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SENSOR-BASED WIRELESS WEARABLE SYSTEMS FOR HEALTHCARE AND FALLS MONITORING

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Abstract- The rapid aging of the world's population, along with an increase in the prevalence of chronic illnesses, requires adaption and modification of current healthcare models. New trends on healthcare technologies fall into the use of autonomous systems that allows the capturing and monitoring of physiological parameters anytime and anywhere. One approach involves tele-health applications, many of which are based on sensor technologies for unobtrusive monitoring. Recent technological advances, in particular, involving micro-electromechanical systems, have resulted in miniaturized wearable devices that can be used. In this paper, based-on our algorithms research, a ubiquitous personal health monitoring and system is designed, which integrates health-related sensory devices with the healthcare center cost-effectively. It can aid senior citizens and patients, especially elderly, who need long-term attention to their physical condition, like chronic diseases and falls, with ubiquitous surveillance and remote management of the recorded health data, and timely help.

Index terms: Health Management, Daily Activity Monitoring, Physiological Parameters, Zigbee, Android, Fall Detection

I. INTRODUCTION

Healthcare problem has become the focus attention of people and the key indicator of the happiness index. Modern people have to deal with the fast-paced learning, work and life, facing more and more competition and challenges, and people with chronic illnesses such as heart disease become more and more. The ever-increasing rise in the number of chronically ill people is a growing burden on healthcare institutions.

The world population is ageing, and the proportion of young workers in developed countries has been shrinking [1, 2]. Elderly people have a greater level of disability due to age-related diseases, a greater need for care and assistance, and are more likely to be admitted to a hospital or nursing home. Permanent admission to a care home is an expensive way of providing care for elderly, most of whom would prefer to remain in their own home [3–5]. Data on health from 30 countries of the Organization for Economic Cooperation and Development (OECD) show that health care expenditures as a proportion of gross domestic product (GDP) are at an all-time high, due to both increased expenditures and to a general economic slow-down [6]. Telecare, telehealth and telemedicine are new models of care already in use, bringing solutions to healthcare issues [7, 8, and 22]. Remote health monitoring of patients residing in their homes helps reduce health care costs. Current telemedicine solutions are used to remotely monitor vital signs such as blood pressure and blood sugar levels. These systems restrict the mobility of the patient, in addition to being limited in the number of vital signs that they support. The rapid developments in wearable devices coupled with the advancements in wireless access technologies have made wearable devices an increasingly attractive platform for delivering remote patient health monitoring services.

Falls are the number one cause of injuries in older adults, including approximately 90% of hip fractures, 40% of vertebral fractures, and 60% of head injuries [9-11]. Falls cause physical and psychological harm to the elderly, such as injuries, limited mobility, worry of living alone and the fear of fall again. Able to move freely is an important aspect for the elderly to maintain an independent living. Falls can result in a reduction of free movement and constitute a major health risk. Even the fear of falls can also lead to the elderly to reduce freedom of movement [12]. The demand for surveillance systems, especially for fall detection, has increased within the healthcare industry with the rapid growth of the population of the elderly in the world. It has become very important to develop intelligent surveillance systems that can automatically monitor and detect falls.

In this paper, a healthcare system is designed with integration of embedded system, multiple physiological signals detection, ZigBee and positioning technology, and health management system. It can be applied to the regional community, hospital, sanatorium, etc. As shown in Figure 1, the proposed system is mainly composed by wearable physiological signal acquisition terminal, ZigBee communication node, smart health management mobile terminal, and health management expert system located in the health management institutions.

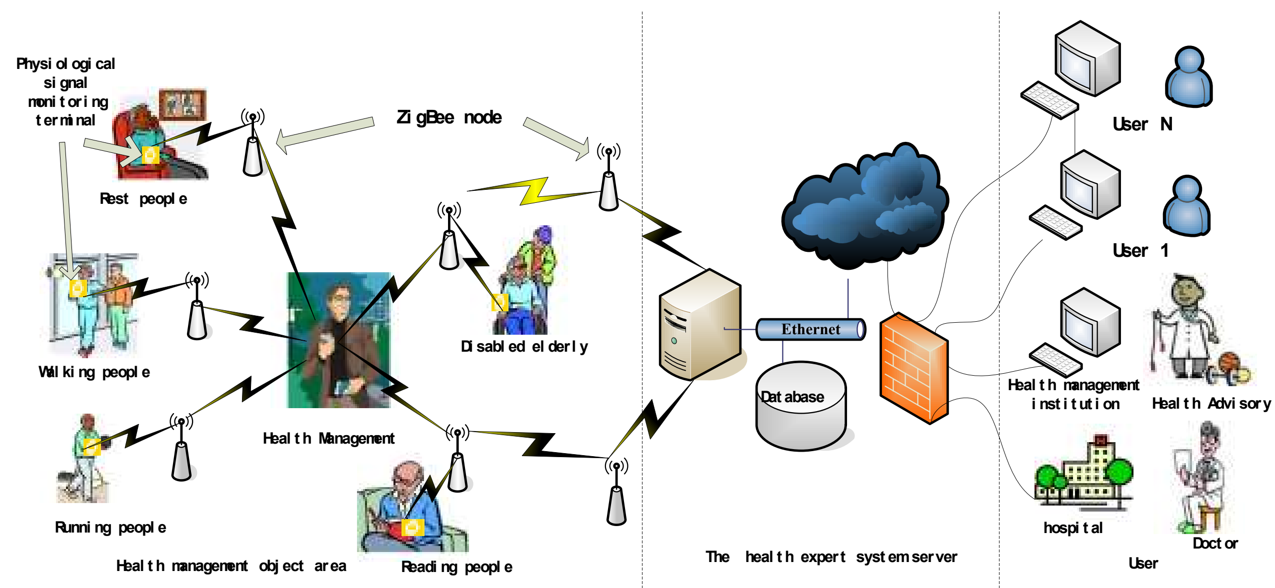

Figure 1. Multi-Physiological Signal Monitoring Scheme Containing Fall Detection

The remainder of this paper is organized as follows. Section 2 presents the wearable device design. Algorithms design is given in Section 3. Section 4 discusses health management expert system and the prototype implementation issues for the proposed system. Section 5 concludes the paper and future work.

II WEARABLE DEVICE DESIGN

Wearable multi-physiological signal acquisition terminal can record and display physiological parameters real timely, such as the blood oxygen saturation, pulse rate, pulse strength, oxygen consumption, energy consumption value, etc.; using three-axis acceleration sensor, energy and step analysis can be acquired, also the special circumstances fall can be detected and alarmed. If any signal exceeds the pre-set value, sound and light warning will be given, warning information also can be uploaded to the health management expert system through the wireless communication module. All data acquired by wearable physiological signal terminal can be uploaded real timely; also health management object can transfer all the data to the health management expert system through the USB interface.

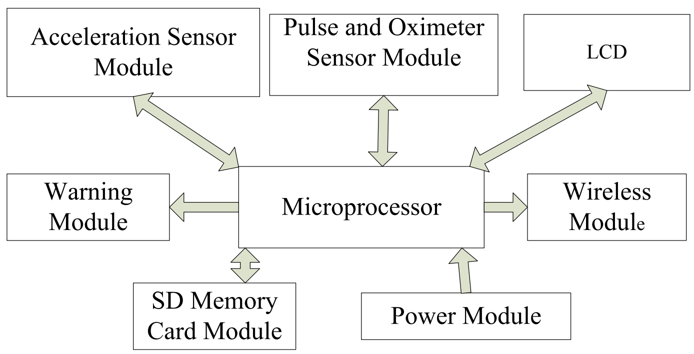

Figure 2. Wrist Wearable Device Prototype **Figure 3.** Schematic Diagram for the Device

People take it for granted to wear a watch on wrist. Therefore the wearable multi- physiological signal acquisition terminal is designed as wrist wearable device. Figure 2 is the prototype of wrist wearable device, and figure 3 is the schematic diagram of the device. The terminal is designed as wrist wearable device. Fig.3 is the schematic diagram of the device.

III. KEY ALGORITHMS DESIGN ON WEARABLE DEVICE

3.1 OXYGEN SATURATION SPO2 CALCULATION

SPO2 detection can be optional using red reflective or transmissive detection. For the purpose of easy to wear, we use reflection detection to detect the wrist blood and can only calculate the pulse.

Refection detection can be used in applications with no need to accurate records of oximetry. As shown in figure 2, the optional transmissive oximeter finger clip detection module can record oxygen saturation accurately and be used for intensity exercise occasions. Dynamic analysis method of dual-wavelength is adopted in this device [15]. SpO2 is a measurement of the amount of oxygen attached to the hemoglobin cell in the circulatory system. The basic measure theory result from apparently distinguish between Spectral region of red and infrared regions of HbO2 (Oxyhemoglobin) and Hb (Hemoglobin). The absorption in red region (600~700 nm) of HbO2 is quite different from Hb, while the difference is relatively small in infrared region [13-14]. The SpO2 formula this paper adopted is as follow:

$$SpO_2 = A + B\rho \qquad (1)$$

The parameter A represents the absorbance coefficient of the red of HbO2, and the parameter B represents the absorbance coefficient of the infrared of Hb. However, parameters need to be achieved through experimental calibration because the discrete feature of the optical sensor needed to be considered. The formula is the calculate method for the parameter ρ [15]:

$$\rho = \frac{AC660 / DC660}{AC940 / DC940} \qquad (2)$$

The AC represents the light absorption of pulsatile artery. AC660 represents the AC in the wavelength 660nm. The DC represents the light absorption of other issues, and DC940 represents the DC in the wavelength 940. The device also can detect the pulse rate of human body, and the principle is to count the numbers of cycles of signal change [15]. The algorithm experiments of red reflective and transmissive detection are tested by FLUKE SpO2 simulator.

3.2 FALL DETECTION

Degen et al designed a fall detect algorithm based on the wrist device, but the total success rate is only about 65% [16]. Based on Degen et al's fall detect algorithm, this paper proposes a new threshold program and test all possible types of body falls and analyzes the experiment results, the results show that the improved algorithm improves the fall detect accuracy greatly.

Flow chart of fall detect algorithm based on wrist-worn device is shown in Figure 4. Algorithm uses a threshold judgment. First, integrated acceleration value g is calculated according to signals from the accelerator, if g is smaller than threshold g_t, then velocity v_1, v_2 and cumulative speed difference C are calculated. If C is bigger than threshold C_t, we calculate exercise intensity ΔG and acceleration value difference Δg. If ΔG and Δg are bigger than their thresholds ΔG_t and $|\Delta g|_t$, we calculate angle θ between human and ground to execute posture auxiliary judgment. Finally, moving or stationary is judged for a long time (40 seconds in this paper), if human is always being in stationary status during the 40 seconds and all above conditions are meted, the fall event is confirmed. The detailed implementation of the algorithm is divided into five steps as described below.

1) Step 1: Basic condition of fall detection

First, acceleration analog signals in three directions x, y, z of human movement is obtained and converted to digital signals g_x, g_y, g_z, then Hanning filter and moving average filtering is used to reduce the noise errors [17, 18, 21]. Integrated acceleration value g can be obtained by the formula 1:

$$g = \sqrt{(g_x)^2 + (g_y)^2 + (g_z)^2} \tag{1}$$

If the value g is less than the set threshold g_t, it is believed that meet the fall to determine the initial fall condition is meted, then the fall detect algorithm enter the next step to judge accumulated speed difference.

2) Step 2: Second condition of cumulative speed difference

We calibrate the integrated acceleration value g using the initial state of the gravity signal (whose initial value is 1), then use equation 2 and equation 3 to calculate v_1 and v_2 [16]:

$$v_1 = \begin{cases} \int (g-1) & if(|g| - 0.99 < 0) \\ v_1 \times 0.95 & if(|g| - 0.99 >= 0) \end{cases} \tag{1}$$

$$v_2 = \sqrt{(\int g_x dt)^2 + (\int g_y dt)^2 + (\int g_z dt)^2} - t \tag{2}$$

v_1 represents the value of the speed of the ultra-weightless state, and v_2 represents the velocity values to consider a slight shake of the change in status (such as shaking hands). v_1 has a great error in the case of large g value, so is constrained for its positive values by the formula 2 ,while

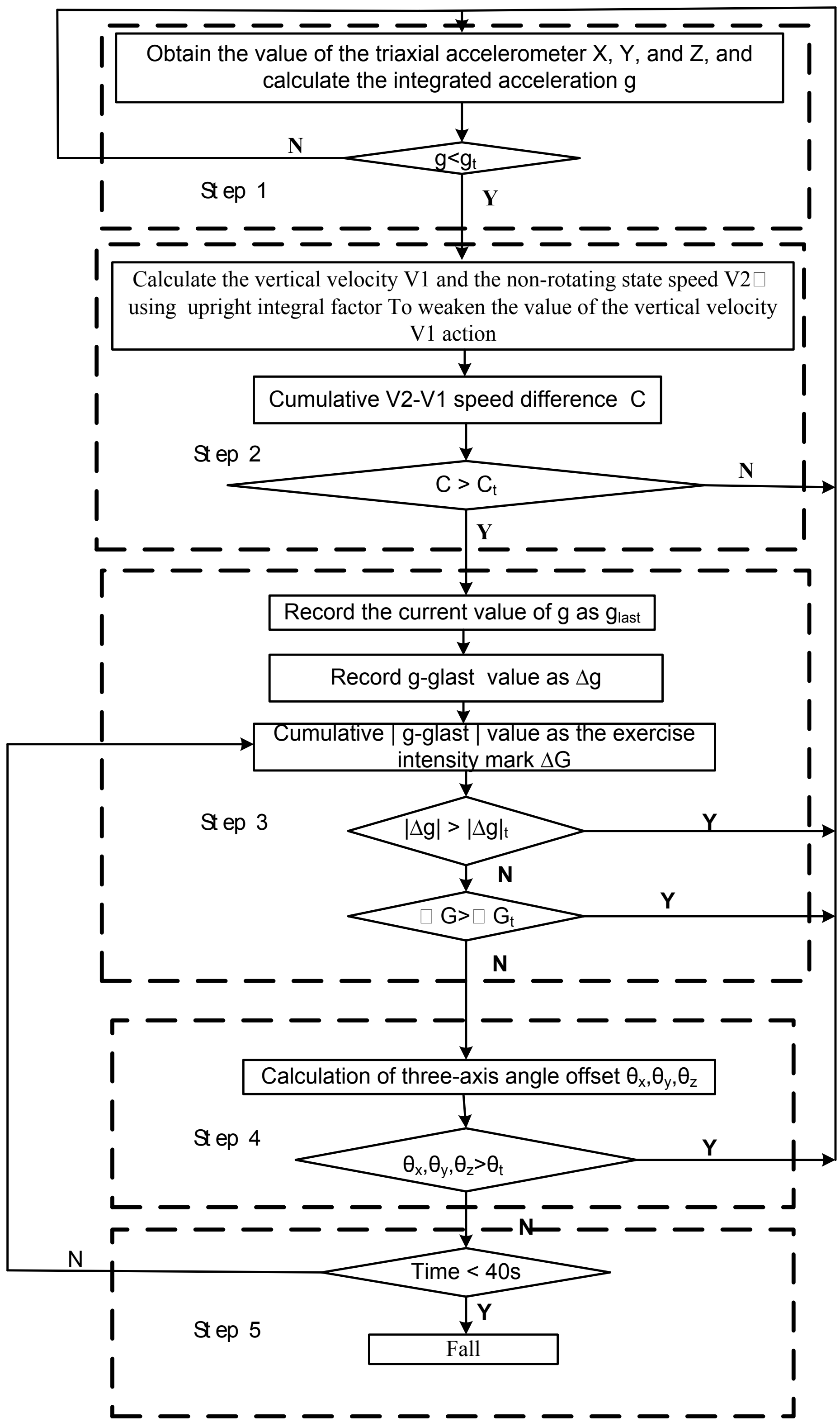

Figure 4. Flow chart of fall detect algorithm

v_2 has a great error when is in rotation, but it is impossible for v_1 and v_2 has large errors at the same time in an action of the human body. Degen et al used Δv, v_1 and v_2 to judge falls[16], and its problems are too many thresholds, cumbersome and large error. In this paper, we use cumulative speed difference to judge. We calculate the cumulative speed difference between v_1 and v_2 within the 3s, and we denote the cumulative speed difference by the symbol C, then we compare C with threshold C_t which is set according to experience. If the result of comparison is meet fall condition, then enter the next step to continue monitor fall event.

The reason we use the C to judge is shown as Figure 5. The time for 23 seconds to 26 seconds is falling process, from the figure it can be clearly seen that v_1 and v_2 has obvious speed difference in the process, therefore we use equation 4 to calculate C as enlarged Δv to judge fall event.

$$C = \int_{t_0}^{t} \Delta V \tag{3}$$

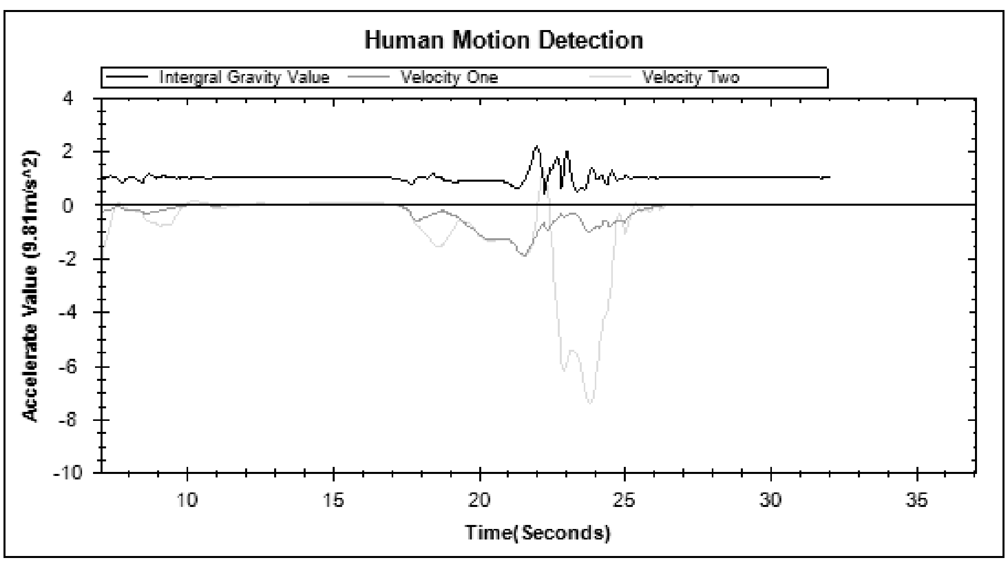

Figure 5. Signals g, v_1, v_2 in the process of falling

In equation 4, t_0 represents the time which meet basic fall condition, that is the above described the time when g is less than the threshold g_t. t represents cumulative ending time，in this paper, t is t_0+3 s. C is the enlarged Δv. C as the judgment condition can greatly enlarge the scope of the threshold value judgment and improve the accuracy of judgment. It can be seen from figure 4 that v_1 has not much fluctuation in the three seconds of time. According to our experiments, v_1 will not have much fluctuation value in the process of falling, and even produce fluctuation, the fluctuation can be ignored by enlarged Δv, and that is C. Therefore, we use C as judgment condition instead of Δv and v_1.

3) Step 3: Exercise intensity screening and posture auxiliary judgment

If the arm does stretching exercises (ups and downs of action), then the detected signal is shown in Figure 6. The conditions of above two steps are easy to meet in the case of Figure 6, resulting in the false positive of fall detection. Taking into account the human who fall will not do a lot of movement, so the third step of the fall algorithm should exclude most of the false-positive event through exercise intensity conditions.

In the third step, we further judge the fall event by the exercise intensity filter. Exercise intensity in 3s after meeting above two steps conditions is calculated using the flowing equation 5.

$$\Delta G = \int_{t_0}^{t} |g - g_{Last}| \tag{4}$$

$$\Delta g = g - g_0 \tag{6}$$

Here, t_0 represents the time which meet step two condition that is the above described the time when C is more than the threshold C_t. g_{Last} is on behalf of the last g values which is used for integration. ΔG means integral sum of the gravity values change within 3 seconds that is a value used to measure the gravity change within 3 seconds. In equation 6, g_0 represents the standard gravity value, which is 1. The integrated acceleration g should be close to g_0 under normal circumstances after fall, which is the stationary state of human body. Δg means the difference between g and g_0.

The exercise intensity calculation method takes into account the large gravity change of weight loss and the impact when fall [19]. Δg and ΔG can be used to detect fall by thresholds at the last moment of the exercise intensity conditions (at the end of 3 seconds). If $|\Delta g|$ and ΔG are less than their corresponding threshold, we can assume that human body is in the stationary state and there is great possibility of the fall. Conversely, if any one of $|\Delta g|$ and ΔG is more than its threshold, it shows that the human body in motion and does not fall. There is special circumstance that any one of $|\Delta g|$ and ΔG is more than its threshold but the human actually falls, it can be sure that human who fall has the ability of free activities, so there is no necessary to warn.

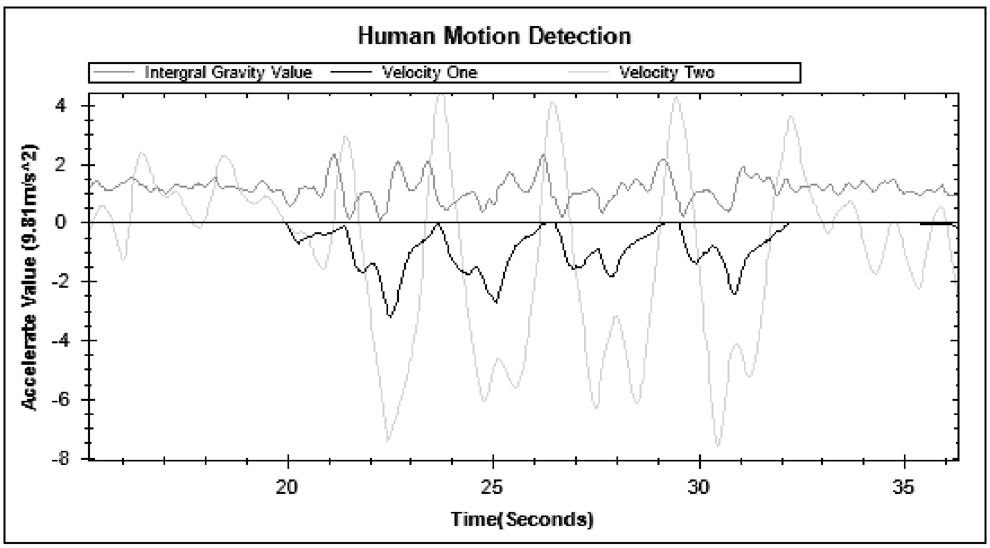

Figure 6. Signals g, v_1, v_2 in the process of arm stretching

Although motion intensity filter can largely rule out false positive, if wrist has a long stay after movement in a certain extent, it may still trigger the miscarriage of justice, such as intermittent exercise shown in Figure 7. In order to avoid false positive judgment, the following step 4 designs to introduce the auxiliary judgment of the angle condition posture.

4) Step 4: It is difficult to calculate angle of overweight and weightlessness status. But it is very easy to draw the angle values with a certain precision using the ratio of three-axis gravity value and integrated gravity value in the stationary state [20].

As shown in equation 7, we can calculate the angle offset of the three directions θx, θy and θz. The default value of the three angles is 0, so we can use the same threshold to judge fall event. If any one of the three angles is bigger than its threshold θ_t , we can exclude the special circumstance which is shown in figure 7. But the angle calculation is not applicable to all cases, and the prerequisite for angle judgment is that human body is in a relatively static state.

$$\theta = \begin{cases} 90 - \arccos\left|\frac{g_{Axis}}{g}\right| & if\,(Axis \perp g_0) \\ \arccos\left|\frac{g_{Axis}}{g}\right| & else \end{cases} \tag{7}$$

5) Step 5: 40 seconds delay judgment. Even if the above three conditions have been met, we cannot rule out the special circumstances leading to false-positive events. For example, assuming that the elderly do morning stretching exercises, if he or she put his or her hand at the chest (angle greater than a certain value) for rest after finishing the action of hand down, it will be judged as fall event. Therefore, the fall detection algorithm uses 40 seconds delay judgment at the end. During the last 40 seconds, if the three angles are not less than the threshold at the same time and |Δg| is less than its threshold, it can confirm that fall event occurs [23].

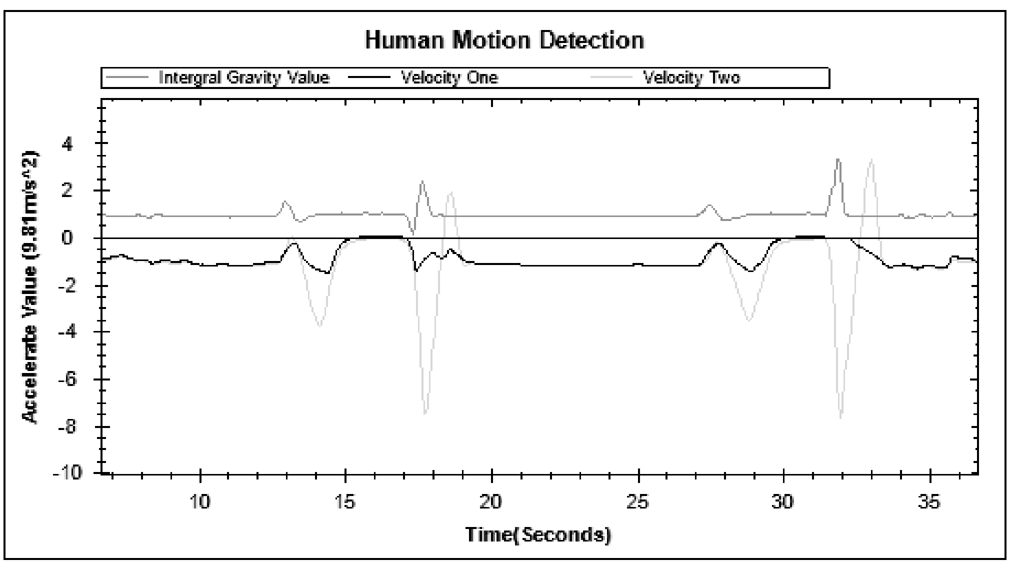

Figure 7. Intermittent exercise (Do exercise between 17-20 seconds, remain stationary after 20 seconds, and do exercise between 31-34 seconds)

3.3 WORKFLOW AND RESULTS OF WRIST WEARABLE DEVICE

After booting, the device initializes all functional modules, and then enters loop record the oxygen saturation, pulse rate, step count, and according to the set threshold to determine whether certain parameters exceed the threshold value, also all the recorded data will be uploaded to the expert system via the wireless module after a certain time interval. If any abnormal condition occurs, the device will sound and light alarm and send message to expert system.

About fall detection, we divide falling-actions into four directions, i.e. falling forward, backward, on the left and right. In order to verify the accuracy of fall detection algorithm, four volunteers have done a lot of fall testing. The test threshold is shown in Table 1, and the experimental results recorded in Table 2.

Table 1: Experimental threshold setting

g_t	C_t	ΔG_t	θ_t	$\lvert\Delta g\rvert_t$
$9.81m/s^2$	$9.81*(t-t_0)m/s$	$9.81m/s$	$\circ$	$9.81m/s^2$
0.59	80	0.69	35	0.02

Table 2. Lab Record Sheet

Testing Action	Testing Times	Number of Alarm	Success Rate
Forward-Falling	60	58	96.7%
Backward-Falling	60	56	93.3%
Falling on the Left Side	60	55	91.7%
Falling on the Right Side	60	50	83.3%
15-Minute Normal Activities	5	0	0%
60-Minute Normal Activities	1	0	0%
Total	240	219	91.25%

The experimental results have shown that the accuracy of forward falling is high, but owing to the hand protective effect on conditioned response from the ground, there is still the possibility of non-detection. The preliminary experimental results have shown that the total success rate of fall detection can still reach 91.25%. Compared to literature [16], the total fall detection rate 65%, the algorithm designed by this paper greatly increased the total fall detection rate, and greatly improved the backward, left and right fall detection rate.

VI. HEALTH MANAGEMENT SYSTEM

Health management applications including mobile handheld terminal and web-based health management expert system (Figure 8). Web-based health management expert system establish dedicated personal user data records for each health management object, and provide real-time online health information services through bringing together experts from the fields of health management and hospital. Historical data of each end-user can be statistical analysis, combined with medical knowledge; health guidance recommendations can be given. Also specialized health management system can be established according to the characteristics of special populations, such as students of primary and secondary schools, the elderly, nursing homes, rehabilitation, and so on.

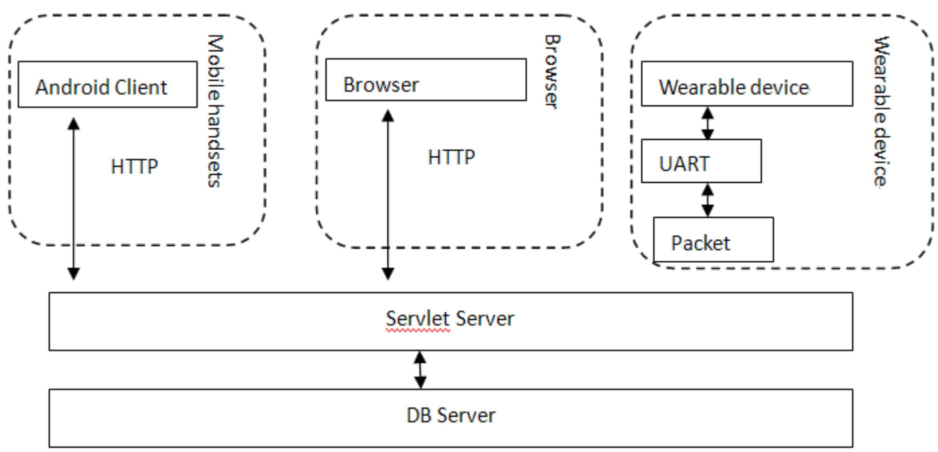

Figure 8. Framework of health management expert system

As shown in Figure 8, wearable device uses Zigbee module as the wireless module by establishing serial communication protocol for wireless communications. In the demo system, a number of wearable devices constitute a cellular network and the collaboration is PC server. The PC server can send commands to gather information related to the individual's physiology and the backend server system can deal with the corresponding statistical model analysis based on the acquired data in a certain time frame. The demo system also provides Android handsets to view data on the server.

IV DISCUSSIONS AND FUTURE WORKS

The proposed sensors-based wireless wearable system includes three domain technologies of embedded system, ZigBee and Internet. The most important goal in sensors-based wireless wearable system is to support ubiquitous health care and fall alarming through intelligent sensors-based wearable device. Compared with traditional hospital health care management system, it has the following advantages:

1) It can measure several physiological signal parameters of vital signs, movement capable of analyze energy and pedometer of human movement, and detect fall situation then alarm;

2) The wrist wearable intelligent terminal does not affect the day-to-day activities of patient, and help reduce their psychological pressure;

3) Not only the secure health sensory information can be cost-effectively delivered and retrieved through Internet, but also the critical health alarm can be reliably sent to emergency contact person via telecom;

4) Low costs of wearable intelligent terminals and wireless communication node network will help reduce the economic burden of health management institutions, as well as management object.

Dr. Subhas Chandra Mukhopadhyay and his team have done a lot of work about ADL monitoring of elderly people similar to this paper [24-27]. The demo system of literature [24] provided has the similar function to our demo system and we used different algorithms to implement monitoring. The demo system of this paper provides a powerful backend website system to offer medical services and mobile nurse workstation (Android handsets).Positioning for the user based on Zigbee technology is been developing and improving.

In the near future, we will further investigate the fall detect and alarm issue in the sensors-based wireless wearable systems to further improve accuracy. We may extend current health data delivery from fixed range to anywhere to improve the practicality of the system. The backend website system and mobile nurse workstation will be developed more functions.

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