A new disaster recognition algorithm for ERESS: Buffering and Bagging-SVM with the grid method

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Abstract: Recently, various disasters such as terrorism as well as natural disasters have occurred. We have developed the evacuation support system named as Emergency Rescue Evacuation Support System (ERESS) to reduce the victims. This network system consists of mobile terminals, recognizes disasters through various sensors, and presents appropriate evacuation routes. In this paper, we propose a method to recognize disasters immediately and accurately by using Support Vector Machine (SVM) and location information. This method uses two different SVM algorithms that are Buffering and Bagging-SVM to analyze owner behavior and recognize disasters. We show the validity of the proposed method by panic-type experiments and simulations.

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

Classification: Network System

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1 Introduction

How to evacuate immediately is important in order to survive in sudden disasters such as fires. To that end, it is necessary to grasp the location of the disaster and know the appropriate evacuation route quickly. Many researchers have developed systems to support such evacuation. Most of them are provided by sensor network systems [1]. In general, sensor networks are very expensive because it requires infrastructure. Another disadvantage is that this system depends on the building where the sensors are located, so it cannot be used anywhere. To solve these problems, we have developed a system called ERESS (Emergency Rescue Evacuation Support System) using MANET (Mobile Ad-hoc NETwork) [2, 3, 4]. This system learns sensor data installed in mobile terminals using machine learning and shares it by MANET to recognize disasters. Moreover, the mobile terminal presents the appropriate evacuation route to the terminal holder.

In this paper, we focus on disaster recognition using machine learning and propose a new method to recognize disasters more accurately than the conventional methods by panic-type experiments and simulations.

2 Concept of ERESS

ERESS is an advanced evacuation support system composed of mobile terminals (ERESS terminals) such as smartphones. For this reason, in an emergency, it is possible to operate with only the terminal without depending on the infrastructure. The main functions of ERESS are as follows.

1. Exchange and sharing of information using MANET.
2. Behavior analysis of ERESS terminal holders.
3. Recognition of disaster outbreak.
4. Search for evacuation routes.
5. Display and guidance of evacuation routes.

First, ERESS terminals establish a mobile ad-hoc network autonomously and share information with nearby terminals. Each terminal uses a 9-axis sensor to analyze the behavior of the terminal holder and transmit the information. By collecting the analyzed behavior data of the terminal holders, ERESS detects an emergency...
such as disaster. If ERESS recognizes a disaster, it searches for the appropriate evacuation routes from the location information. Finally, ERESS supports the evacuation of terminal holders by presenting and guiding the evacuation routes. In this paper, we focus on recognition of disaster outbreak.

3 Recognition of disaster outbreak

In order to recognize disasters, the definition of disasters is important. We first defined the condition of running hard indoors as emergency. We used machine learning such as SVM for the behavior analysis. And then, we defined that if half of the terminals in the network are emergency state, it is a disaster.

However, this method has three serious problems. First, many errors will occur if the running simply equals emergency. Second, since the number of terminals in the network is uncertain, there are cases where disasters cannot be recognized based on the criteria. Third, if the target area was large, it was difficult to recognize small-scale disasters. To solve the first and second problems, we have already proposed a method called Buffering and Bagging-SVM [2]. In this paper, we propose the SVM with the grid method as a new method to solve the third problem. These details are as follows.

3.1 Basic-SVM

This method uses the basic functions of ERESS. Each terminal uses the following basic SVM Eq. (1) to determine whether the 9-axis sensor value per second is emergency state as shown in Fig. 1(a). In the formula (1), $x_i$ is the feature vector of hyperplane, $x$ is the input vector, $b$ is the bias parameter, $D$ is the number of terminals, $\lambda_i$ and $y_i$ denote Lagrange multiplier and class label for each $x_i$. $K(x_i, x)$ denotes kernel function in Eq. (2) and we use Radial basis function kernel and $\gamma$ denotes the kernel parameter [5].

$$f(x) = \text{sign} \left( \sum_{i=1}^{D} \lambda_i y_i K(x_i, x) + b \right)$$ (1)

$$K(x_i, x) = \exp(-\gamma \|x_i - x\|^2)$$ (2)

3.2 Buffering-SVM

Basic-SVM has the problem that the judgment changes intermittently and the state is not stable. Buffering-SVM provides a dedicated buffer for each terminal and accumulates Basic-SVM judgments to determine whether or not there is an emergency state. Since TTL (Time to live) is set for Basic SVM judgment, this method does not recognize disasters unless it is continuously determined to be an emergency for 3 seconds (experimentally reasonable value) as shown in Fig. 1(b). Therefore, this method increases the judgement accuracy of disasters per terminal.

3.3 Bagging-SVM

Bagging is an abbreviation for “Bootstrap Aggregating”, and is a method of giving diversity to a data set by restoring and extracting learning data [6]. By combining bagging and SVM, it is possible to reduce the variance of prediction results and improve judgment accuracy [7, 8]. The algorithm is as follows.
1. Repeat the following procedure $N$ times.
   a. Restore and extract $m$ times from training data to create new data.
   b. Build weak learner $h_i$ from the new data with SVM.

2. The final result is obtained by a majority vote of $h_1, \ldots, h_N$.

Moreover, since Bagging-SVM can be combined with Buffering-SVM, this is called Buffering and Bagging-SVM (BB-SVM).

![Diagram of Disaster Recognition in ERESS](image)

**Fig. 1.** Disaster Recognition in ERESS

### 3.4 Buffering and Bagging-SVM with the grid method

In the conventional methods, it was difficult to recognize small-scale disasters. To solve this problem, we propose to combine grid-like location information into a dataset for disaster recognition. Therefore, this proposed method uses the additional
criteria of disaster occurrence for Buffering and Bagging-SVM (BB-SVM) to recognize small-scale disasters. For example, as shown in Fig. 1(c), if multiple nearby terminals are in an emergency, a disaster may have occurred near the owner.

4 Panic-type experiments and simulation

We have already done some panic-type experiments. In that experiment, we have generated fake-disasters in real environments such as schools and gymnasiums, and have acquired various data. In order to verify the effectiveness of the proposed method in this paper, a large number of terminals are required. Therefore, an

| Table I. Simulation Environment |
|-------------------------------|
| Area Size                     | 100 [m] × 100 [m] |
| Number of terminals           | 100              |
| Simulation time               | 60 [s]           |
| Number of trials              | 1000 to 3000     |
| User node speed               | 0 to 2 [m/s]     |
| Mobility model                | Random waypoint   |
| Type of disasters             |                   |
|     Large-scale 100 [m] × 100 [m] |
|     Medium-scale 30 [m] × 30 [m] |
|     Small-scale 10 [m] × 10 [m] |

Fig. 2. Recognition Accuracy of each scale disaster among four methods
empirical simulation was performed using the knowledge obtained in the experiment. In this simulation, the probability of recognizing a disaster is calculated from sensor data obtained through experiments and used as a parameter for virtual terminal holders. The initial position of the terminal holders are random, and the mobility model until the disaster occurred is random waypoint model. Then, we generated a disaster at random locations in the simulation area, and the proportions of disasters recognized by each algorithm were compared. The simulation environment is shown in Table I. We changed the size of the disaster and simulated three situations. The consideration for each is as follows.

First, we simulated a large-scale disaster such as an earthquake. As shown in Fig. 2(a), in such a disaster, since all terminal holders are in a location where all users can recognize, all methods recognize disasters with high accuracy. Next, we simulated a medium-scale disaster such as a fire. As shown in Fig. 2(b), since only some terminal holders can see the disaster, Basic-SVM and Buffering-SVM have greatly reduced accuracy. Although Bagging-SVM is more than 95% accurate, BB-SVM improves it even closer to 100% accuracy. Finally, we simulated a small-scale disaster such as a terrorism. As shown in Fig. 2(c), since it is a very small disaster, it is hardly recognized by conventional methods. However, BB-SVM recognizes the disaster with close to 90% accuracy. This is because location information is combined with disaster recognition. From the above results, it was found that the proposed method can recognize a disaster even if only a few terminal holders can visually recognize the disaster at an early stage.

5 Conclusions

We have proposed and investigated a Buffering and Bagging-SVM (BB-SVM) with the grid method. In the conventional methods, it is difficult to recognize a small-scale disaster automatically. This is because the criteria for disaster outbreak depended on only the number of terminals. In the computer simulation, we used location information. As a result, it was shown that the BB-SVM can recognize terrorism incidents that occur in one room with high accuracy. In other words, the effectiveness of the disaster recognition method using location information in ERESS was suggested. However, there are some types of disasters that are not yet recognized. For example, if the terminal holder cannot move due to a power failure at night, the 9-axis sensor cannot obtain a valid value. In the future, we will conduct various experiments to develop more versatile disaster recognition methods.

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