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Implementation of Fall Detection System Based on Data Fusion Technology

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Abstract

This paper mainly discusses a fall detecting method for the elderly, implements the wireless positioning and automatic alarm function. The system is designed with low cost Micro-Electro-Mechanical System (MEMS) inertial measurement unit to measures activities data of the elderly people, which has achieved an accurate attitude determination by Kalman filter for the multi-sensor data fusion algorithm, and transfer information to remote medical monitoring system platform by CDMA network, it makes the elderly get treatment in time after the fall. The experiments show that the system can accurately detect the elderly falling, send out alarms and positioning after a fall, its applying will provide a new security guarantee for the elderly health.

Keywords: *MEMS, Kalman filter, sensor fusion, fall detection, CDMA network*

1. Introduction

The number of elderly is estimated to be nearly two billion by 2050 [1]. With the increase of elderly population, a major public health problem of the elderly fall and consequential damage will be serious. In recent years, fall detection has become a hot research topic, including the badly results and troubles caused by a fall. The early detection of fall is most critical to rescue the subjects, in order to avoid the serious consequences. However, how to bring about the safety measure of fall detection with high reliability and accuracy, to cope with the challenges of the aging problem, it is important to put forward an effective fall detection method and timely alarm device [2-5].

Recently, smart-phones with acceleration sensor have been as fall detector and as mobile communication terminal to alert the supervisors [6]. The problems associated with this method are how to solve the equipment fixed position and the short battery lifetime. In these practical applications, a fall detection algorithm was usually used to improve detection sensitivity and decrease misjudgment, at the same time the user could cancel the alarm with a push-button while there was not a real fall [7].

In this paper, we proposed a real-time and wearable fall detection device, which would be installed to the chest or the waist of the user, for confirming the fall of the elderly based on Kalman filtering algorithm to fuse sensor signal of 3-axis accelerometer and 3-axis gyroscope. At present a very popular method is to use kalman filter, which is a kind of time-domain minimum variance estimator with recursive functionality, it needn't take up a more processing power. The experimental results have shown that the kalman filter algorithm for the fall detection is more effective than other methods currently. The conclusive detection for a fall was made according to the acceleration threshold of different human motion. GPS function of wireless module locates fall position and the information was transferred to server via CDMA network.

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2. System Architecture and Hardware

A wireless sensor network (WSN) is a spatial distributed sensing device, known as nodes, each node has the ability of data storage, processing and transmission, which can exchange information between the sensor nodes and send information to the remote terminal through the wireless network. The characteristics of the wireless sensor network fully meet to the fall detection method by wearable way, which enable them to be worn easily and could not restrict user's normal activity, realize portable detection.

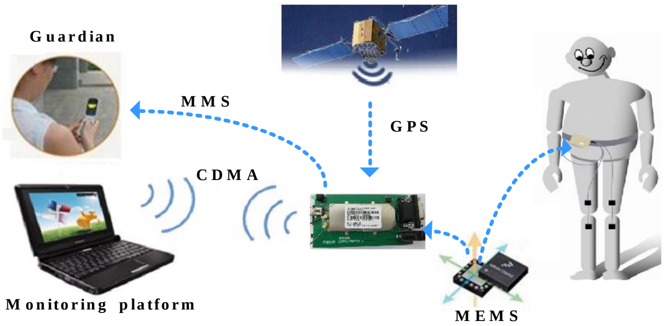

Figure 1. The Overall Structure

The device can be easily worn around the waist or the chest, which had a 3-axis gyroscope (ITG3200, Invensense Inc.), a 3-axis accelerometer (ADXL345, AD Inc.), a CDMA module (SIM5218A, Simcon Inc.), a GPS module (AMY-6M, U-blox Inc.) and a microprocessor (MSP430F149 Texas Instruments Inc.). As shown in the Fig.1 for the fall detection system block diagram, the system is composed of two parts: the wearable device of falling detection and the monitoring platform of wireless alarm. The former mainly collects raw data of inertial sensors for human activities and analysis information of data fusion algorithm. If there was a fall action, the alarm will be triggered automatically through the CDMA network and transmitted to the remote monitoring platform, sent to the guardian in the form of MMS at the same time.

3. Data Acquisition

ADXL345 is a 3-axis digital acceleration sensor of AD Inc. and a low-power digital MEMS devices, mainly used in consumer electronic inertial device. After reading the specification documents of ADXL345 accelerometer, measurement data of acceleration is ranging from [-16g, +16g], the precision can reach 3.9 mg/LSB. ADXL345 accelerometer module is connected to the microcontroller (MSP430F149) via SPI mode of four-wire type, the formula for the raw data to be converted into calculating acceleration (a) is given as:

$$a = \frac{\mathrm{data}(xyz) \times 1000}{256} = \mathrm{data}(xyz) \times 3.9 \tag{1}$$

Where $\mathrm{data}(xyz)$ is raw data output from of the accelerometer, 1g for acceleration of gravity represent numbers for 256, and the final calculated result of a is the acceleration with mg as unit.

First of all, the sampling data of MEMS inertial sensors were taken, and transformed into an angle units, due to external factors such as temperature, noise, the effect of static deviation, the accumulation of calculation error will be increasing caused by acceleration sensor bias, so the initialized need correction, solving the sensor output error formula is:

$$a = a_{new} - a_{bias} \quad (2)$$

Where a is calculated acceleration value, a_{new} is the raw data for acceleration sampling, a_{bias} is the calibration value for initialization error, as unit for the acceleration of gravity. A mean value is selected as the bias to improve the accuracy, and the value is a constant.

In three-dimensional space by the relationship between 3-axis acceleration and the gravitational acceleration, the following two attitude angle, respectively the pitching angle (pitch) and rolling angle (roll) yaw expression is:

$$\theta_{acce} = atan2(a_y, a_z)$$

$$\varphi_{acce} = atan2(a_x, a_z) \quad (3)$$

Where θ_{acce} is the pitch angle and φ_{acce} is the roll angle in degrees. a_x , a_y and a_z are respectively in the X, Y, and Z axis acceleration, $atan2$ denotes the arctangent on the domain [-π , π].

Gyroscope sensor data can also be found similarly by the same method, but the sensitivity coefficient of sensor is different, for example on measuring pitching angle is as follows:

$$\theta_{gyro} = \theta_{g\_prev} + (\omega_{new} - \omega_{bias}) / s \cdot \Delta t \quad (4)$$

Where s is the gyroscope sensor sensitivity; θ_{gyro} , θ_{g_prev} are respectively the calculated value and the previous value in degrees; ω_{new} , ω_{bias} are respectively the angular velocity raw data and the calibration value, Δt is the sampling interval.

The Vector Sum of Acceleration (VSA) is to merge the three dimensional input signal into one acceleration magnitude. The judgment method of acceleration vector amplitude VSA is the common method of human body falls. VSA by calculating acceleration amplitude response of the human body movement intensity, the greater its value, the more intense for movement, VSA can be expressed as:

$$VSA = \sqrt{(a_x)^2 + (a_y)^2 + (a_z)^2} \quad (5)$$

The attitude Angle and VSA are calculated by above method, to judge the difference between a fall and Activities of Daily Living (ADL). If tilt angle (TA) of user lower than the setting threshold, it can be classified as fall or lie. As VSA caused by some activities is larger than that of movements in daily life, also it can be classified as fall or hits some object.

4. Process Model and Sensor Fusion

In order to analyze body posture measurement of linear model of ITG3200 gyroscope, regardless of the error, the input of the gyroscope is angular velocity of coordinate axis, the effective output is attitude angle, the corresponding relationship could be obtain to gyroscope measurement basic linear model:

$$\theta(k+1) = \theta(k) + \omega_{gyro}(k) \cdot \Delta t + v_g \quad (6)$$

Where $\theta(k+1)$, $\theta(k)$ are attitude angle of the ITG3200 gyroscope output at the time step $k+1$ and at the time step k , $\omega_{gyro}(k)$ is angular velocity of the ITG3200 gyroscope output at the time step k , Δt is the time step and v_g is the modeling process noise.

Because of the inertial sensor gyroscope with the external environment, such as time, temperature, the drift of different degrees will be appeared in the practical application. Considering the drift error influence on measurement results, Eq.6 is the basic linear model is transformed into the form below as:

$$\theta(k+1) = \theta(k) + [\omega_{gyro}(k) - error(k)]\Delta t + v_g \tag{7}$$

Traditional attitude sensor signal fusion always regards the gyroscope output angular velocity error as the constant. In this article, $error(k)$ is the output of angle velocity error as time-varying quantity, we assume that the linear relationship with the following:

$$error(k+1) = error(k) + \delta \cdot \omega_{gyro}(k) \tag{8}$$

Where δ is correction factor to determine relationship between gyroscope output $error(k)$ and input $\omega_{gyro}(k)$, we have Eq.7 into Eq.8 and would be get the final system linear model:

$$\theta(k+1) = \theta(k) + [\omega(k) - (error(k) + \delta\omega_{gyro}(k))]\Delta t + v_g \tag{9}$$

Where $\theta(k)$ and $error(k)$ are as the system state, $\omega_{gyro}(k)$ is as the input of system, equation of state matrix form can be expressed:

$$\begin{bmatrix} \theta(k+1) \\ error(k+1) \end{bmatrix} = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \theta(k) \\ error(k) \end{bmatrix} + \begin{bmatrix} (1-\delta)\Delta t \\ \delta \end{bmatrix} \omega_{gyro}(k) + \begin{bmatrix} v_g \\ 0 \end{bmatrix} \tag{10}$$

where

$$X(k+1) = \begin{bmatrix} \theta(k+1) \\ error(k+1) \end{bmatrix}, X(k) = \begin{bmatrix} \theta(k) \\ error(k) \end{bmatrix}, A = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} (1-\delta)\Delta t \\ \delta \end{bmatrix}, u(k) = \omega(k) \tag{11}$$

then get

$$X(k+1) = AX(k) + Bu(k) + v(k) \tag{12}$$

Based on the above system state equation, Kalman filtering algorithm to fuse signal of 3-axis accelerometer and 3-axis gyroscope, the angle output of gyroscope is compensated by the angle output of the accelerometer, it can effectively eliminate the accumulative error and significantly improve the attitude Angle measurement accuracy.

5. Falling Detection Procedure

Because of the different parts of the body with different motion state in movement process, detection device of wearing parts should be attached at the site of changing obviously in the fall process, while very small change in ADL. The impact of the fall in the daily life behavior more distinct than other behavior, therefore threshold value method can be used to judge the fall. The flowchart for fall detection algorithm is shown as Figure 2.

The algorithm first determines whether to break the VSA threshold. If the threshold is broken, we see whether TA has changed within a certain range in 1s, it could reliably determine whether a fall. In order to reduce false alarms rate, the above detection should be keeping for 10s. If the result is true, the algorithm can identify it as a fall; if the test does not meet the fall detection conditions, it will return to the initial state. The algorithm for a fall behavior should determine whether or not two thresholds are broken. Once a fall confirmed, the fall orientation was obtained by the GPS or LBS, and it would send a MMS to the guardian through the CDMA network.

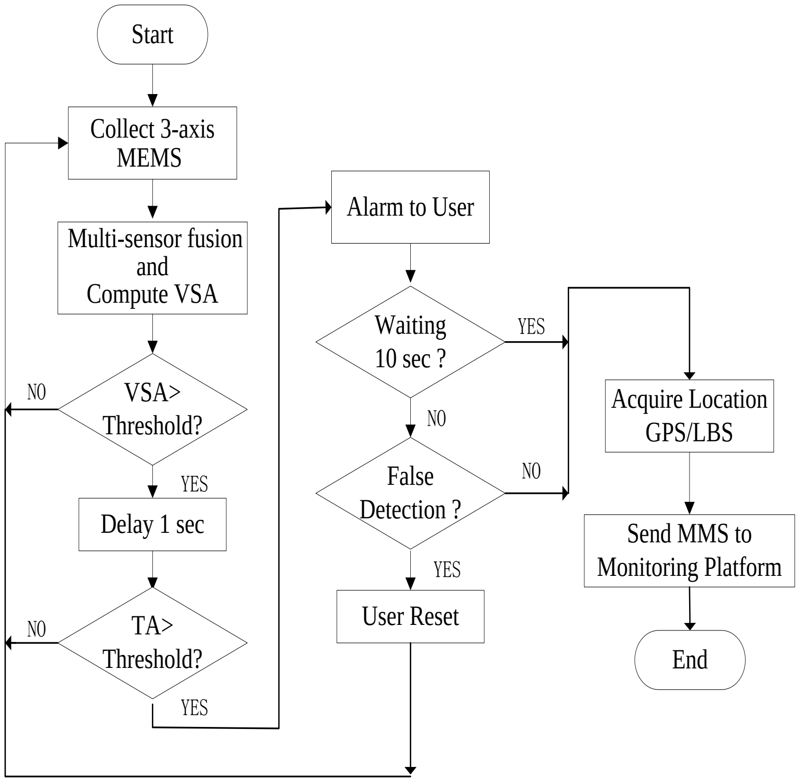

Figure 2. Flowchart of the Fall Detection

6. Experimental Results

As the accelerometer can only compensate roll Angle and pitching Angle measurement error, this study only for roll angle and pitching angle measurement. IMU two angles are set to zero, the output of the acceleration close to zero due to gravity unchanged fluctuations, the gyroscope produced about 0.1°/s of cumulative deviation, the cumulative error is caused by the integral for gyro angular velocity error, which is the main cause of the gyroscope static measurement inaccurate.

To verify the filtering performance of data fusion algorithm, the first roll angle and pitching angle of IMU device respectively set to 0°, make it rotate to 90° around X, Y axis, and then rotate to - 90°, finally back to 0° in turn. Acceleration and gyro sensor output of raw data sampling waveform is shown in Figure 3.

The application of Kalman filtering fusion algorithm for attitude angle of gyroscope and accelerometer signal, in view of the comparison of before and after the application of kalman filtering data fusion algorithm, illustrates the successful to eliminate the noise of the accelerometer and gyroscope sensor drift. The experimental waveform is curve smoothing and tracking acceleration sensor output, high precision attitude angle measurement results, at the same time improve its dynamic characteristics. The approach greatly improved the accuracy of fall detection.

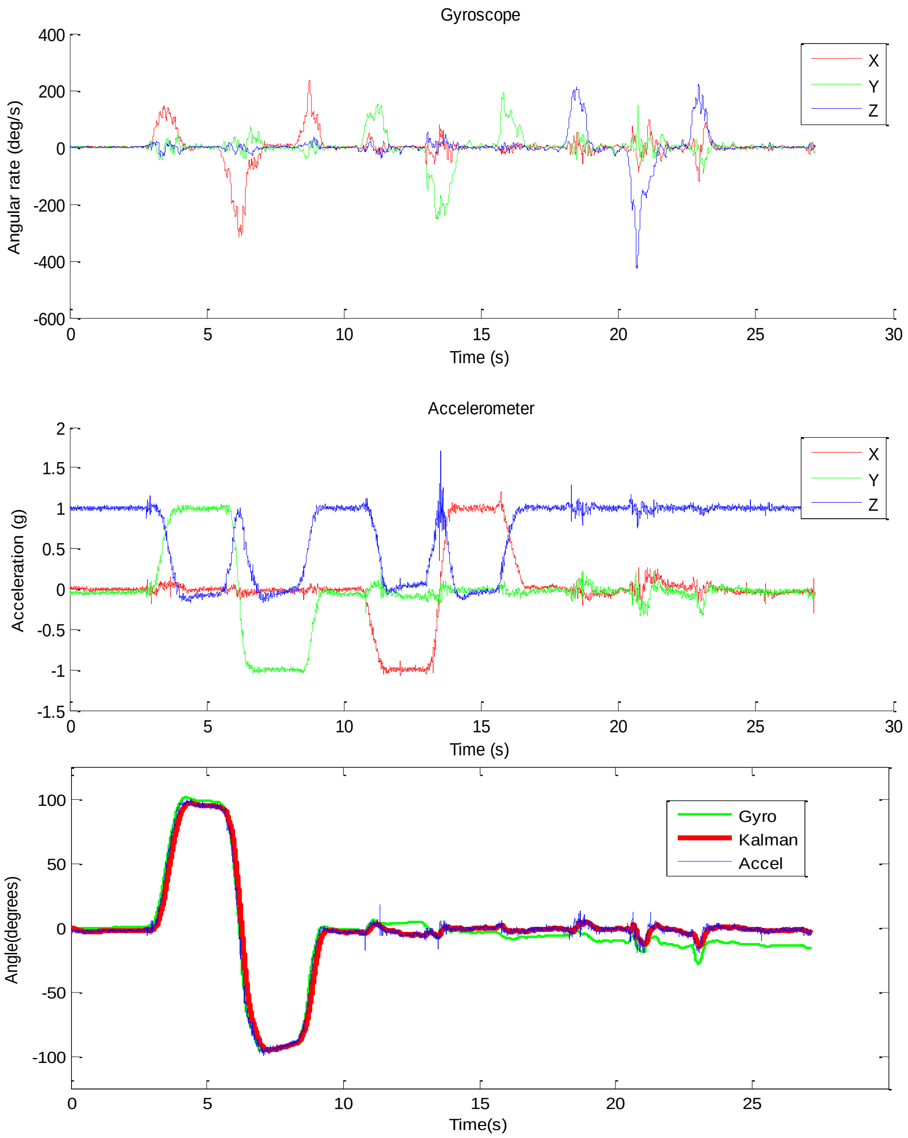

Figure 3. The output of IMU and Kalman filter

The acceleration peak value of VSA is several times the acceleration of gravity, as well as the high angle change is obvious from standing to fall, the main basis of distinguish between falls and daily activities is the threshold of VSA and TA .

According to the experimental results of ADL, set up the criterion values of a fall standards, the threshold for VSA is set to 3g and the threshold for TA is set to 40°. Experimental results confirmed that average acceleration for falls exceeded the 3g threshold; average angular displacement exceeded the 40° threshold. The detection results of forward falls and daily activities (such as standing, walking, lying down) is shown as Figure 4. In addition, the information of fall location was sent to the guardian and server via CDMA network.

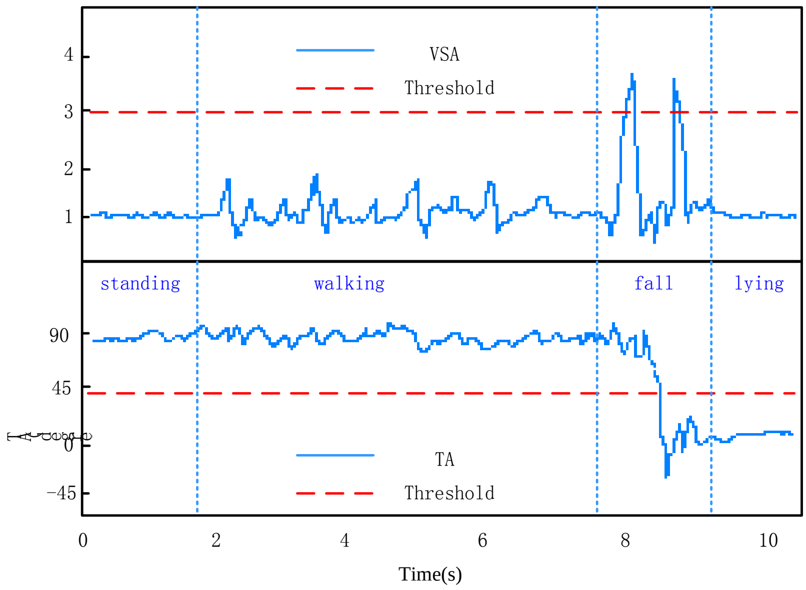

Figure 4. Magnitude of SVM and TA for a Fall

Table 1. Fall Detection Rate for Different Threshold

Threshold	Non-Fall(25)	Fall (25)	Accuracy
VSA =2&TA =40	19	22	82%
VSA =2.5&TA =50	21	22	86%
VSA =2.5&TA =60	22	20	84%
VSA =3&TA =40	24	23	94%
VSA =3&TA =50	23	23	92%
VSA =4&TA =30	22	21	86%
VSA =4&TA =50	22	18	80%

The influence of detection results for different threshold is shown as Table 1, and the different threshold will obtain different precision of experimental detection. As is clear from the above descriptions, the accuracy of the test would be reduced if the threshold is set too big or small. The results show that experimental accuracy as high as 94%, when the VSA threshold is set to 3g and TA threshold is set to 40°.

7. Conclusions

This article puts forward a practical method to distinguish a fall from the activities of daily living with sensor signal fusion algorithm, which established the two condition of fall detection by setting the threshold of VSA and TA. When two threshold conditions can be meet at the same time, to be able to accurately determine the fall. While the elderly falling accident occurs, the help information of fall alarm and location will be send to the guardian or health monitoring platform through the CDMA network. The experimental results show that the system has high reliability, simple, easy to wear, and it offers a timely and effective relief for the elderly people.

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