Empty Scene and Non-empty Scene Detection from Wi-Sun Acceleration Sensor

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***Abstract*—Wireless sensor networks (WSNs) are widely deployed to help detect disaster such as landslides, etc. in countries like Japan due to their efficiency and low cost. But there are various problems in these systems, such as the different kind of noise (such as random visit from animals, which leads to unnecessary false alarms). Orthogonally, context aware activity recognition draws increasing attention recently, where different environmental or martial sensors are adopted for activity recognition in various application scenarios. This paper studies a disaster detection system utilizing the Wi-Sun acceleration sensors together with the Wi-Sun signal fluctuation and considers the detection of human beings in the scene of interest. Hence, the false alarms introduced by the animals' walk in, etc. could be detected using similar method. During the detection process, not only the wireless signal but also the acceleration value collected by the sensors are adopted for a better detection result. Then feature values are calculated for event detection based on the data samples. *K nearest neighbors* (KNN) is used to classify the events in the scene of interest: empty and non-empty. The detection results are promising as shown in the result section and the proposed method is applicable to a real landslide to avoid animal-induced false alarms.**

I. Introduction

Wireless sensor networks (WSNs) have been used in many industrial and consumer applications (such as industrial process monitoring and control), machine and building health monitoring for its efficiency, low-cost and 24-hour sensing ability, etc. Scene monitoring and unusual event detection such as landslide detection [1] are typical applications of WSNs. There are WSNs that have already been deployed to monitor the scene of interest and detect the unusual events automatically and continuously utilizing the Wi-Sun acceleration sensors and Wi-Sun transmission technology[1].

The Wi-Sun acceleration sensors can sense the nearby environment and send the captured acceleration value to the control center using wireless channels. The control center can then immediately understand the situation in the scene of interest. This is useful in terms of automatic disaster detection. Wi-Sun sensors have been used in different scenarios, and deployed to help monitor the scene of interest. One typical application is landslide detection to avoid damage to the transportation system. One critical issue of such landslide detection system is that animals' random walk in, which leads to false alarms and these false alarms degrade the system performance. How to detect the animal' existence in the scene of interest and avoid the false alarms then becomes an important issue. One solution to handle this problem is to detect the animals' walk in from the collected sensor data, which includes the wireless signal strength.

[1]https://www.wi-sun.org/

Context aware detection has drawn more and more attentions due to its various applications such as the caring for the aged people. To detect the defined activities (such as standing, lying, walking, etc.), various types of signals are adopted such as Wi-Fi, ambient FM radio [2]. with promising performance. The general idea is to collect the signal under different conditions (or with different events/activity) and then to adopt state-of-the-art machine learning tools such as *K nearest neighbors* (KNN), *decision tree*, etc. for classification.

This paper adopts the basic idea of context aware detection/recognition to detect the existence of human beings in the scene of interest monitored by the Wi-Sun sensors. And we employ both the signal strength and the acceleration value for the final event detection with a better recognition ratio. Specifically, we treat the presence or absence of human beings as different events. The features used for event detection are selected and calculated. KNN is used as the tool to classify the events 'empty' and 'non-empty', with a high detection accuracy. These classification methods can also be adopted directly in the existing landslide detection system to help avoid false alarms introduced by the animals' random interference.

II. System

This section overviews the system and introduces the features used for detection.

A. System overview

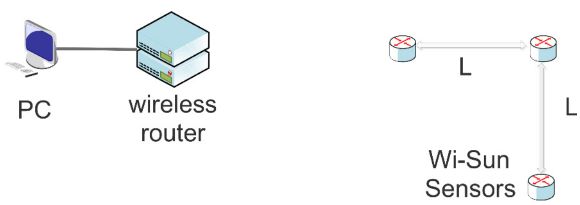


Fig. 1: Human detection system illustration. L=0.8 meter and the distance between the router and the nearest Wi-Sun sensor is around 5 meters.

As illustrated in Fig. 1, there are three Wi-Sun acceleration sensors and a router in the investigated system. The sensors are placed in the position as shown in Fig. 1. The distance between two neighboring sensors are 0.8 meters. And the distance between the sensor and the router is around 5 meters[2]. The sensors can broadcast generated data samples to the router using Wi-Sun. The router connects to the PC with a wired cable, where the data are shown in the control center's display in real-time. Therefore, the control center has full knowledge of the monitored situations.

Sensors sense the nearby environment with a sampling period of 0.004s. One data sample is composed of $(t, x_t, y_t, z_t, RSSI_t)$, where t represents the time when the data sample is generated. x_t,y_t and z_t denote the acceleration value at time t in the x-, y- and z-direction, respectively. $RSSI_t$ is the *received signal strength indicator* (RSSI) value at time t. Due to channel losses caused by the shading, fading, etc., only a subset of the data samples will be collected at the PC for further analysis.

B. Detection features

The features applied in the machine learning process affect the detection performance.The feature value is calculated at the group level, where the groups are divided by the pre-assigned time window. The features we apply in this paper are: *mean* and *standard deviation* of the data samples in each direction. These values are then normalized for the detection.

C. Event detection method

K-nearest neighbors [3], or KNN for short, is adopted to detect the events. We calculate the events' feature value of the training data first, each event has multiple features values. Then we will calculate the distance between the feature value of the testing data and the training data. Then K samples with the smallest distance from the testing data, will be chosen from the training data. The testing data is labeled according to the label of the majority among the K samples (See Alg. 1).

Algorithm 1 KNN detection flow

1: Calculate the feature value, i.e. *mean, standard deviation* in the training data set and the test data set.
2: Calculate the test data feature's distance between all the features in the training set.
3: Select the K samples with the smallest distance between the test data's feature value.
4: The class of the training samples is decided according to the dominant label among the K samples.

III. Experimentation

This section introduces the experiments setup and detection performance.

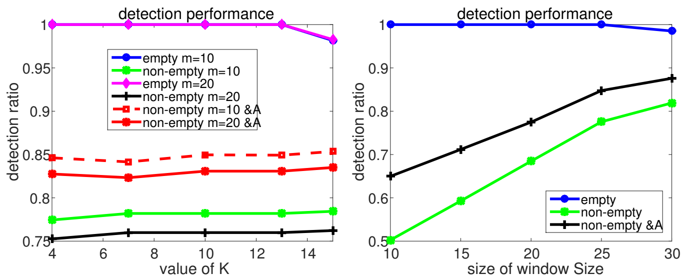
[2]The distance affects the performances, and we will study this in the future.

A. Experimental setup

To conduct the experiments, we capture the data traces using the system as introduced in Fig. 1, which is set up in an office with hard floor. The main purpose is to detect two events: empty, and non-empty. We collect data for these two cases, and during half of the non-empty period, there are two persons walking in the scene. There is one person during the other half of the non-empty period. Note that, the results are based on one set of data. We randomly pick up 40 groups of data from this set of data and the results are the average.

B. Experimental results

RSSI information is used for the event detection. The experimental results are shown in Fig. 2. Fig. 2 (a) shows the detection performance with different k. From the results, we can see the larger k lowers the detection ratio of the *empty*, but improves the performance of the *non-empty*. We also show the results with different window sizes, we can see as the size of the time window increases, the detection performance of *non-empty* becomes better, but the performance of *empty* becomes slightly worse. The performance of *non-empty* is worse than *empty* because the non-empty's data samples are with larger variety and hence not easy to be detected. If all the acceleration value and RSSI (denoted by *&A*)are used, the detection performance is better.



(a) vs K (b) vs window size

Fig. 2: Performance evaluation with different variables.

IV. Acknowledgement

The research results have been achieved by"Research and Development on Fundamental and Utilization Technologies for Social Big Data", the Commissioned Research of National Institute of Information andCommunications Technology (NICT), JAPAN.

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