A Wearable IoT-Based Fall Detection System Using Triaxial Accelerometer and Barometric Pressure Sensor

Chapter *in* Lecture Notes in Computer Science · August 2020

DOI: 10.1007/978-3-030-58008-7_13

A Wearable IoT-Based Fall Detection System Using Triaxial Accelerometer and Barometric Pressure Sensor

Elahe Radmanesh[1](✉), Mehdi Delrobaei[1], Oussama Habachi[2], Somayyeh Chamani[1], Yannis Pousset[2], and Vahid Meghdadi[2]

[1] Faculty of Electrical Engineering, K. N. Toosi University of Technology, 1631714191 Tehran, Iran
e_radmanesh@email.kntu.ac.ir, delrobaei@kntu.ac.ir, schamani2002@yahoo.com

[2] University Limoges, XLIM, UMR 7252, Limoges, France
{oussama.habachi,vahid.meghdadi}@xlim.fr, pousset@sic.univ-poitiers.fr

Abstract. The aim of this research work is to develop a wearable and IoT-based fall detection system that can potentially be integrated within a smart home or a community health center to improve the quality of life of the elderly. This system would enable caregivers to remotely monitor the activities of their dependents and to immediately be notified of falls as adverse events. The proposed hardware architecture includes a processor, a triaxial accelerometer, a barometric pressure sensor, a Wi-Fi module, and battery packs. This unobtrusive architecture causes no interference with daily living while monitoring the falls. The output of the fall detection algorithm is a two-state flag, transmitted to a remote server in real-time.

Keywords: Fall detection · IoT architecture · Accelerometry · Pressure sensing · Elderly care

1 Introduction

The worldwide population of the elderly aged 60 or over is expected to more than double by 2050 and to more than triple by 2100, increasing globally from 962 million in 2017 to 2.1 billion in 2050 and 3.1 billion in 2100 [1]. According to the WHO report, falls are one the leading external causes of unintentional injuries [2].

Roughly 40% of falls in elderly are fatal [3], and 20%–30% of non-lethal falls can lead to severe injuries such as lacerations, hip fracture, and head traumata [4]. In the most optimistic case, falls increase disability and extend the rehabilitation period. Women are more likely than men to be injured, leading to twice rate of hip fractures [5]. When an elder person falls and becomes unconscious or is unable to move their body, they succumb to the injuries caused by the fall [6]. Half of those who experienced an extended time lying on the ground passed away within 6 months of the fall [7].

O. Habachi et al. (Eds.): UNet 2019, LNCS 12293, pp. 158–170, 2020.
https://doi.org/10.1007/978-3-030-58008-7_13

Fall also occurs frequently in medical health care centers or hospitals and there are several risk factors which could lead to falls in such settings. These include changes in cognitive, visual, musculoskeletal, sensory or cardiovascular systems as well as extrinsic factors normally related to the environment such as trip hazards and poor lighting [8, 9].

The degree of danger from a fall for aging persons is frequently decided by the location of the fall, time of detecting the fall, duration and time of transfer and rescue services. Automatic detection of fall along with the locations help medical staff to be dispatched immediately [10].

A variety of different tools and methods have been globally developed for smart homes to execute remote health monitoring of physically-impaired and elderly people. A review of the current literature indicates that most elderly people would benefit from real-time, unobtrusive monitoring systems – mainly utilizing wireless sensor networks. Such systems keep track of the daily activities of the elderly at home, enabling them to live independently [10–22].

To detect physical activities (including adverse events such as fall), sensors are either allocated in the surroundings or placed on the person's body to continuously gather data. Based on pre-described detection algorithms, movements are detected and classified as normal or abnormal patterns. The common types of sensors to achieve such a task are listed in Table 1.

Wearable sensors and vision-based systems were initially proposed and later two emerging technologies, depth camera- and radar-based systems, were proposed. It is emphasized in the literature that elderly people prefer unobtrusive in-home sensing with no need to wearing noticeable devices, no interference with daily living, no need to learn new technical skills, and above all, no need to capture video [25].

Table 1. The common technologies for real-time fall detection systems.

Sensor type	Description	Ref.
Accelerometer	Simple linear acceleration sensing to detect any abnormal changes in x, y, or z accelerations	[11, 12]
IMU	Inertial measurement units positioned on the body that generate an alert if there is an abrupt change in motion	[13, 14]
Pyroelectric IR	Array of wall-mounted thermal detectors (passive infrared)	[15]
Barometric pressure	Measuring the altitude of different positions on the human body	[16]
EMG	Wearable, wireless, and minimally invasive surface Electromyography-based setup	[17, 18]
Vision	Human movement detection using vision-based cameras	[19, 20, 30]
Sound and vibration	Floor vibration and sound sensing	[34]
Doppler radar	Detecting object's motion by analyzing changes in the frequency of the returned microwave signal	[21, 22]

(*continued*)

Table 1. (*continued*)

Sensor type	Description	Ref.
UWB radar	Either wall- or ceiling-mounting ultra-wideband radar, providing 3D depth	[23, 24]
IOT Architecture	Includes many sensing devices such as audio, ambient, video, and wearables	[26, 32, 33]

The sensor data (mentioned in Table 1) have been generally utilized for monitoring, supporting, detecting, informing, and gait analysis of elderly people [26]. The main data analysis and classification techniques for fall detection and prediction are listed in Table 2.

Table 2. Main methods of analysis and classification for fall detection and prevention.

Method	Reference
Fuzzy logic	[12]
Bayesian filtering	[27, 28]
K-nearest Neighbor	[29, 36, 37]
Support Vector Machine	[30]
Neural Network	[38, 39]
Principle Component Analysis	[35]
Multi-layer perception	[40]

A complete review of fusion algorithms has been presented in [41]. Fusion algorithms are recent advancements in fall detection and fall prevention studies. In fall detection, data related to posture, inactivity, and presence is analyzed. In fall prevention, fusion systems provide data on human balance (such as static and dynamic sway and ground reaction forces) and gait (such as step and stride lengths, step and stride time, and center of pressure frequency) indices to assess falling risk [41].

It is finally noted that any literature review on the fall detection systems would lack a common agreement on the performance of the classification methods. The possible reasons could be: (a) each study provides a different classification approach based on the understanding of the nature of the fall detection/prevention problem, (b) aside from the classification algorithm, other factors would potentially affect the sensitivity and specificity of the classification method; factors such as signal conditioning method and the extracted features.

None of the sensor types proposed in the literature seem to be necessarily better or worse than other sensor types. Hence, the selection of the sensors (or sensor fusion strategy) depends on various parameters including coverage area, obtrusiveness, privacy issues, power limitations, and cost. The most promising solution to solve the fall detection problem seems to be an IoT-based system, because of the high reliability especially for the alert system that should be as independent as possible of the elderly and at the same time low error.

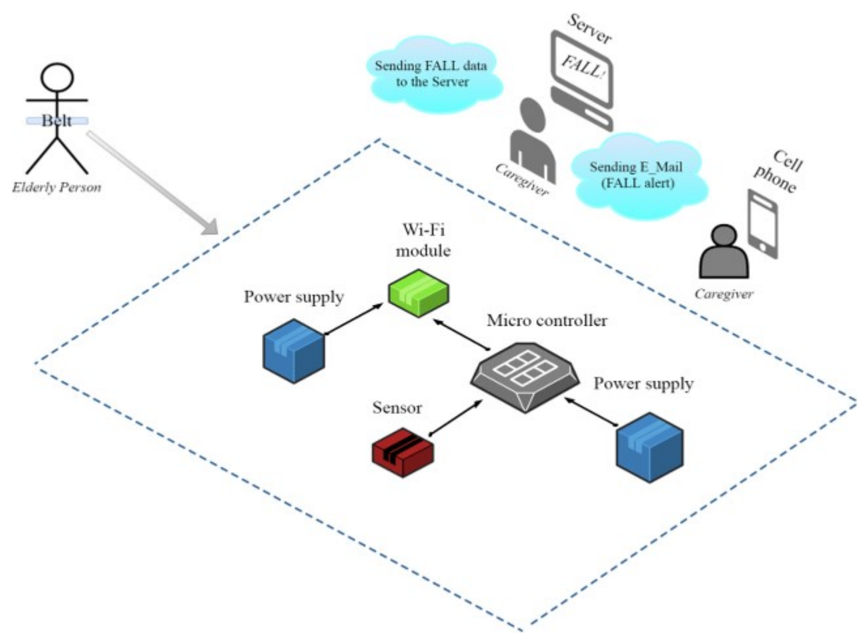

Fig. 1. An overview of the system.

In this paper, we mainly focus on the design preliminary evaluation of a wearable, easy to use, and reliable fall detection system. This system connects to the Internet and transfers a fall-flag to a remote server in real-time (Fig. 1).

2 System Architecture

Figure 1 illustrates an overview of the proposed system and the realized prototype is shown in Fig. 2. The system comprises a microcontroller (main board), a triaxial accelerometer (IMU), a barometric pressure sensor, a Wi-Fi module, and two battery packs (power supply). The sensors are integrated on a single board sized 25 mm by 15 mm (MPU9250, InvenSense Inc., CA and BMP280, Bosch Sensortec, GmbH). The programmable full scale range of the accelerometer is ±2, ±4, ±8 and ±16 g and its normal operating current is roughly 450 μA. BMP280 pressure range is 30,000 Pa to 110,000 Pa with relative accuracy of 12 Pa. The system also employs an STM32 microcontroller (Nucleo-f411RE). The sensors and the microcontroller unit receive data from the sensors via an I^{2}C bus.

As mentioned in Sect. 1, a variety of different fall detection algorithms have already been developed, but most of them are not optimized to be implemented on a wearable real-time system. In this work, we employed a reliable algorithm, specifically developed and optimized for STM32 microcontrollers (MotionFD middleware library, STMicroelectronics Corp, Geneva, Switzerland) [42].

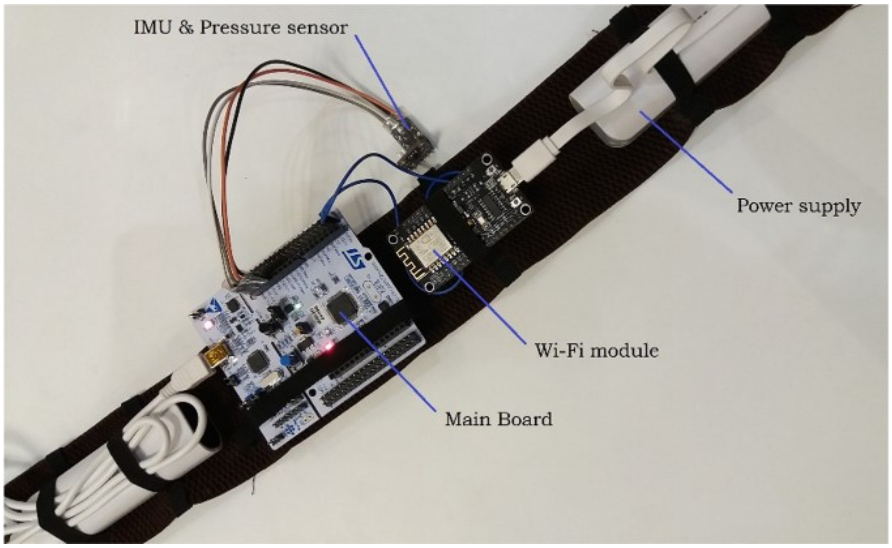

Fig. 2. The hardware architecture of the proposed fall detection system.

This algorithm acquires data from the accelerometers and the barometric pressure data with specific scales and sampling frequencies. The Motion FD API logic sequence and algorithm is illustrated in Fig. 3. According to the method presented in [43], the parameters are calculated as follows:

$$\sigma_{xyz} = \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2} \tag{1}$$

$$\sigma_a = \sigma(\sqrt{A_x^2 + A_y^2 + A_z^2}) \tag{2}$$

$$\theta = Arccos\left(\frac{A_z^2}{\sqrt{A_x^2 + A_y^2 + A_z^2}}\right) \tag{3}$$

where σ_{xyz} is the magnitude of the standard deviations of all three axes, σ_a is the standard deviation of the vector magnitude, and θ is the forward falling angle acceleration. The most important difference between σ_a and σ_{xyz} is their degree of dependence to the angle θ; i.e., σ_a is independent of θ, but σ_{xyz} is sensitive to θ.

In order to use this library with the selected sensors, the sample rate of both sensors was set to 25 Hz, the unit of measurements for the accelerometer was set to mg and of the pressure sensor to hPa. The accelerometer data was initially calibrated by subtracting the zero-g-bias voltage on each axis. The zero-g-bias describes the output voltage under solely gravitational forces.

Detecting the falls refers to a specific register configuration (Fig. 4). The acceleration measured along all the axes is set to zero. In a real case, a “fall zone” is defined around the zero-*g* level (Fig. 4) where all the accelerations are small enough to generate the interrupt. Two important parameters for detecting fall are threshold and duration: the threshold parameter defines the fall zone amplitude while the duration parameter defines the minimum duration of the fall interrupt event to be recognized. The algorithm is able to detect the fall and generate an interrupt if the z-axis acceleration falls below a certain threshold.

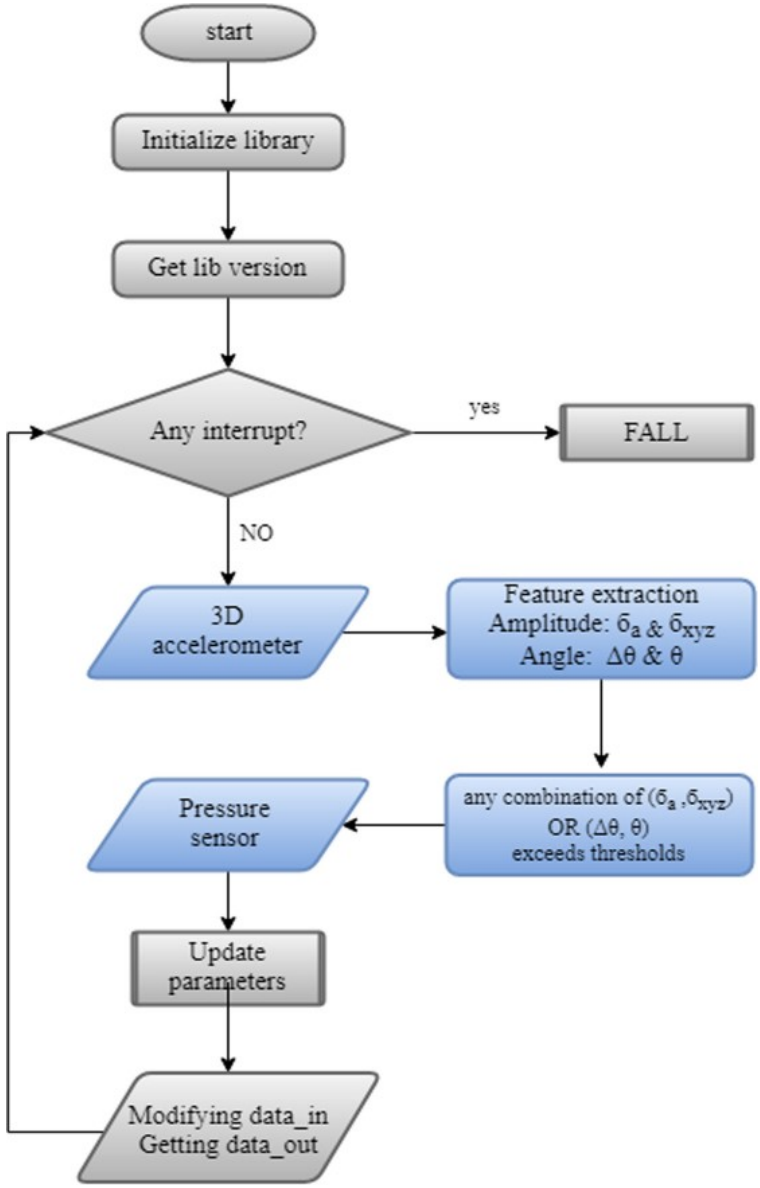

Fig. 3. Motion FD API logic sequence and algorithm.

The suggested settings involve [42] (Fig. 5):

- Input data are the sensor output (select the output data rate ODR >= 25 Hz)
- Thresholds can be set to 0.4 g
- Timeout selectable (e.g. $0 \times 03 = 120$ ms which defines the time duration of the fall)
- Output is an interrupt when a fall acceleration profile is detected for 120 ms

There is a register to control the accelerometer data in which four most significant bits (MSBs) are used for adjusting the sensor data frequency as inputs to the library. To modify the time duration, the fifth MSB of FALL register needs to be adjusted. This specific register is also used to configure the threshold parameter (using the rest of the bits). The unsigned threshold values are listed in Table 3. The values given in this table are valid for each accelerometer full-scale range.

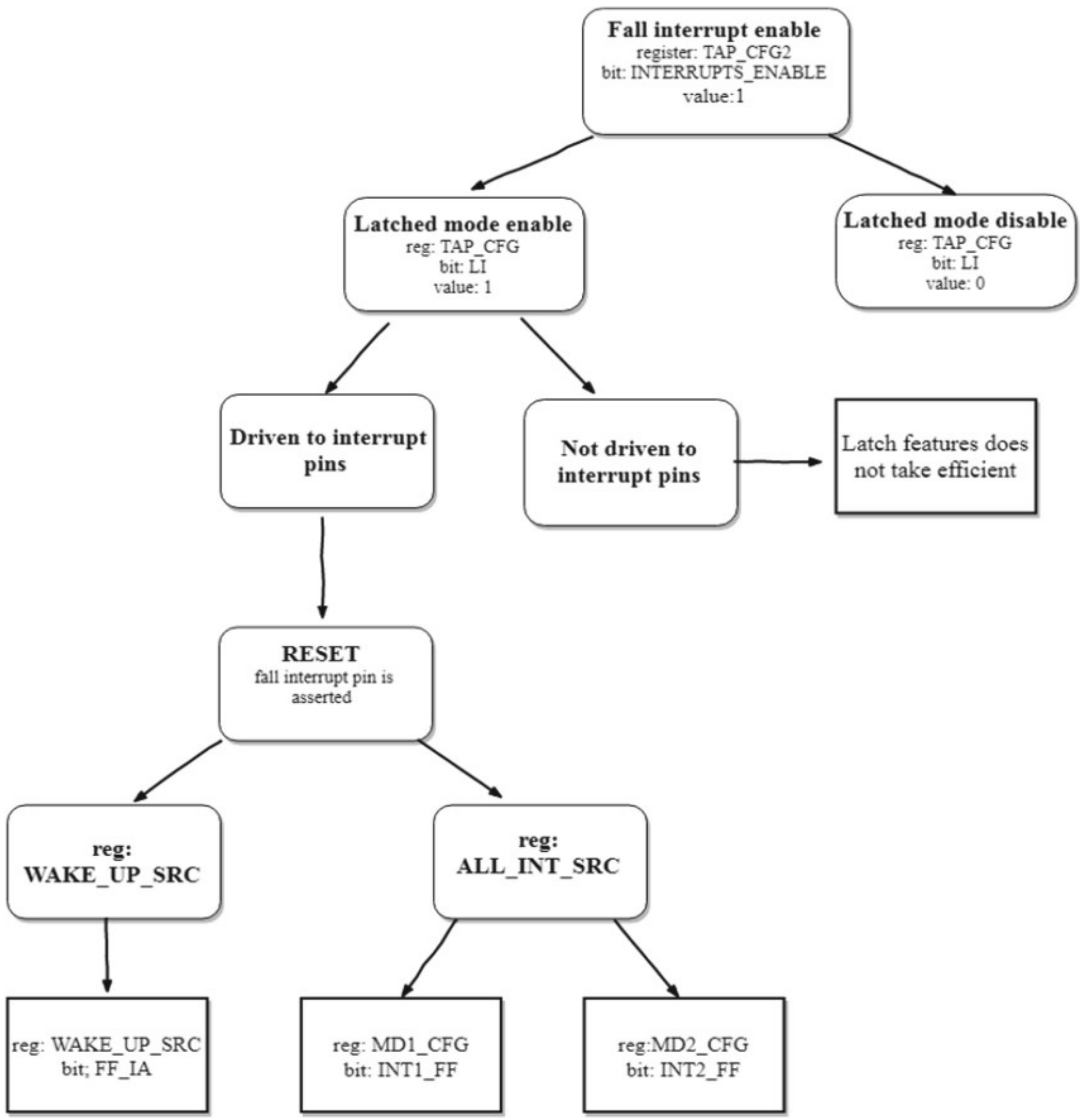

Fig. 4. Registers configuration.

Table 3. Fall threshold LSB value

FALL_FF_THS[2:0]	Threshold LSB value
000	156
001	219
010	250
011	312
100	344
101	406
110	469
111	500

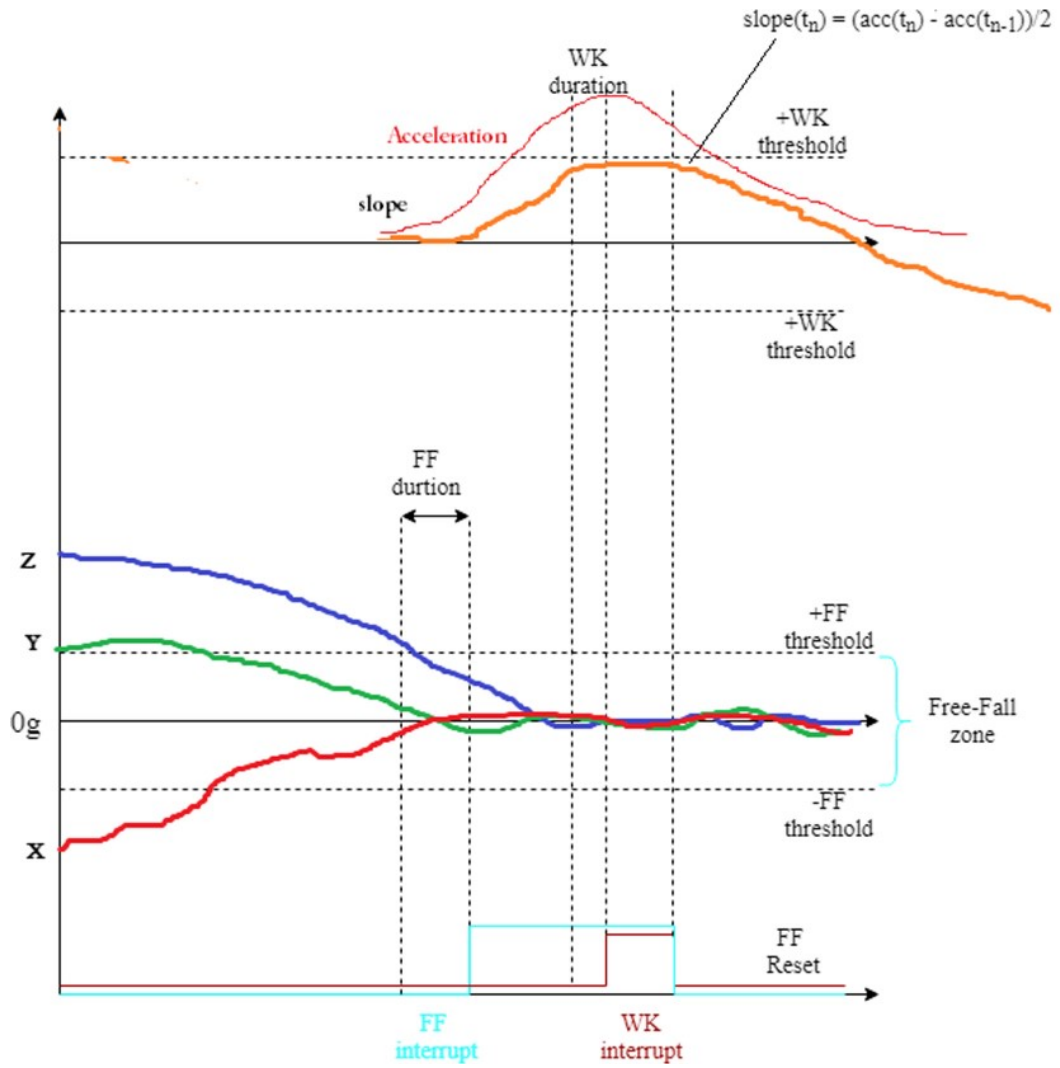

Fig. 5. Fall interrupt and Wake-up interrupt [42].

When two necessary conditions for detecting fall (threshold and time duration) are met, a fall interruption occurs. According to Fig. 4, the tool for resetting the fall interrupt is the WK interrupt. As shown in Fig. 5, the wake-up functionality is based on the comparison of the threshold value with half of the difference between the acceleration of the current and the previous sample data. Therefore, the library will be ready for receiving the next fall interrupt.

Finally, the output of the fall detection algorithm is a two-state flag (either no-fall = 0 or fall = 1). This flag is transmitted in real-time to a server through a low-cost mini WiFi microchip with full TCP/IP stack (ESP8266). The Thinger.io Open Source IoT Platform was also selected to record, manage and display the fall flags in real-time. We can register the data and the time of receiving each data in data buckets and display necessary information on the dashboard section of the server.

3 Results and Discussions

Figure 6 indicates the experimental setup. Once the system is initialized, it begins sending "zeros" to the server which indicates that no fall has initially occurred and the connection with the server is stable. In case a fall event occurs, the system will immediately send a different flag (in the current architecture, a value of 1). The fall event will be displayed and warning messages will be dispatched according to the predefined contacts (either email or text message).

The system was finally tested repeatedly on real (experimental?) falling scenarios at home environment. A single participant performed a variety of different activities of daily living (including sit to stand, body bending, normal walking, and stand to sit). Additionally, forward falls were emulated randomly between the tasks. The participant repeated the tasks (in randomized order) minimum 20 times. None of the normal activities were detected as falls (No false positive). Regarding the falls, only one event (out of twenty) of falls was not detected by the device. The numbers of the errors and the time to display the fall events on the server were recorded. The specifications of the system are listed in Table 4.

Table 4. The specifications of the proposed fall-detection system.

Measure	Value
Net Weight	50 gr
Weight (including batteries and the belt)	300 gr
Processor's power consumption	1.18 W
Transmitter's power consumption	1.44 W
Error rate	$\approx$5%
Execution time (on the wearable device)	$<$1 s
Server display time delay	$<$60 s

Fig. 6. The experimental setup; the below blocks show the screenshots of the sever corresponding to each incident (including time and the fall flag).

Some current IoT solutions focus on developing algorithms implemented on the server side; hence, sensors' raw data needs to be transferred to the server via the communication link. We proposed a stand-alone Wi-Fi enabled architecture and believe that the proposed architecture is reliable since:

a) An efficient algorithm can easily be implemented on a small-sized processor. The data will be processed locally and the fall-flag will be transferred to the server.
b) The system sends a single flag in real-time, therefore if no data was received from the transmitter, a warning message (inaccessible device) could be immediately generated and sent to the family or health professionals.
c) The modular design of the proposed system allows powering the processor and the transmitter separately. So, if the processor suddenly loses power or the processor fails, this failure (i.e., no flag generated) could be detected locally and an appropriate flag value be transmitted to the server. On the other hand, if the transmitter suddenly loses power, the processor could detect this incident (through monitoring the voltage level of the second battery pack) and enable an appropriate output pin on the processor.

4 Conclusions

Fall detection is one of the major challenges in the elderly care, especially for people living alone. Although many fall detection systems have been proposed in the literature, yet few of them can be easily implemented on a wearable platform. The design of a suitable fall detection system requires an effective integration approach, considering aspects such as hardware architecture, algorithm, and implementation characteristics. We proposed and successfully evaluated a wearable, IoT-based fall detection system that enables caregivers to remotely monitor the activities of their dependents and to immediately be notified of falls as adverse events. The system is simple and reliable, capable of sending notifications through a remote server.

References

1. Unies, Nations: World population prospects: the 2017 revision: key findings and advance tables. UN (2017)
2. World Health Organization: Ageing, and Life Course Unit. WHO global report on falls prevention in older age (2008)
3. Doughty, K., Lewis, R., McIntosh, A.: The design of a practical and reliable fall detector for community and institutional telecare. J. Telemed. Telecare **6**(Supplement 1), 150 (2000)
4. Sterling, D., O'Connor, J., Bonadies, J.: Geriatric falls: injury severity is high and disproportionate to mechanism. J. Trauma. **50**(1), 116–119 (2001)
5. Vellas, B.J., Wayne, S.J., Romero, L.J., Baumgartner, R.N., Garry. P.J.: Fear of falling and restriction of mobility in elderly fallers. Age Ageing, **26**(3), 189–193 (1997)
6. Kaluža, B., Luštrek, M.: Fall detection and activity recognition methods for the confidence project: a survey. In: Proceedings of the 12th International Multiconference Information Society, vol. A, pp. 22–25 (2010)
7. Wild, D., Nayak, U.S., Isaacs, B.: How dangerous are falls in old people at home? Br. Med. J. (Clin. Res. Ed.) **282**(6260), 266–268 (1981)
8. King, R.C., Atallah, L., Wong, C., Miskelly, F., Yang, G.Z.: Elderly risk assessment of falls with BSN. In: 2010 International Conference on Body Sensor Networks, pp. 30–35. IEEE. June 2010
9. Mitty, E., Flores, S.: Fall prevention in assisted living: assessment and strategies. Geriatric Nurs. **28**(6), 349–357 (2007)
10. Naranjo, P.G.V., Shojafar, M., Mostafaei, H., Pooranian, Z., Baccarelli, E.: P-SEP: a prolong stable election routing algorithm for energy-limited heterogeneous fog-supported wireless sensor networks. J. Supercomput. **73**(2), 733–755 (2017)
11. Thammasat, E., Chaicharn, J.: A simply fall-detection algorithm using accelerometers on a smartphone. In: The 5th 2012 Biomedical Engineering International Conference, pp. 1–4. IEEE, December 2012
12. Shen, V.R., Lai, H.Y., Lai, A.F.: The implementation of a smartphone-based fall detection system using a high-level fuzzy Petri net. Appl. Soft Comput. **26**(390–400), 2015 (2015)
13. Biroš, O., Karchnak, J., Šimšík, D., Hošovský, A.: Implementation of wearable sensors for fall detection into smart household. In: 2014 IEEE 12th International Symposium on Applied Machine Intelligence and Informatics (SAMI), pp. 19–22. IEEE, January 2014
14. Shastry, M.C., et al.: Context-aware fall detection using inertial sensors and time-of-flight transceivers. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 570–573. IEEE, August 2016
15. Sixsmith, A., Johnson, N., Whatmore, R.: Pyroelectric IR sensor arrays for fall detection in the older population. In: Journal de Physique IV (Proceedings), vol. 128, pp. 153–160. EDP Sciences (2005)
16. Lu, W., Wang, C., Stevens, M.C., Redmond, S.J., Lovell, N.H.: Low-power operation of a barometric pressure sensor for use in an automatic fall detector. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2010–2013. IEEE, August 2016
17. Cheng, J., Chen, X., Shen, M.: A framework for daily activity monitoring and fall detection based on surface electromyography and accelerometer signals. IEEE J. Biomed. Health Inform. **17**(1), 38–45 (2013)

18. Leone, A., Rescio, G., Caroppo, A., Siciliano, P.: An EMG-based system for pre-impact fall detection. In: 2015 IEEE SENSORS, pp. 1–4. IEEE (2015)
19. Yu, M., Rhuma, A., Naqvi, S.M., Wang, L., Chambers, J.: A posture recognition-based fall detection system for monitoring an elderly person in a smart home environment. IEEE Trans. Inf. Technol. Biomed. **16**(6), 1274–1286 (2012)
20. Harrou, F., Zerrouki, N., Sun, Y., Houacine, A.: Vision-based fall detection system for improving safety of elderly people. IEEE Instrument. Measurement Mag. **20**(6), 49–55 (2017)
21. Liu, L., Popescu, M., Skubic, M., Rantz, M., Cuddihy, P.: An automatic in-home fall detection system using Doppler radar signatures. J. Ambient Intell. Smart Environ. **8**(4), 453–466 (2016)
22. Erol, B., Amin, M.G., Boashash, B.: Range-Doppler radar sensor fusion for fall detection. In: 2017 IEEE Radar Conference (RadarConf), pp. 0819–0824. IEEE, May 2017
23. Diraco, G., Leone, A., Siciliano, P.: Detecting falls and vital signs via radar sensing. In: 2017 IEEE SENSORS, pp. 1–3. IEEE (2017)
24. Diraco, G., Leone, A., Siciliano, P.: A radar-based smart sensor for unobtrusive elderly monitoring in ambient assisted living applications. Biosensors, **7**(4), 55 (2017)
25. Wild, K., Boise, L., Lundell, J., Foucek, A.: Unobtrusive in-home monitoring of cognitive and physical health: reactions and perceptions of older adults. J. Appl. Gerontol. **27**(2), 181–200 (2008)
26. Kumar, E.S., Sachin, P., Vignesh, B.P., Ahmed, M.R.: Architecture for IOT based geriatric care fall detection and prevention. In: 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1099–1104. IEEE, June 2017
27. Feng, W., Liu, R., Zhu, M.: Fall detection for elderly person care in a vision-based home surveillance environment using a monocular camera. Signal, Image and Video Processing, **8**(6), 1129–1138 (2014)
28. Liao, Y.T., Huang, C.L., Hsu, S.C.: Slip and fall event detection using Bayesian belief network. Pattern Recogn., **45**(1), 24–32 (2012)
29. Lin, B.S., Su, J.S., Chen, H., Jan, C.Y.: A fall detection system based on human body silhouette. In: 2013 Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, pp. 49–52. IEEE, October 2013
30. Kasturi, S., Jo, K.H.: Human fall classification system for ceiling-mounted kinect depth images. In: 2017 17th International Conference on Control, Automation and Systems (ICCAS), pp. 1346–1349. IEEE, October 2017
31. Han, H., Ma, X., Oyama, K.: Towards detecting and predicting fall events in elderly care using bidirectional electromyographic sensor network. In: 2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS), pp. 1–6). IEEE, October 2016
32. De Luca, G.E., Carnuccio, E.A., Garcia, G.G., Barillaro, S.: IoT fall detection system for the elderly using Intel Galileo development boards generation I. In: IEEE CACIDI 2016-IEEE Conference on Computer Sciences, pp. 1–6. IEEE, November 2016
33. Gia, T.N., et al.: Iot-based fall detection system with energy efficient sensor nodes. In: 2016 IEEE Nordic Circuits and Systems Conference (NORCAS), pp. 1–6. IEEE, November 2016
34. Zigel, Y., Litvak, D., Gannot, I.: A method for automatic fall detection of elderly people using floor vibrations and sound—Proof of concept on human mimicking doll falls. IEEE Trans. Biomed. Eng. **56**(12), 2858–2867 (2009)
35. Hazelhoff, L., Han, J., de With, P.H.N.: Video-based fall detection in the home using principal component analysis. In: Blanc-Talon, J., Bourennane, S., Philips, W., Popescu, D., Scheunders, P. (eds.) ACIVS 2008. LNCS, vol. 5259, pp. 298–309. Springer, Heidelberg (2008). https://doi.org/10.1007/978-3-540-88458-3_27
36. Li, Y., Ho, K.C., Popescu, M.: A microphone array system for automatic fall detection. IEEE Trans. Biomed. Eng. **59**(5), 1291–1301 (2012)
37. Liu, C.L., Lee, C.H., Lin, P.M.: A fall detection system using k-nearest neighbor classifier. Expert Syst. Appl. **37**(10), 7174–7181 (2010)

38. Yuwono, M., Su, S.W., Moulton, B.: Fall detection using a Gaussian distribution of clustered knowledge, augmented radial basis neural-network, and multilayer perceptron. In: 7th International Conference on Broadband Communications and Biomedical Applications, pp. 145–150. IEEE, November 2011
39. Foroughi, H., Aski, B.S., Pourreza, H.: Intelligent video surveillance for monitoring fall detection of elderly in home environments. In: 2008 11th International Conference on Computer and Information Technology, pp. 219–224. IEEE (2008)
40. Tzeng, H.W., Chen, M.Y., Chen, J.Y.: Design of fall detection system with floor pressure and infrared image. In: 2010 International Conference on System Science and Engineering, pp. 131–135. IEEE, July 2010
41. Chaccour, K., Darazi, R., El Hassani, A.H., Andrès, E.: From fall detection to fall prevention: a generic classification of fall-related systems. IEEE Sensors J. **17**(3), 812–822 (2017)
42. STMicroelectronics Homepage. https://www.st.com/en/embedded-software/x-cube-mems1.html. Accessed 25 Apr 2019
43. Tolkiehn, M., Atallah, L., Lo, B., Yang, G.Z.: Direction sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 369–372. IEEE, August 2011