# Elderly Monitoring System with Sleep and Fall Detector

Abdulakeem Odunmbaku[1(✉)], Amir-Mohammad Rahmani[1,2], Pasi Liljeberg[1], and Hannu Tenhunen[1,2]

[1] Department of Information Technology, University of Turku, Turku, Finland
{abadod, amirah, pakrli}@utu.fi, hannu@kth.se
[2] Department of Industrial and Medical Electronics, KTH Royal Institute of Technology, Stockholm, Sweden

**Abstract.** Monitoring of elderly people has drawn attention of healthcare and medical professionals. Various health problems have been attributed to either fall or lack of sleep in the context of elderly people. Falling and sleep problems on a long term basis could eventually lead to sharp deteriorate in health, poor state of health and high cost for covering their health care. In this paper a new accurate and convenient while cost-efficient implementation of a monitoring system is presented. The use of an accelerometer based system was utilized in this work. The targeted device fit for this implementation is a smart watch. The algorithm of both the fall detector and sleep monitor presented in this work have been implemented and tested on multiple subjects. It also includes a database backend which is used to save the information collected from the system for further analysis and can provide healthcare professional with more insight of the person's life and can help more on further health medication being given to the person.

**Keywords:** Fall detector · Sleep monitor · Healthcare · Internet-of-Things

## 1 Introduction

Elderly people are a significant section of the society, with the rise in their population, many organizations are concerned about managing the quality of life being lived by this large population. The average population of this group (age 60 and above) is estimated to be 1.2 billion by 2025 and is expected to rise to about 2 billion by 2050 [10]. A custom way of monitoring the activity of a section of the elderly people's population, who cannot take care of themselves properly in every situation, is the employment of caregivers. However, it is unlikely that a larger amount of caregivers also can cater for continuous monitoring and if that is provided, it overburdening the caregiver and in turn drive up cost [1]. There are different existing solutions to assist the elderly people such as remote robot assistance, entertainment services, and reminder services just to mention a few [1, 2]. Unfortunately it is very difficult to estimate the amount of activities that an elderly person experiences during the night or the rate at which they fall during the day due to their weak leg frame or health status. The researches selection of either a fall detector or sleep monitoring is as a result of surveys


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on the elderly. Examples of simple diagnosis that can be detected by the monitoring sleep pattern in elderly people, long terms of poor sleep time can lead to extensive health problem such as high-blood pressure [3]. In addition to critical conditions that can arise due to falling, fall detecting is a monitoring process that should be taken seriously when the section of our population the elderly.

In papers that have proposed monitoring of elderly people, the approaches have focused most often solely either on the fall detector or sleep monitor. The architecture of our monitoring approach is to combine both the fall detector and sleep monitoring. The fall detector proposed in this work offers accurate detection taking into advantage of existing solutions, as it has three methods to determine a fall event. Our sleep monitoring system also offers accurate results with little or no input from the user. Existing sleep monitoring system detect sleep pattern by attaching sensors to the body, which could actual cause discomfort during sleep and affect the accuracy of the results and quality of sleep.

## 2 Related Works

An asynchronous temporal contrast (ATC) vision sensor that is capable of reporting pixel changes with latency of milliseconds are used to determine fall events is presented in [11]. This ATC image sensor is placed on the perimeter walls of the enclosure. It extracts change in motion events pixels for the background and reports the temporal contrast in manner of milliseconds, which is also equivalent to image reflective change when the lighting effect is constant. However, this approach requires complex installations and is expensive.

Sleep monitoring based on real-time implementation of obtaining the respiration rhythm and pulse rate of a subject using an air-free water filled vinyl tube under the pillow of the subject during the sleep time is presented in [12]. The obtained data is compared to a peak detection system already pre-defined in their algorithm. A sensor unit is placed under the subject's pillow to detect the pressure changes beneath the head area. The pressures components within the tubes are conditioned and connected to embed catheters. A downside of this system is that, if the sensor plate if not correctly placed beneath the pillow of the subject, pressure variation cannot reach the sensor plate appropriately to give readings and the system is complex.

## 3 System Implementation

Implementation of the system consists of both sleep monitor and fall detector for elderly people in the same device. A pre-made device was preferred option to combination of different sensor component to implement this work. This enables us to create a cost efficient and flexible approach. Furthermore, the user can also utilize the device for other purposes as per individual needs. Also the consideration of having a back-end that would be able to receive processed data was included as a part of this work.

The essential component used in this system is an accelerometer. Accelerometers are used in many applications such as prosthetic limbs, drones and the game industry. The emergence of micro-electro mechanical-systems (MEMS) based accelerometers have revolutionizes this technology by changing the structure of components to micrometer scale. The measurement of this accelerometer is based on the movement of a small structure component due to vibration stress on it, the acceleration of the component can then be converted into different forms depending on the function it will be applied [5, 6].

### 3.1 Fall Detector

Implementing fall detector involves several steps. Firstly the accelerometer sensor axes data is extracted and represented in form of sine wavelet. The less significant part of the signals is separated, and only the important part of data is utilized. Discrete Wavelength Transform (DWT) is applied to the data, to yield a representation of the discrete data signal, a mother wavelength $\Psi$ is selected and from the mother wavelength, filters h and g will be determined. The wavelength coefficients for the discrete signals are calculated at first scale, these signals are then passed through a first filter to eliminate noise and further passed through another filter. These filters eliminate the noise and effect of gravitational pull on the accelerometer ball (1) and (2).

$$\mathrm{a_n} = \sum\nolimits_{\mathrm{k}=-\infty}^{\infty} \mathrm{x[k]h[n-k]} = (\mathrm{x} * \mathrm{h})[\mathrm{n}]. \tag{1}$$

$$\mathrm{d_n} = \sum\nolimits_{\mathrm{k}=-\infty}^{\infty} \mathrm{x[k]g[n-k]} = (\mathrm{x} * \mathrm{g})[\mathrm{n}]. \tag{2}$$

From the entire signal frequency of the accelerometer data, an approximated coefficient and detailed coefficient constitutes of about half of the signal frequency. To eliminate the effect of error in the signals, each reading of the accelerometer is calculated to produce the approximated coefficient. This is done by using the previous coefficients to calculate the next ones, this process is done repeatedly therein forming a filter bank for the frequency signals. The subsequent coefficients are shown below in (3) and (4);

$$a_{s+1}[n] = \sum\nolimits_{k=-\infty}^{\infty} \bar{a}_s[k]h[n-k] = (\bar{a}_s * h)[n]. \tag{3}$$

$$d_{s+1}[n] = \sum\nolimits_{k=-\infty}^{\infty} đ_s[k]g[n-k] = (đ_s * g)[n]\ . \tag{4}$$

The $\bar{a}_s$ is the subsequent approximate coefficient while the $đ_s$ is the subsequent detail coefficient. These are performed on all the three axes of the accelerometer, and subsequently used to calculate the acceleration of the accelerometer and will be used in eventually for the fall detection. Below are the equations to validate the three axis of the accelerometer in (3), (4) and (5);

$$\alpha = (X - X_{old}). \tag{5}$$

$$\beta = (Y - Y_{old}). \tag{6}$$

$$\gamma = (Z - Z_{old}). \tag{7}$$

When calculating the acceleration, new data acquired from the accelerometer are used in a way to favor of the previous data. This would eliminate the error in calculation due to incorrect data selection. In the equation, α represents the X axis, β represents the Y axis, γ represents the Z axis, $X_{old}$ represents the previous data of the X-axis, $Y_{old}$ represents the previous data Y-axis and $Z_{old}$ represents the previous data of the Z-axis. The acceleration is shown in (8) and δ, represents the acceleration of the accelerometer.

$$Acce(\delta) = \sqrt{\alpha^2 + \beta^2 + \gamma^2}. \tag{8}$$

For fall to be determined the system undergoes four stages. Firstly is the threshold calculation, which involves the calculation of a threshold *t*. The threshold is to be compared to the acceleration which is constantly computed. After comparison, the system determines if there is a fall activity or not. The expression which explains the comparison is shown in (10). The threshold is calculated by randomly simulating fall activities while collecting their accelerations, the minimum peak values are rounded up and the average is calculated. Secondly is the data acquisition and system calibration which involves the collection of system data. Thirdly is the feature extraction which involves: (i) extraction of the accelerometer axes positions before and after a fall phase, (ii) registering dynamic and static acceleration and (iii) current physical body orientation. For a fall event to be detected by the system, the four stages have to be fulfilled [7, 8].

### 3.2 Sleep Monitor

The method used in the sleep monitor to collect the accelerometer data is same as the one discussed in the fall detector, indicated in Eqs. (4), (5) and (9). The principle employed in the sleep monitoring is as such that, activity of the brain is equivalent to the motion produced by the body during sleep. With the accelerometer attached to the body at sleep, these motions can be easily detected. There are three distinct state than need to be differentiated here; the awake state, when the subject is in constantly movement and awake, the light sleep state, when there is reduced motion of the body that is asleep when compared to the awake state. The third is the deep sleep state, there is minimum amount of body movement. During the sleep period, the acceleration is bounded between $0\mathrm{m/s^2}$ to $1.5\mathrm{m/s^2}$ according to vibration on a bed and the sleep states are represented on different acceleration values between the boundaries [9]. The duration of each sleep states and body movements are collected and used in deriving the sleep quality index. The sleep quality index takes into account also the time of going to bed to wake up time.

$$Sleep\ Efficiency = \frac{A.T + L.S}{T_b^a} * 100\%. \quad (9)$$

$A.T$, represents the awake state times, $L.S$, represents the awake state coefficient and $T_b^a$, represents the total time the subject is at sleep from start point a, to stop time b.

## 4 System Architecture

The system allows the option of choosing either the fall detector or the sleep monitor. As mentioned, collected data is passed through the filter bank. The data from the filter bank are used to calculate the acceleration, and can be used in any of the monitoring process. In the example implementation Simvalley Mobile AW-414 smart watch is utilized. The system architecture is shown in Fig. 1.

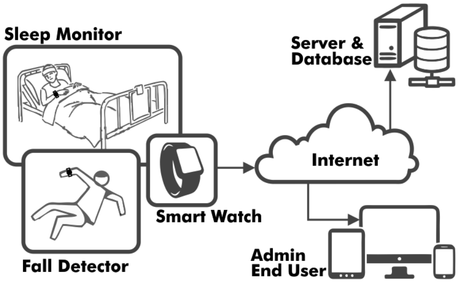


**Fig. 1.** The system architecture.

The system comes with a complementary event-based back-end database system. At each event change in the monitoring system, the information of the system is collected with timestamp of the event and tag of the user. This information is sent to the database for further analysis. On the user side of the system, an internet TCP protocol ensures that the phone is connected. At each change in event, an internet connection will be made to the database. At the administartion side of the system, the terminal is enabled with WebSocket and HTML enabled browser that can be used to access the database information of the users in real time.

## 5 Result

The fall detector was evaluated in a controlled room environment with simulated fall by three subjects, a 26 year old, 1.73 meters tall male volunteer, a 30 year old, 1.80 meters tall male volunteer and a 23 year old 1.62 meters tall female volunteer for ten times on five different occasions. For the tests result, the sensitivity and the specificity (9) and (10) of the fall detector was calculated using the following parameters; True positive (TP) which means that during test, fall happened and the algorithm is able to detect it successfully. False positive (FP), is when a there is no fall activity detected and the algorithm records it as a fall detected. True Negative (TN), is the daily activities of the algorithm that goes undetected and False Negative (FN), is when a fall occurs and the algorithm fails to detect that a fall actually occurred.

The fall parameters were collected and on the first three set of falls, few falls (i.e. FN) were not detected, see Table 1. On the fourth set of fall simulation, the accuracy of the fall detection is noticed to have increased linearly, while in the fifth set of, all falls were detected (i.e. TP) at 100 %, while NF is zero. The success and failure rate of the tests were computed and the sensitivity and the specificity of the tests were evaluated using Eqs. (10) and (11). The accuracy of the tests was also calculated using the success and failure rate to be 95 % of the fall simulated by the test subjects.

$$Sensitivity = \frac{TP}{TP + FN}. \tag{10}$$

$$Specificity = \frac{TN}{TN + FP}. \tag{11}$$

**Table 1.** Results of fall activities test.

| Falls | Subject | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Simulated Fall Activity | | | | | | | | | |
| | 1 | | 2 | | 3 | | 4 | | 5 | |
| | TP | FN | TP | FN | TP | FN | TP | FN | TP | FN |
| 1 | 10 | 0 | 10 | 0 | 9 | 1 | 91 | 1 | 10 | 10 |
| 2 | 9 | 1 | 9 | 1 | 9 | 1 | 9 | 1 | 10 | 0 |
| 3 | 8 | 2 | 9 | 1 | 10 | 0 | 10 | 0 | 10 | 0 |
| Total | 27 | 3 | 28 | 2 | 28 | 2 | 29 | 1 | 30 | 0 |
| | Success rate = 142, Fail = 8; Sensitivity = 95 %, Specificity = 100 %; Accuracy = 94.7 % | | | | | | | | | |

Our result was compared with a tri-axial accelerometer-based fall detector described in [13]. The detector in [13] is also based on a 3D accelerometer that uses FPGA for the computation and ZigBee module to transmit data. The tri-axial based fall detector offers higher sensitivity than our prorposed fall detector, but has lower specificity. The specificity rate shows that there are misses in the data collection rate from the accelerometer which in our system prove to better specificity as shown in Table 2.

**Table 2.** Fall detection result comparison.

| | Sensitivity (%) | Specificity (%) |
|---|---|---|
| Purposed Fall-detector | 95.0 | 100 |
| Tri-axial fall detector [13] | 97.7 | 94.8 |

Evaluation of the sleep monitor was carried out by placing the device next to the pillow of the subject, by this the movement of the subject can be easily tracked as the bed and pillow moves. This evaluation was also carried out with the same three test subjects by monitoring their sleep over the night. The movement of the accelerometer ball, as a result of the body movement, are translated into graphical representation and plotted in real-time against the time of the sleep. At the end of the monitoring the sleep quality is computed (9) and sent to the database for further analysis. The result of the sleep monitor can vary from person to person, and the data can also be retrieved from the database and can be viewed in real time. The information can be further analyzed and possible causes of health problems can be identified and attended to in time.

## 6 Conclusion

Design and implementation of monitoring system architecture for monitoring elderly people activity both during day and at night was presented. The combination of two implementations, i.e. fall detector and sleep monitor, were explored and it turned out to be successful. Most of the existing implementation has custom made devices which turned out to be expensive to build a prototype, but the focus of this work is to have a reasonable priced device that can is readily available. The choice of using a smart watch was perfect for the aim of the work, as it is ready available in the market.

## References

1. Hossain, M.A., Ahmed, D.T.: Virtual caregiver: an ambient-aware elderly monitoring system. IEEE Trans. Biomed. Eng. **16**(6), 102–103 (2012)
2. Peng, Y.-T., Lin, C.-Y., et al.: Multimodality sensor system for long-term sleep quality. IEEE Trans. Biomed. Circ. Syst. **3**, 217–227 (2007)
3. Sposaro, F., Tyson, G.: iFall: an Android application for fall monitoring and response. In: IEEE Conference Publications, pp. 6119–6122, 3–6 September 2009
4. Prado-Velasco, M., Rio-Cidoncha, D., et al.: The inescapable smart impact detection system (ISIS): an ubiquitous and personalized fall detector based on a distributed “divide and conquer strategy”. In: 30th Annual International Conference of the IEEE, pp. 3332–3335, 20–25 August 2008
5. Cao, R., Chen, Y., et al.: Failure mechanism analysis of quartz accelerometer under vibration condition. In: IEEE Conference Publications, pp. 1–5 (2011)
6. Alwan, M., Rajendran, P.J., et al.: A Smart and passive floor-vibration based fall detector for elderly. In: IEEE Conference Publications, pp. 1003–1007 (2006)
7. Soaz, C., Lederer, C., et al.: A new method to estimate the real upper limit of the false alarm rate in a 3 accelerometry-based fall detector for the elderly. In: IEEE Conference Engineering in Medicine, pp. 244–247, 28 August 2012–1 September 2012
8. Rescio, G., Leone, A., et al.: Support vector machine for tri-axial accelerometer-based fall detector. In: IEEE Conference Publications, pp. 25–30 (2012)
9. Scholz, U., Bianchi, A.M., Cerutti, S., Kubicki, S.: Vegetative background of sleep: spectral analysis of the heart rate variability. Physiol. Behav. **62**, 1037–1043 (1997)

10. Hossain, M.A., Ahmed, D.T.: Human caregiver support system in elderly monitoring facility. In: IEEE Trans. Biomed. Eng. **16** (2012)
11. Fu, Z., Delbruck, T., et al.: An address-event fall detector for assisted living applications. IEEE Trans. Biomed. Circ. **2**, 88–96 (2008)
12. Zhu, X., Chen, W., et al.: Real-time monitoring of respiration rhythm and pulse rate during sleep. In: IEEE International Conference on Circuits and Systems, December 2006
13. Rescio, G., Leone, A., et al.: Support vector machine for tri-axial accelerometer-based fall detector. In: 5th IEEE International Workshop for Sensors, pp. 25–30 (2013)