A Bayesian filtering application on iBeacon-based Indoor positioning system

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Abstract

Indoor positioning systems aim to achieve high accuracy while tracking devices within a closed area. In this sense, Bayesian filters offer an original method to reduce the multipath and obstruction errors related to obstacles. This paper presents a fingerprint-based indoor positioning system using iBeacons tags as receivers. The relation between the RSSI power and the distance from a point source allows the system to compute the position of the tags using RSSI samples on different weighted signals. The Kalman filter then processes the data by comparing the measure to a predicted position. The results on the x-axis position of a tag show a good smoothing of the measures.

1 Introduction

In RFID-based positioning systems different errors related to signal propagation laws reduce the accuracy of the position. GPS systems remain sensitive to signal dissipation and frequency variations related to the propagation through the atmosphere. Besides, the environment surrounding the tracker also impact the position with obstruction errors and reflection errors commonly called multipaths errors. Within a closed area, the propagation errors in the air can be assumed as negligible because of the small distances. However, the second source of error usually gives the highest inaccuracy on the position because of the abundance of obstacles.

2 Fingerprint positioning system

In order to overcome such errors, GPS systems regulary use static references to operate a simple-difference.[2] Fingerprints-based indoor positioning systems follow the same method using a set of calibrations as references. The position of a mobile within the environment covered can then be computed using the K-nearest calibrations.

Our RFID system covers an area of 8m*12m in a laboratory of the University of Queensland. Commonly, the fingerprint systems use a mobile device to calibrate the system in a set of given locations. In our system, the fingerprints are represented by fixed Beacon tags, assuming that every tag is identical. The system is then composed of 4 fingerprints represented by 4 fixed iBeacon tags (blue squares) broadcasting at 2.4GHz and 3 RFID readers (orange) with known locations. We want to track 2 mobile Beacons (M1, M2) with linear trajectories in the room. The locations and trajectories are as following:

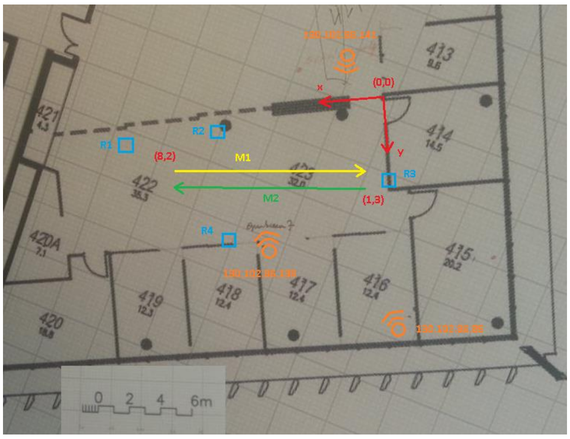

Fig 1. Plan of the laboratory with the different components of the system and the trajectories

3 RSSI Positioning

Mainly, the positioning algorithms for Wireless Sensor Networks (WSN) systems are categorized into two – time based and power based. The time based algorithms use the information carried by the signal such as the time of emission and the time of arrival (ToA) identified by the receiver to compute a pseudo range.[5] Besides, the power based algorithms use the difference between the strength of a received signal and its original strenght to evaluate the position it has been received from. In our system we will use four different strength of signal respectively P1, P2, P3, and P4 from the weakest to the strongest. Then, we balance the different signals to compute the RSSI, giving more weight to the weak signal in order to detect proximity:

$$P_{RSSI} = 4 * P_{1,RSSI} + 3 * P_{2,RSSI} + 2 * P_{3,RSSI} + 1 * P_{4,RSSI}$$

Eq1- weight on the RSSI signals

RSSI is defined as ten times the logarithm of the ratio between the power of the received signal and a reference power. Moreover, the power of a signal dissipates from its point source inversely proportionaly to the square of the distance travelled.[1] Indeed, at a given distance r, the area of emission is the surface S of the sphere with center the point source and radius r. Thus the portion received at a certain location at a distance r is:

$$\frac{P_{ref}}{S} = \frac{K}{r^2} \quad S = 4\pi r^2$$

$$P_{RSSI} = 10 \log\left(\frac{P}{P_{ref}}\right) = K' - c * log(r)$$

Eq.2&3- Relation between distance and RSSI [1]

4 Bayesian filter

Once the position is computed from the RSSI measurements and the relation above, we can process the data to filter the noises. We assume our variables of position linear and normally distributed (white noise). The Bayesian filter is then called Kalman filter, it uses a series of measurements observed over time containing noises and other accuracies and produces an estimation of the position.[4] The filter builds a prediction of the position and adjusts it with various observations from the antenna. The following diagram describes the steps of the filter to estimate the position:[3]

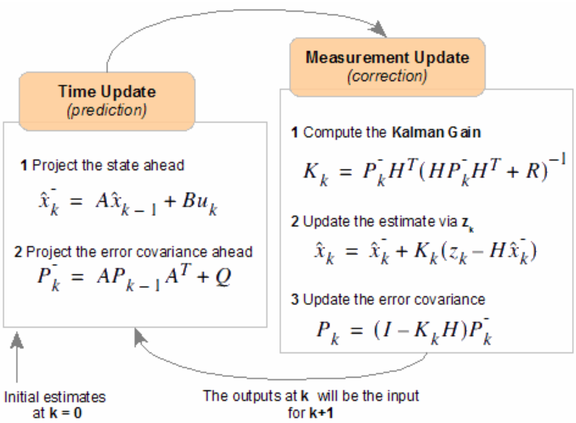

Fig 2. Diagram of the different steps to compute the position within a Kalman filter

5 Results

We record the RSSI data for the tag M1 and we assume the 4-nearest neighbours (K=4) are our 4 fixed tags. After recording the RSSI samples, we obtain the data for our tag from the LOG.txt file modified on Notepad++. Then, we applied the Kalman filter and obtain the following graph of the position of the X_axis as a function of the time. The red dots are the expected trajectory, the black dots are the measures and the green dots are the positions estimated by the Kalman filter:

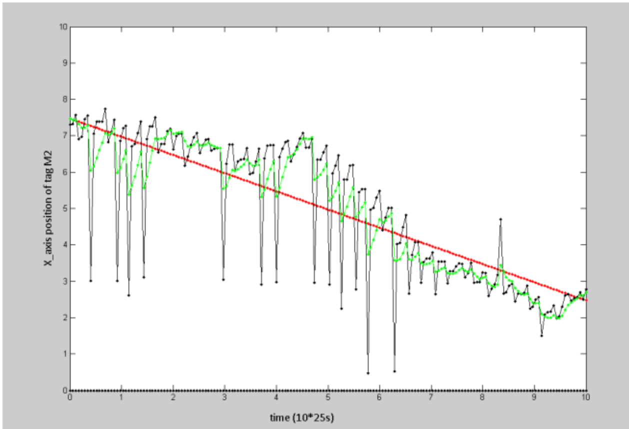

Fig 2. Graph of the X-axis position of the tag M1 as a function of the time.

The results show that the Kalman filter corrects the samples the less accurate and fits the measure closer to the expected trajectory. However, it is yet hard to evaluate the Kalman convergence with such parameters (few samples, few references, few readers). The filter would need more information to filter the noises and inaccuracies more efficiently.

References

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