Research on the ZigBee-Based Indoor Location Estimation Technology

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Abstract. In recent years, as rapid advances in wireless and mobile communications and continuing decreases in hardware costs, applications of the wireless sensor network are widespread; whereas location estimations in the wireless sensor technology are crucial for their use. Among them, Location-based services have been developed rapidly and find their applications in areas such as medical care, warehouse management, and mobile guide systems in public spaces. In this paper, a fingerprint based location estimation technology in the ZigBee networks is investigated, in which the collection method to build the signal strength database and the configuration of sensor nodes are examined. Furthermore, the k-nearest neighbor algorithm is used to increase accuracy of location estimations for compliance with relevant applications.

Keywords: wireless sensor network, indoor localization, fingerprint, k-nearest neighbor algorithm.

1 Introduction

As the wireless sensor technology advances, its applications in environmental, military, and daily home life are numerous. The location based technology is very important for applications such as home care, automated warehouse management, personnel management, and museum tour guide. For home care, the location based technology is used to provide real-time information of the patients and avoid losing traces of them; and with the aide of control systems, it can automatically issue warning messages to signal needed assistance whenever it senses that the elderly stays in the stairway or bathroom too long. For storage management, the location based technology can be used to find the relevant items and automatically send them to their destinations with automatic control systems [1][2][3]. Applications of the location technology are very wide, for more examples, it can be used to seek one's friends or family members in vast venues or public spaces such as supermarkets, museums, and libraries.

T.-h. Kim et al. (Eds.): FGCN 2011, Part I, CCIS 265, pp. 82–86, 2011.

2 Research Methods

In our study, we use the fingerprint approach together with the weight method, and then adjust the weight by the k-nearest neighbor algorithm. These methods are described in the following [4~9].

2.1 Fingerprint Method

In this paper we adopt the fingerprint method reported by Bahl et al. in [10] as the primary location method for indoor environments. The fingerprint method uses the signal intensity as the feature of the reference point. In order to determine the location of a tag, the strength of the received signal from sensor nodes is compared with the signal strength database to estimate similarity of its feature.

2.2 Weighted Scaling for Sensor Nodes

Thus, in our location estimation algorithm higher weights are assigned to sensor nodes with stronger signal strength. In the experiment, the weight is set as signal strength / 100. For applications need to estimate locations for tags in a wider range of place, the weight can be assigned with larger values. Equation (1) is used to calculate the weighted difference value:

$$diff\_val_N = \sum_{i=1}^{K} \left(\frac{RSS_i^{'}}{100} \right) \times \left(RSS_i^{'} - RSS_i \right)^2 \tag{1}$$

3 Experimental Settings and Results

The experimental settings and results are given and discussed in the following.

3.1 Effect of Sensor Nodes Configuration

As expected, the number of sensor nodes and configurations of their location affect accuracy of location estimations. In the experiment, four or six sensor nodes in different configurations are investigated as shown in Figure 1.

1. In Configuration 1, four sensor nodes are placed in B, C, D, and E; in this way, a half of the experimental environment is not surrounded by these sensor nodes.
2. In Configuration 2, four sensor nodes are placed in the four corners of the laboratory, A, C, D, and F.
3. In Configuration 3, six sensor nodes are placed in A, B, C, D, E, and F.

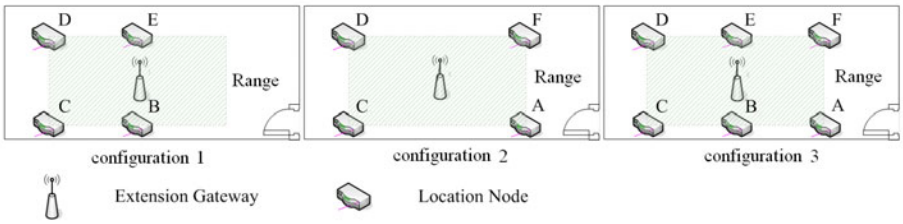

Fig. 1. Three configurations of sensor nodes

Figure 2 shows experimental results of the best, average, and worst location errors for three configurations of sensor nodes. We find that location errors are smallest with Configuration 3, in which the average location error is 86.6 cm; and largest with Configuration 1, in which the average location error is 128.1cm. In the experiment, the location errors are found to be largest at the left and right to the center locations of the laboratory. To solve this problem, two sensor nodes are added to the top and bottom locations in the center of the laboratory in Configuration 3. As shown in Figure 2, the average location error in Configuration 2 is 111.8 cm, and the average location error is diminished to 86.6 cm in Configuration 3. We also observe that the location errors are most uniformly distributed in Configuration 3. We conclude that by placing two sensor nodes at the top and bottom in the center, the location error is effectively reduced.

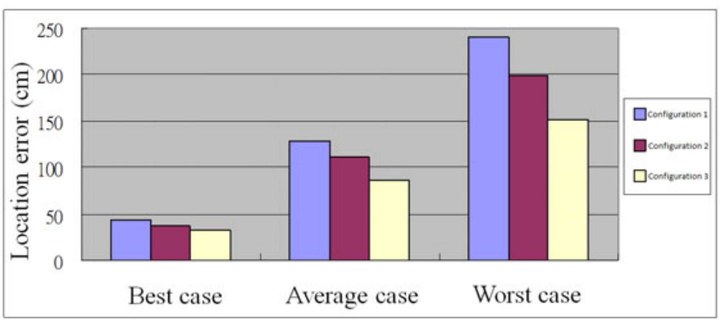

Fig. 2. Location errors for three sensor configurations

3.2 Weighting Effect

Figure 3 shows the best, average, and worst location errors with or without considering weights formulated in Equation (1). We find that the average location error drop from 86.6 cm to 84.8 cm, and in the best case, from 31.9 cm to 28.0 cm, an improvement of 12%.

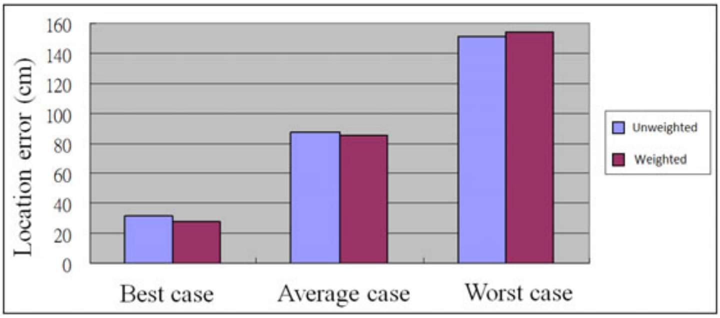

Fig. 3. Location errors with or without considering weights

3.3 Effect of Weight Assignments

Four sets of weight assignments are investigated to find their effects on the location estimation.

In Setting 1, the k-nearest neighbor method is not used, and the location is chosen according to the minimum difference value; whereas in Setting 2 to Setting 4, the k-nearest neighbor method is considered. In Setting 2, both the weights in the condensed and dispersed patterns are set as 1. In Setting 3, both the weights in the condensed and dispersed patterns are set according to their differences. In Setting 4, the weight in the dispersed pattern is set as 1, while the weight in the condensed pattern is set according to the square of the difference.

Figure 4 shows the location errors for the four weight assignments. We find that with the k-nearest neighbor method in Setting 2, the average location error is reduced by 10.1cm, while the average location error is further reduced by 2.8 cm by adjusting weights in Setting 4. Especially, in the best-case scenario the location error is reduced by 5.7cm. For applications that can exclude the worst-case scenario, the improvement on location estimations is even more effective.

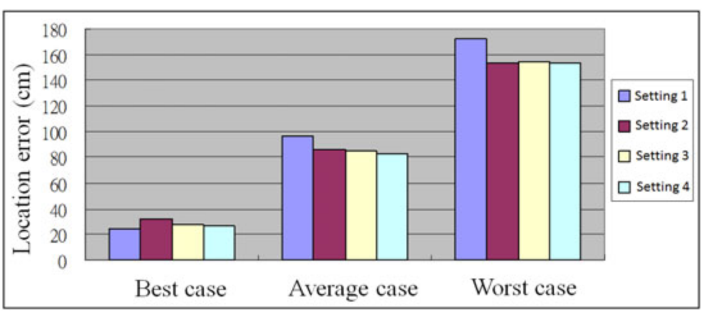

Fig. 4. Location errors with different weight settings

4 Conclusion

We investigate the fingerprint technique with weighted scaling for location estimations in indoor environments. The signal strength database is built with data collected with an all directions transmission approach by a turntable setting to evenly send out signals to reduce directional effect of wireless transmission and effectively reduce data collection time. A variety of sensor nodes configurations are tested to improve accuracy of location estimations. The experimental results show that the average location error is reduced from 128.1 cm for Configuration 1 to 82 cm for Configuration 3 and weighted scaling in Setting 4. For k-nearest neighbor algorithm, various weight settings are examined to reduce location errors. The experimental results show that the location error is reduced from 32.2 cm to 26.5 cm, an 18% improvement. For applications in which events of the worst case can be eliminated, the benefit of weighted scaling will be more significant.

Acknowledgments. This work was supported in part by Taiwan National Science Council under grant: NSC 99-2221-E-029-039 -MY3.

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