Research on intelligent perception and human activity monitoring for people with inconvenient movement

Tianping Zhang¹,², Xiaoping Tang*, Lijie Li²
¹School of Computer Science, Wuhan Donghu University, Wuhan, 430212, China
²School of Logistics Engineering, Wuhan University of Technology, Wuhan, 430070, China;
*Correspondence: zhangtianping@wdu.edu.cn

Abstract. Aiming at the problems of various sensors, complex recognition algorithm poor implement ability and real-time performance in current human activity state recognition methods, a human activity monitor based on single three-axis acceleration sensor is designed. By collecting acceleration data of human waist, using sliding time window method to extract time domain features, four active states are identified: long-term violent active state. Long-term static state, fall state and normal active state. The technical development and the existing difficulties and problems are discussed for future related research.

1. Introduction
Human activity monitor is the core of equipment control and data processing with low power controller; A three-axis MEMS motion sensor is used as the sensing unit to perceive human activity information in real time; Bluetooth Wireless transmission module as alarm data push unit; Display unit OLED low power display; The power supply unit is composed of rechargeable lithium battery and on-board charging circuit; The outer packing of the monitor is a plastic shell with elastic clip. The whole system is compact, user control and display interface is simple, hardware and software stability is high, continuous working time is long. Its composition is shown in Figure 1.

Human activity monitor built-in three-axis MEMS digital sensor as human activity perception unit. The MEMS sensor integrates a three-axis acceleration sensor and a three-axis gyroscope on a four×four×zero point ninemm silicon wafer, which can sense the vibration intensity and rotation rate of the carrier.

Figure 1. Main Components of Human Activity Monitor
By using digital filtering technology and data fusion technology, the original motion information output from the sensor can be processed. The angle, acceleration, human azimuth and other data that directly reflect the human activity can be obtained. As the basic data of human activity evaluation and recognition, these data are rich, accurate and real-time [1]. Figure 2 shows the functions and business processes of MEMS sensors in the monitor.

![Figure 2. Workflow of MEMS Sensor in human activity monitor](image)

Aiming at the short distance transmission of human activity monitor, docking with smart phone and reducing power consumption as much as possible, Bluetooth wireless module is used in wireless transmission parts[2].

The monitor adopts Bluetooth 4.0 module, which can connect with most existing smartphones that support Bluetooth function, use TI-CC2540 chip, configure 256 Kb space, support AT instruction, and users can change roles (master, slave mode) and serial port baud rate. Device name, pairing password and other parameters, flexible use[3].

Considering that the human activity monitor needs 7/24 hours to monitor the user's activity state, it will cause a lot of energy consumption, and Bluetooth communication is the main work of energy consumption, we adopt an event-driven working mode. All the four active states are judged by the MCU. When three abnormal states are encountered, such as fall state, long-term static state and long-term violent activity, the Bluetooth module is triggered and the alarm information is sent to the intelligent gateway.

2. Algorithm Design

For the four kinds of human activity states that need to be recognized, the recognition of fall state has the requirement of real-time to the algorithm, and the recognition of long-term static state and long-term violent activity state has no real-time requirement. But need to reach a certain time length, can be judged as "long-term static "[4].

When the MEMS acceleration sensor is fixed with the human body in a certain position, the positive direction of the x axis, the y axis and the z axis is located in front of the human body, directly above and directly left as Figure 3 shows.

![Figure 3. Three axis direction diagram of acceleration sensor in upright position](image)

The raw data of the sensor collected is \( \mathbf{ar} = (\mathbf{ar}_x, \mathbf{ar}_y, \mathbf{ar}_z) \), \( \mathbf{k}_x, \mathbf{k}_y, \mathbf{k}_z \) are acceleration sensitivity of three axes, \( \mathbf{b}_x, \mathbf{b}_y, \mathbf{b}_z \) are zero drift value. Because the zero drift value is small, it has little effect on this study, so the effect is ignored.
In order to meet the above requirements, the feature extraction method of sliding time window is used to obtain the real-time activity information of human body. Figure 4 is a schematic diagram of sliding time window activity, t is time and Q is information. The time window is divided into three consecutive segments, the previous window is W1f, for later window is W1b, middle time window is W2[5].

T1 is length of W1f and W1b, W2 is length of T2. The sampling frequency of motion information is $f_s=20$ Hz, is the serial number of the current sampling point. According to the experiment, the fall time was about 300 ms, So W2 took 6 sampling points. To avoid delay, W1f and W1b should not be too long, Take 7 sampling points each.

$$\begin{align*}
  a_{ti} &= \frac{a_{ti} + b_x}{k_x} \\
  a_{yi} &= \frac{a_{yi} + b_y}{k_y} \\
  a_{zi} &= \frac{a_{zi} + b_z}{k_z}
\end{align*}$$

In order to reduce the complexity of the operation, the synthetic acceleration amplitude is introduced as

$$\|\mathbf{a}\| = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2}$$

This study selects the following three quantities as eigenvalues, which are described below:

1. $a_{di}$

   Because only gravity acts in the static state, the adi in the static state tends to 0, which is obviously different from other active states is showed in Figure 5, according to which the eigenvalue 1 is extracted.

   (a) Three abnormal active states $a_{di}$

   (b) Three normal active states $a_{di}$

   Figure 5. adi comparison of human activity
When the human body is upright, the acceleration of gravity is mainly concentrated on the y axis, then the acceleration of the y axis accounts for a large proportion of the synthetic acceleration; when the human body falls, the acceleration of gravity is mainly concentrated on the x axis and the z axis. Based on this, the ratio and difference between the two time windows before and after the fall are large, which are obviously different from other active states as figure 6 shows, and the eigenvalue 2 is extracted accordingly[6].

\[
a_{\text{ami}} = \sum_{j=i-(\tau_1+\tau_2)}^{i-\tau_2} \left| a_{ij} - 1 \right| / T_2 f_s
\]

(3) ami

Because the human body will lose weight or be overweight during strenuous activity, the difference between synthetic acceleration and gravity acceleration is obviously different from other active states. The difference between synthetic acceleration and gravity acceleration is also large as figure 8 shows. Accordingly, the eigenvalue 3 is extracted.

According to the above analysis, the feature vector is defined as \( F = [\text{adi}, \text{rofi}, \text{ami}] \). The difference of the above four active states can be described without complicated numerical calculation of the sampling points.

Because long-term static immobility and long-term violent motion are long-term processes, the time of keeping the human body still and vigorous motion should be greater than the corresponding specified time. [7] In order to facilitate the experiment, the long-term time is set to 1 minute. A short period of static and violent immobility is determined as a normal state of activity.
The threshold-based classification method is used to identify the active state of the human body, and the derived features must be compared with the corresponding threshold to determine whether the specific activity is carried out.

3. Experiment and Results
Of the 10 participants, 5 were male and 5 female, 1.5~1.8 m, 45~80. Because the fall state will cause damage to the elderly, it is not considered to do the fall experiment.

| Identification status | Long-term stationary | Long-term intense activity | Fall | Normal activity |
|-----------------------|----------------------|---------------------------|------|-----------------|
|                       | jump                | run                       | Fort   | Backwards | Leftwards | Rightwards | Walk | go up stairs | go down stairs | sit down | Slowly lie down | Quickly lie down |
| Long-term stationary  | 100                  | 0                         | 0      | 0          | 0         | 0          | 0    | 0            | 0             | 0        | 0                  | 0                  |
| Long-term intense activity | 0                        | 100                        | 0      | 0          | 0         | 0          | 0    | 0            | 0             | 0        | 0                  | 0                  |
| Fall                  | 0                    | 0                         | 100    | 98         | 98        | 98         | 0    | 0            | 0             | 1        | 8                  | 8                  |
| Normal activity       | 0                    | 0                         | 0      | 2          | 2         | 2          | 100  | 100          | 100           | 99       | 92                 | 92                 |

4. Conclude
In the experiment, each person maintained a long-term static state (more than 1 minute), ran, jumped (more than 1 minute), fell forward, backward, fell to the left, fell to the right, walked, went upstairs, went downstairs (more than 1 minute each), sat down, lay down slowly and quickly 10 times each.

The experiment should identify running and jumping as vigorous activity, walking, going upstairs, going downstairs, sitting down, lying down slowly and lying down quickly as normal activity. A long period of rest, running, jumping, walking, going upstairs and downstairs must last for a certain period of time and be monitored at 60s. Other action states are rapid, so real-time monitoring.

The experimental results are shown in Table 1. The average recognition rate of long-term static, long-term intense activity, fall and normal activity is 100%, 100%, 98.8%, 98.5%, and the average recognition rate is 99.3% respectively.

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