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Fall Detection by Accelerometer and Heart Rate Variability Measurement

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Abstract

Health monitoring, nowadays become very crucial to tackle huge populations health hazards as technological development is ever upbringing that gives opportunity to help people catering for many health risks in easy way. Nowadays health monitoring is a very crucial research field to address huge population health hazards in effective ways using technologies because availability of human health care personnel are inadequate and costly. Accidental fall is one of the common health risk which leads to severe health injuries, even some cases results in death especially for elderly people (> 65 years old). With the help of wearable sensor system (WSS) many fall detection studies take place to minimize the health injuries; however the studies cannot provide expected efficient result. In this study we have proposed a novel technique to identify successfully fall detection and avoid misclassification using accelerometer and ECG sensors. Analyzing both critical physical movement and mental stress, which are evaluated from the signals of accelerometer and ECG sensors respectively, fall detection process can be greatly enhanced.

Index terms— fall detection, wearable sensor system (WSS), heart rate variability (HRV), accelerometer.

Introduction n today's busy and expensive world everyone is so tied up with their daily works that most of the times no family members can be with the elder people of the family 24/7. Also, external help is not affordable for everyone. Again, there are cases where elder people are living in their home all alone independently. In all of the above cases, the common problem is lack of continuous health monitoring of elderly people living alone. Public health care organizations are working to provide affordable health monitoring systems for the elderly. They are using different types of sensors, cameras in every possible location inside the house and collecting data through them. These systems also analyze the data and generate alerts in case of emergency situations.

Scanaill et. al. [4] evaluated the mobility of elderly people using smart homes and different sensors like pressure sensors, pressure mat, smart tiles, sound sensors, infrared sensors etc. to detect any severe health issues beforehand. They also used wearable sensors like pedometers, accelerometers etc. and also combination systems for health monitoring. Their telemonitoring system regularly checked the data from different mobility sensors and depicted if a person is healthy and can live independently or gradually becoming sick or needed external health care. They got good results in most of the cases. In [2], a speech and face recognition system is used to monitor elderly people. Different cameras installed in different rooms captures the facial expressions and movements and the app of a handheld device records voice. According to the video and speech stored in the cloud, a caregiver generates alerts or call the person if necessary. There are other systems like this which cover the overall health monitoring of elderly people. In this paper, we are concentrating on a particular problem for the ageing people. From the statistics, we get an alarming picture of elderly people suddenly falling for different health issues. It says that at least once in a year, almost 30% of the ageing people tends to fall and 75% of these falls are deadly [15]. Even if the person survives, the experience leaves them in depression. We tried a new approach for fall detection which can predict falling from monitoring the movement of the person and sensing the stress level from heart rate simultaneously for early fall detection. Here, we proposed a novel technique by combining responses from accelerometer sensor and heart rate variability sensor to identify fall more precisely over some identical movement like sit down, lie down on bed and take things from ground etc. Web cam based sensor system have high computation and storage constraints. Moreover there are some cases where privacy may be ignored. In addition, our proposed system gives the freedom to move anywhere regardless only a closed area.

The paper is organized as follows: section 2 discusses about some related works in this field, section 3 describes our proposed method and the steps of our working process, section 4 analyzes the experimental results, section 5 discusses the summary of the complete system and section 6 concludes the paper with some possible future works.

1 II.

2 RELATED WORKS

Several works, projects and applications on fall detection are already out there. Each of them tried some new technique or merged some different applications together to get better results. In [3], a Time-Of-Flight 3D camera which could automatically change orientation and position was used to perceive four specific postures for fall detection. They calculated the distance between the floor and the centroid of the human and the time duration of any inactivity in that position and hence detected the fall events. Image based sensors were also used in [5]. They installed a digital camera on ceiling and evaluated five postures of 21 people to detect fall early. The accuracy of the system was 77% and only 5% false alarms were generated. A single USB webcam placed on the top corner of the room was used in [8] for fall detection. They mainly tracked the head of the person and monitored the movement and velocity of the head to detect fall. 19 images were used to test the system (9 fall sequences and 10 normal activities) and it could detect 2 falls out of 3 falling situations.

As we are working with motion and HRV sensors, some related works based on only these two sensors are described below.

3 a) Motion Sensors

Ilievet. al. [1] used a 3D accelerometer to detect and store the motion of the elderly people. The sensors were placed at different rooms of the house and the signals from the sensors were stored in a laptop to analyze further. They analyzed signals of different movements like sitting, walking, sleeping and other possible postures and generated a formula for fall detection. They built an accurate, extremely useful and simple real time system with no false fall detection. Bourke et. al. [6] used tri-axial accelerometer sensors on trunk and thigh of elderly people to detect fall and differentiate them from day to day activities. They used eight types of falls including forward falls, backward falls and lateral falls left and right, performed with legs straight and flexed and used a dataset with 480 types of movements to get perfect results. Their algorithm used upper and lower fall thresholds and they found that the sensor mounted on the trunk gave the best result with almost 100% accuracy. In [7], they tried the same thing with a bi-axial gyroscope based sensor array mounted on the trunk for fall detection. For the same dataset, the result gave 100% accuracy to distinguish between actual fall and regular activities. In [9], a single waist mounted tri-axial accelerometer was used to detect fall events with only 1.03% false alarm rate. They used SVM classifier with up to fifth-order cumulant features to correctly classify fall events and achieved optimization level higher than 95% with second and fifth-order cumulant. SVM was also used in [10] where a wireless gait analysis sensor was worn by the subjects at T4 or waist and experimented for some intentional fall events.

They got 98.7-98.8% accuracy. They extracted six features from the acceleration and angular velocity of the subject and after transmitting the data wirelessly to a computer, they classified them to check for a fall. Accelerometer based fall detection was also used in [11] where 12 out of 15 falls were detected accurately in a real-life situation with 80% sensitivity and .025 false alarm rate. They monitored 16 elderly people for 15500 hours for their experiments. Accelerometer was used also in [12] integrated in a smart home environment via Bluetooth. The elderly people were to wear a small, cheap and low power consuming accelerometer which can generate alerts after fall detection in a smart home environment. A wrist worn wearable device containing an accelerometer was used to detect fall in [13]. But they took a different approach for their fall detection algorithm and classification algorithm of daily life activities. Their power competent algorithms were implemented in a simple 8-bit microcontroller unit and as they used an interrupt-based system which was activated only after getting an interrupt signal from the accelerometer, they had to work with less data, hence the system was more efficient. 36 humans were tested for total 702 types of movements in a laboratory setting for fall detection in [14]. Their wearable device consist of accelerometer and gyroscope was wireless and worn on chest. Their algorithm presented specificity of 96.2% and specificity of 96.3% for the dataset which was divided into two parts, for development of the system and for assessment. The use of gyroscope improved the results of fall detection than using only an accelerometer.

4 b) HRV Sensors

At the time of critical moment such as any kind of accident which creates acute mental stress in human nervous system, elder persons face unwanted fall unlike normal movement, which create a physiological stress in their nervous system. The mental stress can be identified by measuring heart rate variability (HRV). HRV refers to the beat to beat alteration of heart rate. There are two types of HRV, High HRV which refers a good adaptability of autonomous nervous system or in other word a good mental health and Low HRV that represent abnormal physiological condition and mental stress [18].

Using Electrocardiogram (ECG) biosensor we can trace the electrical signal in the heart [17]. The length between two consecutive heart beat in the signal is called cycle length. In HRV analysis, cycle length variability or in other term "RR variability" is being used [19][20][21][22] **??**23]. R is a point corresponding to the peak of the QRS complex of the ECG wave; and RR is the interval between successive Rs. The P wave represents atrial depolarization, the QRS represents ventricular depolarization, and the T wave reflects the rapid repolarization of the ventricles.

5 PROPOSED METHOD

The method we are proposing is very simple and easy to implement. It needs an accelerometer and a heart rate variability sensor. The algorithm takes the movements of the person from the accelerometer and the heart rates from the HRV sensor as inputs. Then it analyzes both the signals separately to check any abnormality. It shows alerts for fall detection only if it gets abnormal results from both the sensors. Parameters of our proposed sensor as follows: true and signal from heart rate variability sensor response for critical stress in mind is also true then, Identify a true fall detection when both censor response are true. 4. Identify a false fall detection when any one of the two sensors response is false.

6 b) Movement Detection with Accelerometer

The acceleration of the three dimensional axis are the key parameters to define critical state during fall occurs [16]. Following steps are designed to define fall state identification: 1. Collect tri-axial acceleration Ax ,Ay and Az from X, Y and Z dimension respectively. 2. Calculate total sum of acceleration vector, Acc as :Acc = ????? 2 + ???? 2 + ???? 2

3. Set lower fall threshold (LFT) at the local minima for the Acc recorded data, which is known as signal lower peak value. 4. Set upper fall threshold (LFT) at the local maxima for the Acc recorded data , which is known as signal upper peak value. 5. When Acc <= LFT and Acc >= UFT then Fall state identified.

7 c) Stress Detection with HRV Sensor

We have used Time domain analysis for HRV which is simple and less sensitive to noise and signal artifacts than frequency domain method. Time domain analysis can be directly applied onto the successive RR interval values. Time domain parameters mean R-R (MRR), mean HR and Standard deviation of all NN intervals (SDNN) are mostly associated with the overall variability of the R-R intervals. MRR and SDNN is are calculated as follows [16]:MRR = ?? ´ = 1 ???1 ? ??(??) ?? ??=2 MDNN = ? 1 ???1 ? ???(??) ? ?? ´?2 ?? ??=2

Here, N indicates the total number of successive RR intervals of heart beats. The number of adjacent NN intervals differing by more than 50 m sec (NN50count) is calculated. The percentage of differences between adjacent NN intervals differing by more than 50 m sec (pNN50%) is calculated as:

8 EXPERIMENTAL RESULTS

By analyzing different possible movement for elderly people where we have taken most 4 types movement on 1) daily activities like walking, sitting in normal speed, 2) Fall like activity like quickly lay down on the bed or sit down on chair in normal situation, 3) sit down or lay down on bed in normal speed while feeling stress and 4) Quick fall down while feeling stress.

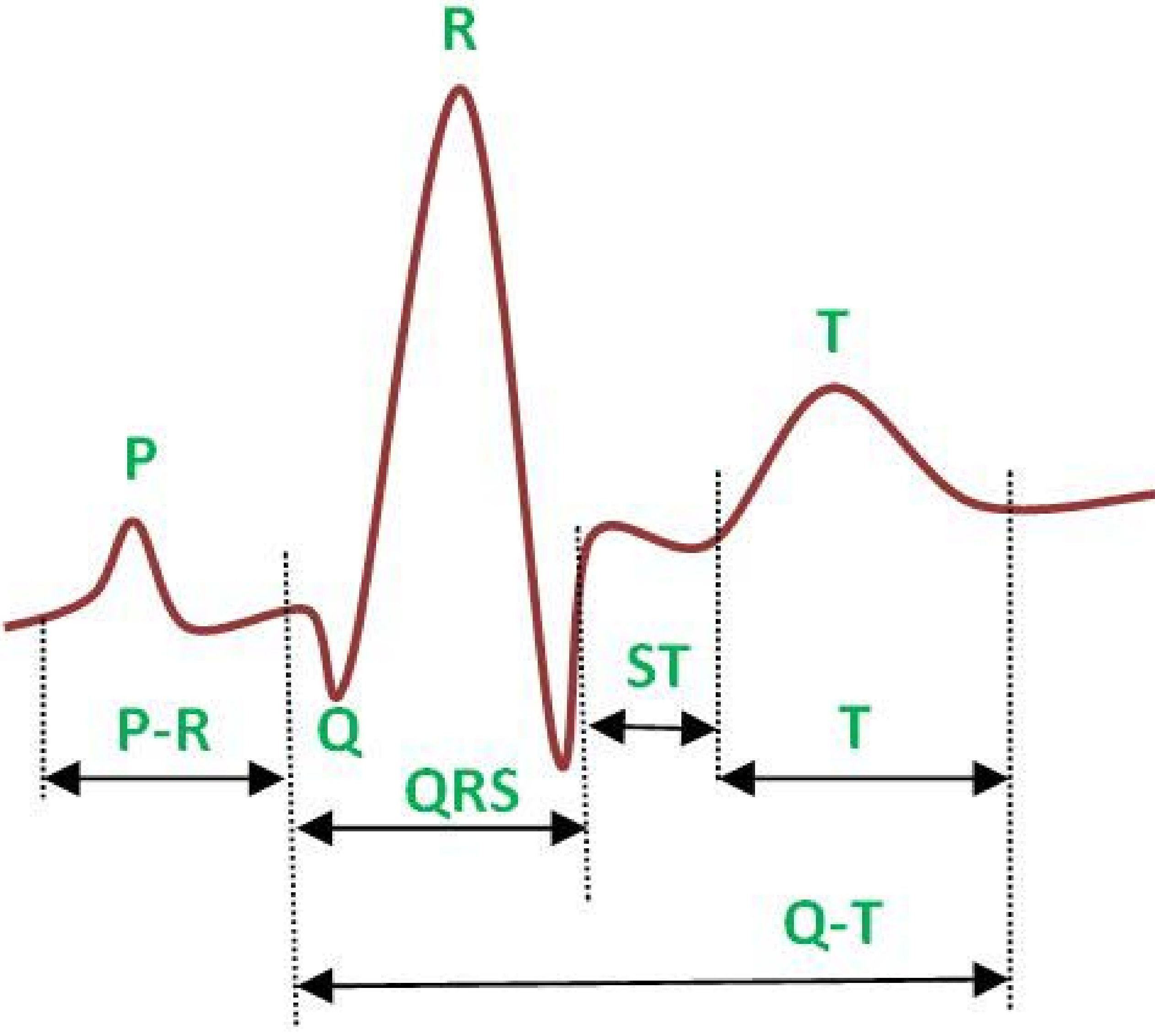
There were total 50 people attendants in our experiment including 30 elderly people (age 60-80) and 20 volunteers (age 20-40). We have collected 400 samples to examine our system.

9 CONCLUSION

Wearable Sensor System is a near optimal technique to identify fall detection in low cost which maintains privacy issues for individuals. Utilizing both movement sensor such as accelerometer and heart rate variability sensor like ECG, we can implement the credible and efficient fall detection for aged people. In future we will develop to a community alert system for a [1]

1

Figure 1: Fig. 1 :



2

Figure 2: FallGFig. 2 :

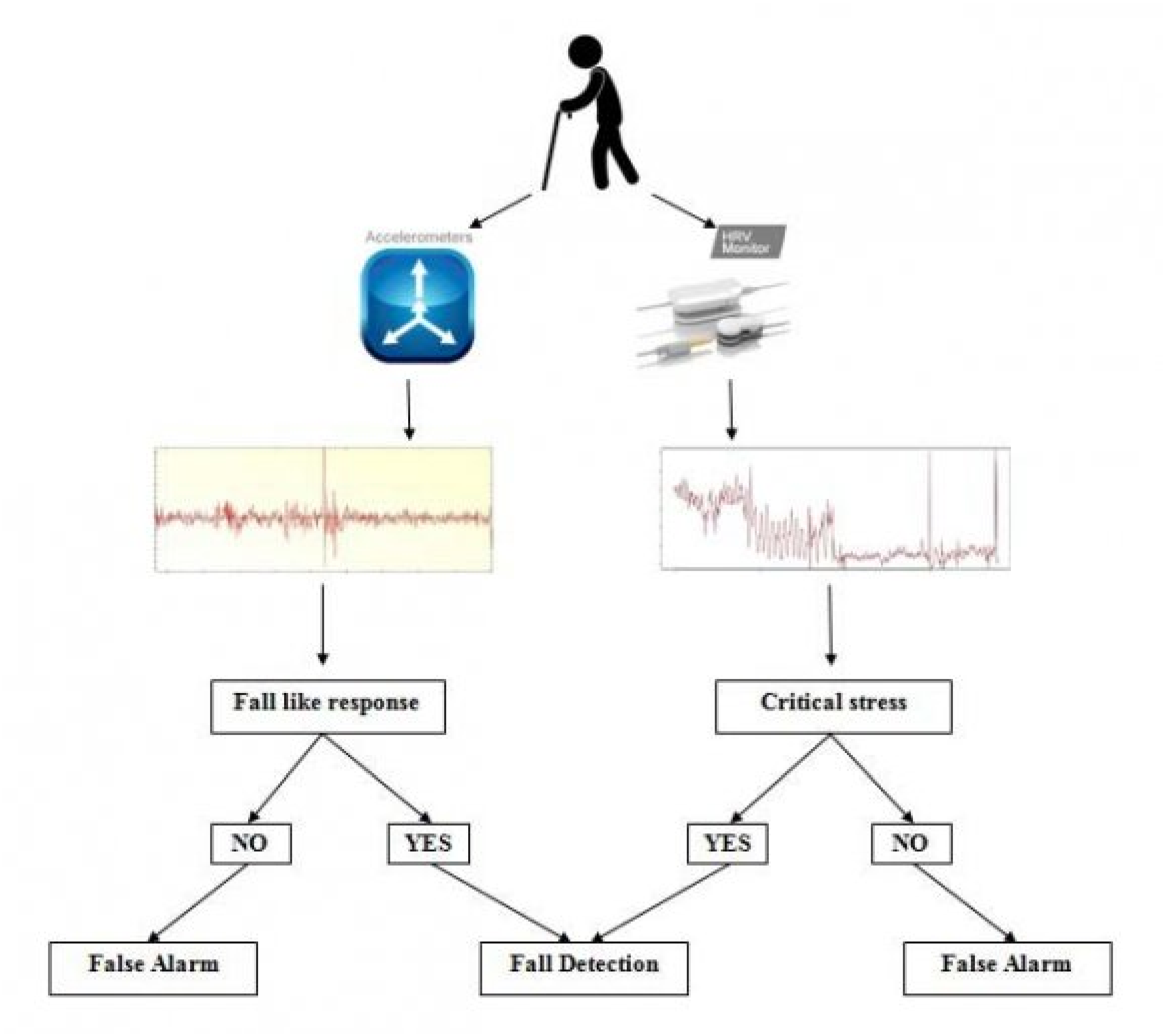


Figure 3:

1

sensor	parameters
Accelerometer	Acceleration of X, Y and Z axis, Total sum of acceleration Acc, LFT, UFT
ECG	Mean RR, SDNN, pNN50, LF, HF, LF/HF ratio

a) Algorithm: 1

1. Receive signal from accelerometer and heart rate variability sensor.
2. Analyze these signal individually.
3. If signal from accelerometer find fall like response is

Figure 4: Table 1 :

2

Sample categories	1	2	3	4
Total samples	100	100	100	100

Figure 5: Table 2 :

3

Sample categories	1	2	3	4
correct	100	98	98	96
incorrect	0	2	2	4
Percentage of correctness	100.0	98.0	98.0	96.0
	V.			

Figure 6: Table 3 :

lonely people when a fall detection identified to take medical care immediately.

[Shibuya et al. (2015)] 'A real-time fall detection system using a wearable gait analysis sensor and a Support Vector Machine (SVM) classifier'. N Shibuya , B T Nukala , A I Rodriguez , J Tsay , T Q Nguyen , S Zupancic , D Y C Lie . *Eighth International Conference on Mobile Computing and Ubiquitous Networking (ICMU)*, Jan. 2015. p. .

[Pan and Tompkins ()] 'A real-time QRS detection algorithm'. J Pan , W J Tompkins . *IEEE Transactions on Biomedical Engineering* 1985. 32 (3) p. .

[Cliodhna et al. (2006)] 'A Review of Approaches to Mobility Telemonitoring of the Elderly in Their Living Environment'. N´i Cliodhna , Sheila Scanaill , Pierre Carew , Barralon , Declan Norbertnoury , Gerard M Lyons , Lyons . *Annals of Biomedical Engineering* April 2006. 34 (4) p. .

[Bourke and Lyons ()] 'A threshold-based falldetection algorithm using a bi-axial gyroscope sensor'. A K Bourke , G M Lyons . *Medical Engineering & Physics* 2008. 30 p. .

[Diraco et al. (2010)] *An Active Vision System for Fall Detection and Posture Recognition in Elderly Healthcare, Design, Automation & Test in Europe Conference & Exhibition (DATE)*, G Diraco , A Leone , P Siciliano . March 2010. p. .

[Tarvainen et al. ()] 'An advanced detrending method with application to HRV analysis'. M P Tarvainen , P O Ranta-Aho , P A Karjalainen . *IEEE Transactions on Biomedical Engineering* 2002. 49 (2) p. .

[Lee and Mihailidis (2005)] 'An intelligent emergency response system: preliminary development and testing of automated fall detection'. Tracy Lee , Alex Mihailidis . *Journal of Telemedicine and Telecare* February 2005. p. .

[Mateo and Laguna ()] 'Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal'. J Mateo , P Laguna . *IEEE Transactions on Biomedical Engineering* 2003. 50 (3) p. .

[Ivo et al. (2011)] 'Automatic fall detection of elderly living alone at home environment'. T Ivo , Iliev , D Serafim , Ivan A Tabakov , Dotsinsky . *Global Journal of Medical research* December 2011. 11 p. .

[Shamim Hossain and Muhammad ()] *Cloud-Assisted Speech and Face Recognition Framework for Health Monitoring*, M Shamim Hossain , Ghulam Muhammad . 2015.

[Mckinley and Levine] *Cubic spline interpolation*, S Mckinley , M Levine . `http://online.redwoods.cc.ca.us/instruct/darnold/laproj/Fall98/SkyMeg/proj.pdf`

[Bourke et al. ()] 'Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm'. A K Bourke , J V O'brien , G M Lyons . *Gait & Posture* 2007. 26 p. .

[Duthie ()] 'Falls'. E Duthie . *Medical Clinics of NorthAmerica* 1989. 73 p. .

[Lin et al. ()] 'Mining physiological conditions from heart rate variability analysis'. C W Lin , J S Wang , P C Chung . *IEEE Computational Intelligence Magazine* 2010. 5 (1) p. .

[Rougier et al. (2006)] 'Monocular 3D Head Tracking to Detect Falls of Elderly People'. Caroline Rougier , Jean Meunier , Alain St-Arnaud , Jacqueline Rousseau . *Proceedings of the 28th IEEE EMBS Annual International Conference*, (the 28th IEEE EMBS Annual International ConferenceNew York City, USA) Aug 30-Sept 3, 2006. p. .

[Quoc et al. ()] 'Optimization of an Accelerometer and Gyroscope-Based Fall Detection Algorithm'. T Quoc , Uyen D Huynh , Lucia B Nguyen , Nazaninghassemian Irazabal , Binh Q Tran . ID 452078. *Journal of Sensors* 2015. 2015.

[Yuan et al.] 'Power-Efficient Interrupt-Driven Algorithms for Fall Detection and Classification of Activities of Daily Living'. Jian Yuan , Kokkiong Tan , Tong Heng Lee , G C H Koh . *Sensors Journal* IEEE. (3) p. .

[Segerstrom and Miller ()] 'Psychological Stress and the Human Immune System: A Meta-Analytic Study of 30 Years of Inquiry'. S C Segerstrom , G E Miller . *Psychological Bulletin* 2004.

[Wang and Huang ()] 'SDNN/RMSSD as a surrogate for LF/HF: a revised investigation'. H M Wang , S C Huang . *Model and SimulEngin* 2012.

[Kangas et al. ()] 'Sensitivity and False Alarm Rate of a Fall Sensor in Long-Term Fall Detection in the Elderly'. M Kangas , R Korpelainen , I Vikman , L Nyberg , T Jämsä . *Clinical, Behavioural and Technological Gerontology* 2015. 61 (1) . (International Journal of Experimental)

[Sprute et al. ()] 'Smart Fall: Accelerometer-Based Fall Detection in a Smart Home Environment'. Dennis Sprute , Alexander Aljoschapörtner , Matthias Weinitschke , König . *Proceedings of 13th International Conference on Smart Homes and Health Telematics, ICOST 2015*, (13th International Conference on Smart Homes and Health Telematics, ICOST 2015Geneva, Switzerland) June 10-12, 2015. p. .

[Satya Samyukta Kambhampati et al. ()] 'Unified framework for triaxial accelerometer-based fall event detection and classification using cumulants and hierarchical decision tree classifier'. Satya Samyukta Kambhampati , M Singh , Barathram Sabarimalai Manikandan , Ramkumar . *Healthcare Technology Letters* August2015. p. .