Approaches and Principles of Fall Detection for Elderly and Patient

Xinguo Yu
Institute for Infocomm Research, 21 Heng Mui Keng Terrace, Singapore 119613,
{Xinguo}@i2r.a-star.edu.sg

***Abstract*—Fall detection for elderly and patient has been an active research topic due to that the healthcare industry has a big demand for products and technology of fall detection. This paper gives a survey of fall detection for elderly and patient, focusing on identifying approaches and principles of the existing fall detection methods. To properly build the classification tree of the methods of fall detection we first study the characteristics of fall. Then according to what sensors and how sensors are used we first divide the methods of fall detection into three approaches: wearable device, ambience device, and camera-based. Further we divide each approach into two to three classes according to the used principles. For each class of algorithm we analyze their merits and demerits. We also give comments on how we can improve some algorithms.**

Keywords--Fall Detection, Algorithm, System, Device, Approach, Principle, Healthcare, Sensor, Camera, Elderly, Patient

I. Introduction

Developing the assistive technology for elderly and patient has been a hot research field due to that the healthcare industry has a big demand for such products and technology. With the rapid growth of the population of the elderly in the world, the demand for the healthcare systems is increased accordingly. At the same time, advances of sensor, camera, and computer technologies make such development feasible. More importantly, this development is greatly supported and pushed by the governments in many developed countries. For example, Singapore government recently has increased the investment in this respect and it has successfully held a conference and exhibition called SiCEX 2008 during Jan. 10-13, 2008 [81], which promoted concepts, products, and technologies related to healthcare for elderly and patient. The assistive technology can not only increase the independent living ability of elderly and patient, but also decrease the pressure of shortage of nurses. An example of products in assisting elderly and patient is the fall detector. This kind of products raises the safety and care level. Hence, it would raise the confidence of elderly and patient in living independently. In developing the assistive technology, all kinds of sensors and all kinds of cameras (generally speaking camera is one kind of sensors, but in this paper we distinguish camera from other kinds of sensors) can work together for monitoring people activity and detecting critical events for elderly and patient [1-80].

The fall among all events gives the biggest threat to elderly and patient [19-20, 29, 36-37, 57-58, 62, 65-66]. The statistics show that in Canada almost 62% of injury-related hospitalizations for the elderly are the results of falls [54]. The immediate treatment of the injured people by fall is very critical. Hence, we should detect the fall as soon as possible if falls cannot be absolutely avoided so that the injured can get an immediate treatment.

In this paper, we give a survey of methods in fall detection for elderly and patient based on their approaches and principles. To classify and understand the literature well we first identify the various kinds of fall and discuss the characteristics of each kind of fall. The contributions of this paper are multiple. First, we identify all kinds of fall and specify the characteristics of each kind of fall. This effort helps us to develop effective methods for different kinds of fall. Second, we propose a class hierarchy of fall detection methods. This will help us position the existing and future efforts. Lastly, we identify the principle of the existing methods and the connections between the used principles and the characteristics of fall.

The rest of this paper is organized as follows. Section II explores the characteristics of fall. Section III discusses the approaches and principles of the existing fall detection methods. We conclude the paper and comments possible research directions in section IV.

II. Specifications of Characteristics of Fall

In this section we not only identify the various kinds of fall but also specify the characteristics of different kinds of fall. We had better identify different kinds of fall because we probably need to solve different kinds of fall one by one. Specifying the characteristics of fall is another important effort because it will help us not only in understanding the existing algorithms but also in guiding us in designing new fall detection algorithms. This is true because an algorithm must be designed based on some characteristics of fall.

Based on the scenarios of fall occurrences, falls can be divided into four types: fall from sleeping (bed); fall from sitting (chair); fall from walking or standing on the floor; and fall from standing on supports such as ladder, tool. Falls from standing on support mainly occur among the working people, though they do sometimes occur among the elderly when they are doing some housework. The elderly and patient are mainly threatened by the first three classes of falls.

Though the first three classes of fall share some common characteristics they possess significant different characteristics. No one has specified the characteristics of fall yet probably because most people think that what is a fall is clear. However, it would be helpful in finding better fall detection algorithms to identify the characteristics of fall. Noury *et al* [46] identified some principles used in existing fall detection algorithms, but it did not specify the characteristics of fall itself. This paper can be considered as an extension of [46]. We list the characteristics of the first three classes one by one as follows.

LIST1: The characteristics of fall from sleeping (or bed)

1. A fall is a process lasting 1 to 3 seconds, consisting of several sub-actions.
2. The person is lying in the bed at the beginning of the fall.

978-1-4244-2281-4/08/$25.00 ©2008 IEEE

3. The body reduces its height from the bed height to the lying height (lying on the floor). Within portion of this period, the body will fall in a free fall manner.

4. The lying body on the floor is nearby the bed.

LIST2: The characteristics of fall from sitting (or chair)

1. A fall is a process lasting 1 to 3 seconds, consisting of several sub-actions.

2. The person is sitting in the chair at the beginning of the fall.

3. The head reduces its height from the sitting height to the lying height (lying on the floor). Within portion of this period, the head will fall in a free fall manner.

4. The lying body on the floor is nearby the chair.

LIST3: The characteristics of fall from working or standing

1. A fall is a process lasting 1 to 2 seconds, consisting of several sub-actions.

2. The person stands at the beginning of a fall. Here we define that a fall is from standing to lying on the floor. Normal people may say that fall does not include standing.

3. The head lies on the floor in the end of fall process. The head would lie on the floor motionless or with little motion for a while.

4. A person falls roughly in one direction. As a result, both the head and the weight center of the person move approximately in one plane during falling.

5. The head reduces its height from the standing height to the lying height (lying on the floor). Within portion of this period, the head will fall in a free fall manner.

6. The lying head is within a circle centered at the foot position of the last standing time and with the radium of the height of the person.

Notice that some characteristics of fall also exist in the normal activities. E.g., a crouch also has a period of rapid reduce of head height. Fall from bed or chair lasts longer time because bed or chair partially supports faller's body. As for tighter fall lasting time bounds for each type of fall, we can obtain them through more statistics.

III. Approaches and Principles of Fall Detection

In this section we first build a hierarchy of fall detection methods according to used sensors and principles. Then we comment the existing fall detection methods in the products and in the literature.

A. *Class Hierarchy of Fall Detection Methods*

Many efforts have made in fall detection due to the big demand and their big potential market and social value of fall detection products and technology. A series of technologies have already been developed in recent years. According to how fall is detected they can be divided into three approaches: wearable device, ambience device, and camera-based (*or vision-based*). Wearable devices can be further divided into posture device and motion device two classes. Ambience devices can be further divided into presence device and posture device two classes. We divide the camera-based methods into three classes according the used principles: inactivity detection, 2D body shape change analysis, and 3D head motion analysis. The class hierarchy of fall detection methods is depicted in Fig 1.

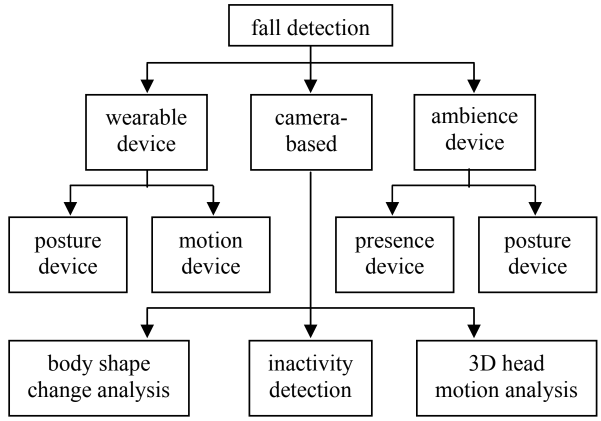

Fig 1. The hierarchy of approaches and classes of fall detection methods for elderly and patient.

Though there were different approaches and methods to detect fall for elderly and patient, existing fall detection devices and systems share a general framework, depicted in Fig 2. The difference of devices and systems lies in the complexity of each component. For example, data acquisition can vary from single simple sensor to sense one indicator to multiple different sensors and different cameras to work together to collect signal and video data. Fall detection can vary from comparing one sensed indicator with a threshold to a complicated image processing algorithm including background subtraction, shape detection, and shape change analysis.

B. *Wearable Device Approach*

The wearable device approach is to hold some devices or to wear some devices or garments with imbedded sensors to detect the posture and/or motion of the body of the wearer and use classifiers to identify suspicious events including fall [1, 4-5, 9, 11-15, 21, 26-27, 30, 37, 45, 47-49, 62, 64, 71, 73-75].

Construction system pte ltd [78] displayed a fall detection device at SiCEX'08 [81]. The principle of its detector is that the mercury in the detector tells whether the detector is in lying status and that it assumes that wearer's posture and detector's posture are the same all the time. If a lying is detected, the detector transmits a fall signal to receiver using bluetooth^{TM} technology. In this device, three components of data acquisition, data processing and feature extraction, and fall detection in the general framework shrink into checking whether mercury reach a certain point on the upper part of device.

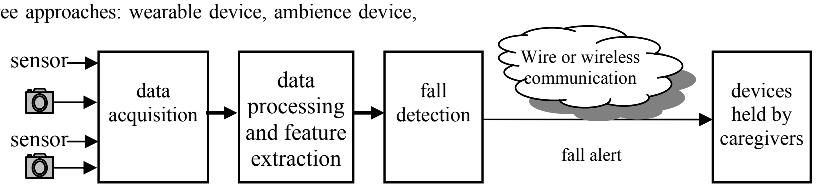

Fig 2. General framework of fall detection and alert device and system for elderly and patient.

Almeida *et al* [1] developed a detector installed on a walking stick to dynamically detect fall and measure pace, which uses gyroscope chip to measure angular velocity of the stick. When device detect a large velocity of stick it infers that the stick is lying down and infers that the holder of the stick has a fall. The principle is that the device detects the posture of the stick and use this posture infers the posture of the holder.

Clifford *et al* [11] patented a system for human body fall detection. The system includes a monitoring unit, including a plurality of accelerometers, a processor and a wireless transmitter. The plural accelerometers provide acceleration measurements to the processor. The processor receives the acceleration measurements and compares the acceleration measurements to a value range to determine if the wearer is currently experiencing a fall event. The processor generates a signal in response to the detection of a fall event and the transmitter transmits the signal to a remote signal receiver. The system and method can further detect non-movement subsequent to the fall event to detect an unconscious wearer.

Depeursinge [12] also patented a device to monitor the activity of a person and to detect falls.

Doukas *et al* [15] developed a wearable device to detect fall of patient, which uses plural accelerometers to collect data and uses a SVM (support vector machine) to distinguish fall from non-fall.

Hasen *et al* [21] developed a fall detection system for elderly. The system consists of three accelerators (sensors) and a processor. Three sensors collect motion data and the processor analyzes the data to detect fall by distinguishing fall pattern from non-fall pattern of motion data.

Lin *et al* [30] developed a micro-sensing device for monitoring human body falls. The device embedded into a coat consists of 10 sensors (micro-mercury switch and optical sensor). A processor processes data from 10 sensors to identify the status of wearer's body.

Noury *et al* [45, 47-48] developed a fall device called actimeter, which collects three types of data: the vertical acceleration shock obtaineded from a piezoelectric accelerator, the body orientation monitored from a position tilt switch, and the mechanical vibrations of body surface. The data are sent to a PC and PC analyzes data and identifies fall occurrences.

Nyan et al [49] developed a garment with functions of detecting falls and daily activity. 3-axis MEMS (Micro-Electro-Mechanical Systems) accelerators are embedded in garment to collect data and a signal processor processes the collected data and identifies fall and activity.

Petelenz *et al* [51] patented an elderly fall monitoring method and device. This device again uses accelerators to collect motion data. The difference is that this device also targets to distinguish the health from threatening fall.

Willianms *et al* [71] designed smart sensor for detecting fall and monitoring activities. The designed sensors measures the impacts associated with a fall. It also judges whether alert is in need by evaluating the status of faller.

Wu [73] identified the unique features of the velocity profile during normal and abnormal (i.e. fall) activities. Such unique features appear during the descending phase of fall. Thus, we can detect fall by using motion sensors to collect motion data of wearer and using algorithm to detect the unique features of motion data.

In the above systems or devices, the principle of fall detection is that fall has a different pattern of motion data from other activity. The wearable device approach has its advantages. First, except wearable garments other wearable devices for fall detection are cheap. Second, wearable device for fall detection are easy to be set up and operated. Its disadvantages are also multiple. First, this approach assumes that the worn device keeps a fixed relative relation with the wearer and this condition is easy to be broken. As a result, this approach is prone to have a high rate of false alarm. Another big disadvantage of the wearable device is that it is intrusive. The general comment from practising doctors is that most of patients have low will to wear device for detecting fall because they feel well before fall occurs.

C. *Ambience Device Approach*

Ambience device approach is to use multiple installed sensors to collect the data related person when person are close to them [2, 59-61, 79-80].

Alwan *et al* [2] used the vibration sensors on the floor. Thus these sensors together tell where the occupant is at any moment. The processor identifies fall through analyzing these location data.

Scott [59] patented a bed exit detection apparatus, which use bladders or other fluid-carrying devices in fluid communication with a pressure sensor so that the pressure sensor registers a bladder pressure in response to the patient's weight, the bladder pressure indicating the presence or absence of the patient on the bladder.

Sixsmith *et al* [60-61] installed pyroelectric IR sensor array on wall for detecting activity including fall. The array sees only the warm moving objects and not the static background, eliminating background subtraction in most of video-based fall detection algorithms. This array collects the location, size of velocity of the moving warm objects. Then a processor detects activity and fall through analyzing the collected data.

Tactex Controls Inc. [79] developed bed sensor to fit under the patient's mattress to monitor bed entry and exit routines for patients at risk of falls or wandering. The company also manufactures the floor sensor to monitor the location of person.

Technical Solutions Australia [80] manufactures devices for bed exit alarm, floor mat switch alarm, which use pressure sensor array to detect the presence of person at each sensor.

The above fall detectors all use pressure sensor to detect the presence of user, hence to obtain user's location. The principle is that when the user is at a place the pressure sensors at that place will sense a high pressure because of the weight of the user. The advantage of this approach is its cheap device and non-intrusive. The disadvantage is that we cannot discern if pressure is from the user's weight. As a result, it also suffers inaccuracy, i.e. there is a high rate of false alarm. Another sharing demerit of both wearable and ambience device approaches is that they cannot be visually verified by caregiver.

D. *Camera-Based Approach*

Cameras are increasingly included in in-home assistive system because they have multiple advantages over sensor approaches and the price of cameras decreases rapidly [43]. First, camera-based approach is able to be used to detect multiple events simultaneously. Second, they are less intrusive because they are installed on building not worn by users. Last, the recorded video can be used for remote and post verification and analysis. There were scores of camera-based fall detection algorithms in the literature. Generally speaking, each algorithm used some of the characteristics of falls. According to the used principles relating to the characteristics of fall they can be divided into three categories: inactivity detection, (*body*) shape change analysis, and 3D head motion analysis.

In *inactivity detection* algorithms, they use the principle that a fall will end with an inactivity period on the floor, which relates with Characteristics 3 in LIST3 in section II.A. Nait-Charif and McKenna [44] uses omni-camera in the system. The algorithm overhead tracks person so to obtain the motion traces of the person. Then it classifies the activities based on the motion traces and context information. Inactivity is one of classes and an inactivity will be said to be a fall if it occurs in certain context. Jansen and Deklerck [24] uses a stereo camera for fall detection. They use the stereo camera to acquire depth image (*called 3D image in their paper*). Then they identify the body area and find the body's orientation. Finally they use the orientation change of body to detect inactivity; fall is detected if inactivity occurs in certain context.

In *shape change analysis* algorithms, they use the principle that the shape of falling person will change from standing to lying, which relates to characteristics 2 and 3 in LIST3 in section II.A. Some of these algorithms use the first characteristics of fall implicitly due to they use HMM (*Hidden Markov Model*), which involves the time constraint. Töreyin *et al* [68] presented an HMM based fall detection algorithm. In this paper an HMM uses video features to differ fall from walking. The features are wavelet coefficients of the ratio of height to width of the bounding box of body shape. Another HMM uses audio feature to differ falling sound from talking. Anderson *et al* [3] use an HMM–based algorithm to detect fall. The HMMs use the multiple features extracted from the silhouette: height of bounding box, magnitude of motion vector, determinant of covariance matrix, and ratio of width to height of bounding box of person. The HMMs are trained to distinguish walking, kneeling, getting-up, and falling. Thome and Miguet [67] uses an HHMM-based algorithm to detect fall. The single feature of HHMM (*hierarchical HMM*) is the orientation of body's blob. The state level of HHMM is the postures of body. The other two levels of the HHMM represent behavior pattern and global motion pattern respectively. Miaou *et al* [40-41] use the rule-based algorithm to detect fall. The rules infer the fall occurrence based on the ratio of width to height of the bounding box of body in image. Other points are that it uses the omni-camera and it also uses the context information in deciding fall. Cucchiara *et al* [10] uses 3D shape of body to detect fall. 3D body shape is obtained by multiple cameras that are calibrated in prior. Hsu [22] used deformable triangulations of body shape to classify the postures of people (one class is fall), in which body shape is extracted from depth images. Williams [72] developed a smart camera network, which consists of a number of low resolution cameras. Though the system has multiple cameras, it does not intend to track people but to detect the result of falls due to all cameras simultaneously take images in a very low frame rate. Lin *et al* [32-33] developed a fall detection algorithm based on 2D shape of human extracted from compressed domain, i.e. without decompressing video.

In *3D head motion analysis* algorithms, they use the principle that vertical motion is faster than horizontal motion in a fall, which relates to characteristics 2 and 3 listed in section II.A. Rougier [53-55] develop an approach to detect fall using monocular 3D head tracking. The tracking component first locates the head, next estimates the head pose using particle filters, and then obtain the 3D position of head. The fall detection component computes the vertical and horizontal velocity of the head and then uses two appropriate thresholds to distinguish falling from walking.

For the algorithms in inactivity detection category, their main merit is that they have light computing load and hence they can be run in small computing devices. However, they are prone to have false alarm even though the context information is used and they have a late alarm because they detect fall only the person lies on the ground for a while. For the algorithms in shape change analysis category, the shape detection is much reliable than head detection because body is a salient object; normally once body shape is obtained the fall detection needs light computing, i.e., the computing load of the algorithms heavily depends on what shape detection method is used. Generally speaking, body shape detection can be real-time, whereas the 3D body shape detection needs more computation or more cameras and unreliable. However, the existing algorithms in this category calculate too few features from shape motion, mainly ratio of width to height of bounding box and they do not detect sub-actions of fall, exception is that HHMM may identify posture of body in its middle layer. In 3D head motion analysis algorithms, the main merits includes (a) the head has less occlusion; (b) the head motion has higher correlation with fall than body motion. However, tracking 3D position of head from single camera is not reliable and time-consuming.

E. *Comparison on properties*

From the above discussion, each class of fall detection methods has its merits and demerits. We summarize the properties of each class of fall detection methods in Table 1. In Table 1 "intru" and "R/V/V" stands for intrusion and remote visual verification respectively.

IV. CONCLUSIONS AND FUTURE WORK

We have presented a survey of the fall detection methods in the existing products and in the literature, focusing on identifying the approaches and principles of the existing methods. In this survey, we have first specified the characteristics of three kinds of falls that claim most of the falls of elderly and patient. Then we identified the approaches and principles of fall detection methods in the existing products and in the literature. We also have presented the class hierarchy of fall diction methods, depicted the general framework of fall detection and alarm systems, and summarized the properties of all classes of fall diction methods. To better understand the existing methods, we have pointed out some connections between the characteristics and principles of fall detection methods.

One remaining job in survey is to study the details of the existing algorithms since this paper focusing on identifying approaches and principles, but not details. Though the existing methods have not completely solved the problem of fall detection for elderly and patient, the knowledge used in the existing algorithms has provided us a baseline so that we can develop new techniques to improve existing ones to achieve better performance. From my point view, we should make efforts in the following fall-related directions.

Camera calibration: In body shape change analysis, we would probably add camera calibration technique to improve the performance of algorithms. As you know the body shape is determined by body posture in the real world, camera projection matrix, and location in the image. In other word, we recover more

Table 1. Summary of properties of various classes of fall detection for elderly and patient.

approach	class	property					
		price	intru	accuracy	live	setting	R/V/V
wearable device	posture device	cheap	yes	no	yes	easy	no
	motion device	cheap	yes	no	yes	easy	no
installed device	presence device	cheap/medium	no	no	yes	easy	no
	posture device	cheap/medium	no	no	yes	easy	no
camera-based	inactivity detection	medium	no	depend	yes	medium	yes
	shape change analysis	medium	no	depend	depend	depend	yes
	3D head motion analysis	medium	no	depend	depend	medium	yes

information of body shape if we know projection matrix, which can be acquired through camera calibration.

Benchmark video collection: As you know, fall is rare event in video recorded by surveillance camera working every day. So it is important to acquire benchmark video in lieu of the effort of the whole research cycle.

Generic fall detection algorithm development: Most of existing algorithms were designed for one case without much flexibility. We need to ask how many scenarios we have in fall detection for elderly and patient. Could we develop generic fall detection algorithm for each scenario?

Synergy of sensor and camera: From the above survey we have known that sensor and camera have their merits in fall detection. With this fact we should study how to use both of them to produce the best fall detection solution.

Nighttime issue: In night we have to use dim light in order not to disturb the sleep of user. We maybe need to develop the fall detection method under dim lighting.

Easy setting for camera-based systems: If we use camera-based fall detection systems we should make sure that the systems are easy to be set up. Otherwise users are hard to accept them because normally elderly and patient need other people to set up systems for them.

Deployment test: For camera-based fall detection systems, we need to do deployment test for them and compare the different systems. Through deployment test we also collect the feedback from users for improving the systems.

Fall prevention: Prevention systems and measures [8, 37] can be used to reduce fall incidence. This is an interest direction to work on because *prevention is better than cure*. Protection to elderly [35] is also good measure to reduce the harm to victim.

REFERENCES

[1] O. Almeida, M. Zhang, and L. C. Liu. Dynamic fall detection and pace measurement in walking sticks, manuscript, 2007.

[2] M. Alwan, P.J. Rajendran, S. Kell, D. Mack, S. Dalal, M. Wolfe, and R. Felder. A smart and passive floor-vibration based fall detector for elderly, *ICTTA '06 (2nd Info. & Com. Tech.)*, vol. 1, pp.1003 – 1007, 24-28 April 2006.

[3] D. Anderson, J.M. Keller, M. Skubic, X. Chen, and Z. He, Recognizing falls from silhouettes, *28th EMBC (28th Int'l Conf. of the IEEE Eng. in Medicine and Biology Society)*, pp. 6388 – 6391, Aug. 2006.

[4] A K Bourke, and G. M. Lyons. A threshold-based detection algorithm using a bi-axial gyroscope sensor, Med. Eng. Phys., 2006.

[5] A. K. Bourke, V. J O'Brien J and GM Lyons. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm, *Gait Posture*, 2006.

[6] G Brown. An accelerometer based fall detector: Development, experimentation, and analysis, *Internal Report, University of California in Berkeley*, 2005.

[7] G. Cambul, M.R. Sahin, and M.E. Karshgil. Automatic fall detection in real time video based applications, *2006 IEEE 14th Signal Processing and Communications Applications*, pp.1– 4, April 17-19, 2006.

[8] K. Cameron, K. Hughes, and K. Doughty. Reducing fall incidence in community elders by telecare using predictive systems, *19th EMBC*, vol.3, pp.1036-1039, 30 Oct-2 Nov 1997.

[9] J. Chen, K. Kwong, D. Chang, J. Luk, and R. Bajcsy. Wearable sensors for reliable fall detection, *27th EMBC*, pp. 3551-3554, 2005.

[10] R. Cucchiara, A. Prati, and R. Vezzani. A multi-camera vision system for fall detection and alarm generation, *Expert Systems Journal*, vol. 24(5), pp. 334-345, 2007.

[11] M. A. Clifford, R. L. Borras, and L. Gomez. System and method for human body fall detection, *US Patent* 7248172 , 07/24/2007.

[12] Y. Depeursinge. Device for monitoring the activity of a person and/or detecting a fall, *US patent* 6,201,476 B1, 13 March 2001.

[13] A. Diaz, M. Prado, L. M. Roa, J. Reina-Tosina, and G. Sanchez. Preliminary evaluation of a full-time falling monitor for the elderly, *26th EMBC*, San Francisco, CA, USA. Sept. 1-5, 2004.

[14] K. Doughty, R. Lewis and A. McIntosh. The design of a practical and reliable fall detector for community and institutional telecare, *J. Telemed Telecare*, 6 Sup 1 pp: S150-4, 2000.

[15] C. Doukas, I. Maglogiannis, P.Tragas, D. Liapis, and G. Yovanof. Patient fall detection using support vector machines, *Int'l Federation for Information Processing,* vol 247/2007, pp.147-156.

[16] V. F. S. Fook, P. V. Thang, T. M. Htwe, Q. Qiang, A. A. P. Wai. Automated recognition of complex agitation behavior of dementia patients using video camera, *9th Int'l Conf. on e-Health Networking, Application and Services*, pp.68–73, 19-22 June 2007.

[17] E. E. Freeman, B. Munoz, G. Rubin, and S. K. West. Visual field loss increases the risk of falls in older adults: the salisbury eye evaluation, *IOVS* 48: 4445-4450, 2007.

[18] M. J. Gibson, et al. The prevention of falls in later life. A report of the Kellogg *Int'l Work Group on the Prevention of Falls by the Elderly, Danish Medical Bulletin*, 34 Supplement 4:1-24, 1987.

[19] M. Gostynski. Prevalence, circumstances and consequences of falls in institutionalized elderly: a pilot study, *Soz Praventivmed*, Vol.36(6):341-5, 1991.

[20] R. J. Gurley, N Lum, M Sande, B Lo, and MH Katz. Persons found in their homes helpless or dead, *New Eng J Med.*; 334(26):1710-6, 1996.

[21] T. R Hansen, J. M Eklund, J. Sprinkle, and R Bajcsy Using smart sensors and a camera phone to detect and verify the fall of elderly persons European Medicine, Biology and Eng. Conf., vol. 3, 2005.

[22] Y. T. Hsu, J. W. Hsieh, H. F. Kao, and H. Y. M. Liao. Human behavior analysis using deformable triangulations, *IEEE 7th Workshop on Multimedia Signal Processing,* Oct. 2005, pp. 1– 4,

[23] J. Y. Hwang , J.M. Kang, Y.W. Jang , H. C. Kim. Development of novel algorithm and real-time monitoring ambulatory system using bluetooth module for fall detection in the elderly, 26th *EMBC*, San Francisco, CA, USA, Sept. 1-5, 2004

[24] B. Jansen and R. Deklerck. Context aware inactivity recognition for visual fall detection, *Pervasive Health Conference and Workshops*, pp.1– 4, Nov. 29-Dec. 1, 2006 .

[25] A. H. Khandoker, D. Lai, R.K. Begg, and M.Palaniswami. A wavelet-based approach for screening falls risk in the elderly using support vector machines, *ICISIP 2006 (4th Int'l Conf. Intelligent Sensing & Inf. Processing)*, pp:184-189, Oct. 15 2006-Dec. 18 2006.

[26] J. Krauss, and J. Zhao. Activity sensor and fall detection, manuscript, 2008.

[27] Y. Lee, J. Kim, M. Son, and M. Lee. Implementation of accelerometer sensor module and fall detection monitoring system based on wireless sensor network, *29th EMBC*, pp. 2315 – 2318, 22-26 Aug. 2007.

[28] T. Lee, and A. Mihailidis, An intelligent emergency response system: preliminary development and testing of automated fall detection. *J. of Telemedicine and Telecare, 11*, 194-198, 2005.

[29] L. J. Lin, F. T. Chiou and H. H. Cohen. Slip and fall accident prevention: A review of research, practice, and regulations, *Journal of Safety Research*, vol.26(4), pp.203-212.

[30] C. S. Lin, H. C. Hsu, Y. L. Lay, C. C. Chiu and C. S. Chao, Wearable device for real-time monitoring of human falls, *Measurement*, vol. 40(9-10), pp. 831-840, Nov.-Dec. 2007.

[31] C. S. Lin, H. C. Hsu, C. C. Chiu, S. L. Lin, and C. S. Chao, A PDA based wearable system for real-time monitoring of human falls, *IETE Journal of Research*, Vol 52 (6), 403-416, 2006.

[32] C. W. Lin, and Z. H. Ling, Automatic fall incident detection in compressed video for intelligent homecare, *ICCCN 2007 (Proc. of 16th Int'l Conf. on Com. Comm. & Networks)*, pp.1172-1177, Aug. 2007.

[33] C. W. Lin, Z H. Ling, Y. C. Chang, and C. J. Kuo, Compressed-domain fall incident detection for intelligent home surveillance, *ISCAS (IEEE Int'l Symp. Circ. & Sys.*), vol. 4, pp.3781–84, 23-26 May 2005.

[34] U. Lindemann. Evaluation of a fall detector based on accelerometersa pilot study, *Med Biol Eng Comput*, 43(5):548-51, sep 2005.

[35] T. E. Lockhart. Fall-sensing systems, hip protector systems, and protective systems, *US Patent*, US2006/0049950 A1, 2006.

[36] C. J. Lord, and D. P. Colvin, Falls in the elderly: Detection and assessment, *13rd EMBC,* 1991.

[37] S. R. Lord, C. Sherrington, H. B. Menz, and J. C. T. Close. Falls in older people: risk factors and strategies for prevention, *Cambridge University Press, 2nd edition*, March 19, 2007.

[38] S. Luo, and Q. Hu. A dynamic motion pattern analysis approach to fall detection, *ISCAS 2004*, Vol 1, pp:5-8, 1-3 Dec. 2004.

[39] M. J. Mathie, J. Basilakis, and B. G. Celler. A system for monitoring posture and physical activity using accelerometers, *23rd EMBC*, Istanbul, 25-28 Oct. 2001.

[40] S. G. Miaou, F. C. Shih, and C.Y. Huang. A smart vision-based human fall detection system for telehealth applications, *3rd IASTED int'l Conf. on Telehealth*, pp.564, May 30-June 1, 2007, Montreal, Quebec, Canada.

[41] S. G. Miaou, P. H. Sung, and C. Y. Huang. A customized human fall detection system using omni-camera images and personal information, *D2H2 2006 (1st Transdisciplinary Conf. on Distributed Diagnosis and Home Healthcare*, pp.39-42, 2006.

[42] A. Mihailidis. An intelligent emergency response system: preliminary development and testing of automated fall detection, *J. Telemed. Telecare*, Vol 11(4):194-8, 2005.

[43] A. Mihailidis, B. Carmichael, and J. Boger. The use of computer vision in an intelligent environment to support aging-in-place, safety, and independence in the home, *IEEE Trans. on Information Technology in Biomedicine*, vol. 8(3), pp.238- 247, Sept. 2004.

[44] H. Nart-Charif and S. J. McKenna. Activity summarisation and fall detection in a supportive home environment, *ICPR 2004*.

[45] 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, *EMBC 2003*, Cancun-Mexico, pp3286-89, sept 2003.

[46] N. Noury, A. Fleury, P. Rumeau, A. K. Bourke, G. O. Laighin, V. Rialle, J. E. Lundy, Fall detection - principles and methods, *29th EMBC*, pp.1663-1666, 22-26 Aug. 2007.

[47] N. Noury, T. Herve, V. Rialle, G. Virone, E. Mercier, G. Morey, A. Moro, and T. Porcheron. Monitoring behavior in home using a smart fall sensor and positionsensors, *1st Annual Int'l IEEE-EMBS Special Topic Conf. on Microtech. in Med. & Biology*, pp.607-610, Oct. 12-14, 2000.

[48] N. Noury, A. Tarmizi, D. Savall, P.Boissy, P.Barralon, G. Virone, and P.Rumeau. A smart sensor for fall detection in daily routine, *SICICA2003*, Aveiro-Portugal, 9-11 Jul 2003.

[49] M. N. Nyan, Francis E. H. Tay, M. Manimaran and K. H. W. Seah. Garment-based detection of falls and activities of daily living using 3-axis MEMS accelerometer, *J. Phys.: Conf. Ser*. 34 (2006) 1059-1067.

[50] G. Pérolle, P. Fraisse, M. Mavros, and I. Etxeberria. Automatic fall detection and activity monitoring for elderly, manuscript, 2007.

[51] T. J. Petelenz, and S. C. Peterson. Elderly fall monitoring method and device, *US Patent*: 6433690 issued on Aug 13, 2002.

[52] M. Prado, J. Reina-Tosina, and L. Roa. Distributed intelligent architecture for falling detection and physical activity analysis in the elderly, *2nd Joint EMBS/BME,* Houston, TX, USA. Oct. 23-26, 2002.

[53] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau. Fall detection from human shape and motion history using video surveillance, *21st Int'l Conf. on Advanced Information Networking and Applications Workshops*, Vol 2, pp. 875-880, 2007.

[54] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau. Monocular 3D head tracking to detect falls of elderly people, *28th EMBC*, pp.6384 – 6387, Aug. 2006.

[55] C. Rougier and J. Meunier. Demo: fall detection using 3D head trajectory, *1st Int'l Workshop on Video Processing for Security (V4PS),* Québec, June 2006.

[56] O. P. Ryynanen , S.L. Kivela, R Honkanen, and P Laippala. Falls and lying helpless in the elderly, *Z Gerontol*.; 25(4):278-82, 1992.

[57] S. Sadigh, A Reimers, R Andersson, and L Laflamme. Falls and fall related injuries among the elderly: a survey of residential-care facilities in a Swedish municipality. *J. Community Health*, vol.29(2), pp.129-40, Apr 2004.

[58] A. Salvà, I. Bolíbar, G. Pera, and C. Arias. Incidence and consequences of falls among elderly people living in the community, *Med Clin (Barc*). vol. 122(5), pp.172-176, Feb 14, 2004.

[59] T. E. Scott, Bed exit detection apparatus, *US Patent* 6067019 issued on May 23, 2000.

[60] A. Sixsmith and N. Johnson. A smart sensor to detect the falls of the elderly, IEEE Pervasive Computing, pp42-47, No 2, 2004.

[61] A. Sixsmith, N. Johnson, and R. Whatmore. Pyroelectric IR sensor arrays for fall detection in the older population, *J. Phys. IV France* 128 pp.153-160, 2005.

[62] J. A. Stevens, P. S. Corso, E A. Finkelstein, and T. R. Miller. The costs of fatal and non-fatal falls among older adults. *Inj. Prev*. 12: 290-295, 2006.

[63] S. Straus. A 16-week tai chi programme prevented falls in healthy older adults. *Evid. Based Med*. 13: 54-54, 2008.

[64] T. Tamura, T. Yoshimura, F. Horiuchi, Y. Higashi, and T. Fujimoto. An ambulatory fall monitor for the elderly, *22nd EMBS*, Vol. 4, pp: 2608-2610, Chicago, IL, USA, 2000.

[65] R. Teasell, M. McRae, N. Foley, and A. Bhardwaj. The incidence and consequences of falls in stroke patients during inpatient rehabilitation: factors associated with high risk, *Archives of Physical Medicine and Rehabilitation*, vol 83(3), pp.329-333, Mar 2002.

[66] M. E. Tinetti, and C. S. Williams. Falls, injuries due to falls, and the risk of admission to a nursing home, *New Eng J. of Medicine*, vol.337, pp.1279-1284, Oct. 30, 1997.

[67] N. Thome, and S. Miguet. A HHMM-Based approach for robust fall detection, *ICARCV '06 (9th Int'l Conf. on Control, Automation, Robotics and Vision),* pp.1– 8, Dec. 5-8, 2006.

[68] B. U. Töreyin, Y. Dedeoğlu, and A. E. Çetin. HMM based falling person detection using both audio and video, *IEEE 14th Signal Processing and Communications Applications*, 17-19 April 2006.

[69] B. J. Vellas, S. J. Wayne, P. J. Garry and R. N. Baumgartner. A two-year longitudinal study of falls in 482 community-dwelling elderly adults, *J Gerontol A Biol Sci Med Sci,* Vol. 53(4), pp.264-274, Jul 1998.

[70] N. C. Voermans, A. H. Snijders, Y. Schoon, and B. R. Bloem. Why old people fall (and how to stop them). PN 7: 158-171, 2007.

[71] G. Williams, K. Doughty, K. Cameron, and D. A. Bradley. A smart fall and activity monitor for telecare applications, *20th EMBC*, vol.3, pp.1151-1154, 29 Oct-1 Nov 1998.

[72] A. Williams, D. Ganesan, and A. Hanso. Aging in place: fall detection and localization in a distributed smart camera network, *ACM MM*, pp 892 – 901, 2007.

[73] G. Wu. Distinguishing fall activities from normal activities by velocity characteristics, *J. of Biomechanics*, vol. 33(110, pp.1497-1500, 2000.

[74] T. Zhang, J. Wang, L. Xu, and P. Liu. Using wearable sensor and NMF algorithm to realize ambulatory fall detection , *LNCS*, Vol 4222, pp.488-491, 2006.

[75] T. Zhang, et al. Fall detection by embedding an accelerometer in cellphone and using KFD algorithm, *Int'l Journal of Computer Science and Network Security*. 6(10) pp: 277-84, 2006.

[76] http://www.monitoringcare.com/medical-alert/fall-detection-sensor.asp

[77] http://www.argussecuritytech.com/pr_iv_applications_slipFall.html

[78] http://www.chhsys.com/asp_chhsys07/detectors.html

[79] http://www.tactex.com/products_bed.php

[80] http://www.tecsol.com.au/

[81] http://www.ageproofyourbrain.com/silver-industry-conference-amp-exhibition-sicex-2008-singapor