Positioning System for Wireless Sensor Networks with Location Fingerprinting

Di Cao, Hock Guan Goh, Michael Gilroy, Kae Hsiang Kwong, Craig Michie, and Ivan Andonovic
Centre for Intelligent Dynamic Communications,
Department of EEE, Royal College Building, 204 George Street, Glasgow, United Kingdom, G1 1XW.

Abstract- **Abstract**- This work addresses the issue of wireless sensor network positioning using location fingerprinting. In the present implementation, Received Signal Strength Indication (RSSI) was selected as being the only practical measurement available. Methods that require accurate timing information eg time of flight are not feasible given the constraints of sensor nodes. This imposes limitations on the performance of the location based algorithm but these can be mitigated using fingerprinting methods. The location mapping is done through 2 phases: the offline and the online phases. In the offline phase, a grid is defined manually (such as Area 00, Area 01, Area 02, …) and 4 sink nodes are setup at each corner of the grid. A mobile sensor node (MSN) is positioned in each of the grids sequentially and 200 data packets are transmitted and used to characterize in terms of the RSSI collected at the 4 sink nodes. The average of RSSI value is calculated and stored in a central base station. In the online phase, the four sink nodes are remained and a sensor node is randomly put at any location of the grid. Once the RSSI data packets are detected from the mobile node, the Euclidean Distance (ED) for each defined area stored is stored and processed to identify the node location.

1. INTRODUCTION

Wireless sensor networks (WSNs) [1] are networks that deploy hundreds or thousands of wireless sensors in a predefined area that can communicate with each other to detect, for example the ambient environment. Each sensor is composed of the four basic elements: transmitting unit, processing unit, power unit and sensing unit. The main task of each sensor is to detect events, perform a restricted set of local data processing tasks and then transmit the data. This technology is still in its infancy and much research is being conducted in relation to optimizing the medium access protocol, routing algorithms, transport mechanisms, and adaptation into various application domains. In this work, the focus is placed on algorithms that can be used to map the location of sensor nodes. Knowledge of the location of the sensor node can be critically important especially in applications where time critical response is required (eg fire detection).

Several metrics can be used for location mapping such as time of arrival (TOA)/time difference of arrival (TDOA), angle of arrival (AOA), and received signal strength (RSS) [3]. TOA is based on the estimation of propagation time between a transmitter and at least three receivers. TDOA uses the similar technique as TOA by taking the advantage of a time difference upon signal received by each receiver. By using the triangulation method [3], the position of the transmitter can be located. However, all of these require highly precise time synchronization between sensor nodes and this is not always possible. Therefore, TOA and TDOA are unable to be used for indoor location mapping. AOA positioning technique uses the angle of the arrival signal received by more than three receivers. This method requires directional antenna and geometric rules to calculate a distance.

WSN are generally by default equipped with omnidirectional antennae therefore it is impossible to tell the direction of where the signal comes from. AOA needs line-of-sight condition to achieve the accuracy which is not suitable to be applied for indoor environment. The sensor node's physical hardware mainly comprises of low specification and low cost components to facilitate mass production which in turn makes large scale monitoring cost effective. As described above, this has creates significant challenges in location mapping for sensor nodes. The research presented here has focused on using received signal strength as the main source in estimating the traveling distance for the received packet and investigates positioning algorithms based on received signal strength i.e. location fingerprinting. In positioning systems, location fingerprinting is also referred as pattern matching of radio signature. Radio frequency (RF) fingerprinting does not require any hardware modifications to the sensor node and in comparison to other algorithms it is relatively immune to environmental influences that cause signal attenuation such as multipath fading, shadowing, reflection, and non line-of-sight reception.

This paper focuses on challenges that relate specifically to the location mapping of wireless sensor nodes including radio propagation of low specification WSN hardware, accuracy, operational range and impact of environmental factors. The optimized positioning system for WSN is documented, and results gained from experiment based on 2.4GHz IEEE 802.15.4 WSN platform is provided.

The remainder of the paper is organized as follows. In section 2, the RF characteristic is discussed. Our proposed location fingerprint for WSN is presented in section 3. Experiment and result are included in section 4 and finally our conclusions are presented in section 5.

2. RF CHARACTERISTICS

In ideal radio propagation, the radio signal is transmitted in a direct line between a transmitter and a receiver. This 'free space' scenario is commonly used used to analyze propagation loss between the transmitter and the receiver. However, this model doesn't reflect the real world, especially for the indoor environment, where signals can be obstructed or reflected by the wall or hard surface material. In another words, shadowing and fast fading need to be taken into consideration. Shadowing, or slow fading, is caused by buildings and trees blocking the transmission line. The signal will suffer increased losses in some paths while others will be less obstructed or receive a higher signal strength. Fast fading takes place if the received signal changes sharply as the mobile user moves over distances which are small compared with the shadowing correlation distance. Both of them will change the received signal heavily, which makes the analysis of these signals complicated.

Experimental data from RSSI measurements are compared with a free space model in Figure 1. The free space model is defined as $P_r = P_t G_a G_b (\frac{\lambda}{4\pi r})^2$ [2]. Where P_r is the received signal strength at the receiver; P_t is the transmission power at the transmitter. G_a and G_b are the values of antenna gain for transmitter and receiver. In this experiment, P_t is set to $0dBm$. G_a and G_b are equal to 9dBi and 1dBi for the transmitter and receiver respectively. λ refers to the wavelength of propagation signal, which can be derived from $\lambda = \frac{c}{f}$ where c is the speed of light and f is the frequency propagation used in the experiment which is equal to 2480 MHz. r is the distance from the transmitter to the receiver. Outdoor measurements were conducted in an open field while indoor measurements were carried out inside a laboratory. For both outdoor and indoor measurements, the antenna heights were 1.5m above the ground. The path loss for the outdoor and the indoor measurements do not degrade as gracefully as the free space model. This is due to reflections from the walls, buildings, ground, and other objects which formulate constructive and destructive signal at the receiver.

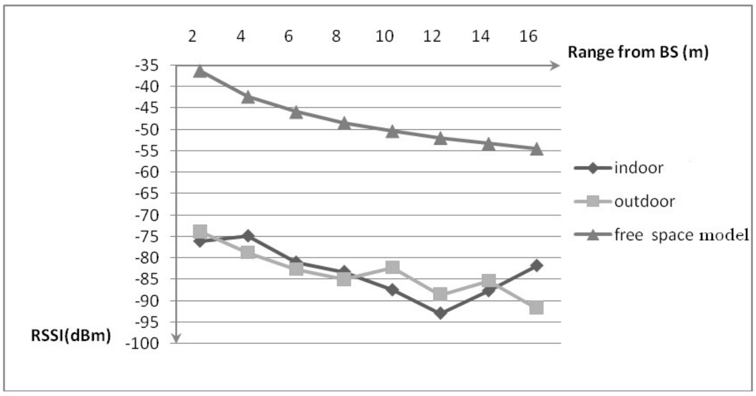

Figure 1. RSSI comparison between indoor, outdoor, and free space model for various distances.

Table 1 and Table 2 show the minimum, the maximum, the average, and the standard deviation for both indoor and outdoor measurements. In the experiment, we calculate the standard deviation in RSSI for all of the measured signals. The standard deviation is a measure of the dispersion of a collection of RSSI which is directly related to distance diversity. For instance, from the graph we can see that the indoor largest value of standard deviation happens at 10m. The fluctuation can be range from -86dBm to -88dBm, which can lead to errors +/- 5m in distance estimation, equivalent to 2 or 3 GED in 2m x 2m grid fingerprinting. Therefore, the fluctuation of signal can affect the accuracy of location mapping. Therefore RSSI alone does notprovide sufficient information for location mapping.

Table 1. Indoor measurement

Distance from the BS (m)	Min (dBm)	Max (dBm)	Average (dBm)	Standard deviation
2	-77	-76	-76.02	0.140
4	-75	-74	-74.78	0.400
6	-82	-80	-80.97	0.244
8	-84	-83	-83.18	0.400
10	-88	-86	-87.44	0.810
12	-94	-92	-92.94	0.373
14	-88	-86	-87.66	0.607
16	-82	-81	-81.75	0.421

Table 2. Outdoor measurement

Distance from the BS (m)	Min (dBm)	Max (dBm)	Average (dBm)	Standard deviation
2	-75	-72	-73.89	0.572
4	-80	-78	-78.78	0.808
6	-84	-82	-82.73	0.674
8	-89	-83	-85.03	1.059
10	-83	-82	-82.25	0.466
12	-90	-86	-88.59	0.950
14	-87	-84	-85.36	0.881
16	-93	-90	-91.71	0.542

3. LOCATION FINGERPRINT FOR WSN

To improve on the above we have investigated a fingerprinting method. The method is implemented in 2 phases: offline and online.

A. Offline Phase

The area to be monitored is first of all manually divided into grids. For our case study, we used 9 x 4 grids with each grid 2m x 2m. 4 sink nodes are placed at the corners of the monitored area. A MSN is then used to characterize the grid. First of all the node is placed at the first grid and broadcasts a pre-set number of packets. The packets are received by the all sink nodes and the average of RSSI collected for each sink nodes is computed as G_{01}: S_1, S_2, S_3, S_4. This process is repeated for the MSN placed at the second grid until the entire grid set up has been characterised.

B. Online Phase

During this phase, the setup of the sink nodes is maintained. The MSN is then randomly placed in a location of the defined grid and broadcasts a preset number of packets which are received by all base stations. The new average of RSSI is computed as s_1, s_2, s_3, s_4 and the calculation of Euclidean Distance, ED, $L = (\sum_{i=1}^{n} |s_i - S_i|^2)^{\frac{1}{2}}$, where i is the number of sink nodes is performed. Finally, the smallest ED is selected and the location is mapped according to the monitored area.

4. EXPERIMENT AND RESULT

In order to measure the accuracy of the proposed fingerprinting technique, an error metric called grid-error-distance (GED) is introduced. Assuming the MSN is placed in the middle of grid, after performing the fingerprint algorithm, if the result shows that the location is in the middle of the grid, the grid-error-distance will be 0. If the location is inaccurately estimated by a grid distance away, the grid-error-distance will be 1. This is applied for the rest of the grids.

The experiment was conducted for the location estimation based on 10 and 50 packets received at the sink nodes. For the performance test, a MSN was sequentially positioned in each of the defined 36-grids. From Figure 2, 15 out of 36 times a location is estimated correctly while from Figure 3, 17 out of 36 times the location is mapped accurately. Transmitting a greater number of packets increases the precision of the location mapping. Less packets save time and resources.

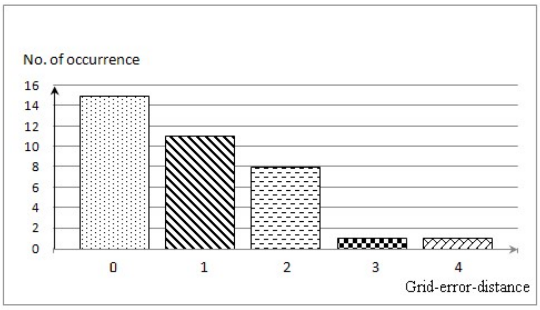

Figure 2. The accuracy of location estimation based on 10 packets received.

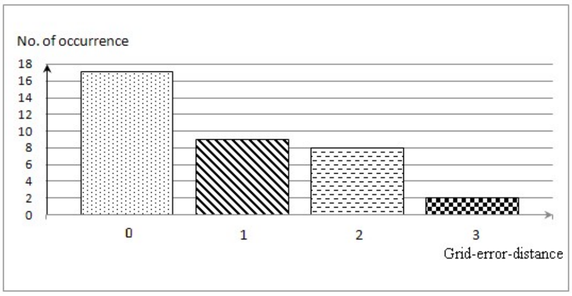

Figure 3. The accuracy of location estimation based on 50 packets received.

In location mapping of fingerprinting, the ED is another key factor to determine the accuracy. It can be used as a trusted level for the scheme. If during the online phase, the selected ED is fall between 0 to 5, it gives higher chance for the scheme to map accurately according to the area. If the selected ED is more than 10, it is likely the scheme will not perform correctly and recollection of packets is recommended. Figure 4 and Figure 5 show the number of occurrences for the ED based on different amount of packets received.

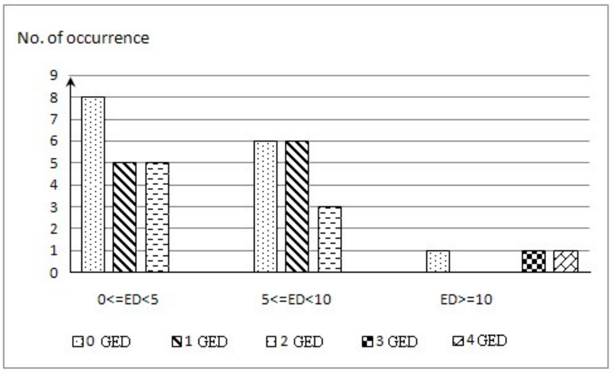

Figure 4. Trusted level of the location estimation based on 10 packets received.

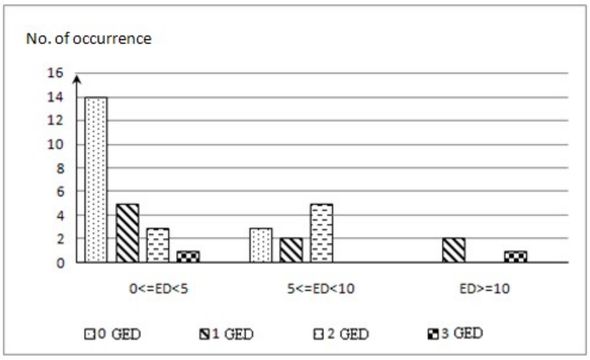

Figure 5. Trusted level of the location estimation based on 50 packets received.

5. CONCLUSION

The paper discusses the effect of radio frequency characteristic for WSNs location estimation. In practical, multipath exits in each communication. TOA, TDOA and AOA are not suitable to be used as indoor location estimation without the hardware modification. RF fingerprinting for WSNs is able to achieve certain level of accuracy and could be considered as an alternative location mapping for indoor environment.

REFERENCES

1. Akyildiz, I. F., S. Weilian, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Communications Magazine*, Vol. 40, No. 8, 102-114, August 2002.
2. Saunders, S. R., *Antennas and propagation for Wireless Communication Systems*, Wiley, 1999.
3. Krzysztof, W. K. and J. Hjelm, *Local Position Systems: LBS Applications and Services*, CRC Press, 2006.
4. Kaemarungsi, K., "Efficient design of indoor positioning system based on location fingerprinting", in *Proceedings of the IEEE International Conference on Wireless Networks, Communications and Mobile Computing*, Vol. 1, 181-186, June 2005.
5. Li, B., Y. Wang, H. K. Lee, A. Dempster, and C. Rizos, "Method for yielding a database of location fingerprints in WLAN", in *Proceedings of the IEE Communications*, Vol. 152, No. 5, 580-586, October 2005.