ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

Account of Techniques Identifying In-House Falling of Elderly People: A literature survey

Rutuja S. Shewale[1], Jyoti M. Pingalkar[2]

ME Student, Dept. of I.T., Siddhant College of Engineering, Savitribai Phule Pune University, Pune, India[1]

Assistant Professor, Dept. of I.T., Siddhant College of Engineering, Savitribai Phule Pune University, Pune, India[2]

ABSTRACT: Elderly persons at times being alone while performing their daily activities fall on the floor injuring themselves, sometimes with bone fracture or more severely. With more and more advances in research, engineers are coming up with different fall detection technologies. This paper is intended to present a key literature survey on the ideas of different fall detection technologies as per their rough classification and features. In earlier era, most of the systems were sensor based and such systems needed the subject to consistently wear the sensor system on the body. This was a major cause of discomfort and annoyance. Thereby with the advances in automation instruments, many systems came up with non-wearable kind of fall detection technologies, which used cameras and floor sensors for example. However, with insipient progress in machine learning algorithms, modern day engineers are taking advantage of superior machine learning algorithms such as support vector machines and extreme learning machines in association to primary devices like cameras which continuously provide the live video feed to these classifiers. These systems are seeing fast, comfortable and highly accurate trends in fall detection.

KEYWORDS: Fall Detection, Camera, Sensor, Support Vector Machine, Extreme Learning Machine, Ambulatory System

I. INTRODUCTION

Average citizen age has been seeing a continuous rising graph with growing healthcare facilities and infrastructure in most of developed and developing nations. While this has been a positive change, there is also a growth of nuclear families and lone elderly people in the society worldwide. Such scenarios where most of the elderly people living a lonely life or alone most of the time in the home and care centres doing daily household routines by themselves often exposed to danger of accidental hurts to themselves. The fall can be an accidental, due to stroke or momentary loss of conscience. A very common observation of such accidents reveals that aging people falling on hard tiled floors resulting bone fractures. The bone fractures in old age are more devastating as the perfect cure doesn't happen with old mature but brittle bones and the pain can be life long lasting. A more serious danger poses when an elderly person falls and being alone in house or room cannot get an attention of raise an alarm for help. Many of modern day researchers and engineers are working to solve this issue across the research centres and universities, with primary objective of detecting the falling action of a senior citizen through variously developed systems & techniques. This particular article intends to summarize such key breakthrough systems published across literature.

Basically, authors had been putting an effort on development of an automatic system to detect the falling action of an elder though use of in–hose surveillance cameras integrated to machine learning based software system capable of identifying such accident and raising alarms. During their efforts a detailed literature study was conducted to know-how of such state of the art systems. Most of the best efforts and developments are summarized in this paper with intention to create a literature survey report available to newer researchers embarking their work in this field. Moreover, apart from fresher researchers the report can be helpful for the medical practitioners, nursing homes and hospitals, healthcare industries, old age homes and volunteers and none the less common people worried to take care of elders in their homes.

As a brief introduction on the account of literature, it shows that many of the automation technologies such as cameras and sensors were fully matured by the end of 20th century. However, their need and use for the reason of detecting in-house fall action of senior people has been considered from early 21st century. One of a remarkable effort in similar effort by Shany et al. [1] in consolidating the literature information primarily shows this fact. It will be also

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

partially correct to say that the change in times from 20th to 21st century has shown the change in living status of a household elderly person. Further to add to the list, use of camera live feeds to more advanced machine learning algorithms that model and classify human actions from such live feeds show an increasing use newer systems. Machine learning is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory in artificial intelligence. Common algorithms such as use of Support Vector Machines (SVM) [2] and Extreme Learning Machines (ELM) [3] are finding their place of use as efficient and faster action classifiers. Moving ahead, it will be also of one's interest to know what distinctive techniques had been considered so far by researchers and what had been their working principles, advantages, disadvantages, and success rates. In the next section, II, of the article one shall see the intended to publish literature summary and thereafter, in the last section, III, authors had put their words of concluding remarks.

II. Related work

This section forms the core soul of this article and intended to be most lucid and generic in providing the ideas in brief of most of the chosen published articles in literature on the systems of fall detection of elderly persons. In order to make it reader friendly and improve its useful effectiveness the section is managed in four different subsections as follows.

A. *Generic Human Motion Identification*

Apart from falling, human bodies do perform multiple movements while executing daily actions and routines. As a research doesn't always start with a single thread, even before specific fall detection systems, earlier it all started with human body motion identification systems. Later on, most of them found the application in particular fall detection system and the research area narrowed down to get more focused on intended efforts.

Bussmann et al. [4] in 1995 presented a detailed account of reasons that why there is need of ambulatory measurement systems was, especially for medical purposes. Also types of available techniques starting from visual inspection, diaries, and video recordings to more advance use of sensors are elaborated in the more elaborate article. They came up with the ambulatory monitoring measurement, AM, system which consists of three uniaxial accelerometers. Out of the three, two of the accelerometers are suggested to be mounted on trunk part of patient body and one on the thighs. Most of their experiments were conducted on young male patients instead of old. Signals from accelerometers are passed through high pass filters, rectifiers and then low pass filters for signal analysis to detect the body motion such as lying, sitting, walking, up and down the stairs and cycling. They haven't reported much anything on the outcome of the experiments with the system on subjects however, a main disadvantage with such a system employing thee accelerometers was observed that multiple sensors could give low compliance and confidence as they verified the outcomes with a reference video measure.

An accelerometer is a device that measures proper acceleration or commonly known as the g-force. Proper acceleration is not the same as coordinate acceleration (rate of change of velocity). For example, an accelerometer at rest on the surface of the Earth will measure an acceleration g= 9.81 m/s2 straight upwards. By contrast, accelerometers in free fall orbiting and accelerating due to the gravity of Earth will measure zero. Accelerometers have multiple applications in industry and science. Highly sensitive accelerometers are components of inertial navigation systems for aircraft and missiles. Accelerometers are used to detect and monitor vibration in rotating subjects. Accelerometers are used in tablet computers and digital cameras so that images on screens are always displayed upright. Accelerometers are used in drones for flight stabilization. Single- and multi-axis models of accelerometer are available to detect magnitude and direction of the proper acceleration (or g-force), as a vector quantity, and can be used to sense orientation (because direction of weight changes), coordinate acceleration (so long as it produces g-force or a change in g-force), vibration, shock, and falling. Falling action is a case where the proper acceleration changes, since it starts at zero, then increases.

Similarly, in 1999, Aminian et al. [5] used two uniaxial accelerometers, mounting them with one on chest and the other at thighs of predominantly young male subjects. The accelerometer signals are processed with 0 to 0.5 Hz low pass filtering. However, unlike Bossmann et al. [4] Aminian et al. [5] have presented the test outcomes of the system as they validated with detailed video recording. They showed the system to be around 90% accurate in identifying the motions such as sitting, standing, lying and moving.

Thereon, use of bi-axial and tri-axial accelerometers instead of uniaxial stuff was introduced in the early 21st century. Also the developments in micro electro mechanical systems (MEMs), contributed to the further development

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

in making more accurate systems, such as using MEMs gyroscopes. These are also equally wearable devices. Mathie et al. in 2003 [6] as well as in 2004 [7] and Karontonis et al. [8] in 2006 demonstrated use of tri-axial accelerometers, primarily mounted on waist of the subject. They commonly used high pass filters, median filters, summed magnitude area Karontonis et al. [8] also employed filters detecting acceleration vector magnitudes, tilt angle and more on constructed a decision tree classifier to detect out specific activities like walking, idle sitting, standing and falling. All these systems were simple in design and robust using only one of the accelerometer sensor mounted comfortably relatively. Their success rate with use of tri-axial accelerometer was very high; particularly it was more of 90 to 100%. However, there had been few disadvantages to that with growing expectations from such systems. As they are using a single accelerometer sensor, these systems are always doubted to have equipotential capabilities to detect individual limb movements, such as hands and legs.

Najafi et al. [9] in 2003 developed a system employing a combination of a bi-axial accelerometer and one uniaxial gyroscope, mounted primarily on chest of the elder subject. They used to pass the signals to primarily for wavelet transform and then employed a decision tree classifier to identify the motion of subject as lying, sitting, standing or walking. The technique was 99% accurate in sensing a change in state of the subject. And the decision classifier was found to be more than 90% accurate in identifying te different types of motions. Only trouble with the system was that the sensors were to be mounted on chest which was quite in comfortable to the subject, especially an elder one.

B. *Wearable Technologies for Fall Detection*

As also mentioned in part of introduction, the most obvious choice of researchers and engineers for developing a fall detection system is with the use of sensors, mainly accelerometers and mechanical machine tools like gyroscopes as part of wearable technologies. Such tools like sensors and gyroscopes are very perfect in detecting the motion and the actions like falling the person and so have a very high rate of accuracy. However, the advantages never come alone or so, the primary disadvantage of such systems include that one cannot wear such system with full comfort as regular attire. They cause a lot of discomfort to the patient. And hence one cannot wear them all the time.

In 2003, Noury et al. [10] employed a system with biaxial accelerometers fixed on monkey bone of the subject patient and tested for fall detection. However, their all subjects were young age and none was an elderly person. They tried to simulate a slow paced forward or backward fall of subject while performing daily activities. Due to use of accelerometers, they were able to measure the signals of inclination of subject body as well as its rotation which in major sense represents the falling action. As per their experimental designs set-up, they continued with detecting fall in slow loss of consciences with slower pace obviously but with great success in detecting fall action. The system showed sensitivity in detecting fall up to 79% and specificity with 83%. However, the system was not that good in detecting a sudden fall like a trip down failure of conscience. Neither the fall action was followed up to complete lying down on ground situation of subject body.

Bourke et al. [11] in 2008 and van de Ven et al. [12] in 2009, both from the same co-working group from Ecole Polytechnic institute, demonstrated use of Tri-axial accelerometers for elderly fall detection system. Bourke et al. mounted their sensors on lower lateral chest of the subjects whereas; van de Ven et al. didn't specify the sensor location in the article. Bourke et al. tried to measure the fall acceleration magnitude through accelerometers, whereas, van de Ven et al. tried to identify the body state or position without much revealing about the system. Bourke et al. had a robust fixure of sensor on the lateral lower chest part. However as they mentioned the testers to must wear the vest of sensor the test persons refused to wear it for a long time due to discomfort. Moreover, their system detected around 115 false falls which was a huge number out of total experimentation. On the other hand, van de Ven et al. system worked great with nearly 99.7% success rate of fall detection in elderly persons.

Bourke and van de Ven et al. [13] combining their efforts together again in 2010, reported a fresh system again using a Tri-axial accelerometer mounted on waist of the subject. However, this time they measured acceleration magnitude of falling subject body, device velocity and its orientation. Later on they used decision tree classifier to specifically detect out the fall action. This system showed a great success of 100% fall detection rate. However, they could not eliminate the drawbacks of false fall recognition but they were successful in lowering the false fall detection rate significantly.

Another effort by Binachi et al [14] in 2010 shows a combination of sensors. Apart from Tri-axial accelerometers they also leveraged air pressure sensors. The entire system was to be mounted on the subject waist. They tried to measure the fall acceleration magnitude, summed magnitude area, postural orientation and pressure difference on multiple body-ground touch points. Use of air pressure sensor helped to reduce false positives and it can also detect slow loss of consciousness. They mostly used all young subjects to test out the system. However, due to use of pressure

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

measuring sensors, many often actions like sitting in chair or lying down on bed was also raising the fall action alarm. The system was 96.9% accurate, 97.5% sensitive and 96.5% specific in fall detection. Moreover, the sensitivity was worse when used outdoor.

Researchers did not limit the inventions only till fall detection. Many of them have gone ahead in fall detection as well as fall risk assessment. In light of the major negatives associated with falls, much effort is being dedicated towards their prevention. Clearly, the first step would be to single out those individuals most at risk. In addition, in light of the multi factorial nature of falling, it is also beneficial to identify the specific risks affecting each individual in order to provide the most suitable intervention. Falls risk assessment is a vast research area with widely disparate approaches being used. There are various scoring systems intended for use in hospitals, nursing homes, or outpatient settings. The available indices are designed to be used by different professionals (e.g., geriatric doctors, nurses, or Physical therapists), and are based on questionnaires, observations, physical examinations, or their combination. Some tools have been reported in the context of only a specific subgroup of the elderly or chronically ill population, or were developed for use in an individual facility. Reliability and credibility are also an issue in some instances.

Najafi et al. [15] in 2002 demonstrated the system of fall detection employing a gyroscope, proposed to be mounted on chest of any elderly person. The system extracted parameters showed significant difference between high or low risk groups. They used reference measures of fall risk using Tinetti tests, cognitive and vision tests, and history of falls records. In another similar effort, Giansanti et al. [16] in 2008 made use of tri-axial accelerometer and tri-axial gyroscope. They used Neural Network classifier post signal processing. However, the system required the subject to stand of foam cushion as the sensor system was mounted on back of the subject and could not be displaced for any other test fall scenarios. As counter verified with Tinetti scores of falls, the system was found to be 97% accurate in distinguishing between low and high risk falling actions. Greene et al. [17] in 2010, used 2 sets of tri-axial accelerometers and tri-axial gyroscopes, mounted to be lower limb on both the legs of subjects. And the system was 76.4% accurate in retrospectively sorting fallers from non-fallers.

C. *Non-Wearable Technologies for Fall Detection*

The major reason for wearable technologies to go disappointed in real life usage was the discomfort in wearing them on body all time. Especially for the elder people it was a cause of annoyance altogether. This lead the engineers and researchers to go further to invent non-wearable technologies of fall detection.

Galglio et al. [18] in a most recent publication of 2015 presented a method for recognizing human activities using information sensed by an RGB-D camera, namely the Microsoft Kinect. Their approach was based on the estimation of some relevant joints of the human body by means of the Kinect; three different machine learning techniques, i.e., K-means clustering, support vector machines, and hidden Markov models, are combined to detect the postures involved while performing an activity, to classify them, and to model each activity as a spatiotemporal evolution of known postures. Experiments were performed on Kinect Activity Recognition Dataset, a new dataset, and on CAD-60, a public dataset. Experimental results show that their solution outperforms four relevant works based on RGB-D image fusion, hierarchical Maximum Entropy Markov Model, Markov Random Fields, and Eigen-joints, respectively. The performance that their system achieved, i.e., precision/recall of 77.3% and 76.7%, and the ability to recognize the activities in real time show promise for applied use.

Falls are a major risk for the elderly people living independently. Rapid detection of fall events can reduce the rate of mortality and raise the chances to survive the event and return to independent living. In the last two decades, several technological solutions for detection of falls were published, but most of them suffer from critical limitations. In an another remarkable effort by Zigel et al. [19] in 2009, presented a proof of concept to an automatic fall detection system for elderly people. The system was based on floor vibration and sound sensing, and uses signal processing and pattern recognition algorithm to discriminate between fall events and other events. The classification was based on special features like shock response spectrum and mel frequency ceptral coefficients. For the simulation of human falls, they used a human mimicking doll: “Rescue Randy.” Their proposed solution was unique, reliable, and did not require the person to wear anything. It was designed to detect fall events in critical cases in which the person is unconscious or in a stress condition. From their preliminary research, their proposed system could detect human mimicking dolls falls with a sensitivity of 97.5% and specificity of 98.6%.

Doukas and Maglogiannis [20] in 2011 presented the implementation details of a patient status awareness enabling human activity interpretation and emergency detection in cases, where the personal health is threatened like elder falls or patient collapses. Their proposed system utilizes video, audio, and motion data captured from the patient’s body

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

using appropriate body sensors and the surrounding environment, using overhead cameras and microphone arrays. Also, appropriate tracking techniques were applied to the visual perceptual component enabling the trajectory tracking of persons, while proper audio data processing and sound directionality analysis in conjunction to motion information and subject's visual location could verify fall and indicate an emergency event. The post fall visual and motion behavior of the subject, which indicates the severity of the fall (e.g., if the person remains unconscious or patient recovers) was performed through a semantic representation of the patient's status, context and rules-based evaluation, and advanced classification. Additionally, a number of advanced classification techniques had been examined in the framework of this study and their corresponding performance in terms of accuracy and efficiency in detecting an emergency situation had been thoroughly assessed and presented in their article.

Computer vision provides a promising solution to analyze personal behavior and detect certain unusual events such as falls. Thereby in 2011, Rougier et al. [21] proposed a new method to detect falls by analyzing human shape deformation during a video sequence. A shape matching technique was used by them to track the person's silhouette along the video sequence. The shape deformation was then quantified from these silhouettes based on shape analysis methods. Finally, falls are detected from normal activities using a Gaussian mixture model. Their work had been conducted on a realistic dataset of daily activities and simulated falls, and gives very good results (as low as 0% error with a multi-camera setup) as compared with other common image processing methods.

Very recently in 2014, Ma et al. [22], presented an automated fall detection approach that required only a low cost depth camera. Their approach combined two computer vision techniques - shape-based fall characterization and a learning-based classifier to distinguish falls from other daily actions. Given a fall video clip, they normally extract curvature scale space (CSS) features of human silhouettes at each frame and represent the action by a bag of CSS words (BoCSS). Then, they utilize the extreme learning machine (ELM) classifier to identify the BoCSS Representation of a fall from those of other actions. In order to eliminate the sensitivity of ELM to its hyper parameters, they presented a variable length particle swarm optimization algorithm to optimize the number of hidden neurons, corresponding input weights, and biases of ELM. Using a low cost Kinect depth camera, they built an action data set that consists of six types of actions (falling, bending, sitting, squatting, walking, and lying) from ten subjects. Experimenting with the dataset shows that their approach can achieve up to 91.15% sensitivity, 77.14% specificity, and 86.83% accuracy.

D. *Machine Learning Techniques*

As also mentioned in part of introduction, common machine learning techniques or algorithm such as Support vector machine (SVM) and Extreme Learning Machine (ELM) are finding their use in most of newer systems like fall detection system. The primary use of these algorithms is to classify the required sample out of the mixture of sample space. It can be classifying the image, video or a video snapshot. Most of the modern day systems make use of numerous tagging mechanisms to such samples. Based on such tags, a vector is defined. The Support Vector machine or SVM then activates to classify the samples.

The original SVM algorithm was invented by Vladimir N. Vapnik and Alexey Ya. Chervonenkis in 1963. In 1992, Bernhard E. Boser, Isabelle M. Guyon and Vladimir N. Vapnik [23] suggested a way to create nonlinear classifiers by applying the kernel trick to maximum-margin hyper planes. The current standard incarnation (soft margin) was proposed by Cortes and Vapnik as published in 1995 [2]. In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

On the other hand, Extreme learning machines (ELMs) are feed forward neural network for classification or regression with a single layer of hidden nodes, where the weights connecting inputs to hidden nodes are randomly assigned and never updated. These weights between hidden nodes and outputs are learned in a single step, which essentially amounts to learning a linear model. The name "extreme learning machine" (ELM) was given to such models

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

by Guang-Bin Huang [3]. These models can produce good generalization performance and learn thousands of times faster than networks trained using back propagation.

III. CONCLUSION

The paper has made an effort in bringing out the problem of human fall detection system, especially for elder persons. A great deal literature has been scrutinized to understand the different approaches researchers have adopted for building a fall detection system. Some of the key identified works from literature has been classified in systems, detecting generic human activity, systems with wearable technologies, and more advanced systems with non-wearable technologies. On one hand where wearable technologies included methods of attaching micro sensors, accelerometers, gyroscopes to the object body yielding quite accurate results with more advances, but the overall system drawback is seen as the wearable instruments causing annoyance and discomfort to elderly persons. On the other hand, some of state-of-the-art systems with non-wearable technologies, employing advanced machine learning tools to capture the fall detection from depth based camera footage provide higher accuracy with ease of implementation.

REFERENCES

1. Shany T, Redmond SJ, Narayanan MR, Lovell NH, "Sensors-Based Wearable Systems for Monitoring of Human Movement and Falls," Sensors Journal, IEEE Volume:12 , Issue: 3, pp. 658–670, April 2011.
2. Cortes C, and Vapnik V, "Support-vector networks," 1995. Machine Learning 20 (3): 273. doi:10.1007/BF00994018
3. Huang Guang-Bin, Zhu Qin-Yu, and Chee-Kheong, "Extreme learning machine: theory and applications," 2006. Neurocomputing 70 (1): 489–501. doi:10.1016/j.neucom.2005.12.126
4. J.B.J. Bussmann, P.H. Veltink, F. Koelma, R.C. van Lummel, and H.J. Stam, "Ambulatory monitoring of mobility-related activities: The initial phase of the development of an activity monitor," Eur. J. Phys. Rehab. Med., vol.5, pp. 2–7, 1995.
5. K. Aminian, P. Robert, E. E. Buchser, B. Rutschmann, D. Hayoz, and M. Depairon, "Physical activity monitoring based on accelerometry: Validation and comparison with video observation," Med. Biol. Eng. Comput., vol. 37, pp. 304–308, 1999.
6. M. J. Mathie, A. C. F. Coster,N.H. Lovell, and B. G. Celler, "Detection of daily physical activities using a triaxial accelerometer," Med. Biol. Eng. Comput., vol. 41, pp. 296–301, 2003.
7. M. J. Mathie, A. C. F. Coster, N. H. Lovell, B. G. Celler, S. R. Lord, and A. Tiedemann, "A pilot study of long-term monitoring of human movements in the home using accelerometry," J. Telemed. Telecare, vol. 10, pp. 144–151, 2004.
8. D. M. Karantonis, M. R. Narayanan, M. J. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," IEEE Trans. Inform. Technol. Biomed., vol. 10, pp. 156–167, 2006.
9. B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. J. Büla, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly," IEEE Trans. Biomed. Eng., vol. 50, pp. 711–723, 2003.
10. N. Noury, P. Barralon, G. Virone, P. Boissy,M. Hamel, and P. Rumeau, "A smart sensor based on rules and its evaluation in daily routines," in Proc. IEEE 25th Annu. Int. Conf. Eng. Med. Biol. Soc., 2003, pp. 3286–3289.
11. A. K. Bourke, P. W. J. van de Ven, A. E. Chaya, G. M. Olaighin, and J. Nelson, "Testing of a long-term fall detection system incorporated into a custom vest for the elderly," in Proc. 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., 2008, pp. 2844–2847.
12. P. van de Ven, A. Bourke, C. Tavares, R. Feld, J. Nelson, A. Rocha, and G. O. Laighin, "Integration of a suite of sensors in a wireless health sensor platform," in Prof. IEEE Sensors Conf., 2009, pp. 1678–1683.
13. A. K. Bourke, P. van de Ven, M. Gamble, R. O'Connor, K. Murphy, E. Bogan, E. McQuade, P. Finucane, G. O'Laighin, and J. Nelson, "Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities," J. Biomech., vol. 43, pp. 3051–3057, 2010.
14. F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, and N. H. Lovell, "Barometric pressure and triaxial accelerometry-based falls event detection," IEEE Trans. Neural Syst. Rehab. Eng., vol. 18, pp. 619–627, 2010.
15. B. Najafi, K. Aminian, F. Loew, Y. Blanc, and P. A. Robert, "Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly," IEEE Trans. Biomed. Eng., vol. 49, pp. 843–851, 2002.
16. D. Giansanti, V. Macellari, and G. Maccioni, "New neural network classifier of fall-risk based on the Mahalanobis distance and kinematic parameters assessed by a wearable device," Physiol. Meas., vol. 29, pp. N11–N19, 2008.
17. B. R. Greene, A. O. Donovan, R. Romero-Ortuno, L. Cogan, C. Ni Scanaill, and R. A. Kenny, "Quantitative falls risk assessment using the timed up and go test," IEEE Trans. Biomed. Eng., vol. 57, pp. 2918–2926, 2010.
18. S Gaglio, Giuseppe Lo Re, Marco Morana, "Human Activity Recognition Process Using 3-D Posture Data," IEEE Transactions on Human-Machines Systems, Vol. 45, No. 5, Oct 2015.
19. Y Zigel, D Litvak, and I Gannot, "A Method for Automatic Fall Detection of Elderly People Using Floor Vibrations and Sound – Proof of Concept on Human Mimicking Doll Falls," IEEE Transactons on Bio-Medical Engineering, Vol. 56, No. 12, Dec 2009.
20. C N Doukas, and I Maglogiannis, "Emergency Fall Incidents Detection in Assisted Living Environments Utilizing Motion, Sound, and Visual Perceptual Components," IEEE Transactions on Information Technology in Biomedicines, Vol. 15, No. 2, Mar 2011.
21. C Rougier, J Meunier, AS Arnaud, and J Rousseau, "Robust Video Surveillance for Fall Detection Based on Human Shape Deformation," IEEE Transactions on Circuit and Systems for Video Technology, Vol. 21, No. 5, May 2011.
22. X Ma, H Wang, B Xue, M Zhou, B Ji, and Y Li, "Depth-Based Human Fall Detection via Shape Features and Improved Extreme Learning Machine," IEEE Journal of Biomedical and Health Informatics, Vol. 18, No. 6, Nov 2014.
23. Boser BE, Guyon IM, Vapnik VN, "A training algorithm for optimal margin classifiers," Proceedings of the fifth annual workshop on Computational learning theory - COLT '92. PP. 144. 1992. doi:10.1145/130385.130401. ISBN 089791497X.