2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

Preprocessing Technique to Signal Strength Data of Wireless Sensor Network for Real-Time Distance Estimation

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Abstract—**There is a real need in the robotics and wireless sensor network (WSN) communities for the estimation of the geolocation of wireless agents. The received signal strength indicator (RSSI), a common metric in most networking hardware, has been reputed as a very unreliable method for doing the job, due to its vulnerability to environmental factors. Nevertheless, it still remains as the most prevalent estimator of distance between agents on many research projects. Multipath fading, shadowing and other effects that the environment exerts over a signal while propagating are regarded as the main cause of such vulnerability. Although some success has been obtained using RSSI outdoors where the effects are less noticeable, indoor settings remain an unconquered territory. The main motivation of this paper is to establish whether, in real time applications, the use of preprocessing techniques over partial raw collected data helps the RSSI to be a suitable estimator of distance. We propose one such technique and the results suggest that its use may indeed assist the obtainment of more accurate distance estimations while using RSSI.**

I. Introduction

FOLLOWING the continuous interest in wireless sensor networks (WSN) and its applications, a large community of researchers have been working with a scenario where nothing is known about the environment, and the agents of the network must obtain as much information as possible by relying solely on their sensor and communication capabilities. The most basic information for an agent to know is its physical location, which in return will help other agents in the network, and even external elements cruising through it, to localize themselves. In fact, many projects on multi-robot motion planning [1], collaborative mapping and exploration [2], formation control [3], robotic localization [4] and communications mapping [7, 8] rely on the fact that agents acknowledged their positions with reference to a coordinate system. When applications cannot lean on external geolocation systems (such as GPS) or when the topology of the environment is not known or is very dynamic, the only way for an agent to localize itself is by using any of its embedded indicators of performance like the received signal strength indicator (RSSI), or by using methods such as the transmission time delay, that measures how long it takes for a signal to go from transmitter (*Tx*) to receiver (*Rx*) at the expense of a high synchronization among agents. Ultimately, the easiness of using RSSI makes it suitable for applications where the agents have not much computational power just as those in WSN.

The strength of a signal varies upon leaving the transmitter due to the multiple effects the environment exerts over it, a fact that is widely known. As a result, the RSSI at any given point in time and space could take a random value lower than the transmitter power. This randomness makes it hard to predict how much the signal strength will decrease, and consequently several models have been proposed to account for as many environmental effects as possible. Some models have tried to correlate the variation of signal strength with distance and although somehow successful in outdoor environments, cluttered environments such as those indoors still represent a challenging task.

We propose a simple and fast technique to preprocess raw collected data in order to obtain fairly accurate estimations of distance between agents in line of sight with each other, so that the calculation can be performed in real time. To do so, we acknowledge that a received signal is the result of the original signal being affected by two types of fading: small-scale and large-scale, where the latter is the one that actually deals with the variation of distance from *Tx* to *Rx*. Consequently, if it were possible to mitigate the effects of the former on the collected dataset, one could be able to estimate distance by using any of the propagation models available. To this end, we propose the use of a technique that, although around for quite a long time, has not yet been utilized for the particular purpose of filtering an affected signal. The technique is the histogramic analysis. Furthermore, we propose a compensation method that will complement the job of the histogramic analysis, so that any posterior calculation will be corrected by using previous estimations. The work presented in this paper is intended to be the first in a series of works dealing with the statistical analysis of collected data for real-time robotics applications.

The paper is organized as follows. Section II reviews previous works and gives a brief survey on signal propagation that would lay the foundations for section III where our approach to the problem is presented. Section IV defines a set of experiments and shows its results. Finally, section V presents our conclusions and discusses avenues for future research.

This work was supported in part by the U.S. National Science Foundation under Grants CNS-0551598 and IIS-0644127.

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II. Previous Work and Brief Survey on Signal Propagation

A. Previous Work

The estimation of link distance on unknown environments has been a topic of research for years because it is the foundation for many different applications [5, 6, 7, 8, 9, 10, 11, 12, 13]. As a result, many recent studies have explored the nature of wave propagation and the viability of using RSSI as an estimator of distance between wireless agents. Most of such studies approach the problem by doing one of the following experiments and using either Chipcon CC1000 or CC2420 radio chipsets, found in most WSN platforms:

- For a given distance, *n* RSSI values are collected, the mean (and sometimes the standard deviation) is calculated and the result becomes the representative RSSI for that distance [14, 15, 18]. The experiment is sometimes repeated many times using different transmission power levels.
- An agent is moved at a constant velocity, *m* values are collected and then plotted in order to see if there is any correlation between RSSI and distance [15, 16, 17].

The results of such experiments are then compared with those obtained by using propagation models. The outcome are two roughly accepted conclusions: either the prediction of indoor distance by using raw RSSI and low power radios is seemingly impossible due to the large amount of characterizations needed to make it precise [18], or it may be possible if used under certain conditions and assumptions [14, 19]. The conclusions are based on results such as those shown in figure 1 where a clear correlation between RSSI and distance is not easily found.

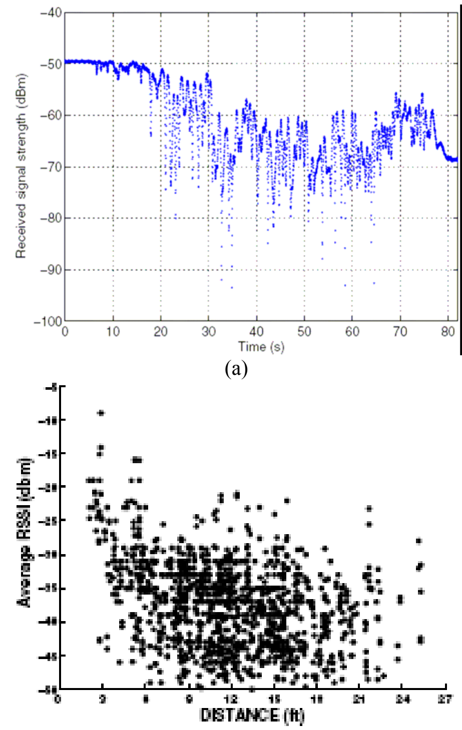

Fig. 1. (a) RSSI vs. time for a mobile receiver in a corridor [15]. (b) RSSI vs. distance for a 38 nodes indoor sensor network [18]

B. Brief Survey on Signal Propagation

One thing that seems missing in most previous studies is the consideration that, when a wave propagates through a medium, it experiments two types of fading: large-scale and small-scale. Most of those studies acknowledge this but just a few such as [17] actually consider the two components of fading to analyze collected data. To gain a clear idea of what is missing we must take a small journey into wave propagation theory. A received signal can be described as the product of the two components [20]:

$$r(t) = m(t).r_0(t) \tag{1}$$

where $m(t)$ is the large-scale part and $r_0(t)$ is the small-scale one. The signal can be pictured as shown in figure 2.

On one hand, large-scale fading is responsible for the attenuation of the signal strength due to changes in distance between *Tx* and *Rx* and the resultant effects exerted by the three basic propagation mechanisms: reflection, diffraction and scattering. There are two basic models for indoor environments: log-distance path loss and attenuation factor. Both models are based on the free-space propagation model with the difference that the former considers a normal random variable that quantifies for the additional losses due to the environment, and the latter considers an attenuation factor for each obstacle the signal runs into, depending on the material and the layout of the building. These models are simple to implement and can be used when accuracy is not a critical requirement [22], when the *Tx-Rx* separation is large and when the environment is not heavily cluttered [11].

On the other hand, small-scale fading is responsible for the rapid fluctuations on signal strength that could give rise to a very pronounce fading over short distances or over short periods of time. This kind of fading, called also multipath, is the result of waves arriving at different times creating wide variations in amplitude and phase when mixing together. In addition, small-scale fading is influenced by physical factors such as the speed of the agents (in dynamic networks), the speed of the objects (in dynamic environments) or the bandwidth of the signal [21]. Changes on the signal strength due to small-scale fading are usually described by stochastic processes, where the selection of the process depends on the

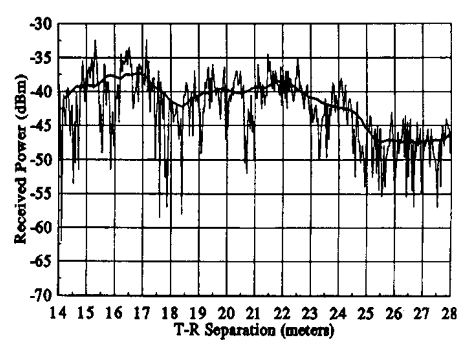

Fig. 2. Small-scale (fast changing line) and large-scale (slow changing line) effects in a received signal [21]

properties of the system and the environment: when there is a line-of-sight, a dominant stationary component is present and the fading envelope can be modeled using a Ricean distribution; when the dominant signal becomes weak, the envelope resembles a Rayleigh distribution. There are many other distributions derived from the previous ones like the log-normal fading model (used to explain large variations on the signal amplitude), the Suzuki model (a mix of Rayleigh and log-normal distributions), the Nakagami model (also called m-distribution, neglected for indoor spaces in favor of others with a better fit to measured data [23]), or the Weibull model (a good fit for some data at 910 MHz, but with no theoretical or direct empirical explanation for its use indoors [24]). The main drawback of all these models is that they are relatively cumbersome and highly time consuming [22].

Comparing figures 1 and 2 it is possible to observe close similarities that could lead to the conclusion that the plots on figure 1 are the result of seeing both fading components mixing up together. Clearly then, to apply large-scale propagation models to raw RSSI data will not yield appropriate results, as neither the calculation of a mean value for a number of measurements will do. The latter is because the mean and standard deviation assume that the dispersion of data for one particular *Tx-Rx* distance follows a normal-Gaussian distribution, which is not realistic [18].

Lastly, the estimation of distance using RSSI is approached basically in two ways:

- Creating new propagation models that reflect as much as possible the behavior of waves on indoor settings given different configurations [25].
- Manipulating full datasets and using existing propagation models [26]. Results vary depending on the configuration of the system (position, direction of antennas) and the settings of the environment (clutter, dynamic, static, etc)

In summary, estimation of distance using RSSI has been regarded as inaccurate, and most methods to improve such accuracy are complex and time consuming what makes them not useful for applications that require real time estimations.

III. Histogramic Analysis and Compensation Method

The need for real-time applications on both the WSN and robotics communities has motivated us to propose a technique to quickly preprocess collected RSSI data in order to estimate distance. The basic idea comes from the observation of figures 1 and 2: if it were possible to decompose the received signal into its two dominant components (small and large scale fading), dispose of the effects of the former and use only what is left, a better estimation of distance may be possible. This could be doable by applying stochastic models such as those mentioned in section II-B, but besides of what was mention there, they require the collection of all the data first in order to be able to analyze it later (not real-time).

Another way to look at the problem is that the effects of small-scale fading are strong but random. Still, the dataset maintains certain distinctive behavior that resembles the propagation model defined by the large-scale fading. It also can be observed that in a given period of time, the measurements are likely to be clustered around one or more points. By obtaining the frequency distribution of a dataset in that period of time, we will be able to determine a small and specific range of prevalent RSSI measurements, values that will then be used to calculate the *Tx- Rx* distance.

There are many techniques to analyze data, e.g. scatter plots, histogramic analysis, linear regression, sampling, curve fitting, parameterized mathematical distribution, cluster analysis, etc. So far, correlation between distance and RSSI has been obtained using only scatter plots. We propose to use a different method: frequency distribution using histogramic analysis. Histograms are mainly used to obtain the shape of data distribution. It also gives an estimation of the frequency of the data in a set. In here, we are planning to use it as a tool to disregard the impact of small-scale fading.

A. Histogramic Analysis

Initially we consider an indoor environment where a *Tx–Rx* pair is placed close to one another. The distance between both elements is unknown, but within the communication range of each other. At $t=0$, *Tx* starts broadcasting packets at a fixed rate. Each packet contains solely the identification number of *Tx*. Each time a packet is received by *Rx*, a counter variable ψ is increased by one and the RSSI value for the packet stored. Once ψ reaches a certain number, *Rx* start estimating how frequent each one of the stored RSSI values appear, resetting the value of the counter ψ to zero, and repeating the process.

Let define A as the set of all data stored by *Rx* upon receiving a packet. Every member a_n of A is an integer, and $Min \leq a_n \leq Max$, where Min and Max are also integers. The interval [Min, Max] is divided into many sub-intervals that will be called from now on as bins. Each bin will count the number of times a value a_n of A is located in that particular sub-interval. In order for the bins to be comparable, they should have the same width. Since the histogram is completely determined by this constant bin width, it is vital to determine the number of bins. To this effect, Sturges' rule is widely recommended and often used as a default in many statistical packages [27]. Sturges' rule establishes that:

$$g = 1 + \log_2(n) \qquad (2)$$

where g is the number of bins and n is the total number of values in the dataset. Generally, (2) applies to data with a normal distribution, which is not our case [9]. Nevertheless, it can give us a rough idea of the number of bins needed to quickly analyze the dataset.

Let define now c_g as a counter for each bin g in the interval [Min, Max], where at $t=0$, $c_g=0$ for all g. Since each member a_n will belong to only one specific bin, each time a member of A is assigned to a bin, c_g in that specific bin is increased by 1. At the end, some few bins will have c_g with the higher value.

Let define W as the set of bins with highest c_g. A dataset A could then be represented by a single value μ (estimated RSSI at time interval k) obtained from the bins in W. In order to obtain μ, the bins in W can fall in one of the next three cases:

- When just one bin has the higher counter value, μ can be defined as the center value of that bin or centroid.
- When two or more consecutive bins have the higher counter value, μ can be obtained by averaging the sum of the centroids of those bins.
- When two or more nonconsecutive bins have the higher counter value, it is clear that there is not a specific region in the dataset A that is prevalent. To solve this we should change resolution of the histogram by changing the number of bins as follows: $g'_k = g_k - 1$. The reason for decreasing g, as opposed to increasing it, is that decreasing the resolution allows for the bin counters c_g to have more elements assigned and consequently protruding the highest counter more easily. The process will be repeated until the bins in W fall into any of the two previous categories.

Upon determining μ, this value will be used to estimate the *Tx-Rx* distance. Since the whole purpose of using histogramic analysis is to decrease the strong variations on the data associated with the effects of small-scale fading, the value μ, might be considered as a RSSI due to large-scale fading and, as so, one of the available models mentioned in section II will be applicable. The calculated value of distance (δ_k) will be stored and the process repeated again for new incoming data.

B. Compensation Method

The results obtained from the histogramic analysis are still susceptible to show strong variations on μ with time. In order to offset those variations we have devise a compensation method. The idea behind it is that the readings on signal strength due to *Tx* transmitting at a fixed high rate should not change radically from one measurement interval (k) to the other, if the measurements are taken during short intervals of time. That is, moderate change on distance cannot cause an abruptly change on the RSSI. The method aims to maintain the trend of the changes on μ by refreshing the present estimation with previous ones every time a sudden variation is detected. This is done while keeping close to the real measured values. The method can be divided into 5 steps:

Step 1: let define ε_k as the difference between the current estimation of RSSI (μ) and previous one:

$$\varepsilon_k = \mu_k - \mu_{k-1} \quad (3)$$

Step 2: let define Δ_k as the absolute value of the variation of the error between different consecutive iterations:

$$\Delta_k = |\varepsilon_k - \varepsilon_{k-1}| \quad (4)$$

Step 3: let define ν_k as the cumulative variation of ε_k, for each iteration from the beginning:

$$\nu_k = \sum_{i=1}^{k} \varepsilon_i \quad (5)$$

Step 4: let define ε^*_k as the updated variation between the current and the previous iteration. It will be used to update the current estimation of μ accordingly to the average variation of the error as it is described in the step below.

Step 5: if from iterations i_A *to* i_B, Δ is bigger than a threshold τ, the estimation of μ during interval of iterations $[i_A, i_B+1]$ will be calculated as:

$$\mu_k = \mu_{k-1} + \varepsilon^*_k \quad (6)$$

with,

$$\varepsilon^*_k = \frac{\nu_{i_B+1} - \nu_{i_A-1}}{(i_B+1)-(i_A-1)} \quad (7)$$

IV. Experiments and Results

In order to show the pertinence of our proposed techniques in real-time tasks, we have performed a series of experiments considering different settings: outdoors, unobstructed indoor space, corridor indoor space, static and dynamic settings, different velocities, and different transmission rates. Due to space constrains we are showing here only the results of three experiments, all of them performed in a long and narrow indoor corridor (30 meters long by 1.22 meters wide). Micaz motes were used in all the experiments.

The transmitted packets contained only the transmitter ID. At *Rx*, it recovered the information encapsulated in the packet and obtained its RSSI. Histogramic analysis and the compensation method were applied to the collected RSSI data every 100 packets. In Table 1, there is a summary of the different settings we use for each one of the experiments.

Experiment #1 considers a static setting (i.e. fixed *Tx-Rx* distance) with *Rx* placed on the middle of the corridor. Experiment #2 and #3 are similar being both dynamic settings, but in experiment #2 *Rx* is moving closer to *Tx* at a constant velocity, and in experiment #3 *Rx* is moving away.

Experiment	**1**	**2**	**3**
Initial *Tx-Rx* distance	15 m.	30 m.	0.6 m.
Final *Tx-Rx* distance	15 m.	0.6 m.	30 m.
Approx. velocity	------	0.68 m/s	0.62 m/s
Transmission rate	4 packet/s	50 packet/s	50 packet/s
Collection time	725 s.	44 s.	48 s.

Table 1. Summary of experiment settings

Figure 3 shows the raw RSSI data obtained from the first experiment on the background, the results from the histogramic analysis, and when applying the compensation method. For figure 4, we use the data of figure 3 to estimate distance by applying the log-distance path loss model for indoor channels [21]:

$$RSSI(d) = P_T - \left(PL(d_0) + 10\eta \log\left(\frac{d}{d_0}\right) + X_\sigma \right) \quad (8)$$

where PL is the path loss at the reference distance d_0 (=1m), P_T is the transmitted power, η is the path-loss exponent and X_σ is a zero-mean gaussian random variable with standard deviation σ. In figure 4 it is included also the indication of the real *Tx-Rx* distance obtained by using a measuring tape. The results for the other experiments are plotted in figures 5 and 6 for experiment #2, and figures 7 and 8 for experiment #3.

The plots in figures 3, 5, and 7 show typical results for raw RSSI data using low power radios either on indoors static or dynamic settings. The random variations due to small-scale fading are very pronounce and not suitable for any precise calculation of distance. The histogramic analysis is successful in bringing those changes to a minimum, although it still exhibits some abrupt ones, like those peaks around t=150 and t=650s on figure 3. The compensation method takes it one step further. From figure 3, it is evident that when combining both methods, the resulting plot remains flat as expected when both *Tx* and *Rx* are static. For the dynamic configuration, the results on figures 5 and 7 show that the two proposed methods achieved the desired attenuation of the effects of small-scale fading, leaving a consistent dataset that is more suitable for estimation of distance using well know propagation models.

The results in figures 4, 6, and 8 show that when preprocessing the data, RSSI becomes a feasible tool for the estimation of distance. This is more evident in the static case where the final outcome surrounds the real value closely. For the dynamic setting, the main result is the attenuation of the strong changes when calculating distance. Although not as close to the real value as in the static case, it still hovers the real value nearly enough to see a correlation between RSSI and distance.

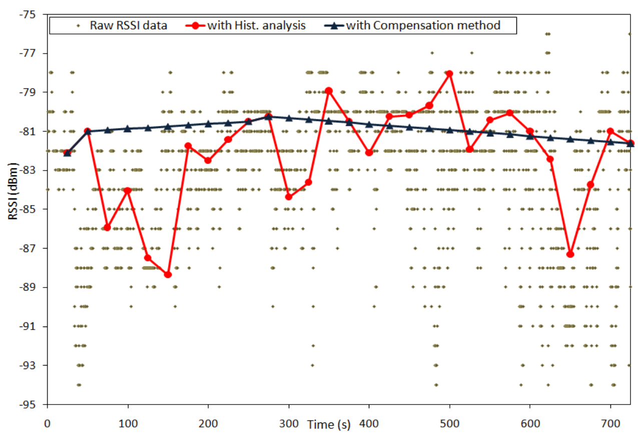

Fig. 3. Experiment #1 – RSSI for static configuration in narrow corridor.

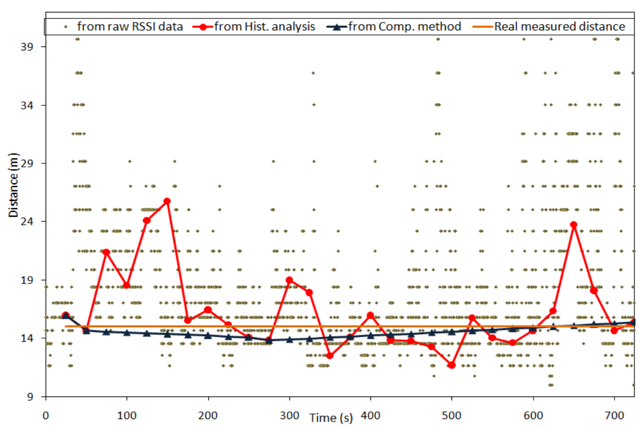

Fig. 4. Experiment #1 – Estimation of distance for static configuration.

Finally, it is worthy to mention that the results from our proposed techniques, and the estimation of distance, vary heavily with the change of the transmission rate, the velocity of the mobile agent, the threshold (τ) and the path-loss exponent (η).

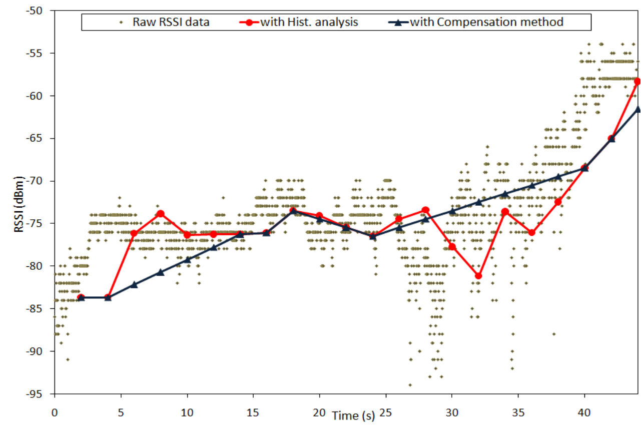

Fig. 5. Experiment #2 – RSSI for dynamic setting *Rx* moving closer to *Tx*.

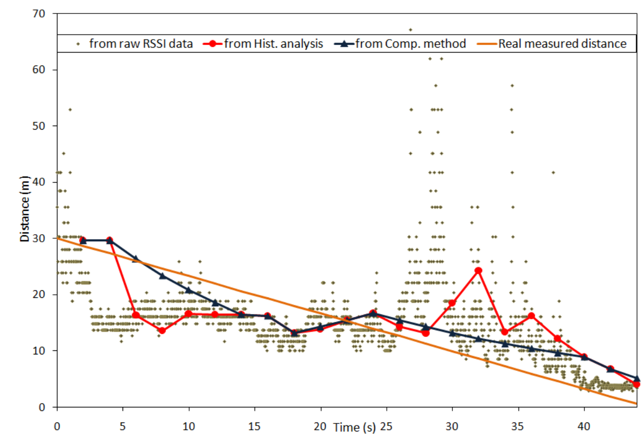

Fig. 6. Experiment #2 – Estimation of distance for dynamic setting.

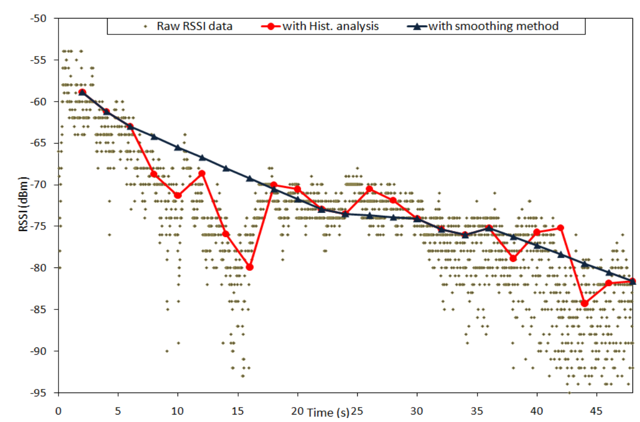

Fig. 7. Experiment #3 – RSSI for dynamic setting *Rx* moving away of *Tx*.

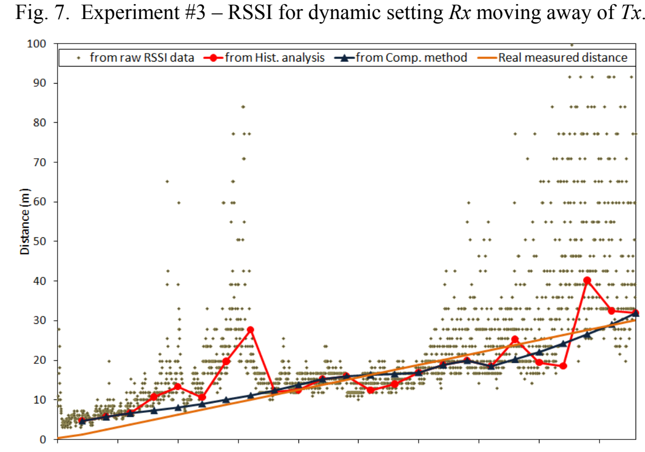

Fig. 8. Experiment #3 – Estimation of distance for dynamic setting.

That is, the change on value of any of these parameters will produce different results to those shown in this paper. Consequently a tuning process is required beforehand in order to obtain optimum results as shown.

V. Conclusions and Future Directives

The localization of wireless agents is an important and challenging task that needs to be addressed if accurate real applications wanted to be put to the test beyond the always forgiving simulation environment. Our approach is based on a simple idea that can be developed efficiently for low-energy, low-processing power agents such as the Micaz motes. Our results show that the RSSI has the potential of being a valid tool for the estimation of distance in indoor settings when used in combination with data analysis techniques.

The results give a good basis in order to extend our analysis to more complicated scenarios: multiple agents, more complex movement patterns, and multi-channel interference. Also, the optimization of the parameters that impact the output of the preprocessing techniques will yield more accurate results. In such an optimization process, it should also be considered the parameters that affect the estimation of distance such as the path-loss exponent, if the log-distance path loss model is used.

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