A New Smart Fall-down Detector for Senior Healthcare System Using Inertial Microsensors

Yongkun Sui, *IEEE Member*, Chanmin Ahn, and Chong H. Ahn, *IEEE Member*

***Abstract*— A new smart fall-down detector for senior healthcare system using inertial microsensors and Wi-Fi technology has been designed, prototyped and characterized in this work. The detector can reduce the risk of severe injury or death caused by falling down with minimum false alarm rate. The different patterns of motion are sensed by a set of inertial sensors composed of a tri-axial accelerometer and a tri-axial gyroscope. The signals of motion are sampled and processed by a microcontroller with integrated algorithms. The smart algorithm integrated with machine learning can be customized according to different habits of different seniors to reduce false alarms. The fall-down signal is transmitted through Wi-Fi to the client via Internet.**

I. INTRODUCTION

According to the Home Safety Council, around 6,000 people die due to fall-down at home each year [1]. Annually at least thirty percent of senior people experience fall-down and get injured [2]. Many of these falls are fatal if medical care is not given in time. Some seniors may become unconscious after falling down thus not able to call emergency by themselves for help. Nowadays, as sensor devices and communication technology grows, automatic fall-down detectors have been explored to improve the healthcare of seniors due the fall-down [3, 4]. Many existing fall-down detectors use smart phones with embedded accelerometers. There are two issues of the smart phone solution. Firstly, not every senior owns a smart phone or carries one with them all the time at home. Secondly, smart phones generate a lot of motion data during general usage. It is difficult to find a safe and effective way to filter those data out.

In this work, a wearable fall-down detector using a set of inertial microsensor, which is composed of a tri-axial accelerometer and a gyroscope, has been explored and developed for monitoring the fall-down of senior people. Data are sampled then processed with a smart algorithm by a microcontroller. If input data reach pre-set thresholds, then an alarm for the dangerous fall-down will be triggered and transmitted. This system will be built into one wearable package with a battery. It has an embedded web server to transmit alarm signal and live data. Seniors can clip the device on belts or pockets. If a fall-down signal is detected, the detection and analysis system can classify it as a usual motion or otherwise the alarm will be triggered. Once the staffs of emergency care (or clients) receive an alarm, they are able to reach the senior immediately then decide whether to call emergency or not.

Yongkun Sui, Chanmin Ahn and Chong H. Ahn are with Microsystems and BioMEMS Laboratory, Department of Electrical Engineering and Computing System, University of Cincinnati, Cincinnati, OH 45220 USA (phone: 513-556-0852; fax:513-556-7326; e-mail: suiyn@mail.uc.edu).

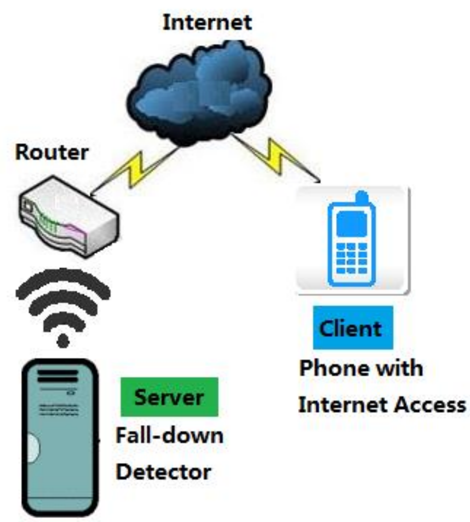

Figure 1. Overview of the smart fall-down detector system.

The developed protocol of the detection and transmission of alarm signals is described in Fig. 1. The fall-down detector acts as a server and is assigned with an IP address. The client software receives data and alarms via Internet from the server.

II. SYSTEM SETUP

A. Hardware

A tri-axial accelerometer and a tri-axial gyroscope are used as sensing components for the system. This combination ensures that all kinds of body motions are detectable by using the device. Both the accelerometer and the gyroscope output digital data that can be sampled by the microcontroller via I^2C protocol. An IC alarm is controlled by the GPIO of the microcontroller to warn the user that an alarm will be triggered. A button is connected to the GPIO to give the signal to clear the alarm. The RF module is embedded in the microcontroller. The system is connected as shown in Fig. 2. The microcontroller embedded with Wi-Fi solution is the key unit in this setup. Fig. 3 shows a picture of the prototype device. The microcontroller was located under the breadboard. The prototype was powered by USB in initial test. Battery would be used after charactering power assumption of the entire circuit.

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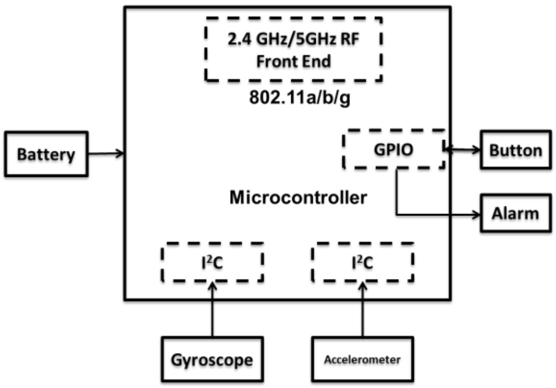

Figure 2. The system diagram of the smart fall-down detector, the main unit is a microcontroller with Wi-Fi solution.

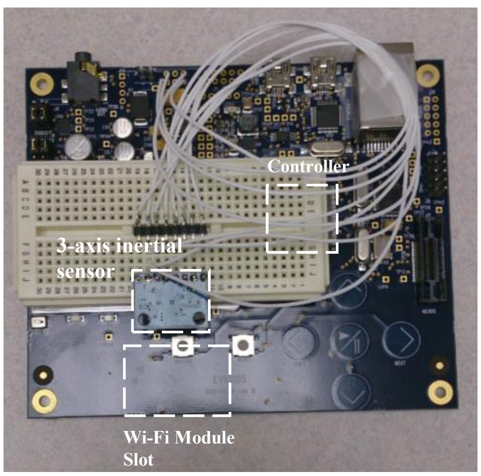

Figure 3. Device prototype. The Atmel microcontroller is under the breadboard.

B. Firmware

The firmware of smart fall-down detectors has four functions: data sampling, storing, processing and transmitting. Acceleration and rotation data are sampled then streamed from I^2C module to on-chip memory by the Peripheral Direct Memory Access (PDMA). Both the accelerometer and the gyroscope are sampled at 1 kHz with 16-bit resolution. A 64KB memory can hold motion data of more than 5 seconds for analysis. The microcontroller copies data of 5 seconds from SRAM to Flash to extract the motion feature.

To interpret accelerometer and gyroscope data, accelerometer and gyroscope fusion is performed by applying the principle of an inertial measurement unit (IMU). An IMU combines the 3 datasets from the tri-axial accelerometer and 3 datasets from the tri-axial gyroscope. The integration drift is reduced by continuously estimating inclination [5]. The combine data include both information of acceleration and orientation. With less datasets, the design and operation of machine learning will be easier.

Fall-down motions have been simulated and modeled with parameters stored in Flash. In the smart fall-down detector's algorithm, a type of machine learning, supervised learning is introduced to data processing. If the input motion data exceed pre-set threshold in the training phase, the IC alarm will sound to warn the user that an alarm will be trigger and button input is requested to clear the alarm. If the user claims the motion to be safe and usual by pushing the button, then motion data that triggered the alarm will be analyzed to extract the motion feature. The motion feature will be permanently stored in Flash. If similar motions triggers false alarm more than 5 times, they will be grouped and labeled as a safe motion. After a safe motion is generates, the prediction phase will be enabled. All input data will be analyzed to extract their features to compare with stored safe motion. If the features match, the alarm will not be triggered. Otherwise, the user can either clear the alarm and store the motion or claim a fall-down. Fig. 4 shows a flow diagram of the supervised learning process.

If the user has no response to a triggered alarm, the alarm signal will be generated and transmitted through Internet to the client software. The firmware design includes wireless module drivers and a simple web server. Besides transmitting alarm signals, the web server collects information such as amount of stored safe motions, battery life and live accelerometer and gyroscope data. The live motion data is used to visually check the functionality of the sensors.

A light-weight real time operating system (RTOS) is embedded to manage the networking tasks and data processing tasks.

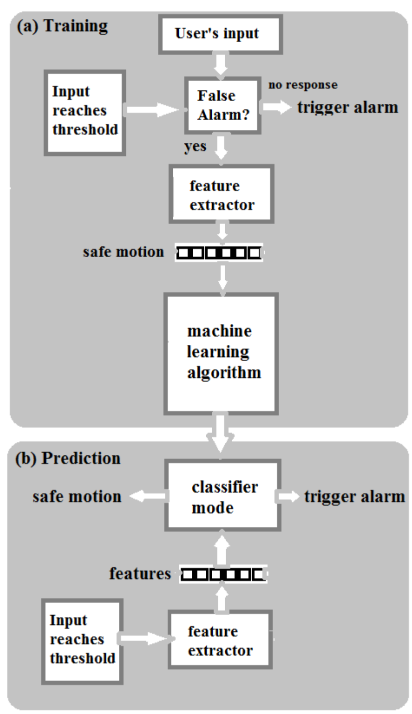

Figure 4. The supervised learning process of the smart fall-down detector.

C. *Software*

The client software should be an application on smart phone that can receive data from the remote web server and warn client users when an alarm signal comes. By checking general information from the detector, the client can remind senior to charge the detector if battery level is too low or check whether senior use the device correctly if the amount of stored safe motion doesn't change for a long time. Other information like live accelerometer and gyroscope data can be protected under password to protect senior's privacy.

III. EXPERIMENTAL RESULT

We conducted several tests to extract the features of fall-down motions. Sensors were clipped on the testing person's pocket or belt as shown in Fig. 5. Then, various motions of interest were performed while the signals generated from the accelerometer and gyroscope as a function of time were recorded. The pre-set threshold was generated by averaging accelerations and orientations of similar fall-down motions in the feature space.

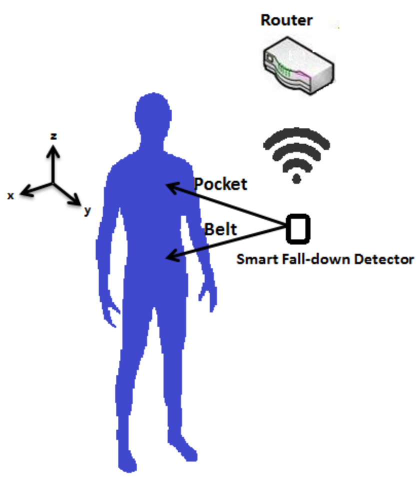

Figure 5. Experiment setup. *The detector can be clipped on either a belt or pocket of testing person.*

To reduce the complexity of machine learning, we started with only one horizontal axis in our initial test. Accelerometer and gyroscope data were transferred to a PC for analysis. Data from x-axis was wiped out thus only falling forward and backward were considered. Several fall-down motions and general motions were measured and analyzed in the test. Figs. 6 - –9 show four different types of fall-down. The figures clearly show that y-axis and z-axis are flipped mainly due to the change of position or orientation of body after fall-down. The slope illustrates a change in orientation of the gyroscope. Vibrations come with the slope is an indication of acceleration change during fall-down. By comparing Fig. 6, Fig. 7 and Fig. 9 we can conclude that the deeper the slope is, the harder the hit is. The amplitude of Fig. 7 illustrates that a fall-down during running is harder than that during walking in Fig. 6.

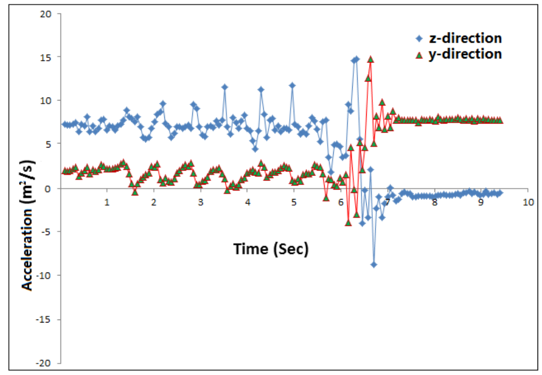

Figure 6. Fall down during walking. Low frequecny triangle waves with low amplitude indicate that the object was walking. The slopes with oscillation illustrate an orientation change with high acceleration.

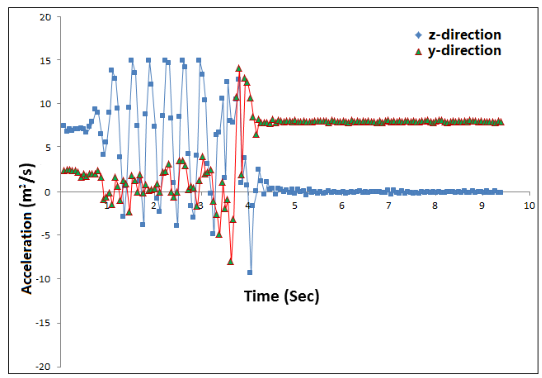

Figure 7. Fall down during running. High frequency triangle waves with high amplitude indicate that he object was running. The slopes with oscillation illustrate an orientation change with high acceleration.

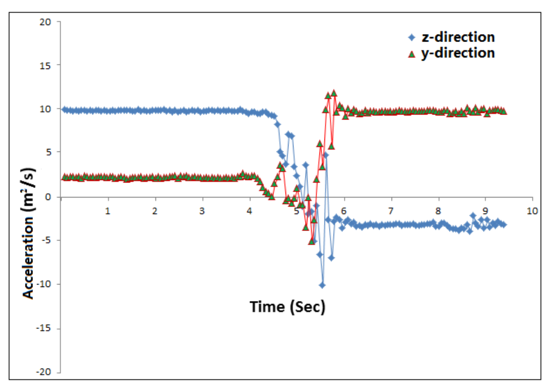

Figure 8. Fall down during standing. The object was stationary befor fall-down. The slopes indicates an orientation change with low acceleration.

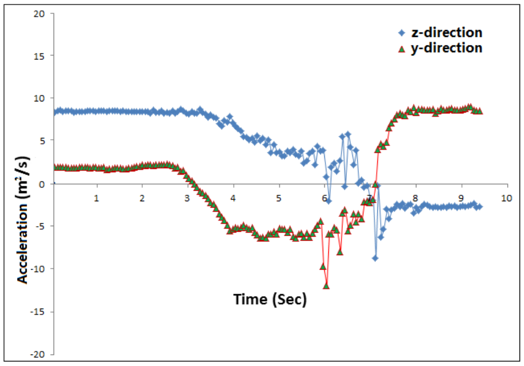

Figure 9. Fall (lay) down slowly. The object was tationary before fall-down. The slopes illustrate that the orientation change was slow with low acceleration.

Fig. 10 and Fig. 11 show two types of safe motion. Vertical jumping and sitting on chairs both feature with high acceleration but neither will not cause a change in orientation.

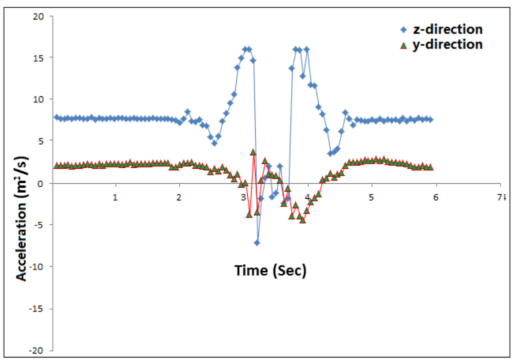

Figure 10. Vertical jump. The object only accelerated and decelerted in z direction. The orientation was not changed.

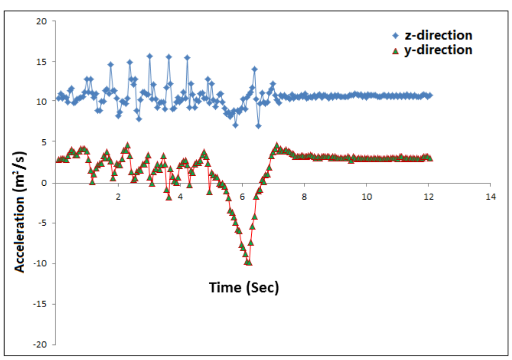

Figure 11. Walk to a chair then sit down. The impulse in y direction indicates a sudden trun-around of the object.

To model different motions we need to extract acceleration and orientation data from the plots. Two variables are used to numerically represent acceleration and orientation. Each sample point consists of data for 10 seconds. The average acceleration is calculated for the first 2 seconds as a_{yi} and a_{zi} and last 2 seconds as a_{yf} and a_{zf}. The maximum acceleration and minimum acceleration are recorded as a_{ymax}, a_{ymin}, a_{zmax}, a_{zmin}. The acceleration variable is calculated as

$$a = [(a_{ymax} - a_{ymin} + a_{zmax} - a_{zmin}) - | a_{yf} - a_{yi} | - | a_{zf} - a_{zi} |] / 2$$

and the orientation data is calculated as

$$r = [|a_{yf} - a_{yi}| + |a_{zf} - a_{zi}|] / 2.$$

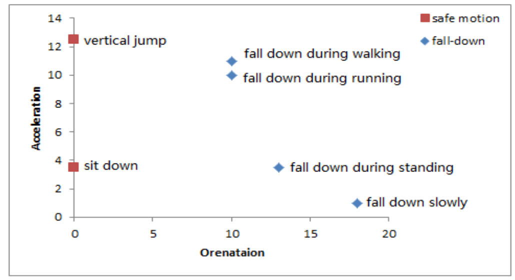

Figure 12. Scatter plot of fall-down motion and safe motions in terms of acceleration and orientation variables.

The previous fall-down motions and safe motions were modeled using this method. Fig. 12 shows the feature space of these motions. The two classes are apparently linearly separable. To generate accurate boundaries and group features for supervised training, more test data are desired.

IV. Conclusion

This paper presents a new smart fall-down detector for senior healthcare system using inertial microsensors and Wi-Fi technology. Different patterns of fall-down motion were characterized and modeled using a set of inertial sensors composed of a tri-axial accelerometer and a tri-axial gyroscope. The signals obtained from the motions were processed and analyzed by a microcontroller with integrated algorithms. The smart algorithm integrated with machine learning was implemented to identify fall-down motions with minimum false alarms. The fall-down monitoring system developed in this work has successfully detected and identified the fall-down motions and sent a warning signal to the staffs of emergency care or clients caring senior peoples through wireless communication. The developed new smart fall-down detector can envisage a practical and convenient warning system to provide a safe and better life for senior people.

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