. And when the accelerometer sensor is used most methods are based on thresholds. Nyan et al. [13] used an accelerometer that has to be settled in the shoulder garment. The absolute peak values of acceleration were considered as the threshold. Based on the threshold, a fall is detected. Kangas et al. [14] proposed using four thresholds for total sum vector, dynamic sum vector, vertical acceleration and difference between the acceleration's maximum and minimum values. But according to their proposal, a fall is considered detected as long as one threshold is exceeded. Other than accelerometer, gyroscope sensor's value is also used in fall detection. Information of body's orientation and pressure are also used to detect acceleration based fall detection [15, 16]. Pannurat et al. [17] offered a commercial off-the-shelf wearable device for fall detection. The most common position for these devices is waist position provided with a 'panic button'. And most products are powered by a lithium-ion battery and employ embedded sensors to detect falls. CARA architecture [18] proposed to send the data of a wearable accelerometer to an external non-portable gateway which applies a threshold method to detect fall. ZigBee is the wireless technology between the wearable sensors and a central server in the system that is portrayed in [19]. Arduino Fio hardware containing a gyroscope and an accelerometer is used as a compact to detect falls by sending an alarm via Bluetooth to a nearby smartphone [20]. These threshold based fall detection systems are less complex because of using less complex algorithms. So these techniques require lowest computational power but they use predefined fixed threshold which are applicable for a predefined fixed place of human body condition. So, they are much more prone to false negativity due to depending only in accelerometer's value.

Though recently, due to the availability of multiple embedded sensors and cost shrinking, smartphones have got the full attention and attraction. But, in previous and still external circuit/device is being used to detect falls. Brickhouse [21] consists of a tele-assist base and a portable sensor. In which base device is needed to be installed indoors. So, the signal transmission distance between the base and the sensor is limited and results in severe drawbacks. Like, the monitoring place is fixed and the installment, adjustment and monitoring cost are quite high. In 2016, 'Gold Award' awarded Medical Guardian [22] for its customer review, provided an economic fall alarm monitor that has a fixed distance range and works by using nation-wide cellular network.

In case of database based fall detection systems, Ganti et al. [23] and Karantonis et al. [24] proposed for storing sensed user behavior data into a database for various activities like, fall down and recognition hereafter. These databases stored with sensed data are very useful. They can also be used for detecting much more activities and for pattern recognition of an individual. Though these databases become handy for any later activity recognition but the system's performance fully depend on the database. So, in case of database compromization or unauthorized modification the system's performance may become inefficient. Fu et al. [25], Sixsmith et al. [26], Miaou et al. [27] and Jansen et al. [28] proposed for capturing images of people and then detecting visual falls based on image processing techniques. Though image processing technique is a promising way of detecting fall, but this technique has limitations on pervasive fall detection and the detection area is limited by the surrounding environment.

But in last few years, the number of fall detection apps in smartphones is increasing day by day due to easy availability of smartphones and multiple sensors embedded in them. And these are being developed in various operating systems of smartphones. Like, initial smartphone based fall detection were developed in Symbian OS on Nokia phones [29]. A Java multiplatform software architecture, using external architecture was employed in both a Symbian phone (Nokia 5800) and Android smartphones (Samsung Galaxy, HTC hero) to detect falls [30]. In the year 2009, Sposaro et al. [31] and Lopes et al. [32] proposed fall detection systems depending on only in-built accelerometer sensor of the smartphone. Then in the preceding years, many fall detection systems were proposed. But maximum of them were designed considering only the accelerometer sensor [33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60]. Very few were designed considering multiple sensors [61, 62, 63, 64, 65, 66, 67, 68, 69]. Even though multiple sensors were considered while designing a fall detection system, all of them considered acceleration as the only parameter.

In android platform, a vast literature on fall detection systems has been generated. The general principles of fall detection for elderly have been summarized by Yu [70] and Noury [71] while different classifications of fall assessment techniques have been presented by Pannurat et al. [17], Hedge et al. [72], Noury et al. [71, 73], Hijaz et al. [74]. However, smartphone-based fall detection and prevention architectures are specifically revised in a great detail by Habib et al. [75].

But, in the prevailing systems there exist some obstacles like; the smartphone’s position is kept fixed or has an unbalanced co-relation between false positivity and false negativity. So, a fixed threshold had to use. But it is inconvenient in real life. Because an individual can keep his/her smartphone in any place in accordance with his/her comfort. So, the existing techniques are not dynamic. Hence, our system approaches to eradicate this limitation.

3. Materials and Methods

A novel dynamic fall detection system using smartphone is presented here. Only bsuilt-in sensors of smartphone are used to detect fall.

2.1 Subjects Intentional falls were performed by one mannequin and two human shaped dummies. The mannequin is of 182 cm tall. And two human shaped dummies are of height 155 cm and 176 cm. Smartphone's position was detected by observing the smartphone's accelerometer sensor's value while walking. For detecting phone position, we conducted extensive experiments on 10 different real persons of different height and weight. The participants are of 23-25 years of age. Five of them are 165-170 cm tall. Other five are 180-182 cm tall. Four of them weight within 55-65 kg, five weight 65-70 kg and one weights more than 70 kg. And the experiments were conducted for both shirt's pocket and pants pocket. A total of 73 falls data was recorded.

Figure 1. Mannequin used for experiment.

Figure 2. Dummy used for experiment.

2.2 Software Description The implemented fall detection system can detect fall dynamically. That is from the very beginning of the system, multiple sensors like accelerometer and microphone will be initiated to detect smartphone position and fall. With the help of accelerometer sensor's value, the smartphone's position will be detected. But there will also be a provision of training the system to get the smartphone's position according to the user's movement. And these training results will be stored and used to obtain the user specific accurate phone position.

Having phone position detected, the system will set the threshold values first to check the fall according to the smartphone's position. The likelihood of happening a fall is checked continuously for every sensor data. If the sensor's value exceeds the threshold value, then a fall is triggered by that specific sensor. If two sensor trigger at a time, the system will check for user movement for 30 seconds. If the stationary condition of the device is found out, only then a fall is considered to have happened. And system will check for user response by sounding an alarm. Depending on the user response, the system will either go for post fall detection phase, that is to notify the care-giver about the fall along with the location of occurring fall via SMS or will continue to monitor the user.

2.3 Fall Detecting Parameters In this system, physical parameters of the user are used to detect fall. The total acceleration of the user $|A_T|$ and surrounding sound level in terms of dB is calculated using the equations (1) and (2).

$$|A_T| = \sqrt{(|A_X|^2 + |A_Y|^2 + |A_Z|^2)} \quad (1)$$

$$dB = \left(20 * log10\left(\frac{pressure}{\text{REFERENCE}}\right)\right) \quad (2)$$

4. Experimental Results

Obtained experimental results are viewed in the following tables. In table 1, the data obtained from 10 participants for Smart Phone position detection are viewed.

Table 1. Data regarding smartphone's position detection.

		Shirt's pocket			Pants pocket		
	Trial time (in minute)	X axis value range (in ms^{-2})	Y Axis value range (in ms^{-2})	Z axis value range (in ms^{-2})	X axis value range (in ms^{-2})	Y Axis value range (in ms^{-2})	Z axis value range (in ms^{-2})
Participant 1	10	4-6	5-7	4-6	20-27	12-15	13-21
Participant 2	10	4-7	6-8	3-5	20-28	13-18	14-22
Participant 3	10	4-6	6-9	3-6	20-26	13-17	13-23
Participant 4	10	4-8	5-9	4-8	20-27	13-17	15-25
Participant 5	10	3-15	4-16	2-14	2-16	1-19	3-21
Participant 6	10	4-11	5-9	5-14	18-29	12-23	14-29
Participant 7	10	4-9	6-10	7-13	16-34	18-27	18-33
Participant 8	10	2-4	6-8	3-9	18-27	15-17	26-32
Participant 9	10	3-5	6-9	3-5	14-23	15-19	29-33
Participant 10	10	2-5	6-9	3-7	17-31	13-22	17-32

Sensor data for first human-shaped dummy are given below in tabular form in table 2 and table 3.

Table 2. Sensor data of first dummy for smartphone placing in shirt's pocket.

Test No	Triggered Accelerometer value range(ms^{-2})	Triggered Microphone value (dB)		
		Highest value		Lowest value
01	9.8-4.24-1.57-0.76-8.8	80.8583	-	49.1261
02	9.8-5.5-1.38-23.6-8.8	82.6055	-	47.6501
03	10.2-3.76-4.78-8.9	80.1791	-	47.9251
04	9.5-5.42-1.15-13.95-8.8	86.2160	-	51.4892
05	9.8-3.3-21.76-8.8	85.3391	-	53.3218
06	11-4.3-20.42-7.3-3.94-1.65-10.26-8.8	85.1860	-	48.7985
07	10.5-5.37-0.37-3.1-8.8	81.1150	-	46.9491
08	9.2-5.5-0.83-23.26-8.8	85.9021	-	49.9327
09	9.5-5.6-2.9-10.3	84.7467	-	50.5228
10	10.6-1.81-2.87-6.72-14.1-10.3	81.6661	-	45.6302

Table 3. Sensor data of first dummy for smartphone placing in pants pocket.

Test No	Triggered Accelerometer value range(ms^{-2})	Triggered Microphone value (dB)		
		Highest value		Lowest value
01	10-6.8-4.3-14.15-8.8	80.3023	-	49.6289
02	9.4-3.9-5.5-8.9	79.7551	-	47.7116
03	10-4.3-30.68-8.8	81.4088	-	49.9619
04	9.8-5.8-4.8-11.92-8.8	80.3526	-	48.0912
05	10.2-6.4-2.5-9.3-8.8	79.1303	-	42.0774
06	10-5.2-21.38-3.2-9-8.9	79.4037	-	48.0254
07	9.9-5.2-7.1-8.8	80.4588	-	38.7683
08	8.8-6.8-5.4-1.7-8.8	79.0109	-	26.6437
09	13-4.1-9-7-8.8	72.3602	-	31.3955
10	11.5-5.5-7.5-8.8	81.2497	-	49.1070

Sensor data for second human-shaped dummy are given below in tabular form in table 4 and table 5.

Table 4. Sensor data of second dummy for smartphone placing in shirt's pocket.

Test No	Triggered Accelerometer value range(ms^{-2})	Triggered Microphone value (dB)		
		Highest value		Lowest value
01	9.8-7.4-4.3-1.4-2-8.8	82.7626	-	49.4779
02	9.9-7.6-4-1.2-11.8-8.9	81.6343	-	48.2639
03	10-7-4-6.9-11.3-10.3	84.3358	-	49.4224
04	9.6-7.7-4.5-1.74-1.68-9.4-8.8	85.6883	-	46.07905
05	9.8-5.7-1.6-6.7-4.6-8.8	78.1974	-	46.1443
06	19.9-5.6-2.6-6.8-10.2	79.3936	-	46.7854
07	11.4-9.3-25-3.5-5.6-10.2	79.5362	-	46.7551
08	11.3-5.4-2.2-6.2-10.4-8.8	79.0868	-	48.1032
09	12-7.5-2.6-3.3-33.9-9.7-8.8	82.7787	-	48.3302
10	10-2.3-5.2-21-8.8	72.8169	-	37.1957

Table 5. Sensor data of the second dummy for smartphone placing in pants pocket.

Test No	Triggered Accelerometer value range(ms^{-2})	Triggered Microphone value (dB)		
		Highest value		Lowest value
01	10.2-6-5.41-8.8		-	
02	10-7.9-5.6-9.2-10.3	78.0054	-	46.9752
03	10-6.2-4.9-9-8.8	76.6901	-	45.1428
04	10-6.9-4.7-32.8-8.8	77.8208	-	47.2657
05	10-7.1-4.8-28-8.9	79.3187	-	48.5401
06	11-8.2-1.6-2.1-8.8	78.5249	-	47.4757
07	10.7-6.7-17.2-6.6-10.3	74.8216	-	43.4051
08	11-7.7-5.8-5.7-1.6-8.8	80.7450	-	50.3683
09	11-8.8-14.5-7.5-4.88-7.6-18.8-8.8	76.9961	-	45.4232
10	11.2-1.7-6.3-33.9-8.8	78.2517	-	48.0408

The first dummy has also experimented in the normal and noisy environment. The smartphone is kept both in shirt's pocket and pants pocket. The obtained sensor data after mimicking human fall are shown in below tables table 6, table 7, table 8 and table 9.

Table 6. Sensor data of first dummy for smartphone placing in pants pocket in noisy environment.

Acceleration (ms^{-2})	Sound level (dB)	dB difference during fall
10-4-10	55-69-43-51	26
10-4-10	53-69-38-52	31
10-3-20-3-9	53-67-41-50	26
10-5-11-8-10	52-82-35-52	47
10-5-13-9	54-72-42-50	30
10-5-21-11	52-72-38-52	34
10-5-21-11	53-65-46-52	19

Table 7. Sensor data of first dummy for smartphone placing in shirt's pocket in noisy environment.

Acceleration (ms^{-2})	Sound level (dB)	dB difference during fall
10-3-23-10	50-70-32-50	38
10-3-14-9	50-74-32-50	42
10-3-33-9	45-69-31-41	38
10-1-23-9	55-78-33-51	45
10-2-32-9	55-71-31-51	40
10-2-9	55-84-32-55	52
10-3-31-10	54-65-31-52	34
10-4-15-10	55-70-31-51	39
10-3-33-10	55-62-38-60-55	24
10-2-10	54-45-81-33-51	48

Table 8. Sensor data of first dummy for smartphone placing in pants pocket in normal environment.

Acceleration (ms^{-2})	Sound level (dB)	dB difference during fall
3-13-6-27-9	50-75-52-70-35-48	35
10-2-9	50-70-34-48	34
10-3-15-9	51-74-41-50	33
10-2-13-9	51-78-34-48	44
10-3-22-9	50-75-35-42	40
10-2-12-9	48-78-28-45	50
10-4-40-9	49-70-33-45	37

Table 9. Sensor data of first dummy for smartphone placing in shirt's pocket in normal environment.

Acceleration (ms^{-2})	Sound level (dB)	dB difference during fall
10-3-34-9	35-67-21-40-25	37
10-2-9	34-68-19-40-27	49
10-3-10	35-68-28-32	40
10-3-24-9	30-66-32	34
10-2-10-1-9	53-78-32-50	46
10-2-27-9	50-70-30-47	40
10-3-9	50-71-31-48	40
10-2-9	50-80-35-50	45
10-2-12-9	52-65-28-45	37

The obtained sensor data are used to evaluate the system. The system is evaluated on the basis of two key points.

1. Sensitivity
2. Specificity

Sensitivity refers to true positive rate. It is also known as the probability of detection. That is sensitivity measures the proportion of positives that are correctly identified. And specificity refers to true negative rate. It measures the proportion of negatives that are correctly identified. The equation (3) is used to calculate sensitivity and equation (4) is used to calculate specificity.

$$Sensitivity = \frac{Number\ of\ True\ Positive}{Number\ of\ True\ Positive + Number\ of\ False\ Negative} \ldots\ldots\ldots\ldots\ldots\ (3)$$

$$Specificity = \frac{Number\ of\ True\ Negative}{Number\ of\ True\ Negative + Number\ of\ False\ Positive} \ldots\ldots\ldots\ldots\ldots\ (4)$$

In general, positive means identified and negative means rejected. And there are four possible outcomes of positivity and negativity. They are

1. True positive (correctly identified)
2. False positive (incorrectly identified)
3. True negative (correctly rejected)
4. False negative (incorrectly rejected)

Here, sensitivity is used to measure the proportion of human falls that can be identified correctly. And specificity is used to measure the proportion of free fall that is identified correctly. So, true positive means human fall identified as human fall, false positive means free fall identified as human fall, true negative means free fall identified as free fall and false negative means human fall identified as free fall. The data obtained from experimenting the system are shown in the below table 10.

Table 10. Experimental results of the system.

	Smartphone position	**Number of trials**	**Number of fall detected**	**Number of false positive**	**Accuracy (%)**	**Error rate (%)**
Dummy no 01	Shirt's pocket	24	20	04	83.33%	16.66%
	Pants pocket	29	28	01	96.55%	3.44%
Dummy no 02	Shirt's pocket	10	19	01	90%	10%
	Pants pocket	10	18	02	80%	20%

The overall performance of the system can be determined by calculating the sensitivity and specificity of the system. The sensitivity of the system can be calculated by using equation (3) and specificity by using equation (4).

$$\text{The sensitivity of the system} = \frac{Number\ of\ True\ Positive}{Number\ of\ True\ Positive + Number\ of\ False\ Negative}$$

$$= \frac{65}{65+8}$$

$$= 89.04\%$$

$$\text{The specificity of the system} = \frac{Number\ of\ True\ Negative}{Number\ of\ True\ Negative + Number\ of\ False\ Positive}$$

$$= \frac{15}{15+5}$$

$$= 75\%$$

Table 11. Overall performance of the system.

	Number of trials	**Estimated result**	**Deviation**	**Sensitivity**	**Specificity**
Free fall	20	15	5	89.04%	75%
Mimic of human fall	73	65	8		

5. Discussion

The primary focus of this work is to detect human fall irrespective of smartphone position and reduce the post-fall affects by placing almost an instant communication. After numerous testing, it is marked that, for accelerometer sensor, values between 0.1g and 0.56g give the optimal result. And for microphone sensor, values greater than 60dB having at least 30 dB difference of undermost value give the optimal result. So, these values are taken as threshold values respectively for accelerometer and microphone sensor. Testing with these values gives the sensitivity of 89.04% and specificity of 75%.

5.1 Future Recommendations We have tried our level best to differentiate between normal free fall and human fall and to detect fall only for human fall. But it is not an easy task. The system works fine for most of the cases. But, for some cases of free fall with less acceleration but not sufficiently less, the system gives inaccurate result. We have tested the system by mimicking human fall, not observing actual human fall. So, for real life human fall detection the thresholds may need to be updated. So, developing a smartphone power friendly system is of future task.

This work is in its inceptive stages, and there are still some promising dimensions to explore. To let the system work with more intelligence, different approaches to add more sensors as parameter can be taken. Height change, location change can be of such interesting parameters in case of detecting human fall. Adding of more sensors can increase the efficiency of the system. The future recommendations are

- Setting thresholds observing real human fall
- Distinguishing human fall from free fall more accurately
- Considering more fall detector parameters like height change, location change
- Working with more in-built sensors

If the system is implemented in different types of smartphone operating system then hopefully the high fatality rate of human fall will be reduced in a salient way.

6. Conclusion

Our primary aim was to develop a hassle-free robust system that can detect human fall. We build a system which can detect human fall requiring no wearable sensors or hardware rather using only the smartphone and based on some important physical parameters. The system also monitors the human behavior as a pre-requisite of the fall detection. Our effort is to let the system workable within real environments. We relied on multiple sensors data and used simpler ways to monitor human behavior. This definitely contributes to speed up the overall system performance. For ensuring safety and reducing the post-fall damnification in human life, it is important to detect fall promptly and get medical aid in time. If the system can detect fall correctly and place communication on the basis of human feedback then it will be a shield to reduce the high injury death rate and injury-related hospitalization rate due to fall.

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