BLE Indoor Localization Based on Improved RSSI and Trilateration

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Abstract **Bluetooth low energy (BLE) operating in the ISM band is prone to signal fluctuations, which affect the received signal strength indicator (RSSI). RSSI is the backbone of most widely used localization algorithms and thus such fluctuations will have a negative impact on the location estimation accuracy. This paper proposes an accurate solution for indoor localization for medical applications. This work shows how to overcome RSSI instability due to equipment and environment, and to calculate the distances of a target from readers. Then the distances are used to get the coordinates of the target by means of improved trilateration algorithm. The proposed localization is based on the following: scanning only one BLE advertising channel, introducing a hard fluctuations removal filter, a weighted Kalman filter before distances calculation, and a weighted trilateration for position calculation. Test results confirm that the proposed system has an error of less than 0.5m for 95% of readings in line of sight testing. Also, the system is scalable and optimized in terms of cost and power consumption.**

Keywords—RSSI, frequency hopping, localization, IPS, RTLS, trilateration, BLE, ESP32, Kalman filter

I. Introduction

Indoor positioning is a key technology for smart buildings with applications in shopping malls, smart museums, hospitals and warehouses. We focus in our research at designing a hospital infection control system by tracking the exact location of the health personnel and detecting whether a sterilization action occurred after a direct contact with patients. Bluetooth low energy (BLE) was adopted as the wireless technologies for indoor positioning system (IPS). BLE is widely supported by many vendors. This has eased the operation of identifying devices and obtaining broadcast information at low cost and energy. BLE chips broadcast short packets in specific interval (advertising interval), which gives a good possibility to use that standard in a wide range [1-4].

Many indoor localizing methods based on BLE have proposed techniques such as Angle of Arrival (AoA), Time of Arrival (ToA), and using Received Signal Strength Indicator RSSI [5,6]. Including the AoA and ToA, can lead to a more accurate indoor position. However, a dedicated hardware is needed for their implementation. The positioning method proposed is based only on the Received Signal Strength Indicator (RSSI). This method has been used extensively in literature due to its ease of implementations, however it suffers from lack of accuracy as the BLE signals are affected by the indoor environment [4]. Even at the same location, RSSI values vary according to obstacles and noise.

A BLE chip continuously transmit its universally unique identifier (UUID), major and minor values for identification [5]. To increase the accuracy of indoor localization using RSSI a novel filtering algorithm, based on Kalman filtering is applied. Distance calculation is based on the getting the ratio of the RSSI over the calibrated transmitter power (TxPower). The rest of the paper is organized as follows. Section II describes related work. In Section III, we discuss the fluctuations and instability of the RSSI values and how to overcome them by means of filtering signals. In Section IV, we describe positioning of the target by using improved trilateration. Section V provides the evaluation, experimental results, and concluding remarks, and future work are given in Section VI

II. Related work

The techniques used for wireless indoor localization are mainly based on Received Signal Strength indicator (RSSI), Time of Arrival (ToA), Angle of Arrival (AoA), or on combinations of techniques as described in [2-4, 6]. The BLE Link Layer does not support time synchronization, which makes ToA not applicable for BLE based localization system. Another interesting candidate algorithm is AoA, which requires the reader device to know the angle from the incoming broadcast signal. The standard BLE devices used do not support angle of arrival measurements and therefore the AoA algorithms will be excluded. The RSSI was used widely in many application for indoor localization with BLE due to its simplicity.

A. RSSI

The RSSI is used to evaluate the distance between the target device and the reader node, according to the RF signal propagation model or mapping the RSSI into distances according to a map already saved in database. The higher the RSSI, the lower is the distance between receiver and transmitter. The significant variance in the RSSI measurements leads to unreliable distance calculation [4]. As such, different filtering stages are needed to be applied prior to position calculation. In [7] a combination technique such as maximum ratio combining is used to combine RSSI from the 3 channels of RSSI to mitigate error.

B. Positioning algorithm

Two important algorithms that utilize RSSI from the target object to the reader points are namely, Trilateration and Fingerprinting. The trilateration algorithm is dependent on the RSSI distance estimated from the propagation model applied. Also, good results for indoor localization have been obtained by the fingerprinting technique but this requires a specific solution for each floor with known hardware and distribution of obstacles and walls. In addition, an overhead of two phase

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operations; an offline phase for making the database and an online one for real time position calculations [6,8].

III. Proposed Algorithms

To avoid the RSSI signal fluctuations, we observed the frequency hopped signal received from each of the three advertising channels of BLE using a spectrum analyzer and by observing the spectrum performance. We decided on using channel 37 at 2.402 GHz to avoid interference from the WIFI band as shown in Fig. 1. Different filters such as the average, median, Gaussian and Kalman filters were used to filter the RSSI [1].

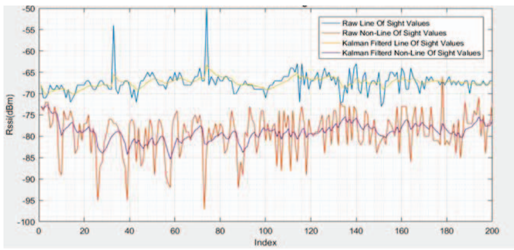

Fig. 1. RSSI values received from 3 channels.

A. Smoothing RSSI filters

The performances of the average filter, maximum filter and Kalman filter were evaluated to decide which filter to apply. Although the maximum filter seems to be the most accurate filter to use as it takes the highest value of RSSI that belongs to the LOS component of received signal, it gave inaccurate results in most cases compared to Kalman filter [9]. Table 1 shows the output and percentage error of mean and Kalman filter at 1 m distance for five samples of readings.

TABLE I. Kalman vs. Mean Filter on RSSI Values

Raw RSSI (dBm)	*Kalman distance*	*Mean distance*	*Kalman error*	*Mean error*
[-68, -71, -47, -51, -52]	0.95	1.06	-5%	6%
[-49, -55, -53, -54, -66]	0.97	0.89	-3%	-11%

B. Proposed Kalman filter

There are three types of Kalman filters; the first type is the Kalman Filter (KF) [3] that was designed for linear systems. The second type is an Extended Kalman Filter (EKF) that was designed for nonlinear system estimation and filtration and the Jacobian must be calculated in every step. And Unscented Kalman Filter (UKF) that is designed for nonlinear function estimation and filtration but doesn`t require calculating of the Jacobian. [10], [11]. Our approach is to use a Kalman filter that changes the certainty factor and transition matrices according to weights given based on the environment.

C. Hard fluctuations removal filter

Fluctuations of the RSSI values can be classified into two classes: Hard Fluctuation and Light Fluctuation. Hard Fluctuations are the RSSI values that have higher standard deviation than the others, and the Light Fluctuations are those who have lower standard deviation as shown in Fig. 2.

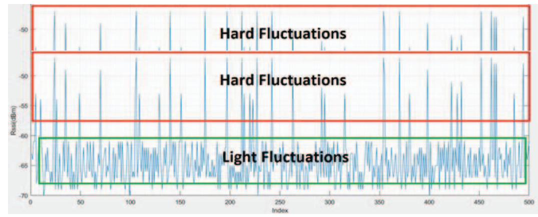

Fig. 2. Hard fluctuations Vs light fluctuations

The output of the designed filter is shown in Fig 3.

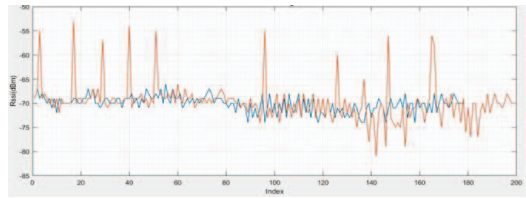

Fig. 3. Filtered RSSI values

The design incorporates a formula for the RSSI value to be accepted in the calculations and is evaluated using the algorithm illustrated in Fig. 4:

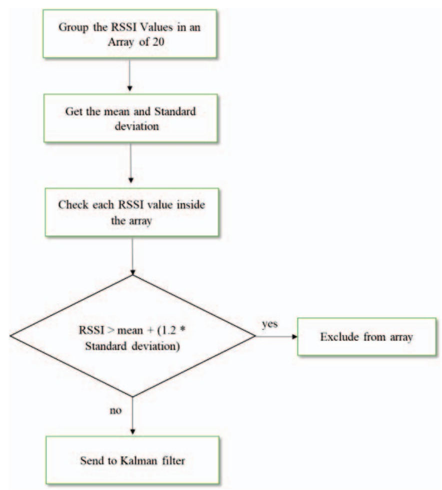

Fig. 4. An illustration of special filter process

The output of the whole filtering system composing of the proposed Kalman filter and the hard fluctuations removal filter is now mitigated from RSSI fluctuations as shown in Fig 5.

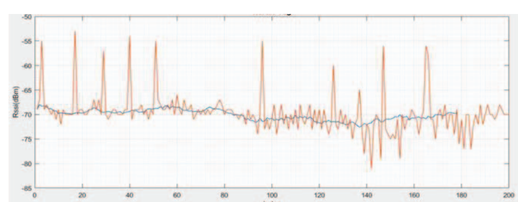

Fig. 5. Kalman Filter applied after the Special filter

D. Path-loss model

Indoor propagation can be modelled using several models such as the common propagation path-loss models such as the ray tracing path-loss model, log-normal shadowing [4] and [12]. Most of these models show that the channel fading characteristic follows a lognormal distribution. RSSI distance measurement generally uses the logarithmic distance path-loss. The model can be expressed as:

$$RSSI = -10n \log(d) + A + X_\sigma \qquad (1)$$

Where d is the distance between the transmitter and the receiver, n is the propagation constant for indoor, its value ranges depending on the environment. A is the RSSI at distance 1 m from the transmitter. X_σ is a Gaussian-distribution random variable. In the proposed system, at the beginning of operation, a large number of readings is taken at 1m to calibrate the values of A and n.

To calculate the distance, the formula shown in (2) is used after calculating the values of A and n. The RSSI and, A values are given dBm, and d is given in meters.

$$d = 10^{(A - RSSI)/10n} \qquad (2)$$

E. Android beacon library model

Like the log shadowing model, Android library model is a parametric model that uses empirical measurements to calculate the constants in a logarithmic equation to map RSSI values to distances [9]. Based on Tx power and average power estimated at 1 meter, Android beacon library uses the following equation to calculate distances in indoor environments:

$$d = (0.89976) \times \left(\frac{PRx}{txPower}\right)^{7.7095} + 0.111 \qquad (3)$$

We also adopted the same equation but with different constants values that are calculated using empirical measurements to fit our BLE chipset RSSI readings as following:

$$d = (1.21112) \times \left(\frac{PRx}{txPower}\right)^{7.560861} + 0.251 \qquad (4)$$

IV. POSITION ESTIMATION ALGORITHM

The calculated distances are used in trilateration, by applying the propagation model as discussed in section III. At least three circles are then formed whose radii are the distances and the centers are the readers coordinates [8], [13].

A. Trilateration

Lateration uses the distances from each reader to the target node calculated from applying propagation model [7] and [11]. Distances between readers and the unknown target can be considered as the radii of the circles with centers at every reader location. Thus, the target location; p is given by the intersection of at least three circles as shown in Fig 5. Ideally, if the circles intersect in one point, the target coordinate are obtained by considering the unique solution from the system above. A problem could be represented by the fact that the intersection will not result in a single point and an area is then defined. Due to measurement errors, the situation of getting a single intersection point is, generally, not realizable and there exist either an area of intersection or no intersection. The approach taken in the proposed solution is to minimize the error and cover all cases to calculate the most accurate place for the target.

- Case I all circles intersect in one point:
  The target node position, P = [x(t), y(t)] can be located using the priori known coordinates of the reference nodes (P1, P2, P3) and their corresponding estimated distances.

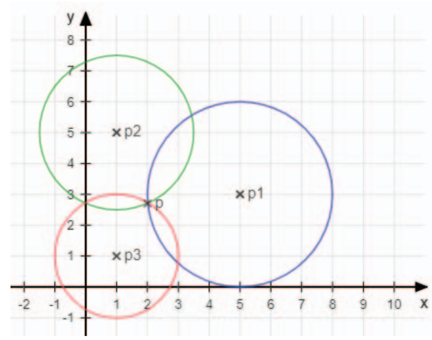

Fig. 6. Trilateration technique

Which can be represented by:

$$d_1^2=(x-x_1)^2+(y-y_1)^2 \qquad (7)$$
$$d_2^2=(x-x_2)^2+(y-y_2)^2 \qquad (8)$$
$$d_3^2=(x-x_3)^2+(y-y_3)^2 \qquad (9)$$

We then solve the set of equations to get one single point P = (x, y).

- Case II Circles intersect in an area:
  As shown in Fig 7., the three circles intersect in 6 points, we remove the outer 3 points and form a triangle of the inner 3 points. The expected position of the target P is the center of that triangle.

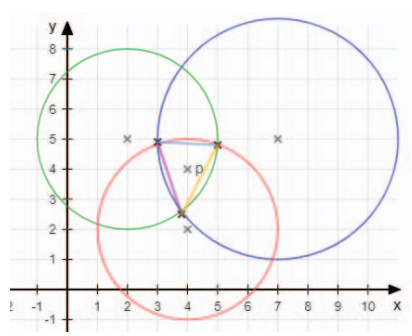

Fig. 7. Circles intersect in an area

- Case III Two circles intersect in an area, the other does not intersect:
  The two intersected circles have two points of intersection; the closer point to the third circle is connected to the center of the third circle by a line. The expected position of the target is the center of that point and the point lying on the perimeter as in Fig. 8.

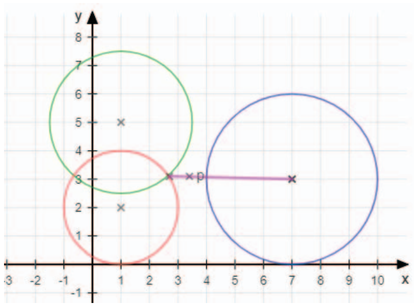

Fig. 8. *Two circles intersect and the third doesn`t*

- Case IV Only one circle intersects with the other two circles:
  Four intersection points. Excluding the outer points and the center of the line formed by the inner points gives the expected target position P as in Fig. 9.

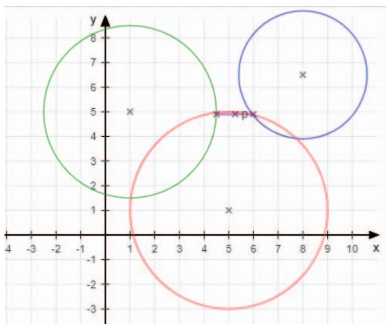

Fig. 9. A single circle intersects with the two others

- Case V Circles do not intersect but tangent to each other:
  The position of the target is most likely positioned in the area formed by the triangle of the tangent points. The center of that triangle is the target position P; Fig. 10.

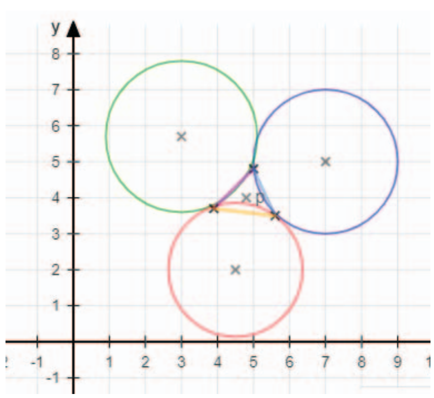

Fig. 10. Circles are tangent

- Case VI Circles do not intersect, and far from each other:
  We draw a circle that is tangent to the three readers circles from the outside, the target is located on the line connecting two points; the first one is generated on the line connecting the smallest two circles closer to the smallest circle than the other with a pre-calculated weight, and the second point is the tangent point between the tangent circle and the big circle. The target is located at a point closer to the smallest circle with the pre-calculated weight.

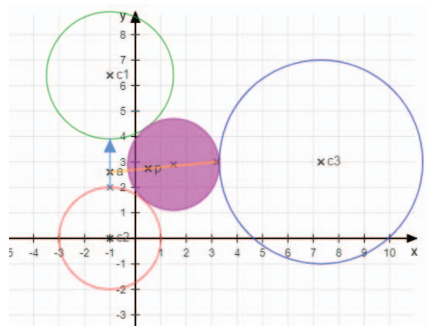

Fig. 11. Circles do not intersect

V. Evaluation and Experimental Results

To evaluate the error performance of the proposed system; a setup of a standard local intensive care unit (ICU) room environment that is 4.4 x 3 m^2 is taken into consideration. ESP32 modules [14] are used as beacons and readers. Three readers are placed on a height of 2.5m from the ground level as shown in Fig 12, they receive RSSI packets from beacons every one second; this time for advertising interval is chosen to save battery lifetime and not to introduce a huge delay in the system. All tests are performed in presence of moving people and interference from different devices. The usage of Kalman and hard fluctuation removal filter excludes the deviation in RSSI readings that may occur due to multipaths and interference from other devices.

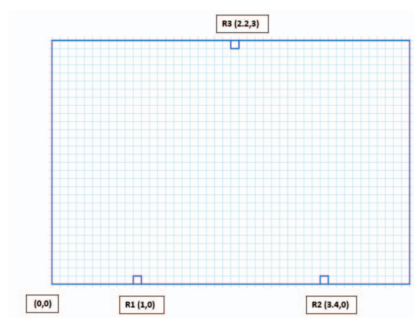

Fig. 12. Illustration of the test environment

The coordinates of the target node are then calculated to get real time information about the position. Initial tests showed that accuracy was fair with a maximum deviation from real values of ~30 cm for line of sight cases. The results are summarized in Table II.

TABLE II. EXPERIMENTAL RESULTS FOR THREE READERS SYSTEM SETUP

Position 1	R1	R2	R3
Filtered RSSI in dBm	-73.38	-87.59	- 82.78
Calculated distance from reader	1.32	3.19	2.38
Actual coordinates	(1.25, 1)		
Best estimated coordinates	(1.375, 0.936)		
Error in best estimated position	(-0.125, 0.064)		
Average estimated coordinates	(1.426, 1.0674)		
Error in average estimated position	(-0.176, -0.067)		
Position 2	**R1**	**R2**	**R3**
Filtered RSSI	-85.477	-91.794	-78.344
Calculated distance from reader	2.77	4.01	1.8
Actual coordinates	(1.25,2)		
Best estimated coordinates	(1.387, 2.3233)		
Error in best estimated position	(-0.137, -0.323)		
Average estimated coordinates	(1.503, 1.774)		
Error in average estimated position	(-0.253, 0.226)		
Position 3	**R1**	**R2**	**R3**
Filtered RSSI	-86.303	-83.091	-75.547
Calculated distance from reader	2.91	2.4	1.51
Actual coordinates	(2.5, 2)		
Best estimated coordinates	(2.533, 1.935)		
Error in best estimated position	(-0.033, 0.065)		
Average estimated coordinates	(2.459, 1.866)		
Error in average estimated position	(0.041, 0.134)		
Position 4	**R1**	**R2**	**R3**
Filtered RSSI	-81.154	-77.363	-83.325
Calculated distance from reader	2.14	1.69	2.44
Actual coordinates	(2.5, 1)		
Best estimated coordinates	(2.465, 0.919)		
Error in best estimated position	(0.035, 0.081)		
Average estimated coordinates	(2.538, 1.196)		
Error in average estimated position	(-0.038, -0.196)		

VI. CONCLUSION AND FUTURE WORK

This paper introduces improvement to BLE localization based on RSSI. Kalman filtering is used, along with a proposed filter to further smooth RSSI values. Choosing to measure RSSI values in a single BLE channel was of benefit to minimize variations in the RSSI values. A weighted trilateration method is also proposed. For future work, we plan to use an IMU sensor [9], [15] to get more information about the target such as acceleration and angle with north, and to apply sensor fusion algorithms to get more accurate position in non-line of sight scenarios.

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