An Enhanced Fall Detection System for Elderly Person Monitoring using Consumer Home Networks

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**Abstract — ***Various fall-detection solutions have been previously proposed to create a reliable surveillance system for elderly people with high requirements on accuracy, sensitivity and specificity. In this paper, an enhanced fall detection system is proposed for elderly person monitoring that is based on smart sensors worn on the body and operating through consumer home networks. With treble thresholds, accidental falls can be detected in the home healthcare environment. By utilizing information gathered from an accelerometer, cardiotachometer and smart sensors, the impacts of falls can be logged and distinguished from normal daily activities. The proposed system has been deployed in a prototype system as detailed in this paper. From a test group of 30 healthy participants, it was found that the proposed fall detection system can achieve a high detection accuracy of 97.5%, while the sensitivity and specificity are 96.8% and 98.1% respectively. Therefore, this system can reliably be developed and deployed into a consumer product for use as an elderly person monitoring device with high accuracy and a low false positive rate[1].*

Index Terms — Wireless Sensor Networks, Fall Detection System, Elderly Monitoring, Heart Rate Fluctuation, Sensitivity.

I. Introduction

In recent years, many types of consumer electronics devices have been developed for home network applications. A consumer home network usually contains various types of electronic devices, e.g. sensors and actuators, so that home users can control them in an intelligent and automatic way to improve their quality of life [1].

Some representative technologies to implement a home network include: IEEE 802.11, Ultra Wide Band (UWB), Bluetooth and ZigBee, etc. ZigBee is suitable for consumer home networks because various sensors can be deployed to collect home data information in a distributed, self-organizing manner with relatively low power. Some typical applications include home automation, home activity detection (like fall detection) and home healthcare, etc. [2].

Kinsella and Phillips [3] found that the population of 65-and-over aged people in the developed countries will approach 20% of total population in the next 20 years and will obviously become a serious healthcare issue in the near future. In China alone, the population over the age of 60 years old is 133.9 Million [4], [5]. Among the elderly, the fall events can be an unpredictable and dangerous event. Statistics show that one among three 65-and-over aged person falls every year [6]. Among these fall events, 55% occur at home and 23% occur near the home. In 2003, the global number of deaths caused by fall events was approximately 391,000 and specifically 40% of the falls were from people over 70 years of age [7]. Thus, reliable consumer based fall detection systems need to be designed, tested and commercially deployed to countries all around the world. Furthermore, the cost of healthcare is highly related to the response and rescue time, and can be greatly reduced by fast detection and delivering signals to the specified operator for immediate consideration [8]. Thanks to the development of wireless sensors and low-power sensor nodes, many novel approaches have been proposed to solve the problem, as discussed in Section II.

In this paper, an enhanced fall detection system for elderly person monitoring through a consumer home network environment is proposed that based on smart sensors which are worn on the body. The proposed system has been deployed in a prototype system and tested with a group of 30 healthy participants, it is found that the system can achieve very high accuracy of 97.5%, the sensitivity and specificity are 96.8% and 98.1% respectively.

The rest of the paper is organized as follows: Section II details related works. Section III describes the system architecture and sensor deployment. Section IV explains the fall detection system in detail. Section V illustrates system performance and Section VI concludes this paper.

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II. Related Works

Many previous and current research projects use medical sensor networks to identify and track human activities in daily life. With the purpose to successfully detect falls, there are primarily three types of fall detection methods for elderly people, namely wearable device based methods, vision based methods, and ambient based methods.

A. Wearable Based Methods

Wearable based methods often rely on smart sensors with embedded processing. They can be attached to the human body or worn in their garments, clothing or jewelry.

Zhang, Ren and Shi [9] proposed HONEY (Home healthcare sentinel system), a three-step detection scheme which consisted of an accelerometer, audio, image and video clips. Its innovation was to detect falls by leveraging a tri-axial accelerometer, speech recognition, and on-demand video. In HONEY, once the fall event was detected, an alert email was immediately sent and the fall video was uploaded to the network storage for further investigation.

Bagalà *et al.* [10] gave an evaluation of accelerometer-based fall detection algorithms on real-world falls. They found that the sensitivity and specificity on real falls are much lower than that in an experiment environment. This inspires researchers to take more real world scenarios into consideration.

Abbate *et al.* [11], [12] proposed a smartphone based fall detection system with consideration of the acceleration signal produced by fall-like activities of daily lives.

Bai, Wu and Tsai [13] illustrated a system based on a 3-axis accelerometer embedded in a smart phone which had a GPS function for the user. However, due to the relatively high energy consumption of current smart phones, their system could only be active for 40 hours with foreground execution or at most 44 hours in background execution, which means continuation of this system is the most significant problem.

B. Vision Based Methods

Vision based methods are always related to spatiotemporal features, change of shape, and posture.

Yu *et al.* [14] proposed a vision based fall detection method by applying background subtraction to extract the foreground human body and post processing to improve the result. To detect a fall, information was fed into a directed acyclic graph support vector machine for posture recognition. This system reported a high fall detection rate and low false detection rate.

Rougier *et al.* [15] analyzed human shape deformation during a video sequence which is used to track the person's silhouette.

C. Ambient Based Methods

Ambient based methods usually rely on pressure sensors, acoustic sensors or even passive infrared motion sensors, which are usually implemented around caretakers' houses [16]-[18].

Popescu *et al.* [16] developed an acoustic-based fall detection system which used an array of acoustic sensors. The fall detection sensors are linear arrays of electret condensers placed on a pre-amplifier board. In order to capture the information of the sound height, the sensor array was placed in the z-axis. The limitation of this method was that that only one person was allowed in the vicinity.

Winkley, Jiang and Jiang [17] proposed Verity, a 2-component system which had a based station and a direct monitoring device. In this particular system, ambient/skin temperatures were measured for real time monitoring. Experiments verified that the proposed classifier outperforms the conventional classifiers in its one-pass training and with higher distinguishing capability.

Yan *et al.* [18] addressed the perceived invasive nature of these wearable devices by developing a system that did not necessarily require the user to be wearing a sensor, yet was able to detect the user's location based on observations of interaction with the home-installed sensor network.

Video based methods are usually more accurate than wearable based and ambient based methods. However, these systems often suffer from high risk of privacy and the prohibitive cost implementing the cameras. Thus, wearable sensor based methods are considered in this research.

III. System Implementation

The structure of proposed fall detection system is shown in Fig. 1, whose core structure is based on a Microprogrammed Controller Unit (MCU). The accelerometer sensor is complemented by other smart sensors including temperature and humidity sensors all integrated on one single board, recording real time acceleration and ambient environment information. Both acceleration and environment information are first captured using an analog-to-digital converter (ADC). Then, the digital signal is transmitted to the MCU for further processing. The heart rate is captured by a pulse pressure sensor and also passed directly to the MCU. The system is complemented with a customer interface designed to monitor information in real-time.

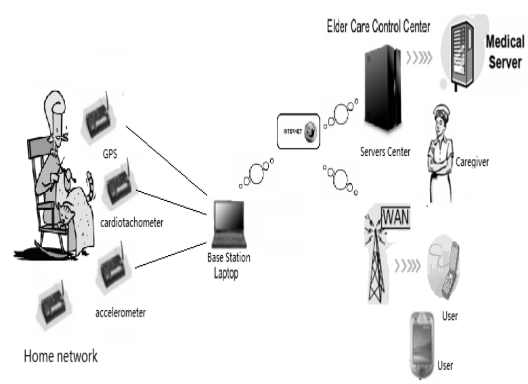

Fig. 1. System architecture using the consumer wireless sensor network.

A. System and Sensors

A multi-functional data acquisition board has been used incorporating temperature and humidity sensors. Besides, it offered a convenient solution to add any custom sensing application in future research. To detect the impact of accidental falls, a small low power tri-axial accelerometer is used as shown in Fig. 2. It can measure the static acceleration of gravity in tilt-sensing applications. Also, it can measure the dynamic acceleration results from motion, shock, or vibration. This specified accelerometer will output acceleration in all three axis at every sample point, with units of m/s^2. The output is an analog signal which must be converted by an ADC before sending to the MCU. However, the other smart sensors used in this system are utilized to detect the heartbeat pulse with sensitivity 0.2mv/pa.

B. MCU System

The key component of this system is a MCU with 128K flash memory. It is a compromise between relatively high performance vs. low-power (2.7-5.5V). This high-density nonvolatile memory based MCU provides an embedded 8-channel, 10-bit ADC, and provides a highly flexible and cost effective solution to many embedded control applications. Information gathered by accelerometer is converted in the chip and forwarded to the wireless communication module along with pulse signals.

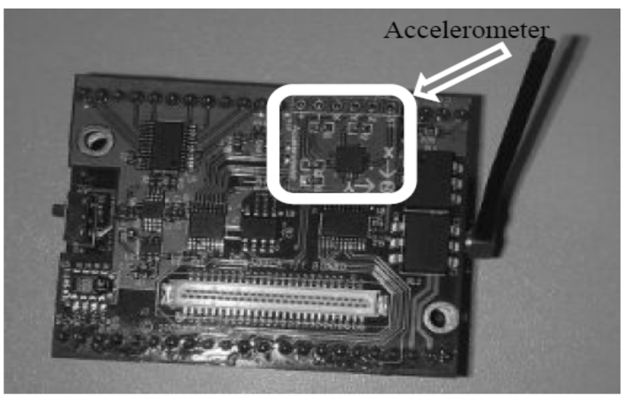

Fig. 2. Wireless communication module with board accelerometer.

C. User Interface

The data gathered from a participants body is appended with a unique ID and transmitted to a remote laptop by the wireless receiver with type number of the base station being used. As is shown in Fig. 3, a user interface is designed to display the accelerometer and heart rate signal. The interface can monitor four participants' data at the same time. In each part, data curves are illustrated on upper left and real-time data are shown on the right of the curves. Once the alarm is triggered, a red marked warning will be shown at the bottom left part of the monitors.

In order to assure that a caregiver, or relatives, get real-time and accuracy information, the location of the wireless sensor network is significant. Modern wireless sensor networks have been highly normalized by ZigBee, but they cannot efficiently handle the specific tasks due to the constrained environment. In order to do so, the wireless communication stack in the wireless sensor network needs to be optimized so many sensor nodes need to be put in one base station. Every sensor node can be freely configured as a master or slave. Considering ZigBee transmission power, propagation does not reliably pass through modern construction walls to the base station, therefore the base station usually does not receive the signal transmitted from a neighboring room, as shown in Fig. 4.

To detect the acceleration and heart rate more accuracy, the whole house can be divided into several clusters based on the room locations. Each room has a fixed access point for data collection and transmission. The sensor nodes represent the accelerometer or cardiotachometer, which could be located anywhere in the house. The signal from wireless module can be transmitted directly to base station or through the fixed access point. The system employs mesh networking to enable communication when it encounters problems of connecting to the base station directly. Fig. 5 indicates how the sensors have been deployed in the patient's home.

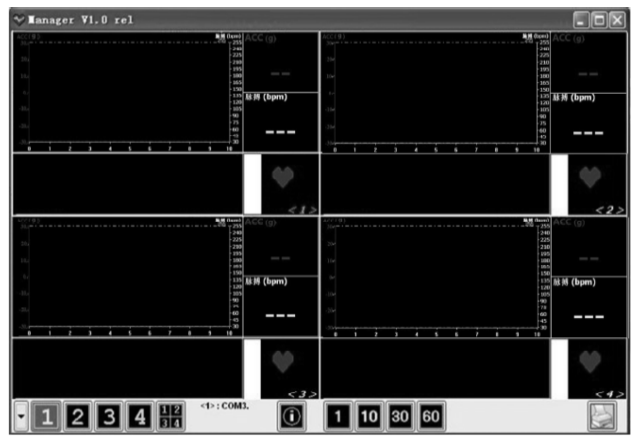

Fig. 3. User interface for the management software

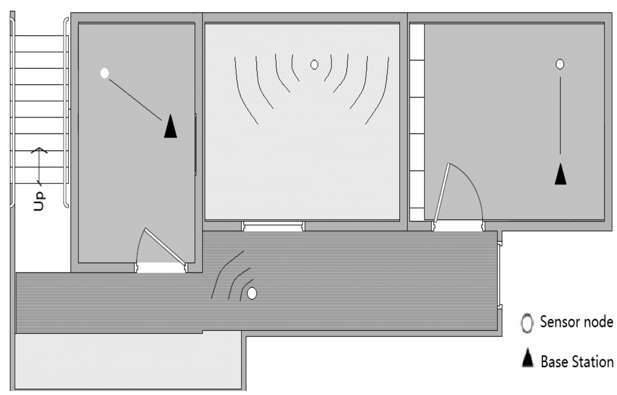

Fig. 4. Sensor and base station deployment

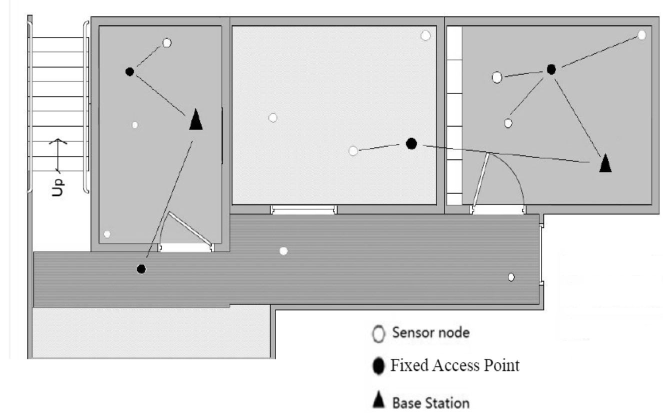

Fig. 5. Sensor, fixed access point and base station deployment

IV. PROPOSED ENHANCED FALL DETECTION METHOD

The proposed enhanced fall detection method is based on three common changes which happen during accidental falls: impact magnitude, trunk angle, and after-event heart rate. Hence, a triple-threshold for the previously fall related event in chronological order is proposed in this paper. A flowchart of the proposed method is illustrated in Fig. 6.

An initiatory estimation of the body movement can be obtained from the Signal Magnitude Vector (SMV) defined as:

$$SMV = \sqrt{Acc_x^{\ 2} + Acc_y^{\ 2} + Acc_z^{\ 2}} \quad (1)$$

where Acc_x, Acc_y and Acc_z represent the outputs of x-axial, y-axial and z-axial, respectively. Since the direction of possible falls cannot be predicted, it is inappropriate to use only one output of the axis. The advantage of using equ. (1) is that it is sensitive to all directions of falls. At the beginning, acceleration due to gravity, *g,* lies in the z direction. The acceleration changes along with body movement, Furthermore, vibration becomes significant when the fall happens. Acceleration threshold had been set to 1.9 *g* as in the literature [9].

A typical fall event ends with the person lying on the ground or leaning on walls, or furniture that will cause a significant change in truck angle. In this case, it is desirable to consider changes on the truck angle to detect whether the detected acceleration was due to a fall event. Trunk angle, θ, can be defined as angle between the SMV and positive z-axis and can be calculated by inverse trigonometric function as equ. (2). The threshold for θ has previously been given as: 0 to 60◦ classified as upright and 60 to 120◦ classified as a lying posture [19].

$$\theta = \arccos\left(\frac{Acc_z}{SMV}\right) \quad (2)$$

The emergency case can then be classified into four levels:

1. Caregiver level: When the system is setup, it will check whether the SMV is over threshold. If not, it would continually check the heart rate. Once the heart rate gets over a preset value, the system will assume an emergency event has happened and would contact the caregivers to check out the elderly’s condition.
2. Relatives level: Once the system convinced the acceleration is over threshold in the first decide loop, the system will then examine the value of heart rate. If it does not get higher than the preset threshold, then relatives will be contacted to request the relatives contact the elderly person’s home.
3. Caregiver and relatives level: In addition, in case the acceleration and heart rate value both get higher than the preset thresholds, then system can contact the caregivers and relatives irrespective of the trunk angle as a distinct floating in heart rate coupled with high acceleration is a significant warning.
4. Ambulance level: If all three thresholds, SMV, heart rate, and trunk angle, are higher than normal, the system as assumed that an accidental fall has happened. The system will contact the emergency center immediately requiring an ambulance.

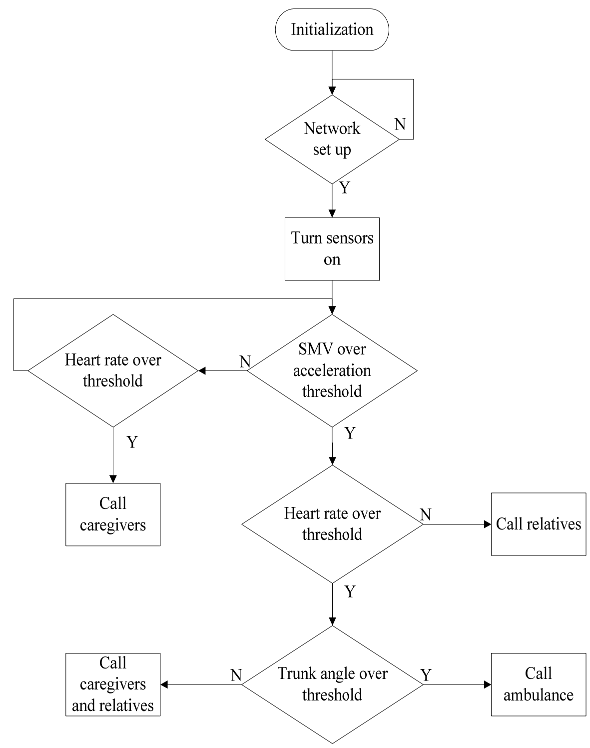

Fig. 6. Flowchart of using heart rate threshold minimizing the false positive rate of fall detection

V. PERFORMANCE EVALUATION

A. Laboratory Based Tests

To evaluate the accuracy of proposed method, 30 healthy male and female participants were invited to take part in this research. Their ages range from 19 to 45 years, weights range from 48 to 80 kg, and heights of 160 to 185 cm. TABLE I lists 13 kinds of fall detection experiments including 6 falls and 7 activities representative of Active Daily Lives (ADL). In order to obtain meaningful data, participants are asked to perform every sub-experiment three times. The tests were accomplished by falling on thin mats in a configured laboratory. Their fall related data was transmitted to a laptop for further analysis.

As discussed in Section IV, SMV and trunk angle thresholds have been proposed by previous research. The threshold of heart rate changes needed to be carefully selected as the heart rate examination acts as the last classifier. Participants are asked to wear a pulse pressure sensor on their wrist and the integrated sensor board on their chest. After sensors are implemented carefully, participants were asked to do the tests set out in TABLE I. Two assistants stood next to the falling participant to make sure that there was no accident during the experiment procedure. After all tests, 900 meaningful results are chosen to calculate the upper limit of 95% confidence interval. Finally, heart rate change threshold can be set as 15%. Fig. 7 depicts all the heart rate test results.

TABLE I
FALL EVENT AND ADL TESTS DESCRIPTIONS

	No	EXPERIMENT
Fall	1	Backward fall, lying on ground
Fall	2	Backward fall, seating on ground
Fall	3	Backward fall, seating on chair
Fall	4	Forward fall, landing on knees
Fall	5	Forward fall, lying on ground
Fall	6	Seating in bed, falling to ground
ADL	7	Ascending stairs
ADL	8	Descending stairs
ADL	9	Running down the stairs
ADL	10	Walking and suddenly stop
ADL	11	Pick up an object from the floor
ADL	12	Fast stand up from a chair
ADL	13	Fast sit down to a chair

Fig. 7 illustrates the heart rate change before and after fall events. Participants under 30 years old have relatively small fluctuation when suffering a fall event. As to those over 30 years, the fluctuations are apparently high, which are 18%, 21%, and 22% respectively. Therefore, if a fall event happened on an elderly person, the proposed heart rate threshold will normally be triggered.

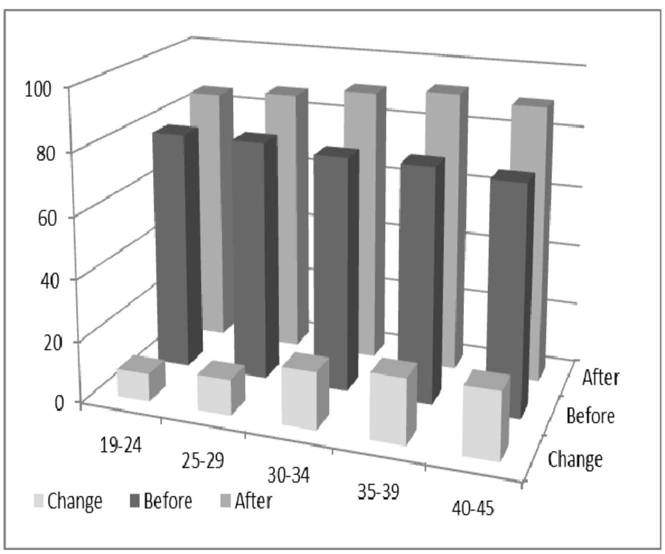

Fig. 7. Heart rate test results and changing ratio

As the system does not need any user feedback, the fall alarm can be sent within a few seconds. Fig. 8 shows the user interface in operation. As is shown in Fig. 8, the distinct vibration of the Acc curve illustrates a fall event may have occurred. In the meantime, the participant's heart rate changed from 62 to 74 bpm. Along with the backgrounder trunk angle calculation, a fall is alarmed as positive.

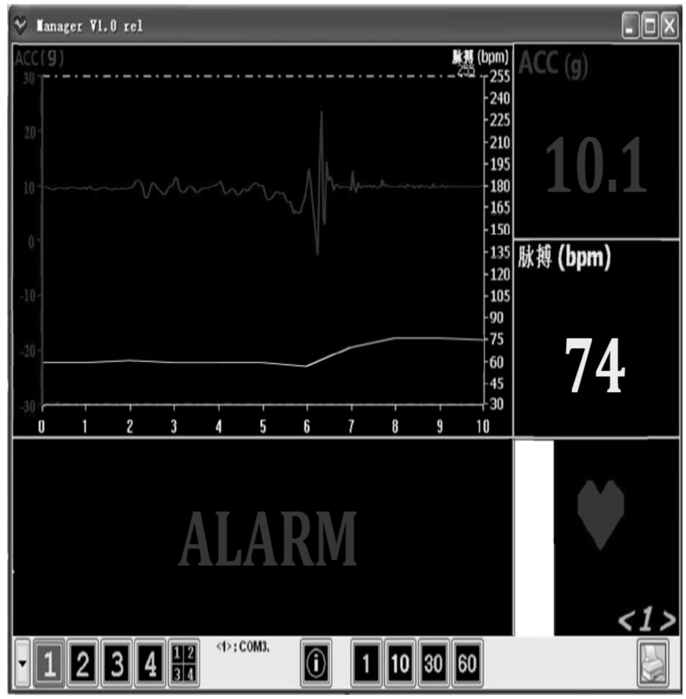

Fig. 8. GUI of Channel 1 in use.

The definition of sensitivity and specificity are respectively given in equ. (3) and (4), where TP is the true positive and FN is false negative. Similarly, TN represents true negative and FP represents false positive.

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

As illustrated, sensitivity indicates likelihood of a fall event did occur, but had not been detected. On the contrary, represents the system triggered fall event alarm that actually had not happened.

Table II shows the detection results of the 6 prescribed fall events and Table III shows the detection results of the 7 prescribed ADL activities. The system accuracy was found to be 97.5%. The sensitivity was found to be 96.8% and the specificity was found to be 98.1%. A balance between sensitivity and specificity has thus been achieved.

TABLE II
FALL EVENT TESTS RESULTS

Fall	TP	FN	SENSITIVITY
1	90	0	100%
2	90	0	100%
3	89	1	98.9%
4	83	7	92.2%
5	90	0	100%
6	80	10	88.9%

TABLE III
ADL TESTS RESULTS

Fall	TN	FP	SENSITIVITY
7	90	0	100%
8	90	0	100%
9	86	4	95.6%
10	90	0	100%
11	85	5	94.4%
12	87	3	96.7%
13	90	0	100%

The most inaccurate term in fall event tests tends to be due to falling out of bed. This may be caused by the fact that some participants subconsciously brake the fall with their arms causing low acceleration and therefore not reaching a trigger threshold. Also there are 8 false negatives reported in a forward fall, landing on knees and seating on a chair. After checking the raw data, this was because that trunk angle did not exceed the preset threshold. A lower trunk angle threshold may solve this issue. However, reducing the trunk angle threshold will cause the increase of false positive reports. This inconsistency always exists in threshold based systems. Thus, searching a balance between sensitivity and specificity is one very important issue under practical implementation.

When using the system to do the ADL tests, 16 false positive reports existed, including running down the stairs, picking up an object from the floor, and standing up fast from a chair. Among the three events, the system missed 5 times in picking up an object from the floor. This was predominantly caused by fast head down movements that in turn caused marked changes in acceleration, trunk angle and heart rate. Four misses were found in running down stairs were caused by suddenly stopping at stair corners but as running is rare among elderly persons then these false positive reports were not considered further.

B. *Practical Tests*

The proposed system achieved a relatively high sensitivity and specificity in laboratory conditions. However, in order to validate the system in practical tests, the system was implemented with people aging from 5 to 70 years for two weeks, but as other researchers have found, there was no accidental fall that occurred when the system was deployed. However, during the 2-week monitoring a false positive alarm did not occur. A substantial amount of ADL data was collected which indicates the system to be stable and robust.

In future work, a new device with lower energy consumption and longer communication distance will be developed to make the system more suitable for a broad-range of healthcare applications.

VI. CONCLUSION

In this paper, an enhanced fall detection system based on on-body smart sensors was proposed, implemented, and deployed that successfully detected accidental falls in a consumer home application. By using information from an accelerometer, smart sensor and cardiotachometer, the impacts of falls can successfully be distinguished from activities of daily lives reducing the false detection of falls. From the dataset of 30 participants, it is found that the proposed fall detection system achieved a high accuracy of 97.5%, and the sensitivity and specificity are 96.8% and 98.1% respectfully. The proposed system is ready to be implemented in a consumer device.

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Eur Ing Professor Sherratt has served the IEEE Consumer Electronics Society as a Vice President (Conferences) (2008/9), AdCom member (2003-2008, 2010-) and Awards chair (2006/7). He is a member of the *IEEE TRANSACTIONS ON CONSUMER ELECTRONICS* Editorial Board (2004-) and is currently the Editor-in-Chief (2011-), the IEEE International Conference on Consumer Electronics general chair (2009) and the IEEE International Symposium on Consumer Electronics general chair (2004). He received the IEEE Chester Sall 1st place best Transactions on Consumer Electronics paper award for 2004 and the best paper in the IEEE International Symposium on Consumer Electronics in 2006.