RSSI Signatures for Outdoor WSN Applied to IoT and Smart Campus

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Abstract - The implementation of IoT solutions in open environments brings challenges regarding the characterization of radio frequency signals, which impacts in the performance of the network. In this paper we propose the identification of radio frequency signal signatures of sensor nodes located in open environments. We analyse the results of a field test conducted in a rural property. For the signatures identification, we employed strategies that use the original signal and the signals as estimated by moving average and Kalman filters. The results indicated the feasibility of using Kalman filters and the original signal to create rules to identify the signal signature.

Keywords - Wireless Sensor Networks; WSN; Link Quality Estimator; Kalman Filter; Moving Average Filter; RSSI.

I. Introduction

The advent of the Smart City in the context of the Internet of Things (IoT), will depend upon the massive deployment of Wireless Sensor Networks (WSN) in outdoor environments [1]. For that reason, it is interesting to characterize the open environment and identify the particularities of signal propagation, so to work in the development of network management strategies and the elaboration of metrics to be used in Quality of Service (QoS). These metrics will be useful in the preparation of Service Level Agreements (SLA) [2].

In this paper, we propose the creation of a strategy to identify the signature of radiofrequency signals through the analysis of Received Signal Strength Indicator (RSSI) and its treatment by means of Kalman and moving average filters. This work compares these two strategies and identifies their utility in QoS metric creation for WSN. This work approaches the management of autonomous networks and the identification and characterization of radiofrequency signal behaviour for different scenarios in open environments. These management strategies can then be used in the preparation of SLAs.

This article is organized as follows: in Section II, we present a literature review that provides theoretical basis for the proposal; in Section III, we introduce the criteria proposal to identify the radiofrequency signal signature in open environments; in Section IV, we present the materials used for the data collection in a rural property, in Section V, we show the collection methods used; in Section VI, we present the results; in Section VII, we bring a discussion about the results, identifying the pertinence of each method and in Section VIII we, present the conclusion and future work.

II. Related Work

In this section we map the articles found in the literature regarding the scope of this work. We researched for ways of estimating the radio channel for WSN, evaluating the quality of the radiofrequency communication, based on WSN operating in the 915 MHz and 2.4 GHz. In [3], an estimation-based model using Kalman filtering was presented, it is a software implemented predictive filter. In this model, the experimentally obtained data was processed by the filter, producing an estimated RSSI. From that estimation and the system noise (which depends on the type of hardware, antenna characteristics, operating temperature, frequency, among other factors), it was possible to obtain the Signal-to-Noise ratio (SNR) and then trace the Packet Success Rate (PSR) as a function of the estimated RSSI [3].

In [4], [5], several strategies for channel estimation and radio link quality measurements were presented. They went from RSSI-based Hardware estimators, Link Quality Indicator (LQI) and PSR to software implemented indicators, such as simple and exponential moving average filters, Kalman filtering, estimation of stationary probabilities by Markov chains, fuzzy logic, among others. Also, temporal and spatial correlations showing how the received signal intensity varies over time and space and strategies involving RSSI were presented [5]. The analysis over time consisted in varying the transmission time between data packets. The temporal analysis consisted in varying the environments in which the experiments were carried out.

It is well known that wireless communication is sensitive to obstacles, such as people, walls, trees, buildings, among others [5].

III. Proposed RSSI Signature Mapping Criteria

In this section, we present the proposal for the elaboration of a RSSI signature mapping criteria, i.e. how the RSSI behaves over time and space, considering what was said in Section II.

In WSN, it is frequent to estimate the quality of the radio frequency (RF) link as a function of hardware parameters, such as RSSI, LQI and PSR [4], [5]. In this work, the RSSI was the parameter selected to develop the statistical analyses and evaluations regarding the RF link behaviour, as there are many related works in the literature that addresses this metric [5]. In addition to the conventional tools for statistical analysis such as average, maximum, minimum and standard deviation, it was decided to estimate the down and uplink RSSI using Kalman filter and moving average. The objective was to find the signature of the radio signal, identifying patterns considering both the instantaneous signal and the values treated by Kalman filters and moving average. In addition, an evaluation and comparison of these two strategies was made.

IV. MATERIALS

As the farm where the tests were carried out has approximately 78 hectares, the long range BE990 module was used. It consists of the CC1101 radio transceiver, an ATMega 328 microcontroller and a CC1190 power amplifier [6]. The total power is of 26 dBm (0.5 Watts) at the output of the amplifier and the distance covered is greater than 5 km, which was enough for the tests. The BE990 operates in the industrial, scientific and medical band (ISM) of 915 MHz. It is certified by the Brazilian National Telecommunications Agency (ANATEL), and its sensitivity is close to -112 dBm [6]. Figure 1 shows the BE990.

Figure 1. Module BE990.

The sensor nodes were equipped with the DK106 application board. We assembled four Sensor Nodes (SN) and a base radio station (ERB). Figure 2 shows the ERB and one of SN. Each SN relayed to the ERB data regarding: the link RSSI (focus of this work), air temperature, humidity and soil moisture.

Figure 2. ERB and SN.

V. METHODS

The ERB and all four SN were programmed using the Arduino IDE, since the BE990 module is compatible with that platform. For the communication between the ERB and the SN we used the Radiuino protocol [7]. It is a flexible and easy to implement protocol, suitable for the development of applications of WSN. For the tests, we used a point-to-multipoint (star) topology, with the ERB establishing communication with each SN sequentially. Although it is not in the scope of this work, the Radiuino protocol can be adapted to work with dynamic routing, with the objective of covering areas of shading and reaching great distances [8].

The data gathering was done by a central processing unit, using a network management script, developed in the Python programming language [9]. For the visualization of the data, a Zabbix server [10] was used, as it offers a user friendly graphical interface for the benefit of the clients.

The system was set up as follows: the network manager software requested data from the SN; the ERB then, in turn, sent a data packet to each SN, upon receiving it, each SN replied with a data packet containing the requested data. The ERB received the packet and, via Serial UART communication, updated the manager software; the data then was analysed, and the information sent to the Zabbix server.

The system operated for eighteen consecutive days, collecting data. In addition to conventional statistics, such as mean, maximum and minimum and standard deviation, the MATLAB software [11] was used to implement the Kalman filtering algorithm and simple moving average, in order to create rules to trace the RSSI signature. The Kalman filter is a predictive software filter, which objective is to eliminate possible random noise, estimating future values [3].

The equations are based on the propagation and updating of the current state, based in the fact that the future is the present with some corrections and corrupted by random noise [3]. The signal propagation equations are given by (1) and (2):

$$\hat{x}_k^- = \hat{x}_{k-1}^+ \tag{1}$$

$$P_k^- = P_{k-1}^+ + Q \tag{2}$$

Where $\hat{x}_k^-$ and $\hat{x}_{k-1}^+$ are the *a priori* and *a posteriori* state propagation estimates, P_k^- and P_{k-1}^+ are the *a priori* and *a posteriori* error covariance propagation estimates and Q is the state covariance.

The measurement updating equations are given by (3), (4) and (5):

$$K_k = P_k^-(P_k^- + R)^{-1} \tag{3}$$

$$x_k^+ = \hat{x}_k^- + K_k(z_k - \hat{x}_k^-) \tag{4}$$

$$P_k = (1 - K_K)P_k^- \tag{5}$$

where K_k represents the gain of the Kalman filter, R is the noise in the module receiver and z_k is the gross RSSI value collected by the Python script.

In the experiments, the state covariance Q was 0.5 and the receiver module noise R was 10 dBm. The moving average corresponds to a sliding window average, allowing the average value to be updated in real time. For this reason, compared to the average, the moving average provides more information about the radio communication since the average value is always updated based on the number of samples in sliding window. For these experiments, we used a sliding window with ten samples.

VI. RESULTS

In this section we present the results from only one SN since those can be replicated to the others. The SN selected was the node 1 as it was powered by mains power generating a larger volume of data if compared to SN powered by batteries, as those had to made use of sleep mode strategies. Tables 1 and 2 show basic statistical analyses: mean, standard deviation, maximum and minimum for the RSSI down and uplinks, respectively.

TABLE 1. BASIC DOWNLINK RSSI STATISTICS FOR SN 1.

RSSI Downlink - Sensor node 1	
Average	-82,65
Standard deviation	2,08
Maximum	-74,5
Minimum	-99,00

TABLE 2. BASIC UPLINK RSSI STATISTICS FOR SN 1.

RSSI Uplink - Sensor node 1	
Average	-79,05
Standard deviation	2,30
Maximum	-72,00
Minimum	-100,50

Figures 3 and 4 show the RSSI after processing by the Kalman filter.

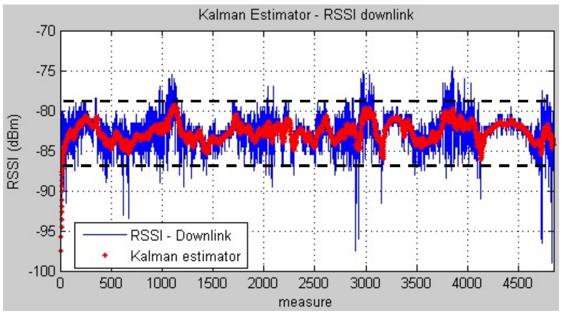

Figure 3. Downlink RSSI – Kalman Estimate.

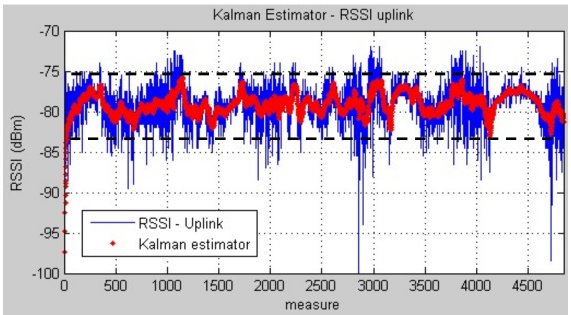

Figure 4. Uplink RSSI – Kalman Estimate.

In Figures 5 and 6, an estimate was made using the moving average. The blue lines are the RSSI original values, obtained by the Python script, while the red lines represent the estimates, that is, the outputs of the Kalman filters and the moving average.

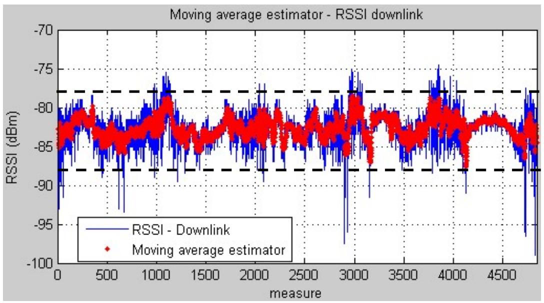

Figure 5. Downlink RSSI – Moving Average Estimate.

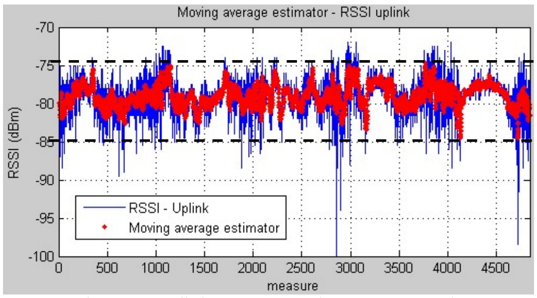

Figure 6. Uplink RSSI – Moving Average Estimate.

VII. RESULTS EVALUATION

According to Tables 1 and 2, we observe a reasonable difference between the maximum and minimum RSSI, which can be justified by the value of the standard deviation. When comparing the down and uplink averages, we observed a variation of 3dB, indicating a small asymmetry. In the outdoor environment where SN 1 was located, there are several obstacles, such as poles, trees, motors, electric pumps (potentially generating electromagnetic noise), metal grids, among others. In addition, the SN 1 was located 700m away from ERB, without a line of sight.

Using the results shown in Figure 3, it is possible to observe that the downlink RSSI processed by the Kalman filter causes a smoothing of the radio signal, allowing for the drawing of future RSSI estimates, eliminating possible random perturbations. This is evident in Figure 4, between measurements 2500 and 3000. There that the -100.5dBm point, which was the minimum uplink RSSI value (also shown in Table 2), was discarded in the process, because a just single measurement don't have a significant impact for a output signal in Kalman and moving average estimators. In Figure 5, we can observe that the moving average filtering also generated a RSSI smoothing (in the same way as the Kalman filter), however with an estimate more like the original signal. In both methodologies, it is notable the existence of possible RSSI signature rules, both for up and downlink. For example, in Figure 3, the Kalman estimated RSSI remained between -79 dBm and -87.5 dBm. This means that, according to the estimated value, the RSSI must follow this same pattern and stay in this range for most of the time. The other rules are shown in Table 3.

TABE 3. RSSI SIGNATURE RULES.

Rules of RSSI behavior		
	Kalman Filter	Moving Average Filter
Downlink	-87,5 ≤ RSSI ≤ -79,0	-87,5 ≤ RSSI ≤ -77,0
Uplink	-83,5 ≤ RSSI ≤ -75,0	-85,0 ≤ RSSI ≤ -75,0

Comparing the Kalman filtering to the moving average in terms of efficiency, the former results in a more smoothed RSSI curve, due to the parameter values used in the algorithm. For example, for Kalman filtering, both the state variable and the measured value can be corrupted by a zero average Gaussian white noise perturbation with a certain covariance, allowing for more sensitive statistical analyses.

The moving average is a good strategy to estimate the average over time, but it is less complex than the Kalman strategy, which in turn performs the data treatment taking into account several external factors (number of network devices, random sensor noise, initial values, etc.) [20]. In addition, a decision was taken to work with smaller sliding windows for the moving average, considering that the larger the window, the greater the processing. In this way, it is possible to estimate the development of efficient statistical tools to estimate the quality of the RF link, and then discover the signal signatures in time and space.

VIII. CONCLUSIONS AND FUTURE WORK

The focus of this work was to collect RSSI data from one SN in the network and analyse how the radio signal behaves over time and space. For this, simple statistical strategies were used as mean, standard deviation, maximum and minimum and later, Kalman filtering and moving average. The objective was to analyse the values estimated by the filtering methods and then draw behavior rules to characterize the down and uplink RSSI signatures. Results from this work showed that through estimations, it is possible to draw rules for signal behaviour, as can be seen in Table 3. Future work should focus on new rules to make more precise received signal characterizations, seeking a better channel estimation so to guarantee an improved RF link quality. With information regarding the communication behaviour, it will be possible to develop more efficient WSN management strategies, ensuring high levels of QoS in the SLA of the WSN.

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