Decision method of holding a mobile terminal and abnormal behavior by machine learning for ERESS

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Abstract: We have proposed an Emergency Rescue Evacuation Support System (ERESS) that is effective in sudden disasters. This is intended to detect disasters by collecting moving data of mobile terminals. In this research, in order to realize behavioral analysis without restricting the terminal holding state, we propose a terminal holding judgment method and an abnormal behavior judgment method using machine learning. Experimental results show the effectiveness of the proposed method.

Keywords: ad-hoc network, MANET, support vector machine, ERESS

Classification: Navigation, Guidance and Control Systems

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1 Introduction

It is difficult for evacuees who have encountered local disasters such as fire and terrorism to obtain accurate position of disaster outbreak and safe evacuation route. So there are disaster navigations and sensor networks that use communication means of mobile phones as typical evacuation support systems during disasters [1, 2, 3]. However, since the information acquisition of disasters and center locations depends on the server, information cannot be acquired if the server is damaged during a disaster.

In order to solve the problems of these systems, we are developing the Emergency Rescue Evacuation Support System (ERESS) [4, 5]. ERESS is a system that automatically detects disasters at an early stage and provides evacuation support to evacuees. Communication works only between mobile terminals without a communication infrastructure, so it is possible to operate without depending on servers. In the conventional ERESS, the behavior of the terminal holder is judged using the acceleration sensor installed in the ERESS terminal. By using SVM (Support Vector Machine) for the data obtained from the accelerometer, basic actions such as stop, walk and run are discriminated. It is assumed that run is emergency state and walk or stop is normal state.

There are two problems in behavior analysis. The first is the problem of the terminal holding state. Since we do not consider the recognition of the holding state of the terminal, the judgment for each holding method is not practical. The second problem is the feature amount used for judgment. The basic behavior is determined by SVM using the sum of deviation squares of the three-axis composite acceleration as a feature value, but the determination accuracy is not sufficient. Therefore, we propose a decision method of terminal holding state by using machine learning in order to realize behavior analysis without limiting the terminal holding state. Gravitational acceleration and posture information of a smartphone are used as feature quantities, and the holding state is determined using SVM or random forest. In addition, we propose an abnormal behavior determination using new features.

Other methods of recognizing behavior using machine learning extract features from accelerometers and gyro sensors and classify them using SVM and deep learning [6]. However, since deep learning requires a large amount of calculation, there are some problems with real-time processing. On the other hand, we propose a method that can be executed without increasing the amount of calculation by using a combination of random forest and SVM according to the situation. In other methods [7] that do not use machine learning, high accuracy can be obtained in the operation in the ideal indoor corridor, but it is recognized the accuracy will drop in the behavior recognition when there is other disturbance. We also recognize the unique behaviors that occur during a disaster, such as falls, crouching, and lying down.
2 Recognition of behavior

In order to solve the problems of the conventional behavior analysis, we propose (1) terminal holding judgment method and (2) abnormal behavior detection method for each holding state. The proposed method consists of three elements i.e. terminal holding determination, basic action determination for stop, walk or run, and abnormal action detection for fall, crouching, and lying down. By determining the terminal holding state using gravitational acceleration and posture information, there is no limitation on the holding state in behavior analysis. We use random forest to improve the accuracy of basic behavior determination. Abnormal behavior detection is performed for each holding state using 3-axis composite acceleration and angular velocity.

2.1 Decision of holding state of terminal by machine learning

We judge four types of terminal holding state: handheld, in use, pants, and breast pocket as follows.

(1) Handheld: A state where the terminal is held by hand. The hand is lowered to the side of the foot without using the terminal.

(2) In use: The terminal is being held by hand. The terminal is held near the face and used continually.

(3) Pants: A state where the terminal is stored in the pocket of the pants. The upper part of the terminal faces downward.

(4) Breast pocket: The device is stored in a breast pocket such as a suit. The top of the terminal faces upward.

Posture information is an angle that represents the orientation of the terminal and is expressed as −180 to 180 degrees on the terminal. Posture information is divided into three axes, pitch, roll, and yaw. The holding state of the terminal is judged using two indicators that change depending on the attitude of the terminal by machine learning. We acquire terminal holder data in advance and create a teacher data. Two types of machine learning are used: SVM and random forest. The holding state is determined by using different teachers and features. The judgment procedure is shown below.

Step 1: Classification of terminal holder state as stop or move by SVM

The sum of the deviation squares of the three-axis composite acceleration is used to classify the state of the terminal holder as stop or move by using SVM.

Step 2: Judgment of the holding state by the teacher data

A different teacher data is used for each result of Step 1 to determine the holding state by using random forest. Gravity acceleration (x, y, z) and posture information (pitch, roll) are used as features during stopping. In addition, the average and minimum of the gravitational acceleration on the Y axis are used in addition to the previous five features at stopping as features during action. If it is determined to be in use or breast pocket, the result is the final determination.

Step 3: Additional judgment by SVM for handheld or pants

As a result of Step 2, if it is determined to be handheld or pants, an additional determination is made for each state and classified as handheld or pants. SVM is used for judgment. Gravitational acceleration on the X axis and the pitch of
posture information are used as features when stopping. The average and minimum gravitational acceleration in Y axis are used as features during action. If the pants are determined here, the result is the final determination.

Step 4: Determination of handheld or in use by SVM

If the result of Step 3 is determined to be handheld, we use SVM to classify the holding state into handheld and in use. The Z axis gravitational acceleration is used as the feature value.

2.2 Process of behavior analysis

We show outline of the behavior analysis in Fig. 1. The process is as follows.

Step 1: Detect fall by using angular velocity

When falling, the angular velocity changes abruptly. Hence, the fall is detected using the sum of deviation squares of the three-axis composite angular velocity. If it is determined to fall, the action determination is terminated.

Step 2: Determine how to hold the terminal using gravity and posture

By using the holding judgment method, the terminal holding state is classified into four types: handheld, in use, pants, and breast pocket. We use the teacher data of the determined holding state.

Step 3: Analyze the behavior of the terminal holder using an acceleration sensor

Random forest is used to classify the behavior of terminal holders into three types: stop, walk, and run. The teacher data used for the judgment is different for each holding state in Step 2. If it is determined stop or run in this step, the behavior determination is terminated.

Step 4: Detect crouching and lying down using angular velocity

If the walk is determined in step 3, the behavior is classified into walk, crouching, and lying down using the angular velocity. The sum of deviation squares, average, and median are used as the calculation method of the classification features.

3 Experimental results

We ask examinees to hold a mobile terminal and take the behavior specified by the holding state, and the judgment result is compared with the actual holding state. For basic behavior determination, we compare with the conventional method of SVM using the sum of deviation squares. In this experiment, we measure three actions of the terminal holder: stop, walk, and run during 10 seconds, respectively. These three
actions are measured for 60 seconds in total, 20 seconds for each action repeatedly. Based on the teacher data obtained in the above procedure, a teacher for each holding state is created and behavior determination is performed. The data is acquired twice for six holding states of 11 examinees. Decision interval is 0.5 second.

Table I shows the correct decision rate in six holding states. R and L are right and left handheld. Inside and outside are screen surface. We find that the average correct decision rate is 79.6% with the conventional method and 85.2% with the proposed method. The rate can be improved by 5.6% with the proposed method. Table II shows the correct detection rate of each abnormal behavior. From this result, we find that the detection rate of 81.2% on average can be realized.

| Holding state          | Conventional | Proposed |
|------------------------|--------------|----------|
|                        | First | Second | First | Second |
| Handheld (R)           | 77.8% | 75.1%  | 85.4% | 79.3%  |
| Handheld (L)           | 79.3% | 77.2%  | 85.2% | 82.5%  |
| In use                 | 84.6% | 83.7%  | 86.0% | 87.2%  |
| Pants (inside)         | 75.8% | 80.2%  | 82.3% | 87.6%  |
| Pants (outside)        | 77.9% | 77.0%  | 84.0% | 85.8%  |
| Breast pocket          | 82.9% | 83.1%  | 87.8% | 88.9%  |
| Average                | 79.7% | 79.4%  | 85.1% | 85.2%  |

| Average (two)          | 79.6% | 85.2%  |

Table II. Correct detection rate of each abnormal behavior.

|                | Fall  | Crouching (Stop) | Crouching (Walk) | Lying down |
|----------------|-------|------------------|------------------|------------|
| Handheld (R)   | 90.5% | 76.2%            | 78.6%            | 78.6%      |
| Handheld (L)   | 85.7% | 73.8%            | 57.1%            | 78.6%      |
| In use         | 92.9% | 81.0%            | 64.3%            | 83.3%      |
| Pants (inside) | 83.3% | 95.2%            | 81.0%            | 71.4%      |
| Pants (outside)| 92.9% | 92.9%            | 78.6%            | 73.8%      |
| Breast pocket  | 92.9% | 78.6%            | 85.7%            | 81.4%      |
| Average        | 89.7% | 82.9%            | 74.2%            | 77.8%      |
| Average (four) |       |                  |                  | 81.2%      |

4 Conclusions

In this study, we have proposed a decision method of holding a mobile terminal and abnormal behavior by machine learning. Without limiting the terminal holding state, the proposed method can perform that the correct decision rate for each holding state is 85% and the correct detection rate for abnormal behavior is 81%.
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