Improving Distance Estimation in Object Localisation with Bluetooth Low Energy

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***Abstract*—The arrival of Bluetooth Low Energy (BLE) creates opportunities for great innovations. One possible application is object localisation. We present our unique software that can track objects and help finding their location within a house perimeter. With the help of Bluetooth beacons that can be attached to different items, we can estimate the distance between the mobile device and the object with an accuracy of less than one meter. In this paper, we describe our system and the techniques we use, the experiments we conducted along with the results. In addition, we briefly present some work in progress using an indoor positioning system that helps locating the objects.**

***Keywords*—object localisation; mobile application; Bluetooth Low Energy**

I. INTRODUCTION

Improving the quality of life of elderly people with the help of technology is a key topic in the current research. There are numerous advantages of using technology in order to complete tasks that otherwise would be very difficult for a human. Technology can help elderly overcome different challenges. One particular problem that we try to solve is finding lost personal items. Locating objects has a wide variety of practical applications, not only for elderly people. On a daily basis people deal with losing important items (like wallets, keys, etc.). Having your phone telling you where a desired item is, or giving you information about how far the object is from you, could save a lot of time and effort for a person. Additionally, it would help people for which it is difficult to remember where they keep such items.

Currently, there exists a wide range of systems and technologies that provide real-time locating. Different technologies include WiFi [1], RFID (Radio-Frequency Identification) [2], ZigBee [2], etc. They all differ in terms of cost, infrastructure complexity, availability, maintenance costs, etc. These differences make each of them more appropriate for certain problems with different characteristics, further presented.

We describe distance estimation improvements when locating lost objects using the Bluetooth Low Energy technology. We developed a unique approach to reduce the noise and lower the error up to 1 meter for short distances and below 3 meters for long distances.

In this paper, we present firstly previous work that is relevant to our research along with some of the existing systems used for locating objects. Next, we provide a detailed description of our proposed model, and the techniques we use. In Section IV, we describe the results of our experiments. Finally, in Section V, we discuss several directions of current and future research along with the conclusions.

II. RELATED WORK

Locating objects is not a new problem. Over the past years, there were many attempts to find a generic solution and currently there are numerous approaches and technologies that address this issue. Each of them is more suitable for certain contexts and constraints that we present below.

One of the most common approaches is tracking objects and their movements in a video sequence, using a camera. This is well suited for traffic, surveillance and robots that need to identify objects based on images [3][4][5]. The vision-based techniques are not ideal in a mobile context, due to several reasons. Firstly, the lost object might be visually inaccessible, despite the fact that it can be close to the person. Secondly, these techniques are very computationally expensive, which makes it not suitable for a mobile device.

A different category of Real-Time Location System is based on WiFi. The main components are the tag (active or passive) that is attached to the object, and the reader, that can establish a wireless communication with the tag. It has been successfully used for autonomous mobile robots [6] and for locating people in the underground (subway) [7]. However, WiFi is better suited to locate smart devices rather than objects.

Although RFID is primarily used for identifying objects, real-time location based on RFID has been studied extensively over the past years, with applications in health-care [8] and warehouse operations [9]. However, RFID id not a technology accessible to most of the people, expensive devices (RFID readers) are required.

Bluetooth Low Energy has a lot of potential for object tracking. It is a mainstream technology available on latest mobile devices. The distance between the tags and the readers can reach up to 50 meters.

Bluetooth has been successfully used for indoor positioning. L. Pei et al. [10][11] present their system that finds the location using fingerprinting. The position is calculated using the RSSI (Received Signal Strength Indication) probability distribution combined with the Weibull distribution. The accuracy obtained has a standard deviation of 10 meters. A different approach is proposed by F. Subhan et al. [12] that use trilateration for computing the position. The distance is estimated based on the

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radio propagation model combined with the Gradient filter for reducing the noise. The accuracy obtained using this method is 2.67 meters.

In contrary, the technology proposed in our paper is based on BLE, as most portable devices come already equipped with it, hence we can benefit without additional cost and effort. The system setup cost is low which makes it more affordable in comparison to above mentioned solutions. In addition, the accuracy of the distance we achieve in our system is proven to be higher than in previous approaches.

There are several recent commercial products that offer the hardware and software to help finding objects [13][14], based on BLE. However, they all give only information regarding the intensity of the communication, or whether the object is in range or not.

III. Solution overview

Our goal is to provide a mobile application that helps people find their belongings, without the need of expensive infrastructure. Secondly, the set-up must be minimal and easy to use by a person without technical background. Thirdly, the technology must be accessible to everyone who owns a smart device.

Based on all these criteria, Bluetooth Low Energy was chosen. Our system uses the StickNFind [14] beacons which can be attached to the objects. Their battery lasts up to one year based on 30 minutes a day use [14].

The distance between the emitter and the receiver can be estimated using the Log Normal Shadowing model (LNS)[15] detailed in (1).

$$P_d = P_0 - 10n\log(\frac{d}{d_0}) + X_\sigma \quad (1)$$

- P_d represents the power of the signal strength (RSSI),
- P_0 is the offset (the signal strength at the reference distance d_0),
- n is a coefficient characteristic to the device and the surrounding environment, d represents the distance between the emitter and the receiver,
- X is the noise added to each measurement.

The parameters that can be tuned are P_0 and n. These are specific to the environment and the layout of the room. Using the appropriate values of P_0 and n we can estimate the distance between the receiver and the emitter, using (1). Computing the distance is not just a simple estimation. The process consists of several steps showed in Figure 1.

A. Data Acquisition

The StickNFind beacons broadcast data one time per second when they are not paired with the smart device. Once paired, they broadcast every 100 milliseconds. The RSSI (Received Signal Strength Indication) value of the Bluetooth signal received by the mobile device is used for estimating the distance between the beacon and the mobile device.

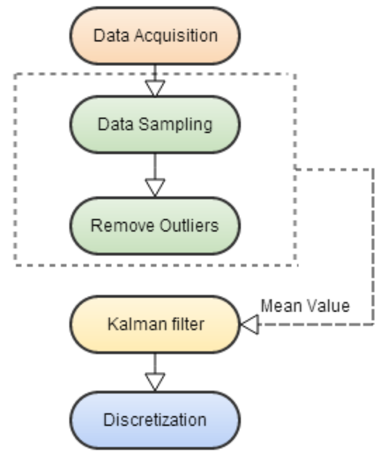

Fig. 1. Diagram

B. Data Sampling

The Bluetooth signal is not sufficiently stable to estimate the distance based solely on one measurement. In Figure 2, we show an example of different measurements of the RSSI for the same distance between the emitter and the receiver. In order to reduce the noise and attenuate the extreme values, we use a sample of ten measurements for computing the distance, instead of a single one. For every value of the distance, we use the last ten measurements to which we apply filtering techniques which we detail later.

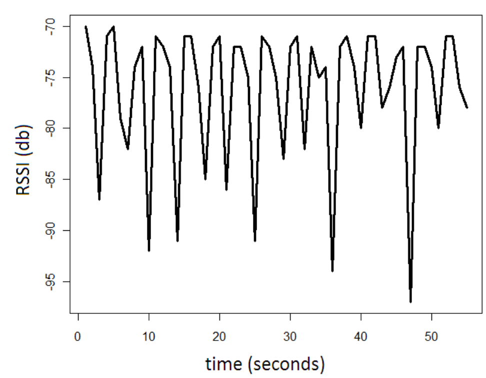

Fig. 2. RSSI variation for a fixed distance

C. Outliers Removal

The experiments (Figure 2) show that the signal is very unstable. Due to noise, spikes appear in the signal which should not be taken into consideration. We remove the outliers with the help of Chebyshev Outlier Detection based on Chebyshev's theorem detailed in (2). We apply the inequality for k=2, which was proven to be a good choice according to other researchers [16]. As a consequence of (2), 75% of the data must be in the range of maximum two times standard deviation distance from the mean value. Based on this probability, we remove all the values that fall outside the domain. The values inside the domain are used to calculate the mean value.

$$Pr(|X - \mu| \geq k\sigma) \leq \frac{1}{k^2} \quad (2)$$

D. Filtering

We consider the mean value calculated above as the current value of the signal strength. We use the Kalman filter [17] to better estimate the mean, which is proven to add more stability to signal.

E. Discretisation

The final step is to approximate the value of the distance with the closest value from a predefined set. From a human point of view, the little variation of the value creates more difficulty in interpreting the distance. For instance, we approximate all the values between 0.76 and 1.25 to 1, all between 1.26 and 1.75 to 1.5, etc. This gives better stability to the estimated distance displayed to the user. In the same time, the little error added does not create an impediment in the process of finding the object.

IV. RESULTS

A. Tuning the parameters

The distance can be estimated based on the RSSI value as shown in (1). The different parameters described in (1) can be tuned, in order to acquire a good accuracy of the estimation.

We conducted measurements at distances up to 25 meters. A set of measurements contains 20 values of the RSSI for every value of distance. The average of the set is calculated. The parameters are further calculated using linear regression, that minimize the error of the measurements. The parameters are used in estimating the distance between the beacons and the mobile device. The best values of these parameters were found to be $P_0 = -63.506$ and $n = 1.777$. We used this values in all our experiments.

B. Experimental setup

The experiments were conducted in two different ways. For the first set of experiments the beacon was placed at a distance of 0 meters from the mobile device, and moved with a constant speed from 0 to 18 meters away from the target. The RSSI was measured and the distance computed based on (1), and following the steps presented in Section III. The results obtained are shown in Figure 4, Figure 5 and Table I.

For the second set of values, we performed different measurements of the RSSI at distances from 0 to 25 meters. In Figure 3 we show the distance computed based on the RSSI value, the estimation using our method, along with the actual measured distance.

C. Results

We can clearly see an improvement of the distance estimation as a result of applying Chebyshev's theorem combined with the Kalman filter. Moreover, the discretisation of the distance values adds stability and reduces the noise as shown in Figure 4.

In Figure 3, we plot the estimated distance against the measured distance between the tag and the smart device. The points tend to be closer to the first diagonal (pictured in green) when the distance is smaller which shows that we obtain a smaller error for a shorter distance. This has a direct implication on the process of finding an item. The closer we are to the object, the more accurate the distance becomes, which makes it easier to find the object.

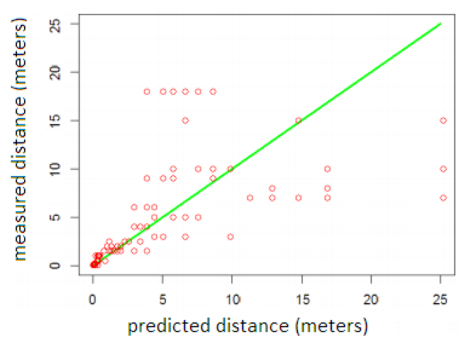

Fig. 3. Estimated distance against measured distance

In order to have a numerical quantification of the error, we defined 3 domains of accuracy for which we compute the average error in meters, and as a percentage. The first chosen range (4 meters) is based on the average room size in the typical elderly residence we collaborate with. This will give us an indication of the efficiency of our system, in the perimeter of a room. The second domain (4-10 meters) corresponds to the average overall length of the whole apartment. The last range (10-18 meters) represents the size of bigger, non typical household.

We show the results in Table I. The first two rows of the table show the error produced when we estimate the distance based on the signal measurement without any filters applied. Although the absolute value seems to increase with the distance, the percentage decreases. On the other hand, the use of our techniques produce different results, as we can see in the third and fourth row. The average error is roughly 3 times better after applying the filters, with an average error below one meter for distances up to 4 meters. Even though an error of 43% can be considered not reliable in certain circumstances, it is a significant improvement in the context of our application. While searching for a lost item, this accuracy gives a good indication on how close the object is. Additionally, the average error obtained with our approach is proven to be smaller than the previous approaches found in the literature [12].

TABLE I. Error results

Distance	0-4 meters	4-10 meters	10-18 meters
Error Measured %	182%	127%	111%
Absolute value Measured	3.61 m	8.95 m	8.95 m
Error Filtered %	43%	34%	36%
Absolute value Filtered	0.865 m	2.45 m	2.90 m

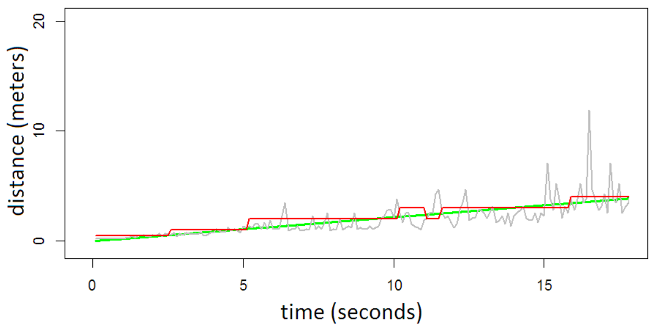

Fig. 4. Distance over time

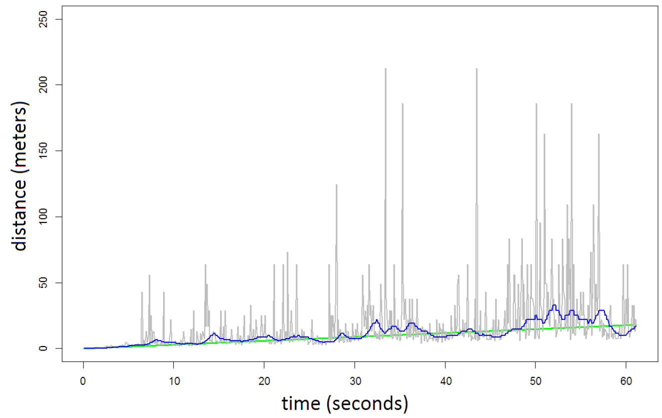

Fig. 5. Distance over time

In Figure 4 and Figure 5, we show the evolution of estimated distance for a moving receiver, as described in Section IV-B. On the x-axis we have the number of discrete values for which we measured the RSSI. The green straight line shows in both pictures the measured distance between the beacon (receiver) and the emitter (the tablet in our case). In Figure 5 the estimated distance based on the RSSI is shown in grey, while the value computed with our method is displayed in dark blue. Our method is clearly improving the distance estimation. We show the results for short distance (lower than 4 meters) in Figure 4. Similar to Figure 5, the green line represents the actual distance, and the grey one shows the estimated value based on one RSSI value. In red we show the values computed using our method. The stability is clearly improved with our method, and the extreme values affect very little the distance estimation.

It is important to mention some limitations that our system still has, which will be addressed in the future. Firstly, the effect of the battery level of the beacons is not studied yet. Additionally, the setup of our experiments didn't include walls or other obstacles that can interfere and increase the noise.

V. Conclusion and Future Work

We presented our model that can successfully guide people into finding their lost items. As opposed to the currently available products which give only a non quantifiable information about how close the object is, our application can locate objects by estimating the distance between the BLE beacons with a good accuracy. We showed that Chebyshev inequality combined with the Kalman filter can be successfully applied to Bluetooth. In addition, discretising the distance adds a certain stability to the signal, which makes the application easier to use from a human-machine interaction point of view.

We are currently working on a more advanced version of the application that is able to locate the object in the perimeter of the home. We use an indoor positioning system to locate the user, and based on the person's movement (location at different moments) and using the different distance between the person and the object we can determine the location of the object. The location is displayed as an area and not as a point.

Lastly, we will study the impact that the battery level and the interference of obstacles have on the distance estimation.

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References

[1] "WIFI", 2014, URL: http://standards.ieee.org/about/get/802/802.11.html [accessed 2014, 09, 19].

[2] "PANs", 2014, URL: http://standards.ieee.org/about/get/802/802.15.html [accessed 2014, 09, 19].

[3] M. Irani, B. Rousso, and S. Peleg, "Detecting and tracking multiple moving objects using temporal integration", *Computer Vision ECCV 1992, Lecture Notes in Computer Science*, Volume 588, 1992, pp. 282-287.

[4] A. Gilbert and R. Bowden, "Tracking Objects Across Cameras by Incrementally Learning Inter-camera Colour Calibration and Patterns of Activity", *Computer Vision ECCV 2006, Lecture Notes in Computer Science*, Volume 3952, 2006, pp. 125-136.

[5] F. Fayad and V. Cherfaoui, "Tracking objects using a laser scanner in driving situation based on modeling target shape", *Intelligent Vehicles Symposium*, 2007.

[6] B. G. Amidan, T. A. Ferryman, and S. K. Cooley, "Data outlier detection using the Chebyshev theorem", *Proceedings of Aerospace Conference*, 2005.

[7] N. Kawaguchi, et al., "Underground Positioning: Subway Information System using WiFi Location Technology", *Tenth International Conference on Mobile Data Management: Systems, Services and Middleware*, 2009.

[8] P. Najera, J. Lopez, and R. Roman, "Real-time location and inpatient care systems based on passive RFID", *Journal of Network and Computer Applications*, Volume 34, Issue 3, May 2011, pp. 980989.

[9] H. K. H. Chowa, K. L. Choya, W.B. Leea, and K.C. Lau, "Design of a RFID case-based resource management system for warehouse operations", *Expert Systems with Applications*, Volume 30, Issue 4, May 2006, pp. 561576.

[10] L. Pei, et al., ”Inquiry-based Bluetooth Indoor Positioning via RSSI Probability Distributions”, *Second International Conference on Advances in Satellite and Space Communications*, 2010, pp. 151-156.
[11] L. Pei, et al., ”Using Inquiry-based Bluetooth RSSI Probability Distributions for Indoor Positioning”, *Journal of Global Positioning System*, Volume 9, Issue 2, 2010, pp. 122-130.
[12] F. Subhan, H. Hasbullah, A. Rozyyev, and S. T. Bakhsh, ”Indoor Positioning in Bluetooth Networks using Fingerprinting and Lateration approach”, *International Conference on Information Science and Applications*, April 2011, pp. 1-9.
[13] ”TrackR”, 2014, URL: http://www.thetrackr.com/ [accessed 2014, 09, 19].
[14] ”StickNFind”, 2014, URL: https://www.sticknfind.com/ [accessed 2014, 09, 19].
[15] T. S. Rappaport, ”Wireless communications principles and practices”, *Proceedings of Aerospace Conference*, 2002.
[16] B. G. Amidan, T. A. Ferryman, and S. K. Cooley, ”Data outlier detection using the Chebyshev theorem”, *Proceedings of Aerospace Conference*, 2005.
[17] R. E. Kalman, ”A New Approach to Linear Filtering and Prediction Problems”, *Transaction of the ASMEJournal of Basic Engineering*, 1960, pp. 35-45.

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