Evaluation of the Reliability of RSSI for Indoor Localization

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***Abstract*—In wireless sensor networks, nodes can be static or mobile, depending on the application requirements. Dealing with mobility can pose some formidable challenges in protocol design, particularly, at the link and network layers. These difficulties require mobility adaption algorithms to efficiently localize mobile nodes and predict the quality of link that can be established with these nodes. An off the shelf development platform that uses Radio Signal Strength Indication (RSSI) is mostly selected as the sensor localization method, especially in the indoor environment. Despite this, not much research work has been done to practically demonstrate the reliability of RSSI for indoor localization. Therefore, in this paper, we aim to calibrate and map RSSI to distance by doing a series of experiments. The result shows that the RSSI technology gives an unacceptable high error and thus is not reliable for the indoor sensor localization.**

***Keywords*-distance; localization; RSSI; wireless sensor networks;**

I. Introduction

Several applications in wireless sensor networks require sensor localization technologies. Some of these applications use location information to infer the activity of mobile objects, animals, or human beings [7]. For example, biomedical sensor nodes can be attached to the bodies of patients [6] and nurses [5] to monitor their activities; workers in disaster recovery scenes [18] and oil extraction and refinery areas [4] can carry sensing devices to avoid dangerous situations; mobile sensor nodes can also be employed to report or debrief soldiers the events encountered during a mission [16].

Another reason why the location information is useful is that it can assist mobile nodes in remaining connected with a network. Mobility of sensor nodes can lead to the deterioration of the quality of an established link. This in turn may make data transmission prone to failure and increases the cost of packet retransmission. Mobility can also cause frequent route changes and thus produces a considerable packet delivery delay, since a mobile node cannot immediately begin transmitting data upon joining a network. Instead, it has to wait for a certain amount of time before it can be fully integrated [9].

In order to reduce the end to end latency of a data transmission caused by the movement of nodes, several mobility-aware MAC protocols require location information [8]. The usefulness of the protocols highly depends on how accurately they determine the location of mobile nodes. Most of the protocols employ RSSI for real-time localization, especially in the indoor environment. Nevertheless, not much research work has been done to practically demonstrate the reliability of RSSI for indoor localization. Therefore, in this paper, we aim to calibrate and map RSSI to distance by carrying out a series of experiments. Based on the observations, the conclusion that whether RSSI is reliable and thus feasible for indoor localization can be drawn.

The remaining part of this paper is organized as follows: in Section II, related work is summarized. In Section III, a brief introduction to RSSI technology is described. In Section IV, the experiment settings are presented. In Section V, the reliability of RSSI for indoor localization is investigated and the observations are discussed. Finally, in Section VI, concluding remarks are given.

II. Related Work

Determination of location can be done in a number of ways. Here, only some of the approaches are briefly discussed.

1) Global positioning system (GPS): GPS gives the absolute coordinates of a mobile node, but it is expensive and energy consuming [20]. It also suffers from frequent satellite disconnections in indoor environments [24].

2) Pedometers: A pedometer is a portable and electronic/electromechanical device that counts each step a person takes by detecting the motion of the person's hips. Algorithms for navigating a mobile node by using the hop-count based metric is simple and scalable [17]. This method, however, is highly dependent on the network density and path length, and thus is coarse-grained and error-prone [23].

3) Robotics: A robot can localize itself in both mapped and unmapped terrains by employing the method which represents the posterior distribution of possible locations via a set of weighted samples. New measurements such as observations of new landmarks are incorporated to filter the previous mobility prediction and update the data of location [12]. However, such estimation suffers from rotational and translational errors [26], even if a map of the environment and sensory information is given.

4) Radio frequency identification (RFID): RFID is a technology that employs radio frequency signals to exchange data between a reader and an electronic tag attached to an object for the purpose of identification and tracking. RFID

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readers are located strategically in the field [22]. One of its drawbacks is the relative short communication range $(1-2m)$ and the inhibition to future extensions.

5) Anchor node: Anchors are a set of static nodes with globally known or unknown positions. In the literature, they are also referred to as reference nodes or seeds [12]. Anchor nodes periodically broadcast beacon messages. By receiving beacons from enough sources, mobile nodes can localize themselves. In some cases, robots equipped with GPS are deployed into a wireless sensor network to act as reference nodes, so that sensors can localize themselves with the information given by the robots [27]. The accuracy of the localization depends on the distance between the mobile and the reference points as well as the number of the anchor nodes [25]. If the distance is too long or the anchor nodes are too less, the location estimation errors can be high. Moreover, the loss or malfunctioning of anchor nodes can affect the estimation mechanism [28].

6) Time of arrival (TOA): TOA finds the distance between a transmitter and a receiver via a one way propagation time by exploiting the relationship between the light speed and the carrier frequency of a signal [2]. However, all the nodes, with no information when messages will come, have to keep awake all the time.

7) Angle of arrival (AOA): AOA is usually employed as prior-knowledge for the triangulation localization method [13]. The information of the arriving angle can be obtained by using either goniometers, gyroscopes or compass.

8) Signal-to-Noise ratio (SNR): Deriving connectivity information from position information is not straightforward, since it requires a one-to-one mapping between distance and signal quality. SNR, that is utilized as a measure of a node's link state, is easy to be monitored and does not require any special hardware [11].

9) Ultrasound: A mobile node with an ultrasonic sensor measures the distance to a node by exploiting the ultrasonic signal propagation time. However, the transmission range of an ultrasound signal is small as it cannot propagate further than radio frequency wave [17]. It also adds size, cost, and energy supply to each device. Therefore even though ultrasound based localization approach can achieve high accuracy, it is not suitable for wireless sensor networks.

10) Accelerometers: Accelerations are generated due to both translational and rotational movements of an object. An accelerometer-based mechanism is shown to be an accurate, robust and practical method for objectively monitoring the free movement of objects and persons. The mechanism responds to both frequency and intensity of movement [28]. However, these devices increase the cost and size of a node and may not always be available or deployable. Moreover, accelerometer readings are sensitive of the node placement [21].

11) Triangulation and trilateration: The localization of mobile nodes can also be accomplished through triangulation in a one-hop neighborhood [3]. Once a local estimation is made for each node, a global localization can be established by calculating differences in terms of the distance and direction between each node and a particular central node, or a dense group of nodes [3]. However, this mechanism requires the use of isotropic antennas, which is expensive and less practical.

A trilateration requires priori-knowledge of the location of at least three nodes. The distance between nodes can be determined only within a certain degree of certainty [13].

III. RSSI Description

Unlike all the localization approaches discussed above, RSSI [10] represents the relationship between a transmission and a received powers. It can be employed to compute the distance of separation between a transmitter and a receiver when a good portion of the electromagnetic wave propagates in a line-of-sight (LOS) link. This approach has been assumed for handling mobility in a number of mobility-aware MAC protocols.

If there is a direct path between two nodes placed in an environment in which no signal interference occurs, the received signal power, P_r, is related to the distance, d, between the transmitting and the receiving nodes in the inverse square law [15].

$$P_r \propto d^{-2} \tag{1}$$

However, Equation 1 expresses the ideal relationship between RSSI and the relative distance. In the real world, many factors influence the value of the received signal strength, such as reflection, refraction, diffraction, and scattering of waves caused by the nearby objects. It has been found empirically that a wall can reduce the signal power by approximately $3dBm$ on average [14]. Due to multi-path fading and non-uniform propagation of the radio signal, the received power may decay at a faster rate. This transfers the relationship between P_r and d to:

$$P_r \propto d^{-\gamma} \tag{2}$$

Here γ denotes the loss exponent. Another factor that affects the received power and thus affects the location prediction is antenna polarization. In order to obtain the maximum received power, the antenna of the receiving node should be adjusted to the same orientation as the transmitting node [14]. The loss due to a misaligned antenna polarization [19], L, can be expressed as:

$$L = 20log(cos\theta) \tag{3}$$

IV. Experiment Settings

The aim of our experiments is to investigate whether RSSI is reliable and, hence, feasible to be used for indoor localization. The sensor platform we employed is SunSPOT motes from Sun Microsystems. These nodes integrate 802.15.4 radio (CC2420) with a built-in 2.4GHz antenna. Each RSSI value is obtained by averaging over 8 symbol periods (128μs) in the register [1]. The distance estimation model proposed by Texas Instruments for the Chipcon CC2420 radio is given as:

$$RSSI = -(10 \times n)log_{10}(d) - A \tag{4}$$

In Equation 4, RSSI is the radio signal strength indicator in dBm, n is the signal propagation constant or exponent, d is the relative distance between the communicating nodes, and A is a reference received signal strength in dBm (the RSSI value measured when the separation distance between the receiver and the transmitter is one meter).

The experiments were carried out in a long corridor made up of a glass wall on one side and a concrete wall on the other side. One node was used as a base station directly connected to a laptop via a USB cable. The other node was mounted on an ankle of a user. Both nodes operated with a full battery. There were no additional obstacles standing in the communication path between the two nodes during the experiments. As a result, a good portion of the signal was propagated in a line-of-sight.

V. Experiments

A. Reference Curve Establishment

In order to verify whether RSSI can reliably determine the distance between two communicating nodes, a reference curve should be established prior to the mobility experiment. The reference curve is regarded as the standard showing the one-to-one relationship between RSSI and the relative distance. To start with, the user moved away from the base station to check the maximum radio transmission range of the node, which was tested to be $27.5m$.

RSSI is measured as an integer value and can be converted into its corresponding dBm value by subtracting a constant (the default value is 45 [1]). Since an RSSI value cannot be a decimal or a fraction, it cannot offer enough resolution to distinguish fine-grained changes in distances. Instead, it can only provide resolution to distinguish between distances that are large enough to cause at least a unit change in dBm of the signal power at the receiving node. Therefore, it is unnecessary to test RSSI values by using small increments in distances. In our experiment for setting up a reference curve, the RSSI value was tested every $1.6m$ and each testing lasted for 10 seconds. By averaging all the values received during this time, the valid RSSI value at each testing location could be obtained. All the data sets sampled during the experiment are displayed as red asterisks in Figure 1.

Based on the collected discrete data sets, there are two approaches for setting up a reference curve. The first approach starts with the evaluation of the parameter A in Equation 4. The evaluation is made by testing the RSSI value of the base station which is one meter away from the transmitting node. A is tested to be -60.3754 dBm. By inserting this value along with each pair of d and $RSSI$ values obtained from the samples into Equation 4, a suite of values of n can be acquired and the average value of n is calculated as 4.2119. The values of n and A enable us to establish a reference curve, which is shown as the black dotted line in Figure 1.

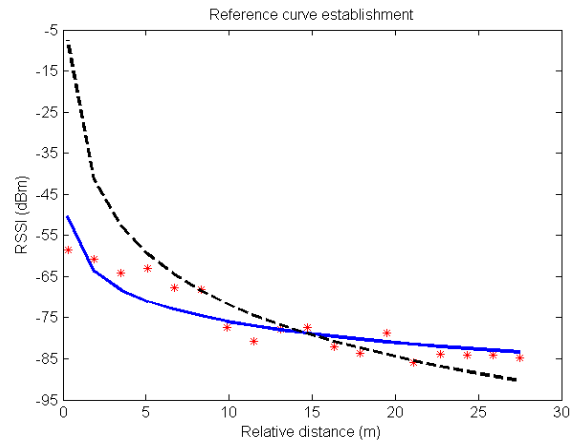

Figure 1. The establishment of the reference curve

The second approach is curve fitting. By assuming that $x = (-10)log_{10}(d)$, a linear relationship between RSSI and x can be established ($RSSI = nx - A$). Then, by taking advantage of the polynomial fitting technique in which the highest power of x is set to be one, both the values of n and A can be calculated. For our case, they are equal to 1.6838 and -59.0668 dBm, respectively. The reference curve made by this approach is illustrated by the blue solid line in Figure 1.

As can be observed from Figure 1, there is a deviation between the two reference curves. The distinction demonstrates – from one perspective – the accurate RSSI values cannot be obtained as long as the two communicating nodes are very close to each other. After noticing this phenomenon, another experiment was conducted to double check the variation of RSSI. This was carried out by placing a node on a waist, knee, and ankle of the user, respectively, and keeping the user one meter away from the base station. The result shows that the RSSI value becomes quite different as the position of the node changes. In other words, RSSI becomes more and more sensitive with the decease of the distance. Therefore, the reference curve established from the second approach is considered more precise and thus is preferable to be used for the verification of the reliability of RSSI.

B. Verification of the Reliability of RSSI

In order to prove or disprove the reliability of RSSI for the sensor localization in the indoor environment, an experiment should be carried out and the data obtained from the experiment should be processed. If the processed result well fits the reference curve, RSSI is demonstrated to be reliable for determining the distance. This is because the reference curve gives the accurate position for each RSSI. Therefore, if the RSSI value processed from the experiment is very close to the accurate one, by looking it up in the reference curve, the corresponding precise distance can be obtained.

The user binding a node with one of his ankles moved from the edge of the radio transmission range to the base station in a straight manner. The reason why the movement begins from the maximum radio transmission range is that it can align the distance traveled during all the experiments ($27.5m$). The raw data collected from the experiment were a series of a pair of RSSI and time values. Since the movement of human beings is slow, the walk speed can be regarded uniform. As a result, for each pair of the data sets, the time can be transformed to the corresponding distance. The transformation is expressed as:

$$d(i) = \frac{R}{t_{max} - t_{min}} t(i) \qquad i \in [1, n] \tag{5}$$

Here n is the total number of data sets, R is the maximum radio transmission range, and t_{max} and t_{min} are the beginning and the end time of the experiment. Equation 5 sets up the relationship between each RSSI and its corresponding distance during the mobility experiment. Before verifying the reliability of RSSI for indoor localization, a few mathematical methods have to be applied to process the data collected from the experiment.

1) Raw Data: The first and, obviously, the simplest method to test the reliability of RSSI for node localization is to directly use the raw data obtained from the experiment. As described in Figure 2, the signal fluctuation was considerably high during mobility. Moreover, for a given RSSI value, there were multiple corresponding distances. Still worse, the difference between these distances were large. For example, the RSSI value -90 dBm indicated at once a distance of $7m$ and $26m$. Therefore, the raw data of RSSI is absolutely weak in determining the distance of a mobile node in an indoor environment.

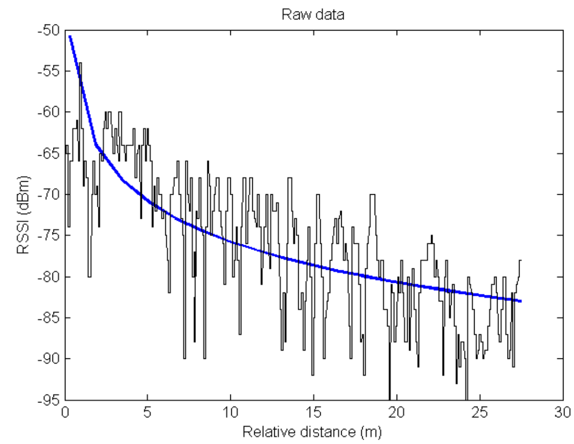

Figure 2. Utilization of the raw data for localization

2) Moving Average Method: In order to reduce the fluctuation of the signal, the moving average method is applied. Instead of directly using the collected RSSI values, the RSSI value at each time point was calculated by averaging all the previously received one hundred RSSI values. The time consumed in walking from the edge of the radio transmission range to the base station in the experiment was $21.86s$. This makes the average moving speed of the node to be $1.375m/s$. Since the data sets were generated every 10 millisecond, one hundred RSSI samples would take 1 second to produce. This indicates that the RSSI value at each location can be represented by all the RSSI values in its nearby positions ($1.37m$). The moving average method enables a comparatively smooth RSSI curve, as displayed in Figure 3.

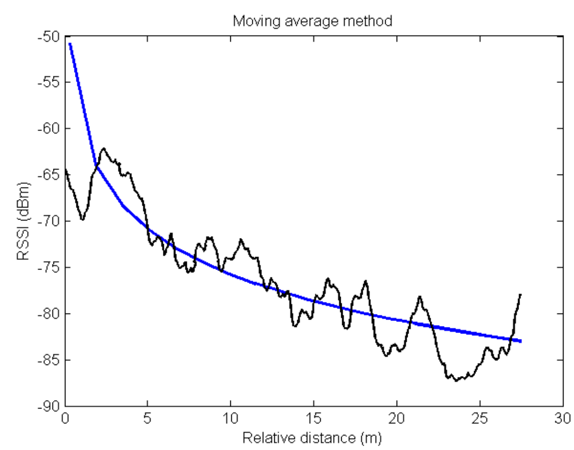

Figure 3. Utilization of the moving average method for localization

3) Weighted Average Method: Theoretically speaking, the change of the RSSI value should be a gradual but steady process. For a unique RSSI, its value should mostly approach the sample that is collected next to it. As a result, instead of giving the same weight for all the previous data sets, different weight should be applied to the collected samples to enable a more accurate RSSI estimation. The weighted average method assigns a higher weight to the sample that is closer to the target data whose RSSI value is aimed to be evaluated. However, due to the strong fluctuation of the signal, the result is quite similar with the one obtained from the moving average method. This is illustrated in Figure 4. One optimization of this approach is that the trajectory of the processed RSSI values better fits the reference curve. This indicates that the RSSI values handled by the weighted average method are able to realistically determine the distance on the whole. Nevertheless, for each RSSI sample, the distance it gives is far away from the actual position.

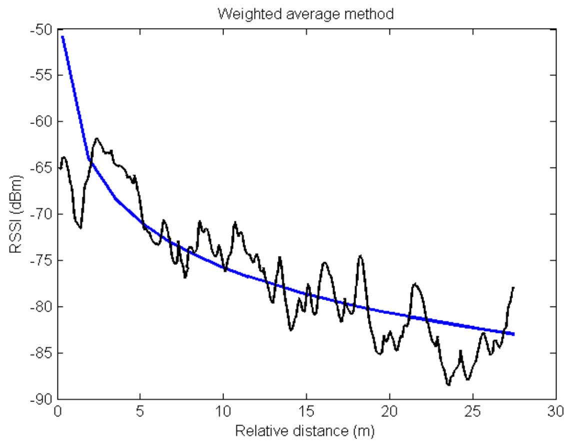

Figure 4. Utilization of the weighted average method for localization

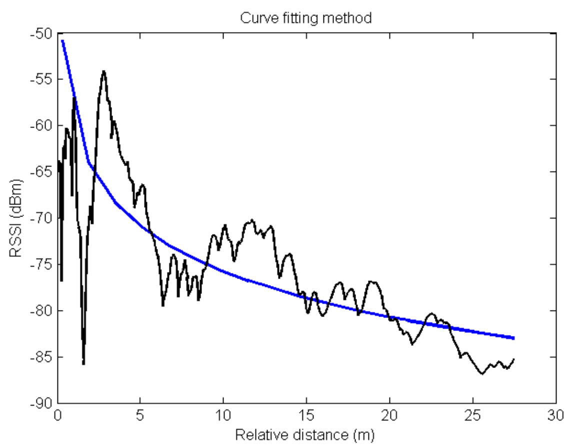

Figure 5. Utilization of the curve fitting method for localization

4) Curve Fitting Method: The curve fitting method uses all the occurred samples in the experiment to predict the value of the data in the next time instant. The more samples provided, the more precise the prediction will be. Therefore, the curve fitting method will generate more accurate values of RSSI as time goes by. The curve obtained by this approach is shown in Figure 5. As can be observed, the processed RSSI value is far away from the value that is given by the reference curve when the distance between the transmitting and the receiving nodes is less than $6m$. However, with the increment of the distance, the difference between the RSSI value obtained from the curve fitting method and the RSSI value provided by the reference curve decreases. Even though the result exhibits convergence to a certain extent, the localization errors cannot be disregarded.

VI. Conclusion

In this paper, we investigated the reliability of RSSI for indoor localization. First, we statically measured a series of samples, based on which a reference curve that gave the accurate one-to-one mapping between the RSSI and distance values was established. Then, we conducted an experiment during which the nodes are mobile. Based on the collected data sets, we used four estimation techniques to smooth the RSSI values that showed a considerable fluctuation in the mobile scenario. According to the observations that the processed RSSI does not fit the value given by the reference curve, RSSI is rendered unreliable as the only input to determine the location of a mobile node in an indoor environment.

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