Sensors & Transducers

Data Fusion Research of Triaxial Human Body Motion Gesture based on Decision Tree

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Abstract: The development status of human body motion gesture data fusion domestic and overseas has been analyzed. A triaxial accelerometer is adopted to develop a wearable human body motion gesture monitoring system aimed at old people healthcare. On the basis of a brief introduction of decision tree algorithm, the WEKA workbench is adopted to generate a human body motion gesture decision tree. At last, the classification quality of the decision tree has been validated through experiments. The experimental results show that the decision tree algorithm could reach an average predicting accuracy of 97.5 % with lower time cost. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Decision tree, Motion gesture, Data fusion, Body wear, Health care.

1. Introduction

With the accelerated process of population aging, the elderly's health care has become the focus of attention. Older people are suffered from high blood pressure, stroke and other diseases, and thus the probability of fall occurrence is also increasing rapidly. Therefore, their body motion posture detection becomes one of the key elements for the elder health care. With the rapid development of BSN (Body Sensor Network) technology, the research on human motion attitude detection and information fusion has gradually unfolded. Existing research are mainly on the basis of information through the multi-axis acceleration sensors, gyroscopes and other acquisition on the human body motion gesture, human movement posture is detected by using information fusion algorithm. Study abroad in this area is relatively deep [1-3]. ATR Media Information Science Laboratories in Japan has developed a wearable device for detecting the status of nurses day activities within the hospital environment. The device is placed in the human arms, chest and waist, and the body motion information is captured by the triaxial acceleration sensor, which is sent to the hospital server through the Bluetooth module. In the server, the body motion gesture data is processed by using a decision tree algorithm (C4.5) and nearest-neighbor (1-NN) respectively. Another, the University of Tokyo in Japan has developed a motion capture suit with advantage of inertial sensors and touch sensors which are covered in the whole body, and the body's various postures are identified by using the extended Kalman filter algorithm [2]. National research in this area is relatively small. China Tianjin University has designed a human gesture detection device, and information on human movement is collected by using triaxial acceleration sensors, and a simple threshold method is used to determine whether the body falls [4].

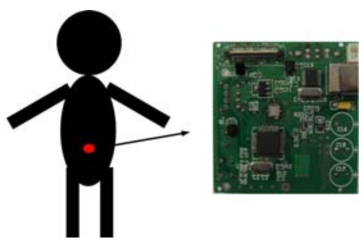
By using the nearest neighbor and extended Kalman filter algorithm, average classification accuracy can reach more than 98 %, but spending time is too much, which is not suitable for the needs of wearable computing data integration. In threshold determination method, algorithm is simple, and time overhead is small, but it is difficult to set an appropriate threshold for different wearers, and its classification accuracy is lower. The calculating amount is small in the Decision Tree Algorithm, which is easy to understand, and the continuous and discrete values can be handled, and the most decision-making power attribute can be explicitly given, which is very suitable for computer implementation.

In our wearable human motion gesture detection system, three-axis acceleration data fusion is treated using decision tree algorithm, which is used to discriminate whether human body fall occurred.

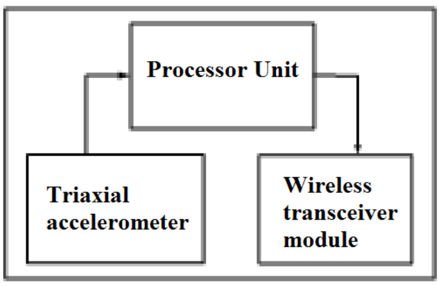
2. Human motion Gesture Detection System Hardware Platform

2.1. The Overall System Architecture

Fig. 1(a), the system is worn on the waist of the body when using, and human motion attitude information is detected in real-time. An acceleration sensor of the system, the processing unit and the wireless module are shown in Fig. 1(b). Body acceleration data is collected by acceleration sensors, and it is transmitted to the processing unit, after the collected data is for pre-processed by the post-processing unit, the data are transferred to a PC by the wireless module, and they are fusioned, body motion posture is detected.



(a)



(b)

Fig. 1. Development of human motion gesture detection system: (a) detection system schematic; (b) the overall structure of the hardware platform.

2.2. Triaxial Accelerometer

Triaxial accelerometer model is ADXL345 MEMS sensors in Analog Device Company [5, 6]. The sensor is an ultra-low-power device, and its resolution is up to 13 bit, its measuring range is up to ±16 g, the accuracy is 3.9 g/LSB [7, 8]. The digital output data is 16-bit twos complement format, which is accessible through the SPI digital interface, a small ultra-thin plastic package is applied, which is ideal for wearable systems, human motion pose detection is applied.

Before triaxial accelerometer is used, the proper body coordinate system is must created, as is shown in Fig. 2. Principles are established in accordance with right-handed coordinate system, the right-hand direction of the body is defined as the X direction, and the front is the Y direction of, the opposite direction of the gravitational acceleration is the Z direction. After you create the coordinate system, the orientation of the three-axis sensitivity acceleration sensor must be consistent with the body coordinate system [9, 10].

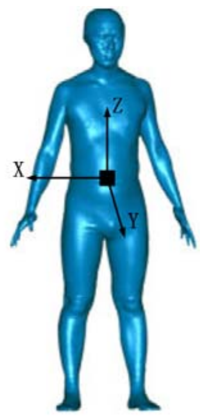


Fig. 2. Body coordinate system schematic.

2.3. Wireless Transceiver Module

Wireless transceiver modules are low-power RF chip of TI's CC2500. It is a 2.4 GHz wireless transceiver in work, and its sensitivity is high, output power is adjustable, just a few external devices will be able to build a low-cost high-performance radio system, and it provides access to SPI interface [11-13].

2.4. Processor Unit

TI's MSP430F5438 microcontroller is selected in processor unit. The microcontroller maximum operating frequency is up 18 MHz, and there are 256 kB embedded FLASH, 16 kB RAM, the built-in hardware multiplier and four universal serial communication interfaces, and these are able to meet the demand for the large data processing and transmission.

3. Decision Tree Algorithm and Implementation Principles

3.1. The Basic Principle of the Decision Tree Algorithm

In a decision tree, a training set of attributes is used as nodes, and the property values are used as tree branches. The root of the decision tree is the most informative property in the all samples, and the sub-tree contains the sub-sample in the root node, the intermediate node of the tree is the greatest property which is focused on the amount of information. Tree leaf node is a category value of the sample.

The concept of information theory is introduced in the decision tree algorithm, the information gain is used as the attribute selection criteria. If the current training set was S, wherein the samples were from m categories (C_1, C_2, ..., C_m), the sample in the training set S belongs to the class C_i, which its probability is P_i. The amount of information I and the entropy E are defined as follows:

$$I = \log_2 P_i \tag{1}$$

$$E = -\sum P_i \log_2 P_i \tag{2}$$

If s_i in the training set S is the number of samples which belong to the class C_i, before the decision tree is established, the system total entropy is:

$$E(s_1, \ s_2, ..., \ s_m) = -\sum_{i=1}^{m} P_i \log_2 P_i \tag{3}$$

If there are A has v different values (a_1, a_2, ..., a_v) in attribute A, according to the attribute A, a training set S can be divided into v subset $\{S_1, S_2, ..., S_v\}$. If the property A was chosen as the test attribute, there are v branches in the current node. If s_{ij} is the number of samples which are belonging to the class C_i in the subset S_j, then the sample partition is made based on the value of the property A, the total entropy of the system is:

$$E(A) = -\sum_{j=1}^{v} (\sum_{i=1}^{m} s_{ij} / s) \sum_{i=1}^{m} P_{ij} \log_2 P_{ij} \tag{4}$$

where $(\sum_{i=1}^{m} s_{ij}) / s$ represents the right weight of the j-th subset, $s=|S|$, $-\sum_{i=1}^{m} P_{ij} \log_2 P_{ij}$ is subset S_j entropy. Information gain $Gain(A)=E(s_1, s_2, \ldots, s_m)-E(A)$. Information gain represents the amount of information which is obtained by system classification. The purpose of the classification is to extract system information. So the best classification is the maximum classification scheme of Gain (A).

3.2. Realization of the decision tree algorithm

Decision Tree flow chart is shown in Fig. 3.

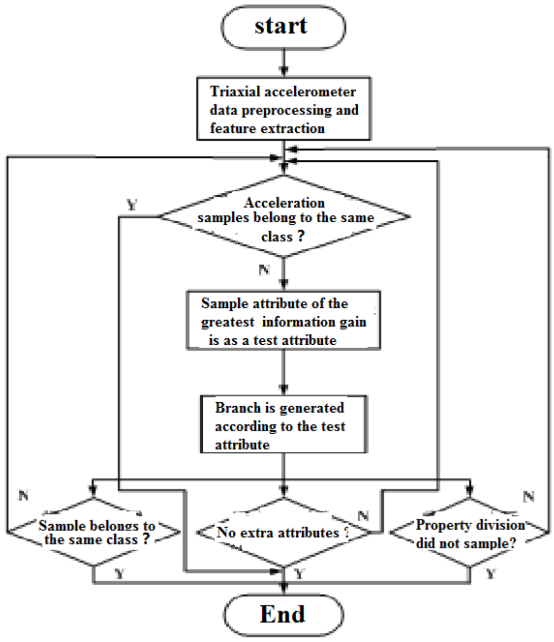


Fig. 3. Decision tree flowcharts.

First, the collected triaxial accelerometer data is preprocessed, and its feature is extracted, and a training sample set is constructed, which can be inducted by decision tree rule. You need to select the appropriate statistic of acceleration data as a sample property. Then all the samples are checked in the training set, which belong to the same class movement posture? If it is yes, the algorithm ends, if it is not, the sample information gain of each attribute is calculated by using the method of the 3.1, the training set with the largest information gain sample attribute is chosen as a test property, and a branch is generated based on the value of the property. Algorithm recursive calls are done, this step is continued to generate node down until the end of the algorithm, which is satisfies the following three conditions:

1) All samples within the nodes belong to the same class of attitude;

2) No extra attribute node samples are used for classification;

3) After the property division, there is no sample in the node.

3.2.1. Data Preprocessing and Forming a Training Set

When triaxial accelerometer works, due to various factors, the output may contain noise, so the first job is to be the software filtering in the output of the acceleration sensor. An effective filtering algorithm is as follows:

```
int data[0x02]; // Acceleration before filtering
int data_filter; // the acceleration after filtering
SoftwareFilter()
{
 if(abs(data[0x00]-data[0x01])<0x80)
 {
 data_filter=data[0x00];
 data[0x01]=data[0x00];
 }
}
```

Before the decision tree is generated, another important work is the sample data window treatment. Single discrete sample values are not able to react to any gesture information, the current human body posture is inferred only based on the sample values over time. It is appropriate how long this time is taken, this is related to the selection of the window size. To select a size too large or too small is not conducive to identify the body posture correctly. A large number of experimental results show that the system window size selection is 0.2 s, which is able to achieve a good classification results. In the actual sample rate of 100 Hz, each windowed sample contains 20 points (three axes are 60 sample points).

After the window size is selected, which properties are chosen to achieve the best classification results, which is the key feature extraction problem to be solved. A window of data is Taken for the current study, the X-axis sample points are $\{X_j \mid 1 \le j \le 20, j \in N\}$, Y-axis sample points are $\{Y_j \mid 1 \le j \le 20, j \in N\}$, Z-axis sample points are $\{Z_j \mid 1 \le j \le 20, j \in N\}$. Now the X-axis, Y-axis, and Z-axis sample point mathematical expectations are used as the test properties, when the human body is static, the three expectations plays an important role in the posture and the position determination.

$$E(X) = \frac{1}{20}\sum_{j=1}^{20} X_j \tag{5}$$

$$E(Y) = \frac{1}{20}\sum_{j=1}^{20} Y_j \tag{6}$$

$$E(Z) = \frac{1}{20}\sum_{j=1}^{20} Z_j \tag{7}$$

Further, the variances of X axis, Y axis and Z axis sample points are:

$$D(X) = \frac{1}{20}\sum_{j=1}^{20} (X_j - E(X))^2 \tag{8}$$

$$D(Y) = \frac{1}{20}\sum_{j=1}^{20} (Y_j - E(Y))^2 \tag{9}$$

$$D(Z) = \frac{1}{20}\sum_{j=1}^{20} (Z_j - E(Z))^2 \tag{10}$$

The variance can measure the data dramatic change degree in the size of a window, which can make an assessment of the intensity on the current movement of the human body, which is necessary for the test properties of the body posture detection.

Acceleration amplitude a is defined as:

$$a_j = \sqrt{X_j^2 + Y_j^2 + Z_j^2} \tag{11}$$

Acceleration amplitude is an important parameter which characterizes the intensity of human motion, the greater the acceleration amplitude, the more intense the human activity degree.

In terms of window acceleration sample, the mathematical expectation and variance of acceleration amplitude is also our concern content, they are defined respectively as follows:

$$E(a) = \frac{1}{20}\sum_{j=1}^{20} a_j \tag{12}$$

$$D(a) = \frac{1}{20}\sum_{j=1}^{20} (a_j - E(a))^2 \tag{13}$$

In summary, the feature attributes are extracted from a window sample, the mathematical expectation and variance are defined for three-axis accelerometer (X, Y, and Z), and the three-axis acceleration amplitudes are corresponded to mathematical expectation and variance.

3.2.2. The Decision Tree Building and Testing Based on WEKA

WEKA full name is Waikato Environment for Knowledge Analysis, and it is based on Java, which is an open source project for data mining and knowledge discovery.

After ten years of its development, WEKA has become one of the most comprehensive data mining tools today. WEKA greatest feature is that its source code is open, which allows designers to perform the algorithm design and in-house packaging according to their needs. WEKA platform is used to build a decision tree, first of all the attributes are extracted, and they are changed into WEKA, which ARFF text format can be accepted. ARFF format is actually a two-dimensional table, each column corresponds to an attribute, each row corresponds to one instance. According to body motion gesture detection system, the acceleration data is actually collected, and a two-dimensional table is created, which is shown in Table 1.

Table 1. Three-axis human motion attitude information 2-dimensional table.

E(X)	E(Y)	E(Z)	D(X)	D(Y)	D(Z)	E(a)	D(a)	Fall
0.193750	-0.03281	0.910352	0.001472	0.002395	0.001142	0.933365	0.001139	No
0.217969	-0.03789	0.991211	0.003109	0.004657	0.053811	1.020392	0.051823	No
…	…	…	…	…	…	…	…	…
1.021875	-0.10234	0.313867	0.703583	0.237005	0.541042	1.401106	0.671747	Yes

In the Classifier menu of the Classify tab of WEKA, a variety of classifiers are offered for selection. Under tree children, J48 algorithm is commonly C4.5 algorithm. This is an improved version of the original ID3 algorithm, and the continuous attribute values and their default values can be handled, and a lot of improvements are also done for tree pruning. Here we use the C4.5 algorithm to classify human motion gesture. The default settings are taken in the confidence factor and other parameters for tree, the last generation of the decision tree is shown in Fig. 4.

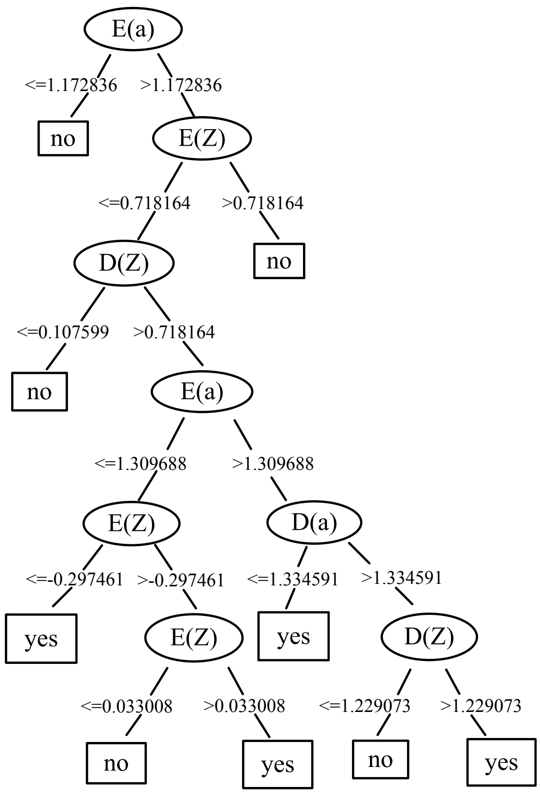


Fig. 4. Human motion gestures decision tree.

4. Experimental Evaluation

4.1. Prepare Test Set

In order to evaluate the classification performance of human motion gestures decision tree, and it must be evaluated by the test set. Here we are for the convenience, the generating human motion gestures decision tree is tested by using 10-fold cross-validation method. Such training sets and test sets can share a sample set.

4.2. Decision Tree Performance Testing

The test set data are imported into WEKA platform for evaluating the classification performance of the decision tree which is generated. A classification result of human motion gesture decision tree is in Fig. 5. Wherein the abscissa represents the sample Fall properties, the ordinate represents Fall properties which the decision tree algorithm has predicted. Blue dot indicates Fall attribute value, which is No sample, the red dot indicates Fall attribute value which is Yes samples. Fig. 5 shows that, in 1635 samples, there are 1595 sample Fall property values which are predicted correctly, and the forecast accuracy is 97.5535 %. The formula (14) is for the confusion matrix of decision tree model. From this matrix, the 1578 Fall attribute value is No sample, there are 1569 sample Fall attribute values which are correctly predicted, the correct rate is 99.4 %. In 57 Fall attribute value Yes samples, there are 26 samples Fall property values which are predicted correctly, the correct rate is 45.6 %. Experimental results show that the average prediction accuracy of decision tree algorithms are the higher in human motion posture information fusion, but fall prediction accuracy will be improved. Also in the 1569 sample points and the case of nine attributes, decision tree set-up time is only 0.06 s, it is with good classification speed and scalability.

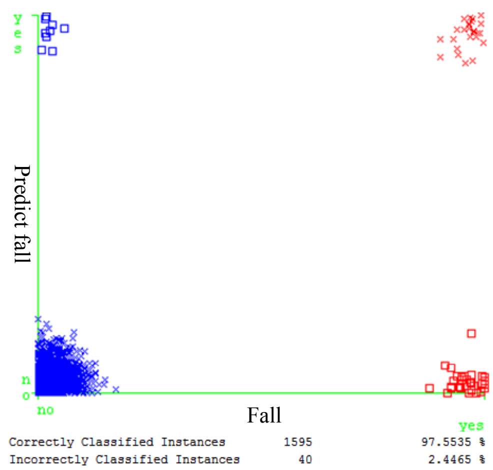


Fig. 5. Decision tree classification results.

$$\textit{Fusion Matrix}=\begin{bmatrix} 1569 & 9 \\ 31 & 26 \end{bmatrix}, \qquad (14)$$

5. Conclusions and Outlook

According to the experimental results, the decision tree algorithm is used to process information fusion in human motion posture, the average prediction accuracy and time overhead has some advantages, but the prediction accuracy is not satisfactory discrimination against falls. the more effective test attributes are chosen, achievement method is optimization, when the body falls, to improve forecast accuracy will be the next step.

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