elderly, fall detection,
smartphone, accelerometer

Krzysztof DOBOSZ[1], Paweł WRECZYCKI[1]

FALL DETECTION OF THE ELDERLY USING A SMARTPHONE

Fall detection of the elderly is a major public health problem. The probability of falls makes them dependent on others and restricts their freedom of movement. Although many fall detection methods have been developed to recognize falls in a real-time, most are inaccurate and inconvenient to use. In this paper we describe two methods for detecting the fall of a human body that can be implemented for the smartphones with built-in accelerometer. The first one used the raw data obtained from the sensor, and the second one - filtered data. In addition to the measuring a load factor, an important role in the algorithms has also a mobile device orientation to the ground. The assumption for the study was the localization of the smartphone in a right pocket of trousers - common in right-handed people. The experiment consisted in simulation the falls from different initial postures (standing, sitting, kneeling) in four directions (front, back, left, right). The results are satisfactory for detection of falls from a standing position. In conclusion, correct detection of falls based on the accelerometer built into the smartphone is possible after the filtration of the raw data, although the location of this device, the initial body position and direction of the fall have significant impact.

1. INTRODUCTION

There is a demographic decline currently in Poland and other European countries. Low fertility translates into a relative increase in the number of older people. At present, the data indicate fertility in Poland at 1.3, this means 1.3 children per family. The scale of this phenomenon can be illustrated by a simple comparison. Today, we have in Poland 435 740 people at age 20, and 488 730 people aged 65 years. In 2049, according to current forecasts, the situation has become critical. It is expected that the number of people at the age of 20 will be 302 570 people (about 133 thousands less), and at age 65 - 589 260 (about 100 thousands more) [29]. Such statistics suggest a significant increase in the number of the elderly. It may result in problems with the health care, the national budget will be lower by the lower number of people depositing money. This is one of the reasons why now we should be interested in the fate of society. Even it will be possible to reverse the declining demographics, the provided studies can improve the quality, safety and life expectancy of the elderly.

Older people often struggle with various diseases that are beginning to develop in the elderly. Many of them, due to the advanced stage of the disease, requires constant care. Mobile devices allow us to monitor the health to some extent, and with the growing number of embedded sensors, the possibility of observation of the state of health are more effective.

[1]Institute of Informatics, Silesian University of Technology, 16 Akademicka Str., 44-100 Gliwice

The aim of the study was the developing a method for detecting the fall of a human body that can be implemented for the smartphones. A sudden change in posture is usually the atypical behavior of the elderly living alone. This may be a consequence of an accident or the result of disease. The detected anomalies should notify a defined guardian that could provide assistance to the victim. For the study, it is assumed that the monitored person has a smartphone with a built-in accelerometer in right pocket of trousers, that is commonly use by right-handed people.

2. STATE OF ART

Falls are commonly defined as ”inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects”. Falls are prominent among the external causes of unintentional injury. They are coded as W00-W19 in International Classification of Disease (ICD-10) [2], which include a wide range of falls including those on the same level, different levels, and other unspecified falls. There are many causes of falls, and their number escalates with age, each year falls one-third of people over 65 year of age [1]. The number of falls is heighten by diseases such as dementia, Parkinson disease, or degeneration of the spine and joints, but the cause of the fall may also be a pharmacological therapy.

The fall may cause damage or broken bones, abrasions and soft tissue injuries. In addition, the fall can cause psychological problems. Fear of falling may result in mental deterioration, isolation and general deterioration of life comfort. Scientists studying falls show that the person who happened to fall can reduce their daily activities due to fear of another fall [31].

Fall detection of the elderly is a major public health problem. Thus it has generated a wide range of applied research and prompted the development of telemonitoring systems to enable the early diagnosis of fall conditions [19]. There are various solutions to detect falls. Among them computer vision based approaches offer a promising and effective way. In [30] authors describe framework for fall detection based on automatic feature learning methods. In another paper, authors propose a fall detection system using a motion history image to analyze the fall behavior [16]. Other solution detects falls by analyzing human shape deformation during a video sequence [24]. To effectively track the elderly, a smartphone camera can be used to take real-time pictures along the user’s path as he or she moves about [15]. Then the smartphone can be used for detecting early-warning of fall based on pre-impact phase and post-fall based on impact phase [17].

Solutions for fall detection always use sensors. Through data coming from an accelerometer [8], a gyroscope [7], a magnetometer, and a barometer sensor [6] integrated into device, it is able to obtain a highly accurate estimation about posture and altitude of the subject. Some of authors praise they reach almost 100% of accuracy of fall detection from a standing posture of a human body [21]. Unfortunately, the implementations of their methods are not available for verification. While the mobile applications that are available (e.g. Fade Fall Detector, Emergency Fall Detector) are not described in scientific articles, and it is unknown, what algorithms are implemented in them.

Besides the sensors, a fall detection system using wearable devices, e.g. smartphones [3], and tablets, can additionally analyze the cameras data [20]. Mobile solutions for falls detection can be also suplemented by biofeedback monitoring collecting sensed data from body, and then forwarding them to a smartphone or tablet through Bluetooth [12].

Algorithms for fall detection use various methods: it can be a threshold-based [23], it can use artificial neural networks [26], a short time min-max feature based on the specific signatures of critical phase fall signal and a neural network as a classifier [13], or it can use a combination of information derived from machine learning classification applied in a state machine algorithm

[4], [18]. Very good results are possible in case of long-term machine learning, when classifiers can be applied to a large time-series feature set to detect falls [27].

The location of the sensors is very important for the efficiency of detection of falls. One of approaches is the use of the acceleration data of a widely available smartwatch [10]. Another studies show that the wrist did not appear to be an applicable site for fall detection [14]. A system which combines threshold based and pattern recognition techniques in both devices can be efficiently used in the specificity of the fall detection strategy [28]. High fall detection performance is able to achieve placing wearable sensor on the waist [22]. Accelerometer sensors, can also be mounted on the trunk and thigh [8].

Another problem is that many proposed methods considered only one device placement and did not investigate how different positions influence recognition accuracy. There are also systems, which use a smartphone worn on an arm, the chest, waist or thigh [25]. Other approach developed a fall detection system and algorithm incorporated into a custom designed garment [9]. The accelerometer to detect impacts and monitor posture is attached to a custom designed vest, prepared to be worn by the elderly person under clothing.

Detection the fall can be also one of the functionalities available in a smart home monitoring system for elderly people to monitor their health and provide them with a safe and secure living [11], or making the fall detection system coupled with the wireless intelligent personal communication node covering a set of sensors [32].

3. DETECTION OF FALLS

3.1. MEASUREMENT OF THE ACCELERATION

The problem of detecting the fall is solved by searching for a specific change in the data provided by the sensor. An accelerometer is a device that measures proper acceleration in X, Y, and Z axis. Any change in the spatial position causes the device to obtain other values of acceleration for each axis. An accelerometer at rest on the surface of the Earth will measure the acceleration equals $g = 9.81 m/s^2$ (Earth's gravity). The quotient of the acceleration vector and gravitational acceleration results in load factor. For that situation, when on the accelerometer measures only the Earth's gravity, load factoring will be $1G$.

Growth of the acceleration also results in the increase in congestion, while the decline in acceleration - decrease of load factor. This is the critical dependence of the developed methods to detect falls. It should be converted on the fly, whenever there are new acceleration values obtained from the sensor.

The fundamental assumption of the developed methods is the vertical position of the phone in the user's pocket (Fig. 1). This location helps differentiate between the upright posture and lying. It is necessary to calculate the angle of inclination of the device relative to the Y axis.

Fig. 1. Smartphone location

$$\theta = arccos(\frac{a_y^2}{\sqrt{a_x^2 + a_y^2 + a_z^2}}) \tag{1}$$

where: $[a_x]$ - the acceleration value for the X axis, $[a_y]$ - the acceleration value for the Y axis, $[a_z]$ - the acceleration value for the Z axis.

If calculated value of the angle equals zero degrees - the phone is in the vertical position, value of 90 degrees implies a horizontal position with the screen facing up or down.

3.2. THE METHOD WITHOUT FILTRATION

Detection of falls bases on the continuous observation of the phone slope angle on the Y axis and the load factor. Changes in angles are a result of changes in the user's posture. Changes in the load factor inform about vertical movement. The algorithm consists of detection the following stages:

1) free fall - load factor is below the $1G$,
2) impact - load factor is more than $2G$,
3) inertia - the slope angle is about 90 degrees.

The fall is preceded by a free falling, during which the load factor is below the $1G$. At the time of impact the load factor reaches the maximum value, often greater than $2G$. The highest value can be directly preceded by a few of samples greater than $1G$. The set of samples may contain the maximum value that does not correspond to the fall. For this reason, top 5 values is searched among 50 samples of the current set (last 3 seconds of the measurement). For them, it is verified they are preceded by the samples in a downward trend ending at the minimum value less than $1G$. Then the difference between the measured maximum and minimum is calculated, and compared to the empirically determined threshold. When the threshold is exceeded. The last stage is the three second intervals at which the user's phone orientation is tested again. If the phone is in a horizontal position to the ground, the detected anomalies is finally confirmed.

3.3. THE METHOD WITH FILTRATION

This method also uses stages and ideas known from the method without filtration (the Euclidean norm, normalization, calculation of the angle (1)). However, the process of detecting the fall uses RC filters: high-pass and low-pass. High-pass filter allows us to get the value of the acceleration, which reduces the effect of gravity on the measurement result. In contrast, low-pass filter corresponds closely to the acceleration related to gravity [24].

First, the RC filter must be calculated:

$$RC = \frac{1}{2\pi f_c} \tag{2}$$

where f_c is a cut-off frequency determined empirically for best results.

When the free fall and impact are analyzed, data about the acceleration obtained from the sensor are be converted to load factors for each axis separately. Then the value of smoothing the high-pass filter is determined. The expression use the calculation of RC (2) and the time interval dt resulting from the sampling frequency of the sensor.

$$\alpha_h = \frac{RC}{dt + RC} \tag{3}$$

Then the filtered values of the load factor are determined for each axis.

$$a_{hn} = \alpha_h(a_{hn-1} + a_n - a_{n-1}) \tag{4}$$

where

a_{hn-1} - filtered value of the previous measurement,
a_n - the value of the acceleration obtained from the sensor,

a_{n-1} - the value of the acceleration obtained from the sensor during the previous measurement.

Next, the acceleration in three-dimensional space is calculated using the Euclidean norm. If the determined value is greater than the threshold value, the next condition (inertia) will be tested. After about three seconds, a low-pass filtering is provided. As in the high-pass filter, at the beginning the α_l is determined.

$$\alpha_l = \frac{dt}{dt + RC} \tag{5}$$

Then, 50 acceleration values are undergoing normalization. The obtained values and the α_{ln} parameter are used for low-pass filtering.

$$a_{ln} = a_n \alpha_l + a_{ln-1}(1 - \alpha_l) \tag{6}$$

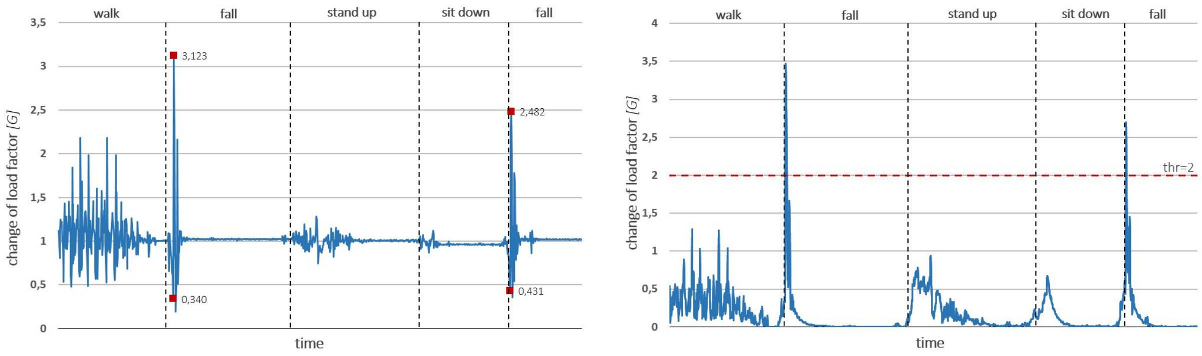
Based on the calculated filtered values, θ angle is tested in the relation to the Y axis. Then, after next 3 seconds, the sum of the last high-pass filtered samples is calculated. For them the position in a space is also determined using the Euclidean norm. The calculated sum allows verifying the changes in the user's posture. In the case of being in motion, the fall is likely to be incorrectly detected. If the motion is not recognized and the angle relative to the Y axis suggests lying posture, then the alarm of the fall is triggered by the mobile application.

4. EXPERIMENTS

4.1. THE LOAD FACTOR THRESHOLDS

In our methods, the threshold needs to be determined for the difference between the maximum and minimum value of the sample. Both values must be placed close together in time. The minimum sample is measured in free fall, while the maximum after the collision with the ground. Previously obtained acceleration is converted into the load factor, and all axes - to the Euclidean norm. Fig. 2(a) shows the changes of described values. The difference between the minimum and maximum during a fall from a standing posture to the front was approximately $2.74G$. After the fall from the sitting posture, the difference was about 2.05. A fall from a sitting position was posture on the left side, and the phone was placed in the right pocket. During the walk the value was about 1.68. Based on this observation, the parameter was set to a value of 1.85, in the middle between walk value and the fall from sitting position.

For the method with filtration, the primary threshold is a filtered value of the load factor. The current load factor is affected by the current sample, the previous sample and the parameter α. The important factor is also RC value, which is an essential component needed to define the cut-off frequency. The value of the cutoff frequency has a big influence on the results. Well-chosen allows to get significant differences between the fall and the other activities. The search for good frequency was based on the analysis of several of them in the range 0.1Hz - 0.5Hz. For the cut-off frequency of 0.1 Hz, the influence of previous measurements is more significant. However, the difference between the fall of the chair, and the upright position is much smaller. For $0.5Hz$, fall moments are clearly different on the graph from other physical behavior, but the impact of previous measurements on the next ones is not so clear. Finally the frequency of 0.2 Hz was chosen (Fig. 2(b)), which has been implemented in a prototype tool. The choice was justified by the relatively small impact of the results of previous measurements for the next, and a large difference between the falls and other physical human behavior.



(a) measured load factor (b) absolute change of the load factor

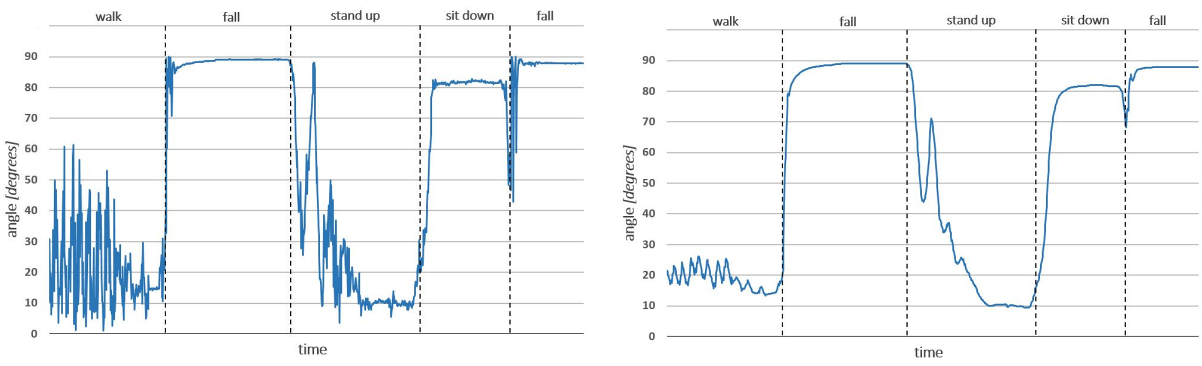
Fig. 2. Human physical behavior

4.2. THE ANGLE THRESHOLDS

The second determined threshold is a value of the inclination angle of the mobile device after the fall. The method with filtration to determine the angle, uses low-pass filter using the value of the cut-off frequency of the high pass filter. Fig. 3(a) illustrates how the angle is changing when the calculation uses the method without filtration.

Changing the angle while walking, oscillate very much in the range $0°$ - $60°$. The device did not moved in a such way, so it is suggesting that the measurement is very inaccurate. Changes of angles are very dynamic. Immediately after the fall, the value reached nearly $90°$. As a threshold that suggests the fall the value greater than $65°$ was selected. Although the presented values after the fall achieve almost a right angle to the axis Y, the falls do not happen always on a flat surface.

Fig. 3(b) shows the process of changing the angle after filtering its value. The changes are not as sharp as in the previous method. The algorithm tests the current angle of the device in 9 seconds after suspected detection of a fall. In this case, the fall is considered when value of the angle is above $60°$.



(a) the method without filtration (b) the method with filtration

Fig. 3. Change of the angle

4.3. EVALUATION AND DISCUSS

The developed method was dedicated to the elderly. Its evaluation was based on a large number of controlled falls. There is some risk of injury, which is much higher for older people. Hence, it was decided to involve voluntaries in the age range 23-47. It was five men. In our opinion, the age of the people had no effect on the detection method falls.

The smartphone, where the prototype application was started, was located in the right pocket and was placed about 20 cm from the belt. In the standing posture a smartphone in the pocket was about 68-80cm above the floor (the distance between the floor and the nearest edge of the device). Persons sitting on the chair hold a smartphone about 60cm above the floor, and while kneeling: 25-32cm.

Experiments for both methods were performed under the same conditions. Falls were performed with a variety of body postures that can occur in daily activities (additionally, in the last moment we decided to consider kneeling). The value in the *Arm support* column means the use of arms to protect the body against a strong impact on the ground. There was also a mattress laying on the floor to protect volunteers from injuries. Additionally, an assistant protected the fall on the back.

Table1 presents the number of detected falls for both algorithms. Voluntaries are numbered starting from the shortest one. Each person made 10 attempts for each type of events.

Table 1. Result of the experiment

Type of fall	Arm support	The method without filtration						The method with filtration					
		Volunteers					stats	Volunteers					stats
		1	2	3	4	5		1	2	3	4	5	
From a standing posture...							91,00%						94,40%
... to the front	yes	10	9	10	10	10	98%	10	10	10	10	10	100%
... to the front	no	9	10	10	10	10	98%	10	10	10	9	10	98%
...on the back	no	9	9	10	8	9	90%	9	10	9	9	10	94%
...on the back; legs bent	no	5	4	7	6	6	56%	6	5	8	7	8	68%
...to the right side	yes	10	9	10	10	10	98%	10	10	10	10	10	100%
...to the right side	no	10	9	10	10	10	98%	10	9	10	10	10	98%
...to the right side; legs bent	no	9	10	10	9	10	96%	9	10	10	10	10	98%
...to the left side	yes	9	8	9	10	10	92%	9	9	10	10	10	96%
...to the left side	no	9	9	10	10	10	96%	10	9	10	10	10	98%
...to the left side; legs bent	no	8	9	10	9	8	88%	9	9	10	9	10	94%
From a sitting posture...							35,71%						71,14%
...to the front	yes	2	2	3	1	4	24%	5	5	4	6	7	54%
...to the front	no	2	4	2	2	3	26%	5	5	6	8	7	62%
...on the back	no	3	3	4	1	3	28%	4	3	7	7	7	56%
...to the right side	yes	5	4	6	5	7	54%	7	8	10	9	8	84%
...to the right side	no	6	5	7	7	6	62%	8	8	10	10	10	92%
...to the left side	yes	3	2	1	2	4	24%	7	6	7	8	7	70%
...to the left side	no	2	4	3	3	4	32%	8	7	8	9	8	80%
From a kneeling posture...							49,67%						55,00%
...to the front	yes	3	1	4	4	3	30%	3	5	6	4	7	50%
...to the front	no	5	2	5	7	7	52%	7	7	7	8	8	74%
...to the right side	yes	5	6	6	7	8	64%	4	2	5	4	5	40%
...to the right side	no	4	5	9	9	8	70%	5	8	9	8	9	78%
...to the left side	yes	3	1	4	5	4	34%	3	4	2	3	4	32%
...to the left side	no	4	3	5	7	5	48%	3	6	5	8	6	56%

The smartphone was placed in the right pocket. Algorithms detecting the falls gave much worse results when where the person fell from a position other than standing on the opposite - left side. Such dependence is caused by the body damping the forces affecting the accelerometer. Both methods detecting the falls from a standing posture works very well (91% and 94,4%). However, with the lower location of the phone, the effectiveness of detection was worse due to less impact force at the time of the fall (from a sitting: 35,71% and 71,14%, from a kneeling: 49,67% and 55%). The falls, which were performed on the back were not detected well from a standing posture, when leg remained bent at the knees after the collision with the ground (56% and 68%). The reason for the lack of detection was too small angle of the device relative to the Y-axis. The solution for the improvement of these results may be placing the phone at waist.

Daily activities such as slow walking, running, climbing stairs not cause incorrect alarms. However, some actions should not be performed when the phone is out of pocket. For example, false alarms can be caused by throwing the phone on the table or dropping it on the ground.

5. CONCLUSIONS

The aim of the project was achieved. We developed two methods for detecting the falls and we implemented them in the research tool for smartphones with Android OS. The first one used the raw data and the second one - data after processing, in this case: after filtration. The method with filtration allows to obtain better results than the method using a raw data. The systematic comparison of fall detection algorithms tested on real-world falls [5] presented that the average of the thirteen different methods was about 83.0%, maximum value was equal 98%. Our results of falls from standing posture (about 95%) appear to be quite good. However, we can not be completely satisfied. There are many factors affecting the accelerometer indications. Most of them depend on human behavior, while others depend on the influence of the environment.

The assumption of a single threshold for the detection of the fall is a simplification. The application should recognize the posture just before the fall (standing, sitting, kneeling) to use appropriate threshold. The correction rate for fall detection is influenced by the position at which a person wears the smartphone. Such system should provide fluently modifiable threshold.

Mobile phones are relatively large in size, and it is difficult to place them in a particular part of a dress, which would give the best results in detection of falls. Unfortunately, often the only place where we can put a smartphone is the pants pocket. On the other hand, every other place will be higher than the pocket of trousers. This will positively affect the amount of change of acceleration, and here the effectiveness of the fall detection.

Moreover, the distance of the smartphone from the floor should be known, especially in the standing posture. Even with the restriction that the device is in the pocket, the influence on the distance has a human altitude, proportions of the human body (including the length of the legs) and the cut of trousers (pocket placement). While these features can be measured, unfortunately there is no certainty in what position will be laying leg and the phone in its pocket, after a fall. What's more, the fall may take place on an inclined surface or a large object. This, unfortunately, can not be predicted.

ACKNOWLEDGEMENT

Publication has been financed by the Institute of Informatics at Silesian University of Technology, statutory research no. BK-219/RAu2/2016

BIBLIOGRAPHY

[1] Global report on falls prevention in older age. Tech. rep., World Health Organization, 2007.

[2] International statistical classification of diseases and related health problems 10th revision (icd-10). Tech. rep., World Health Organization, 2016.

[3] ABBATE S., AVVENUTI M., BONATESTA F., COLA G., CORSINI P., VECCHIO A. A smartphone-based fall detection system. *Pervasive and Mobile Computing 8*, 6 (2012), 883–899.

[4] AGUIAR B., ROCHA T., SILVA J., SOUSA I. Accelerometer-based fall detection for smartphones. In *Proceedings of the IEEE International Symposium on Medical Measurements and Applications* (2014).

[5] BAGALA F., BECKER C., CAPPELLO A., CHIARI L., AMINIAN K., HAUSDORFF J., ZIJLSTRA W., KLENK J. Evaluation of accelerometer-based fall detection algorithms on real-world falls. *PLoS ONE 7*, 5 (2012). cited By 141.

[6] BIANCHI F., REDMOND S., NARAYANAN M., CERUTTI S., LOVELL N. Barometric pressure and triaxial accelerometry-based falls event detection. *IEEE Transactions on Neural Systems and Rehabilitation Engineering 18* (2010), 619–627.

[7] BOURKE A., LYONS G. A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor. *Medical Engineering and Physics 30*, 1 (2008), 84–90.

[8] BOURKE A., O'BRIEN J., LYONS G. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait and Posture 26*, 2 (2007), 194–199.

[9] BOURKE A., VAN DE VEN P., CHAYA A., LAIGHIN G., NELSON J. Testing of a long-term fall detection system incorporated into a custom vest for the elderly. In *Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2008), pp. 2844–2847.

[10] DEUTSCH M., BURGSTEINER H. A smartwatch-based assistance system for the elderly performing fall detection, unusual inactivity recognition and medication reminding. *Studies in Health Technology and Informatics 223* (2016), 259–266.

[11] GNANAVEL R., ANJANA P., NAPPINNAI K., PAVITHRA SAHARI N. Smart home system using a wireless sensor network for elderly care. In *Proceedings of 2nd International Conference on Science Technology Engineering and Management* (2016), pp. 51–55.

[12] HORTA E., LOPES I., RODRIGUES J., PROENCA M. A mobile health application for falls detection and biofeedback monitoring. In *Proceedeings of the IEEE 15th International Conference on e-Health Networking, Applications and Services* (2013), pp. 36–40.

[13] JANTARAPRIM P., PHUKPATTARANONT P., LIMSAKUL C., WONGKITTISUKSA B. A system for improving fall detection performance using critical phase fall signal and a neural network. *Songklanakarin Journal of Science and Technology 34*, 6 (2012), 637–644.

[14] KANGAS M., KONTTILA A., LINDGREN P., WINBLAD I., JMS T. Comparison of low-complexity fall detection algorithms for body attached accelerometers. *Gait and Posture 28*, 2 (2008), 285–291.

[15] KO C.-Y., LEU F.-Y., LIN I.-T. *Using a smartphone as a track and fall detector: An intelligent support system for people with dementia*, Vol. 2. IGI Global, 2015.

[16] LIN C.-Y., WANG S.-M., HONG J.-W., KANG L.-W., HUANG C.-L. Vision-based fall detection through shape features. In *Proceedings of the 2016 IEEE 2nd International Conference on Multimedia Big Data* (2016), pp. 237–240.

[17] MAO L., LIANG D., NING Y., MA Y., GAO X., ZHAO G. Pre-impact and impact detection of falls using built-in tri-accelerometer of smartphone. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 8423 LNCS* (2014), 167–174.

[18] MARTINEZ M., DE LEON P. A smartphone-based gait data collection system for the prediction of falls in elderly adults. In *Proceedings of the International Telemetering Conference* (2015), Vol. 82, pp. 256–265.

[19] NOURY N., FLEURY A., RUMEAU P., BOURKE A., LAIGHIN G., RIALLE V., LUNDY J. Fall detection - principles and methods. In *Proceedings of Annual International Conference of the IEEE Engineering in Medicine and Biology* (2007), pp. 1663–1666.

[20] OZCAN K., VELIPASALAR S. Wearable camera- and accelerometer-based fall detection on portable devices. *IEEE Embedded Systems Letters 8*, 1 (2016), 6–9.

[21] PIERLEONI P., BELLI A., MAURIZI L., PALMA L., PERNINI L., PANICCIA M., VALENTI S. A wearable fall detector for elderly people based on ahrs and barometric sensor. *IEEE Sensors Journal 16*, 17 (2016), 6733–6744.

[22] PIERLEONI P., BELLI A., PALMA L., PELLEGRINI M., PERNINI L., VALENTI S. A high reliability wearable device for elderly fall detection. *IEEE Sensors Journal 15*, 8 (2015), 4544–4553.

[23] RASHEED M., JAVAID N., ALGHAMDI T., MUKHTAR S., QASIM U., KHAN Z., RAJA M. Evaluation of human activity recognition and fall detection using android phone. In *Proceedings of the International Conference on Advanced Information Networking and Application* (2015), Vol. 2015-April, pp. 163–170.

[24] ROUGIER C., MEUNIER J., ST-ARNAUD A., ROUSSEAU J. Robust video surveillance for fall detection based on human shape deformation. *IEEE Transactions on Circuits and Systems for Video Technology 21*, 5 (2011), 611–622.

[25] TSAI P.-Y., YANG Y.-C., SHIH Y.-J., KUNG H.-Y. Gesture-aware fall detection system: Design and implementation. In *Proceedings of the 5th IEEE International Conference on Consumer Electronics* (2015), pp. 88–92.

[26] VALLEJO M., ISAZA C., LOPEZ J. Artificial neural networks as an alternative to traditional fall detection methods. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2013), pp. 1648–1651.

[27] VERMEULEN J., WILLARD S., AGUIAR B., DE WITTE L. Validity of a smartphone-based fall detection application on different phones worn on a belt or in a trouser pocket. *Assistive Technology 27*, 1 (2015), 18–23.

[28] VILARINHO T., FARSHCHIAN B., BAJER D., DAHL O., EGGE I., HEGDAL S., LONES A., SLETTEVOLD J., WEGGERSEN S. A combined smartphone and smartwatch fall detection system. In *Proceedings - 15th IEEE International Conference on Computer and Information Technolog* (2015), pp. 1443–1448.

[29] WALIGORSKA M., KOSTRZEWA Z., POTYRA M., RUTKOWSKA L. Prognoza ludnosci na lata 2014-2050. http://stat.gov.pl/obszary-tematyczne/ludnosc/prognoza-ludnosci/prognoza-ludnosci-na-lata-2014-2050-opracowana-2014-r-,1,5.html, 2014.

[30] WANG S., CHEN L., ZHOU Z., SUN X., DONG J. Human fall detection in surveillance video based on pcanet. *Multimedia Tools and Applications 75* (2016), 11603–11613.

[31] WOOD S., BELLIS M. A., LYONS R. A., MACDONALD D. *Falls in older people. A review evidence for prevention for the UK local point to violence and injury prevention.* Liverpool John Moores University, 2010.

[32] YI W.-J., SARKAR O., GONNOT T., MONSEF E., SANIIE J. 6lowpan-enabled fall detection and health monitoring system with android smartphone. In *Proceedings of IEEE International Conference on Electro Information Technology* (2016), Vol. 2016-August, pp. 174–178.