Analysis of RSSI Feasibility for Sensor Positioning in Exterior Environment

Qian Dong*
Department of Computer Science
Jinan University
Guangzhou, China
dongq8@jnu.edu.cn

Feng Zhu
School of Physics and Astronomy
Sun Yat-Sen University
Guangzhou, China
zhufeng25@mail.sysu.edu.cn

Yanning Cai
Department of Computer Science
Jinan University
Guangzhou, China
caiyanningmitl@sina.com

Liangda Fang
Department of Computer Science
Jinan University
Guangzhou, China
fangld@jnu.edu.cn

Mi Lu
Department of Electrical and Computer Engineering
Texas A&M University
College Station, USA
mlu@ee.tamu.edu

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***Abstract*—Mobility of nodes in Wireless Sensor Networks (WSNs) brings formidable challenges to protocol design. A mobility estimation algorithm is the prerequisite for evaluating link quality, localizing nodes and excogitating a signal threshold to trigger possible handoff. The radio Received Signal Strength Indicator (RSSI) integrated in sensors has been widely used due to its low economy cost and moderate energy consumption. The distance of separation between adjacent nodes can be estimated by reading RSSI when a good portion of electromagnetic wave propagates in a line-of-sight link. However, the measurement results of RSSI fluctuate heavily because of fading signal and disturbing background noise. This paper investigates the reliability of RSSI for exterior sensor positioning. To display the one-to-one mapping between RSSI and distance, a series of static experiments are conducted and a reference curve is established. To mitigate the fluctuation of raw RSSI samples, a set of mobile experiments are carried out and five filtering methods are employed. The mitigation effects are evaluated by the Root Mean Square Error (RMSE) values. Though the overall optimal RMSE achieves 0.84, which is significantly lower than that of the raw samples, it is still possible that one RSSI corresponds to two or more distances, and the maximum difference between them can reach 2.97 meters. Because this error is intolerable for many applications, it is not authentic to gauge the distance between mobile nodes only based on RSSI in exterior environment.**

***Index Terms*—RSSI; localization; outdoor positioning; wireless sensor network; distance**

I. Introduction

There are multitudinous applications of WSNs need solutions to cope with the challenges that the strong mobility of sensor nodes bring. Strong mobility can be recognized as concurrent node failures and joins, physical movement of nodes caused by external forces such as wind, water, or air, and movement caused by nodes attached to moving persons or objects [7], [8], [11].

Strong mobility of nodes leads to serious difficulties in protocol design, especially at the network and the data link layers. This is because the strong mobility can cause the quality of an established connection to deteriorate, which will in turn make data communication easy to fail, result in frequent topology changes, raise the probability of data retransmission, and increase the packet delivery latency. Usually, a mobile node cannot start to transmit data immediately after joining the network, but has to wait for a long time to be completely integrated into the network [3], [15].

To solve the problems caused by strong mobility, it is imperative to localize the position of mobile nodes accurately and promptly. Applications of WSNs with location information can conjecture the activity and behavior of mobile objects, assess the link quality, predict the moving trajectory of sensor nodes, and excogitate a distance threshold to trigger seamless handoff when necessary. For instance, smart sensors are used to display real-time traffic monitoring for vehicle detection, velocity evaluation, light indication, and congestion warning [18], [20]; biomedical sensors are bound to the bodies of nurses and patients to track their health conditions and behaviors [16]; workers in post disaster recovery scenes [12] and oil refinery sites [17] are carried with sensors to avoid dangerous accidents; the sensing devices are also be used for soldiers to report emergencies encountered in a military mission [2], [10].

To adapt to strong mobility in WSNs, the location information of mobile nodes needs to be collected timely and accurately. Due to the low cost, low energy consumption and no need for additional devices, the RSSI approach is widely employed to pinpoint the positions of sensors in real-time. Our previous studies have demonstrated that due to the refraction, reflection and diffraction of signals by walls, ceilings and other obstacles, RSSI is not reliable in indoor positioning [14]. Since there are fewer interference sources that affect the outdoor electromagnetic signal, in this paper, we extend our work on the investigation of the reliability and feasibility of RSSI for exterior sensor positioning. To fulfill the evaluations, a set of static and mobile experiments are conducted, a reference curve showing the one-to-one mapping between RSSI and distance is established, five filtering methods are developed and combined to alleviate the fluctuation of raw mobile samples, and the alleviation effects are evaluated by the RMSE values with respect to the static reference curve. The overall optimal RMSE is reduced to 0.84, which is significantly lower than that of the raw RSSI samples. Nonetheless, it is still possible to have one RSSI corresponding to two or more locations, and the maximum difference between them can be as high as 2.97 meters. Because this estimation error is intolerable for many applications, it is not authentic to gauge the distance between mobile nodes only based on RSSI readings in exterior environment.

The rest of this article is organized as follows: in Section II, an introduction to RSSI positioning approach is described. In Section III, the experiment settings are presented. In Section IV, a static experiment is carried out and the reference curve is modeled. In Section V, a mobile experiment is conducted and the reliability of RSSI for exterior positioning is investigated by measuring the RMSE of five filtering approaches. In Section VI, the de-noising effects of different filtering methods are discussed and compared. Finally, in Section VII, the concluding remarks are summarized.

II. RSSI Introduction

Determination of the location of a node can be done in a number of ways. Among these approaches, the RSSI technique [14] is the most concerned, because it does not need extra device help and costs [4], [5], [13]. It can represent the relationship between a transmitting and a receiving powers, and 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 link. This approach has been assumed for handling mobility in a number of mobility-aware MAC protocols [6], [19].

If there is a direct path between two nodes placed in 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.

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

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 3 dBm 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. The loss due to a misaligned antenna polarization, L, can be expressed as:

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

III. Experiment Settings

The objective of our experiments was to investigate whether RSSI was reliable to be applied for outdoor positioning. The sensor platform we employed was Imote2 motes developed at Intel, which built around the low-power PXA271 XScale CPU and integrated IEEE 802.15.4 compliant radio with a built-in 2.4GHz antenna. In order to use the RSSI to express the relative distance between a pair of communicating nodes d, the distance estimation model proposed by Texas Instruments for the Chipcon CC2420 radio was given in Equation 4, where n denoted the signal propagation exponent, and A indicated a reference RSSI value in dBm measured when a transmitting node was one meter apart from a receiving node.

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

Our experiments were conducted on a sidewalk with few people, with trees planted on both sides, and on one side was an urban traffic road, where cars passed by from time to time. One node was used as a base station directly connected to a laptop via a USB cable. The other node was placed on the palm of the experimental operator with a fixed position in front of his body. Both nodes worked with a full battery. There were no other obstacles standing in the communication path between the two nodes. This enabled a good portion of the signal to propagate over a line-of-sight link.

IV. Static Experiment and Analysis

A. Static Experiment

In order to verify the reliability of RSSI for determining the relative distance between a pair of nodes in exterior environment, before doing experiments in the mobile condition, it was necessary to establish a reference curve in the static condition. The static reference curve showed a standard one-to-one mapping relationship between RSSI and relative distance of nodes.

The transmission power of the sending node was first set to $0dBm$. As the node moved away from the base station gradually, the maximum radio transmission range was tested to be 30 meters (m), with positive and negative deviations of $1m$. The maximum transmission power $0dBm$ could make the sensitivity of the receiving power to reach -94dBm. However, when RSSI was less than -90dBm, packet loss began to occur and the loss rate increased exponentially with the decrease of RSSI. To ensure that all data packets can be successfully received, our experiment took -90dBm as the RSSI boundary value, which corresponded to the relative distance between the two nodes of $25m$. This required the power register and the transmission power to be 25 and $-2dBm$ or so, respectively.

Because the RSSI value was measured as an integer rather than a decimal or a fraction, it could not provide sufficient resolution to distinguish fine-grained changes in distance. This was why it was not necessary to test RSSI at very small intervals over distance in our static experiment. The principle of how many meters should the distance be measured was that two adjacent measurements could at least recognize the unit change in dBm of the signal power at the receiving node, while keeping the interval as small as possible. This enabled the test results to completely and accurately describe the relationship between RSSI and distance to the greatest extent.

B. Reference Curve Establishment

To establish a reference curve, the RSSI value was collected every $0.5m$ starting with a distance of $25m$ between the two nodes, each test lasted for 10 seconds, and the test frequency was 100 times per second. By averaging all the 1000 test samples, the valid RSSI value for each test location could be calculated, which was shown by the red asterisk in Figure 1.

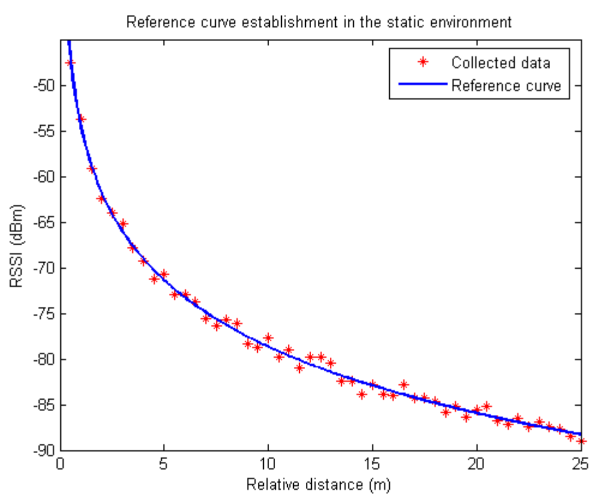

Fig. 1: The establishment of the reference curve

The reference curve was established by the curve fitting method on the data sets collected in the static environment. We first assumed that $x = (-10)log_{10}(d)$ to establish a linear relationship between the parameters $RSSI$ and x with $RSSI = nx + A$, and then applied the polynomial fitting technique where the maximum power of x was set to be 1. By doing so, the values of n and A could be worked out and they were equal to 2.4148 and -54.54dBm. The reference curve built from the curve fitting method was illustrated as the blue solid line in Figure 1.

During the experiment, we found that if a node was bound to a human body, when its position or height changed (such as on a wrist, knee, or ankle), the RSSI value would be quite different, and became more sensitive with the decrease of distance. The same phenomenon was observed when there were obstacles (such as trees, vehicles, and pedestrians) standing between, surrounding, or passing by the transceiver. Even weather conditions (such as wind, rain, temperature, humidity, and sunshine) could affect the signal reception intensity, resulting in certain changes in the receiving distance, ranging from $1m$ to $5m$.

V. Mobile Experiment and Analysis

A. Mobile Experiment

The significance of establishing the reference curve in the static environment was that it could be used as a standard to accurately describe the relationship between RSSI and relative distance of two communicating nodes. However, when one or both nodes became mobile, the mobile curve built from the historical RSSI values would fluctuate greatly, causing one RSSI corresponding to multiple distances. Because a node could not determine its relative distance from its partner by reading RSSI values, we would use some noise removal methods to make the mobile curve smooth. After that, if the mobile curve well fitted the corresponding part of the static reference curve, a node by comparing it with the reference curve, was able to determine and predict its current and next relative distance with its communication partner.

In order to investigate the reliability of RSSI for the sensor positioning in the outdoor environment, an experiment where nodes had mobility characteristics should be carried out first. The experimenter held the transmitting node in hand and moved from a distance of $0.5m$ to $25m$ with respect to the receiving node at the RSSI sampling frequency of 100 times per second. To coincide with the distance traveled by the node in the static experiment, the flashing of LED light of the sending node was used as the sign to start RSSI acquisition. The experimenter tried to control his movement speed to about $1.3m/s$ in a straight line. Since the movement was rather slow, the walking speed could be considered constant. This could result in a total RSSI sample amount of about 1884.

The raw data collected from the mobile experiment were a series of RSSI and time values. Since the movement of experimenter was regarded as uniform, for each pair of data sets, the time could be converted to the corresponding distance. Given that n was the total number of data sets, R and d_{min} were the maximum radio transmission range without data loss and the minimum signal reception distance, and t_{max} and t_{min} were the beginning and the end time of the experiment, the transformation could be expressed as:

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

Equation 5 enabled to establish the relationship between each RSSI and its corresponding distance in the mobile experiment. Before verifying the reliability of RSSI for outdoor positioning of sensor nodes, several methods aiming to eliminate the noise and smooth the fluctuation of raw data from a mathematical point of view would be applied. Through data analysis, whether and how close the mobile curve was consistent with the static reference curve would be determined.

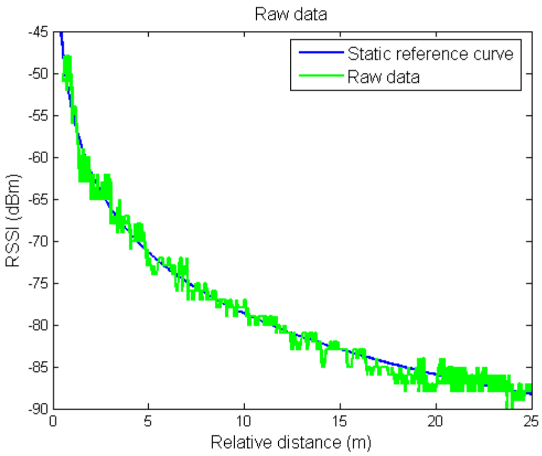

Fig. 2: Raw data

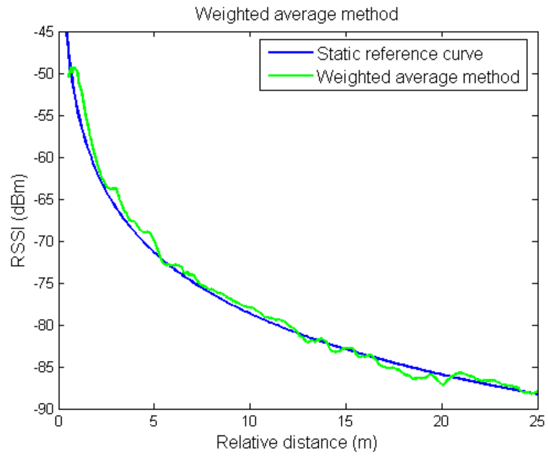

Fig. 3: Weighted average method

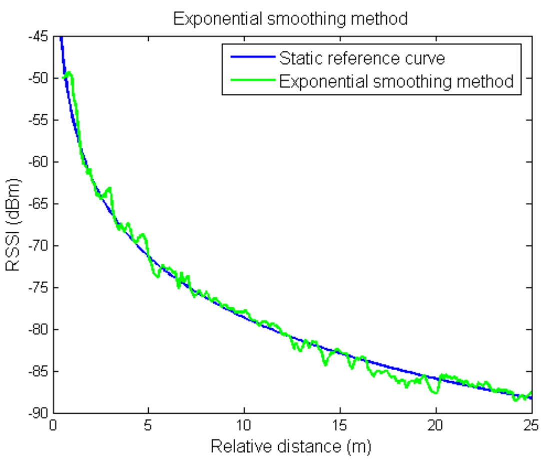

Fig. 4: Exponential smoothing method

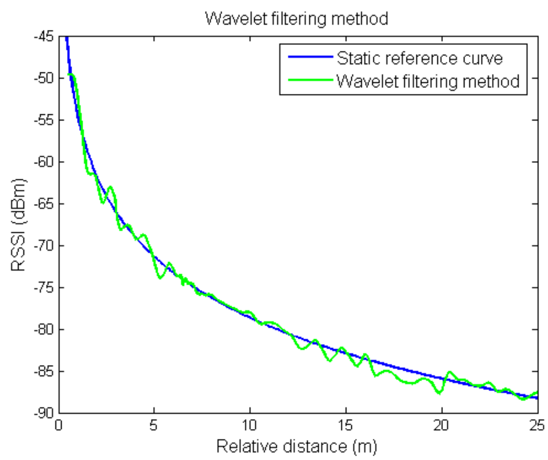

Fig. 5: Wavelet filtering method

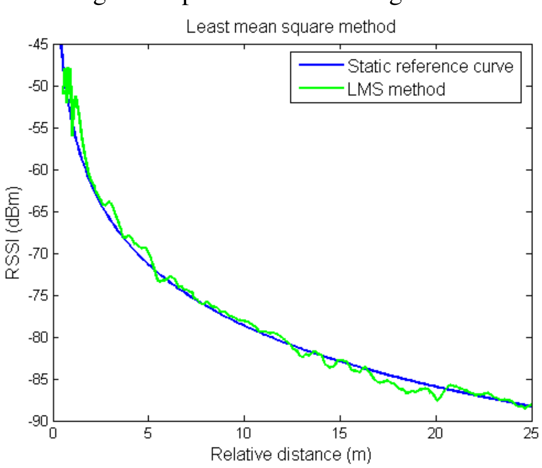

Fig. 6: LMS filtering method

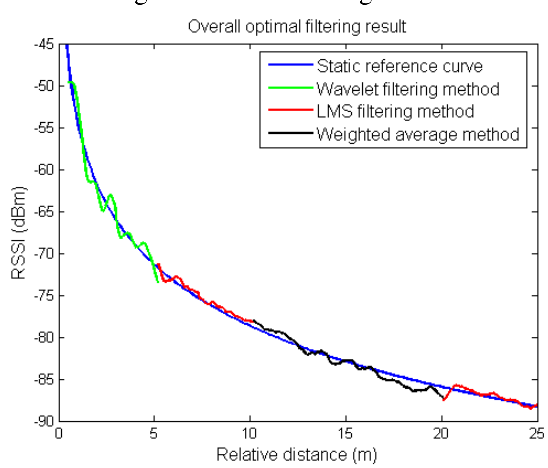

Fig. 7: Overall filtering result

TABLE I: Comparison of RMSE for mobile positioning approaches

Method \ Distance(m)	0.5-5	5-10	10-15	15-20	20-25	Overall
Raw data	0.77	0.43	0.40	0.57	0.40	1.19
Weighted average	0.86	0.26	**0.23**	**0.33**	0.21	1.01
Exponential smoothing	0.64	0.28	0.28	0.44	0.22	0.90
Wavelet filtering	**0.55**	0.24	0.28	0.48	**0.20**	**0.84**
LMS filtering	0.78	**0.21**	0.24	0.41	**0.20**	0.96
Optimal filtering	**0.55**	**0.21**	**0.23**	**0.33**	**0.20**	**0.84**

B. *Verification of RSSI Reliability*

*1) **Raw Data**:* To start with, we tried to directly use the raw data collected from the mobile experiment. As depicted in Figure 2, the green curve represented all the 1827 RSSI samples obtained during the movement. Due to the large fluctuation of the curve, it might appear that a specific RSSI value corresponded to multiple distance values, and the difference between these values could be very large. For instance, the RSSI -88dBm indicated a distance of 18.4m and 23.5m at the same time. From this perspective, the raw data of RSSI was regarded as unreliable for the mobile node positioning in exterior environment. Nevertheless, it could be observed that the changeing trend of the mobile curve and the reference curve was basically consistent, which proved that when the experiment was carried out in the same condition and environment, RSSI had no relationship with whether the node was stationary or moving, if the influence of noise was out of consideration.

*2) **Weighted Average Method**:* Based on the raw data, the weighted average method computed the RSSI value for each position by averaging its previous 29 and the current 1 RSSI values with different weights ranging from 0.065 to 0.002. The closer to the current position, the greater the weight of the RSSI value. Since the raw data were sampled at the rate of 1/10 milliseconds, and the total number of data was 1827, a mobile node would consume 18.27s to move from the base station to the edge of communication radio of its partner, and its average moving speed can be inferred as 1.34m/s. Since the relative distance between a mobile node and its communication collaborator was bounded between 0.5m and 25m, it could be calculated that 74 RSSI samples were collected per meter, and 30 neighboring RSSI explained that the RSSI value for each position was the weighted average of all the RSSI values obtained within 0.4m of its vicinity. As shown in Figure 3, the fluctuation of RSSI values was highly reduced after the weighted average method was used.

*3) **Exponential Smoothing Method**:* The RSSI revision value of each position depended on the defined decay coefficient, the sampled RSSI value of the previous position and the revised RSSI value of the previous position. The important feature of the exponential smoothing method was the data changes could be tracked, because the revised RSSI value for each position was related to all the RSSI values generated before, and the closer the signal was to the current position, the greater the exponential weight would be. After adding the latest sampled RSSI in the revision process, the updated RSSI value would replace the old one, and the old one would gradually occupy a secondary position until it was eliminated. In this way, the revised RSSI value could always reflect the latest data structure. In order to minimize the deviation of the filtering curve from the static reference curve (RMSE=0.90 as shown in Table 2), the decay coefficient was set to 0.1 in our study. The median filtering method was illustrated in Figure 4.

*4) **Wavelet Filtering Method**:* The RSSI signal could be mapped to the wavelet domain. The wavelet filtering method was able to find the best approximation to the static reference RSSI values in the function space expanded by the scaling and translation version of the wavelet generating function according to a specific criteria, so as to complete the distinction between the static reference data and the raw data with noise. The de-noised curve was obtained by thresholding the wavelet coefficients. In our investigation, the wavelet coefficients we adopted were the selection threshold rule defined by $sqrt(2{*}log(1827))$, the wavelet shrinkage threshold $soft$, the multiplicative threshold re-scaling one, the desired orthogonal wavelet $sym8$, and the level at which the wavelet decomposition was performed 5. The higher the level, the more noise would be removed, and the more smooth the filtering curve would be. But at the same time, the more likely the useful part of the signal would lose its original characteristics. This was why the level 5 was used, and the wavelet filtering curve was not quite satisfactory, as shown in Figure 5.

*5) **Least Mean Square Filtering Method**:* The Least Mean Square (LMS) filtering method was to iteratively update the coefficient of the filter, so that after the raw data were given, the error between the static reference RSSI and the output filtering RSSI could be minimized. In the process of updating the coefficient, the iterative step size, which was used to control the stability of the signal and the convergence rate of the adaptive algorithm, was set as the reciprocal of the maximum eigenvalue of the autocorrelation matrix of the collected RSSI samples with the value of (8.7045×10^{-8}). The filtering order was set to 50, and thus the filtering curve was the same as the curve before filtering from the distance of $0.5m$ to $1.18m$. This explained the reason that the filtering curve fluctuated heavily at the beginning, as displayed in Figure 6.

VI. Comparison

Each filtering method applied the RMSE to estimate its degree of deviation from the static reference curve, where the RMSE served as a standard to judge the quality of de-noising for these methods. The comparison of RMSE for the five mobile positioning approaches was given in Table 2. The distance between $0.5m$ and $25m$ was divided into five segments, each of which was about $5m$. For each distance segment, the RMSE of the filtering RSSI data in each method was calculated, and the overall RMSE for each method was also computed based on the 1827 RSSI values over the entire distance of $24.5m$.

As highlighted in Table 2, the best filtering methods with the minimum RMSE from the $1st$ segment to the $5th$ segment were the wavelet filtering method, the LMS filtering method, the weighted average method, the weighted average method, and both the LMS and the wavelet filtering methods, respectively. Among these five methods, the wavelet filtering method showed the best overall de-noising effect. It could also be observed that the RMSE of each filtering method decreased when the relative distance between two communicating nodes increased from $(0.5-5)m$ to $(5-10)m$. This happened because it took time for a receiving sensor node to respond from the initial state to the steady state. In addition, the number of historical data used to evaluate the updated RSSI value at the distance to be predicted increased. It was deserved to be noticed that each filtering result was not unique except for the raw data, but influenced by the revised input parameters of the filter. Our decision was to choose the parameters that minimized the RMSE under the premise that the filtering curve showed a comparatively smooth appearance.

As displayed in Figure 7, the four filtering methods with the smallest RMSE in each distance segment were combined to form an overall optimal filtering result, with the RMSE value of 0.84. This figure showed that the curve obtained from the overall filtering method was basically consistent with the static reference curve, and the signal fluctuation was small. But even so, it was possible that one RSSI corresponded to two or more distances, and the maximum difference between these distances could reach $2.97m$, although RSSI was only read as an integer.

VII. Conclusion

This paper investigated the reliability of RSSI for exterior sensor positioning. First, according to a set of static RSSI samples, a reference curve showing the one-to-one mapping between RSSI and the relative distance of nodes was established. Then, a mobile experiment was carried out and based on which, five filtering methods were proposed to alleviate the fluctuation of receiving signals, and the alleviation effect was measured by their RMSE values with respect to the static reference curve. Because none of the methods was completely satisfactory in de-noising, they were combined to form an overall optimal filtering method and the RMSE was reduced to 0.84, which was significantly lower than that of the original RSSI. Though the overall filtering curve was basically consistent with the static reference curve, it was still possible that one RSSI corresponded to two or more distances, and the maximum difference between them could be as high as $2.97m$. Because this estimation error was intolerable for most applications, it was not authentic and feasible to gauge the distance between mobile nodes only based on RSSI readings in exterior environment.

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