Improving Accuracy of Person Localization with Body Area Sensor Networks: An Experimental Study

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***Abstract*— With the evolution of wireless sensor network, body area sensor networks are expected to realize many realtime monitoring applications. Localization is one of the most important amongst all contexts. In indoor environments signal strength-based localization algorithms usually fail to achieve good accuracy due to deficient antenna coverage and multipath interference. We propose spatial diversification method, which solves this problem by combining multiple receivers in a body area sensor network to estimate the location with a higher accuracy. This method mitigates the errors caused by antenna orientations and beam forming properties. With a range free localization algorithm that we developed, we show with experimental results that with spatial diversity the localization accuracy is improved compared to using single receiver alone.**

I. Introduction

The rapid development of embedded devices, especially wireless sensor networks can enable better care of patients and senior citizens. Such networks consist of a number of devices equipped with sensors, micro-controllers with radio components embedded in them. The devices monitor important parameters, such as body temperature, momentum, glucose levels, blood pressure or heart rate of the person who wears them. They can help patients return to their normal life at home with their physical conditions closely monitored by doctors remotely. Another application of such body area sensor networks is helping senior citizens to manage their life in houses or even in public places. To provide patients or senior citizens first-aid in case of an emergency, their location information is very important as and when they may move around. Moreover, the location information also provides doctors with the movement patterns of patients so that their living habitat can be analyzed and used for disease prevention and diagnosis. In fact some of the futuristic ideas are, with the aid of localization information, cameras and some control console can be activated – in case of patients with alzheimer disease when they are moving around in kitchen for example.

One of the most well known localization systems is the Global Positioning System (GPS). However, due to poor penetration of the radio signals this system is not suitable for indoor localization [1]. An evolving technique in indoor environment is to use already deployed wireless sensor devices (in hospitals and buildings), together with wearable Body Area Sensor Networks (BASN) to estimate the locations of the persons wearing the BASNs. This technique is highly practical and cost effective since all the sensors are already deployed and connected wirelessly for their usual tasks. Hence, localization does not add any investment on hardware infrastructure.

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Received Signal Strength Indicator (RSSI) is widely exploited for localization in the literature. However, because of the small size, wearable characteristics and cost restrictions, health care wireless sensor devices normally use on-chip antennas. Which in turn has no perfect omnidirectional beam properties. As a consequence, the antenna orientation of the devices has a large influence on the received signal strength. Factors such as complex indoor radio propagation and the movement of people usually cause RSSI-based localization algorithms to fail to achieve a good accuracy. In this paper, we propose a method, which takes advantage of multiple wireless devices in a BASN to improve the accuracy of estimates of location of a person in an indoor environment. The highlights of this paper are: (a) nullifying the effects of antenna orientation by using multiple devices; (b) using the spatial redundancy in the estimations; and (c) implementation of the system to show our method perform better under similar circumstances.

We have verified our method by conducting several experiments and we show with results how much we gain in terms of accuracy with multiple devices to get better performance than a single one. The rest of the paper is organized as the followings. In Section II, we introduce closely related localization algorithms in the literature. Section III presents the multiple devices method and the corresponding algorithms we used in the experiments. The experimental setup and results are shown in Section IV. We conclude in Section V.

II. Related Literature

It is well known from many studies that the radio propagation is essentially related to the transmission distance. Given the transmitted signal power, RSSI is highly influenced by the distance. This motivated extensive body of research on localization systems that make use of RSSI. RSSI-based positioning algorithms are generally divided into two categories according to the classification in [2]: range-based and range-free. The

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former makes use of the absolute distance or angle calibrated from the pre-measured RSSI map, which can be a set of "signatures" or RSSI to distance/angle relation map [3] [4] [5] [6]. The latter, rather than using the information concerning the absolute distance, utilizes the geographic relationship between target motes and anchor motes [2] [7]. Our earlier work on range-based [3] and range-free [8] test-bed shows the two algorithms give adequate room-level estimation accuracy – able to pin point in which room the target is under favorable situations. Comparatively, the range-based system is less power consuming because rather than requiring all the anchors and the target sending out BEACON packets periodically, only the target needs to do that, which is really beneficial for power-limited sensors. Whereas, range-free systems improve the scalability in the sense that they alleviate the laborious offline work of database creation and RSSI measurements for mapping, and increases the error tolerance of the system, by using position relation to compensate the vulnerable nature of RSSI. However, less attention has been paid to combining multiple devices in the vicinity to improve the accuracy.

III. Localization with Multiple Devices and Range Free Algorithm

RSSI-based localization algorithms usually fail to achieve good accuracy due to deficient antenna embedded, fading, shadowing, and people movements. In this paper, we try to solve the first two problems by combining multiple wireless devices in a BASN. Their diverse antenna orientations and small distance can be exploited to increase the localization accuracy. Moreover, it was shown in the literature that the relation between RSSI and range is not one to one. Transceivers apart of different distances, sometimes up to 10s of meters, can receive packets with the same RSSI [9] [10]. Therefore, an absolute distance estimation is tricky and probably impossible using standard RSSI measurements. Instead of using a range-based algorithm, we calculate the locations with a range-free algorithm which eliminates the requirement of the point-to-point absolute distance estimation.

A. Localization with Multiple Devices in a BASN

Due to the low-cost and small size, BASN devices are often embedded with on-chip antennas. These antennas' transmission pattern is far from perfect omnidirectional. For instance, the on-chip antenna of the Tmote-Sky sensor mote [11] has a radiation pattern as shown in Fig. 1. We verified the deficient coverage of the antenna by putting the transmitting and receiving motes 4m apart within the line-of-sight [3]. We measured the RSSI values at 8 different antenna directions in steps of 45 degree. In Fig. 2, we show that the antenna has the strongest strength at 0° of -50 dBm and the smallest signal strength at 90° of about -65 dBm. We observed that RSSI varies in a range of around 15dBm for the static case. This problem can be solved by continuously rotating the antenna direction and taking the average of the RSSI values received from different directions. However, this method is neither agile nor feasible. Since there may be many wireless sensor devices

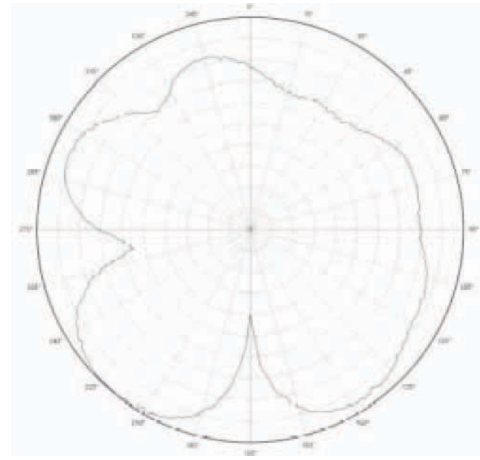

Fig. 1. Radiation pattern of the Inverted-F antenna with horizontal mounting [11]

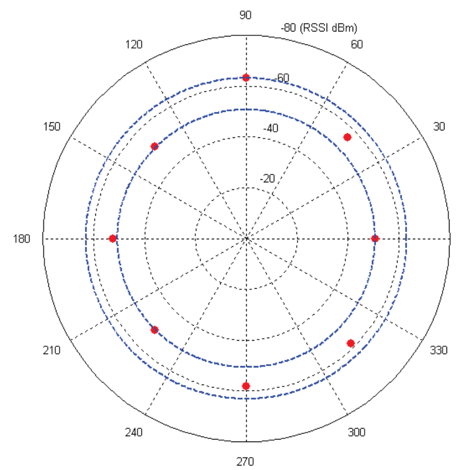

Fig. 2. Antenna Orientation Effect [3]

in a BASN, we can actually use the RSSI from different devices to calculate the location with the average RSSI. Or we can let the devices calculate the location independently and take the average of the calculated locations. Both ways may mitigate the estimation error induced by the deficient antenna radiation pattern. We will show the performance of both methods in Section IV.

Using multiple devices can also reduce the estimation error caused by fading, since the signal is transferred in different paths. We can use the so-called microdiversity, which refers to that the antennas are at a distance of an order of a wavelength, to combat fading.

B. Range Free Localization Algorithm

Range-free localization algorithms utilize the relative position to decide the possible region where the target mote may reside [8]. Take for example, Fig. 3, Anchor A receives packets from Anchor B and estimates RSSI, so as Anchor C, and Target T. Thus we may expect the relationship $RSSI_{AB} > RSSI_{AT} > RSSI_{AC}$. Therefore, we can conclude that the

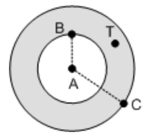

Fig. 3. An Illustration of Range-free Localization Algorithm [8]

TABLE I
EXAMPLE OF SELECTING RELIABLE RSSI

Neighbor list of Target (ID 1)		Neighbor list of Anchor (ID6)	
Anchor ID	RSSI (dbm)	Node ID	RSSI (dbm)
2	-54.387	4	-64.7273
3	-83.801	8	-66.3333
4	-73.778	2	-76.4667
5	-65.529	5	-78.5714
6	-80.029	1	-80.0294
7	-82.002	7	-82.7143
8	-85.791	3	-88.6316

Target T is most likely to be in the grey ring. We can derive a series of such grey areas so that the estimated position is decided as the gravity center of the final intersectional area.

We extend this basic algorithm by ensuring more credibility to the measured RSSI. We know from previous study [3] that if the distance between transceivers is small, the RSSI rapidly changes with a tiny increment or decrement of the distance. Contrarily, a large change of distance may only lead to an imperceptible change of RSSI if the distance is large. Therefore, we assign lower reliability if the RSSI has lesser value which corresponds to a bigger estimation error, i.e., a longer distance. In our algorithm, each anchor node has a neighbour list sorted in descending order based on the received RSSI. We briefly explain the algorithm with an example. In Table I, Anchor 6 decides that Target T is in the ring between Anchor 5 and Anchor 7. However, if $d_{65} > d_{67}$, the ring cannot be generated. Therefore, we refer to Target T's neighbor list. Target T also has a sorted neighbor list based on the RSSI from the anchor nodes, which is also shown in Table I. In Target T's list, the RSSI from Anchor 5 is higher than the RSSI from Anchor 7. Thus, we envisage that RSSI from Anchor 5 has a higher reliability than the RSSI from Anchor 7. Therefore, we ignore Anchor 7 and move to Anchor 3. If Anchors 5 and 3 can generate a ring, we proceed to the next step. If Anchor 5 and 3 still cannot generate a ring, we go back to trust Anchor 7 and ignore Anchor 5. If Anchor 2 and 7 can generate a ring, then algorithm proceeds further. The accuracy of the process is based on the assumption that, the majority of RSSI are reliable. Although RSSI is disturbed by a multitude of factors, the above assumption is usually true in most of the situations when averaged over a small duration.

After generating a series of rings, we count the number of times an area is covered. Every time a ring covers an area, the counter of the area increases by one. Then, we calculate the gravity center of the area to find the location. However, since we already know that higher RSSIs has higher reliability, we give overlapping areas with a higher RSSI more weight. If an area is covered by a ring, the increase of the area counter is related with the reliability weight of the ring. For Anchor I, the reliability weight is defined as:

$$w_{TI} = \left(\frac{1}{RSSI_{TI}}\right)^n$$

where, $RSSI_{TI}$ is the RSSI received by Anchor I from Target T and n is the exponential index of the radio propagation model. Now we use the refined RSSI conceived from multiple sensors (acting as a bunch of targets) into the above expression to get a better accuracy.

IV. EXPERIMENTAL SETUP AND RESULTS

A. Setup

We conducted a series of experiments at the 19^{th} floor of our faculty. The devices used in the experiments were TMote-Sky sensors with 2.4 GHz IEEE 802.15.4 compliant Texas Instruments CC2420 transceivers [12]. The transceiver provides RSSI in a range of 100 dBm for every received packet, which is the received strength signal reading averaged over eight symbol period. IEEE 802.15.4 [13] uses 2.4 GHz DSSS RF modulation with a data rate of 250 kbps. In our experiment, the IEEE 802.15.4 packet header and payload of 17 bytes and 9 bytes were used resulting in 26 bytes packet.

We bound four motes oriented in four directions on a 30 cm high platform made of polystyrene. The distance between any two motes was about 6 cm, which is half the wavelength of 2.4 GHz radio. We expected that distance may help us to combat the effects of fading. The four motes were connected to a PC via USB cables. Thus, the received packets were directly relayed to the PC, which acts as the sink of the BASN. The environment was checked to be WiFi free. All the experiments were carried out during weekends minimizing the effect of human movements and other activities.

We deployed in total 11 anchors on a straight line in the middle of the corridor. All the anchors were also lifted with the 30 cm high polystyrene. The distance between any two anchors was 4 m. All the anchors were powered by external DC supply to avoid the fluctuation in power supply due to different battery levels. The arrangement of the motes is shown in Fig. 4. The blue nodes in the figure are anchors and the red nodes represent the positions of target nodes. The horizontal distances between the anchors and the targets are 2 m. We tested 10 target positions in line with the anchor nodes, called Scenario-A and another 9 positions which were close to the wall, called Scenario-B. With Scenario-B, we want to check the influence of reflections from the wall on the accuracy.

In each target location, we run an experiment for 60 s. During each experiment, the anchors randomly sent a beacon message every second and the target randomly selected one in each 1 s interval. Hence, for each measurements, 60 beacon messages were sent by every anchor mote. Meanwhile, the target motes reported the received packets to the sink and the anchors recorded the beacons they received into their local memory. Afterwards, one of the target motes polled all the anchors of the recorded data. For each received beacon, sender, receiver, packet identifier, and RSSI were collected

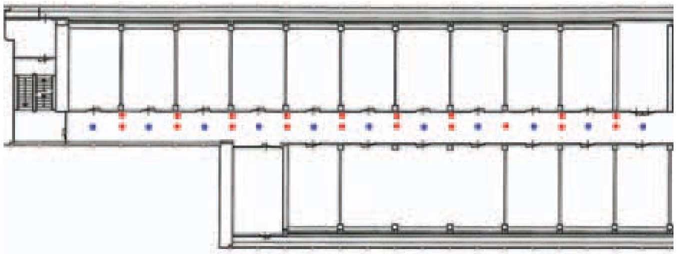

Fig. 4. Location of anchors and Targets

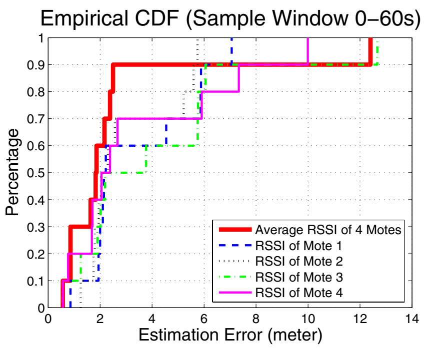

Fig. 5. Estimation Error Comparison in Scenario-A: 60 Samples Each Target

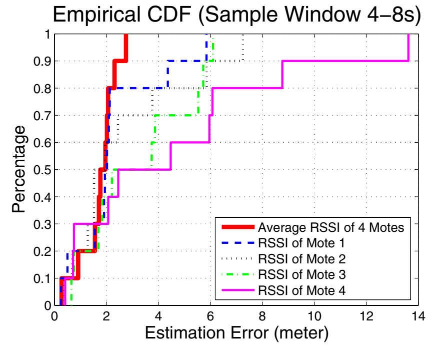

Fig. 6. Estimation Error Comparison in Scenario-A: 5 Samples Each Target

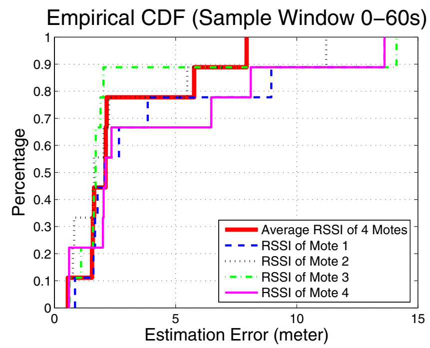

Fig. 7. Estimation Error Comparison in Scenario-B: 60 Samples Each Target

and gathered at the PC for further computations and analysis. Then, all the motes were reset and we moved the target motes to the next location.

B. Results

First, all the 60 beacons collected by each target mote were used for the estimation. Fig. 5 shows the estimation result comparing the sample RSSI averaged on four target motes and the RSSI from each target mote. In general, using the average gives higher accuracy, which is indicated by the thick red line in the figure. In 80% of the cases, the average gives the best estimation with lesser error. We observe that it does not perform worst estimation. The median error is less than 2 m and in 90% of cases the deviation from the actual position is less than 2.5 m. The only exception happened when there was some human movements around, during the experiments which caused the estimation of one position fail. It verifies that the multi-receivers method does not solve the problem of shadowing and multipath fading. This requires further refinements.

Considering the requirements of a real-time indoor person tracking system. It is then important that location updates are done frequently. We note that historical values are not of much use. Hence, for a moving person, we must typically not use more than 5 samples. Therefore, we reduced the number of the samples used for estimation to 5 samples. We compared the result by using the averaged RSSI values of the four target motes and those of each individual target mote. As shown in Fig. 6, using the averaged RSSI still gives best estimation and all the estimation errors are smaller than 3 m.

For Scenario-B, the estimation results when using 60 beacons is drawn in Fig. 7. In general, the average method outperforms and provides better accuracy than using an individual target mote. However, due to extra reflections and shadowing, the median error is around 2 m and in the 90% of the cases the errors are below 6 m.

For the estimation using a small number of beacons, we also examined the estimation stability on the time scale. We divided the whole 60 m data into 20 estimations of 5 s each. The 10 locations in Scenario-A and the 9 locations in Scenario-B are all plotted in Fig. 8. The curves show the average estimation error of the 20 estimations and the bars show the standard deviation. In Scenario-A, the largest error is more than 5.5 m. Due to the structure of the floor, some places have more obstacles than others and thus suffer more from shadowing effect, which degrades the estimation accuracy. The estimation errors also vary with time. Interestingly, the locations with larger error also have larger deviations due to the complex structures around the location. In Scenario-B, the average error is a little less than 7 m and the standard deviation is more than 4.5 m. In general, the estimation of Scenario-B is worse than Scenario-A. This is due to the fact that target positions in Scenario-B are very close to the walls, therefore RSSI measurements are expected to have higher influence from radio reflections and shadowing.

We are also interested in the comparisons in estimations between 5 beacons case (4 s to 8 s) and 60 beacons case. In Fig.9, which is plotted with data from Scenario-A, we can see that the estimation accuracy is generally the same except for

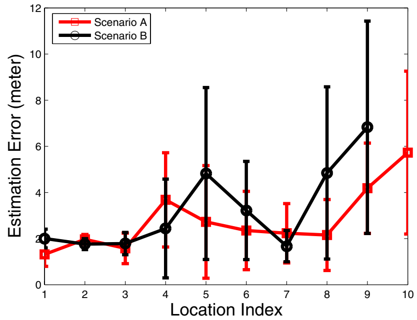

Fig. 8. Variation on Time Scale: Update every 5 seconds

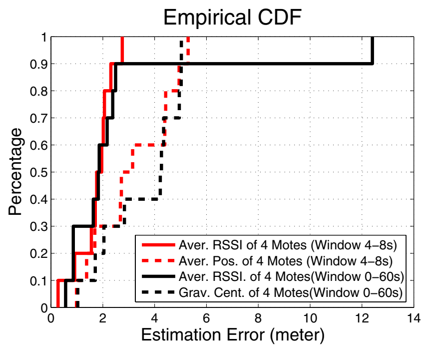

Fig. 9. Estimation Error Comparison: 5 Samples Each Target

the exception introduced in Fig. 5.

Another method to utilize the RSSI from multiple devices is to estimate the location of each individual targets and then calculate the average location. In Fig. 9, we investigate the accuracy of this method. However, we can see that the average RSSI method outperforms the average position method in general. This is due to the fact that an individual measurement going haywire can pull the location farther away since slight change in RSSI contributes to higher distance when the target is away. Thus it is better to use averaged RSSI than averaged estimated location.

V. Conclusions

In this paper, we proposed and investigated a method that uses multiple receivers in a BASN to locate the person who carries them. Compared to a single receiver, this improves the localization accuracy by mitigating the errors caused by deficient antennas and combating fading with spatial diversity. We note that this is at a slight computational cost which is very minimal. With the results from our experiments, we show that the method together with our range-free localization algorithm, achieve higher accuracy than a single receiver. We also show that the accuracy may change over time significantly. Nevertheless, the proposed method is still not able to combat the error introduced by shadowing. The results in this paper are still in the nascent level. A few important issues that begs further attention are: (a) improving the accuracy by further measurements and algorithms; (b) methods to sieve the improper RSSI measurements used in the average computations; (c) errors due to shadowing, fading, reflections, etc.; and (d) innovative algorithms to speed up the estimation and optimizing the resources while using multiple sensors.

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