Emender: Signal Filter for Trilateration based Indoor Localisation

Paul Crane, Zhiyi Huang, Haibo Zhang
Computer Science, University of Otago
Dunedin, New Zealand
Email: {pcrane,hzy,haibo}@cs.otago.ac.nz

***Abstract*—Various applications of indoor localisation (e.g. tracking firemen in a burning building, or navigation for the blind) require accurate location estimates. A common indoor localisation approach using commodity mobile phones is to perform trilateration with distance estimates derived from the strength of radio signals, however, they can vary wildly especially indoors. We propose a simple filtering technique to exclude measurements which adversely effect localisation accuracy. Through experimentation in a real building, across state of the art geometries and filtering techniques, our proposed filter shows an increase in accuracy by at least 30% and decrease the time taken to estimate the location by an order of magnitude.**

***Keywords*—Distance estimate, filtering, localisation accuracy, trilateration, signal strength, RSSI, indoor localisation**

I. Introduction

Research efforts for indoor localisation are often concerned with improving accuracy of location estimates. Existing solutions for accurate location estimates often require specialised hardware, or are computationally expensive, or decrease in accuracy when the environment changes (e.g. movement of furniture or people) [1]. Such solutions are not practical for ubiquitous commodity mobile devices with limited resources.

A more pragmatic approach uses the Received Signal Strength Indicator (RSSI) as almost all mobile devices have radios capable of measuring the RSSI as part of their normal operation. There are two general approaches for locating a device using RSSI: fingerprinting or trilateration [2]. Both approaches try to locate a query node using statically deployed anchor nodes and measurements of RSSI.

Fingerprinting constructs a database associating measured RSSI measurements to locations. The resulting location estimate is acquired from the record which closely matches the query RSSI [3]. In order to provide good accuracy a large fingerprint database is needed [2], which requires a large effort to construct. Another consequence of using a large fingerprint database is that it will take more time to search for the closest matching location.

Trilateration, on the other hand, models the radio propagation. The model parameters are tuned using (RSSI measurement, distance) tuples. This tuned model and measured RSSIs are used to estimate the distances between the anchor nodes and query node. Once we have the distance estimates, we calculate the position of the query node using geometry. Compared to fingerprinting, trilateration requires much less data in calculating the model parameters and is faster to estimate the distance [2].

The challenge for the trilateration method is that distance estimates are sensitive to poor RSSI measurements. These measurements are variable [4] which impacts the accuracy of trilateration. Existing approaches to improve accuracy of the location estimates occur throughout the trilateration process, including: radio propagation models [2]; methods of fitting data to the model [5]; and, different geometries [6] [7] [8]. When the model of radio propagation is finely tuned and a good geometric method is chosen, the main localisation errors from trilateration will be largely caused by the short term variability in the RSSI measurements made by the query node. Thus we focus on removing highly variable RSSI measurements from trilateration based approaches.

Many filtering and smoothing approaches were proposed to remove the short term variability or fluctuations of RSSI measurement. However, smoothing over multiple queries requires a longer time to collect enough data to be effective. We will discuss the problems of this approach in more detail in Section II-B. Another approach is to find an appropriate threshold through trial and error and use the threshold to filter out the unreasonable RSSI measurements [9]. But the threshold is sensitive to environmental changes and unique to each environment. We will show in our experiments that the performance of this approach is still not satisfactory.

In this paper we propose Emender, which can exclude poor RSSI measurements based on the commonly used Log-distance Path Loss (LDPL) propagation model. It avoids the long costly data collecting process of previous filtering methods while preserving the advantages of trilateration. As far as we know, this work is the first time that a filter utilises the LDPL model to remove the variability of RSSI measurements for indoor localisation.

The contributions of this work are, firstly, we propose a novel filtering technique, Emender, to identify the RSSI measurements that adversely effect the location estimates. Secondly, based on Emender, we propose a novel trilateration approach to indoor localisation. Thirdly, we conduct thorough experiments in a building to show that Emender can achieve more accurate location estimates in a very short time.

The rest of the paper is organised as follows. Section II gives an overview of the trilateration process and recent work on filtering and smoothing techniques. In Section III we present a localisation scenario to illustrate our approach and derive our filter, Emender. Our testing procedures and environment are discussed in Section IV. In Section V, we present the results from a thorough evaluation in a real environment. Related indoor localisation work using other technologies is discussed in Section VI. Finally, we draw conclusions in Section VII.

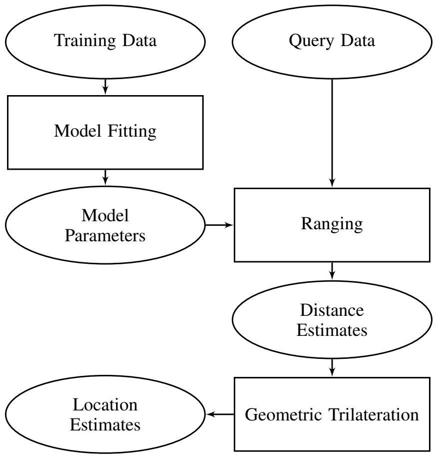

Fig. 1: Generic process of Trilateration. Boxes indicate phases and ovals indicate data or results of computation.

II. TRILATERATION

Trilateration is a three-phase approach depicted in Figure 1. The first phase is *model fitting* which creates a model mapping RSSI measurements to distances. Once the model is available the second phase, *ranging*, uses the model parameters along with the RSSI measurement of the query node, denoted as the query RSSI measurement, to compute distance estimates. Once we have the distance estimates, we can use *geometric trilateration* to compute the final location estimate. Below we briefly outline these phases with a focus on existing filtering and smoothing techniques used in ranging.

A. Model Fitting

The initial phase is to train a model given a mapping between RSSI measurements and known distances. There are different choices for the model in the literature; for instance, a curve-fitting model [10], a polynomial model [11], or a different propagation model - the Friis Equation [6]. In our work, we chose the commonly used LDPL model as shown in (1), though the idea of our filtering method Emender can be applied in other models.

$$P_l = P_{\text{tx}} - P_{\text{rx}} = P_0 + 10\gamma \log_{10} \frac{x}{x_0} + \mathcal{N}(0, \sigma^2) \quad (1)$$

In (1) P_l is the path loss, P_{tx} is the transmission power level, P_{rx} is the received power level, P_0 is the received power at distance x_0 (typically 1m), γ is the environment dependant path-loss factor, x is the distance between the anchor node and query node. The $\mathcal{N}$ parameter is a Gaussian distribution with zero mean and variance σ, used to account for the variations of RSSI.

B. Ranging

The ranging phase generates distance estimates from the tuned model and the query RSSI measurement. It is important to remove the short term variability of RSSI measurements in order to improve the accuracy of localisation. We will discuss existing filtering and smoothing techniques and our novel contribution of Emender at this phase in Section II-D.

C. Geometric Trilateration

During the geometric trilateration phase, we use the distance estimates from ranging, along with the known positions of the anchor nodes, to produce a location estimate. It can be performed via algebraic (e.g. the use of simultaneous equations [12]) or geometric means, though both are mathematically equivalent. We briefly discuss advantages and disadvantages of recent geometries in the literature.

A basic geometric method is to use circles centred on the anchor node, with the radius set to the distance estimate. If the distance estimates are accurate then there will be a single point that results from the location estimation calculations. This is the method used by the Global Positioning System (GPS) [2]. While this is simple to compute it does not handle non-intersecting geometries well (the centre of the minimum enclosing disk of intersection points is used as the location estimate in these cases). Secondly, Bounding Boxes compute the minimum and maximum of the coordinates [6]. This is quick to compute, the resulting position is susceptible to the outlier of RSSI measurements. More recent techniques overcome these shortcomings. The Geo-n approach [7] uses circles as their base geometry but includes a method of calculating approximate intersection points when the geometry does not overlap. The main disadvantage is that these additional calculations take significantly more time. Another method, Heron-Bilateration uses Heron's formula for area of triangles [8], and requires a specific deployment of anchor nodes.

It is worth noting that Emender is orthogonal to these methods and can improve localisation accuracy once applied to them, which will be shown in our experimental results.

D. Filtering Techniques

We can filter based on RSSI measurements or on distance estimates. Table I shows recent works classified in this manner. Most of these works rely on the use of multiple query RSSI measurements or distance estimates which takes more time. Below we discuss these filtering methods in detail.

Firstly, Transmission Power filtering uses the absence of low-power transmission signals to eliminate distant anchor nodes from the localisation [13]. It implicitly relies on the environment to derive an appropriate threshold at which measurements can be discarded. However, the time taken to collect the data is longer than sampling a single query RSSI measurement. Secondly, Kalman Filtering is a method that makes predictions based upon the previous data then updates those predictions with new measurements [2]. This method has been used widely and provides good results at the expense of time taken to obtain more query RSSI measurements [5] [6] [8] [14]. The Moving Average is a simple technique that averages the previous n query measurements to smooth out short term fluctuations and keep longer term trends [5] [15]. To gain the advantages of this technique, multiple query RSSI measurements are required. The Peer-based method [16] uses information from neighbouring nodes to assist in the localisation effort. This approach requires cooperation from other query nodes, or peers. These peers may, themselves, suffer from poor location estimates. The final method for RSSI measurement filtering techniques is the Savitzky-Golay filter [5]. It smooths data without distorting it significantly by performing polynomial fitting to increase the signal to noise ratio. However, discovering appropriate values for the polynomials requires experimentation. Static Distance is a

TABLE I: Filtering techniques for ranging in the literature.

Technique	Filter Parameter	Queries	
Transmission Power	RSSI	one	[13]
Kalman Filter	RSSI & dist.	many	[8]
Moving Average	RSSI	many	[15]
Peer-based	RSSI	many	[16]
Savitzky-Golay	RSSI	many	[5]
Static Distance	dist.	one	[9]

filtering method where it excludes distance estimates that are over a pre-determined threshold [9]. However, this approach is inflexible to new locations as it requires trial and error to find optimal parameters.

In summary, most previous filtering methods require multiple query RSSI measurements or distance estimates to improve localisation accuracy. They take more time than the methods using a single query such as Transmission Power and Static Distance. However, these approaches either add additional time for collecting more query measurements or are too environment-dependent to generalise to different environments. In the following section, we will present Emender which is a fast filtering technique based on the LDPL model and general enough for use in any environments. More importantly, it significantly improves accuracy and decreases time taken to calculate location estimates.

III. EMENDER

In this section we first present an example to illustrate the effects of the variability of RSSI measurements. Then we discuss the rationale behind Emender and finally its filtering algorithm.

A. Motivating Example

In Figure 2 we give an example that is modelled from real situations. There are four anchor nodes (A,B,C,D) participating in our localisation estimation of a single query (at the position indicated by the $\times$ which is the ground truth location). The locations of the anchor nodes A,B,C are close to the query point but D is slightly further away. Suppose that, these anchor nodes all transmit at the same power level ($-55\,\mathrm{dB}$), that their signals follow the LDPL model with the same pathloss parameter ($\gamma = 2.2$) and have a measured variability of $4\,\mathrm{dB}$ (i.e. measurements are $\pm 4\,\mathrm{dB}$ of their true value) when received at the query location. The measured and expected RSSI measurements at the query location are given in Table II along with the real and calculated distance estimates computed from the LDPL model tuned with the given parameters. From Table II, we can see that the distances to A and D have been overestimated, while those to B and C are underestimated. We use these distance estimates and the circle-based trilateration strategy (as described in Section II-C), and present the resultant location estimates in Table III.

By setting a threshold (in this case $2.4\,\mathrm{m}$ as calculated by Emender) we can clearly see, from Table III, that including the distance estimate from anchor node D increases the error of the location estimate. In Figure 2, the point indicated by $\triangle$ is the distance estimate using trilateration with node D, whereas $+$ is without. In this example, we improve the accuracy by 30% by excluding distance estimates from D. This example shows that we should filter out some RSSI measurements in order to improve localisation accuracy.

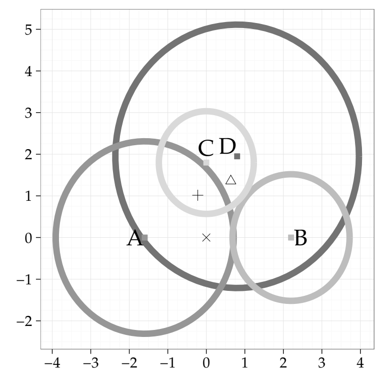

Fig. 2: Effects of large distance estimates in localisation. The query point is at $\times$, two localisation results are at $+$ and $\triangle$. The circles' radii (the centres are anchor nodes - A,B,C,D) show the distance estimates.

TABLE II: Example expected and measured RSSI measurements and the corresponding real and calculated distance estimates. The distance estimate from node D is excluded by Emender

	RSSIs (dB)		Distances (m)	
Node	Expected	Measured	Real	Calculated
A	-59	-63	1.6	2.3
B	-63	-59	2.2	1.5
C	-61	-57	1.8	1.2
D	-62	-66	2.5	3.2

B. Rationale

How can we know which RSSI values should be excluded? Figure 3 will answer this question. The figure depicts the LDPL model. Based on this model, we can see the effects of variability of RSSI measurements on distance estimates.

Following on from our example, when we are close to the anchor node (e.g. $2\,\mathrm{m}$), as depicted in Figure 3, the errors of distance estimates fall in a small range ($0.9\,\mathrm{m}$ at d1). Conversely, when we are far from the anchor node (e.g.$14\,\mathrm{m}$), we observe that the same RSSI measurement variation causes a larger range of estimate errors ($6\,\mathrm{m}$ at d2). This leads us to our key observation that near anchor nodes are more trustworthy compared to far anchor nodes. Therefore, as a general rule, to avoid large errors of distance estimates, we should use RSSI measurements from near anchor nodes. This is why we saw that excluding anchor node D improved the localisation accuracy in the motivating example.

TABLE III: Geometric errors using a circle trilateration geometry when including and excluding node D.

Result	Point	Estimate	Error
with D	$\triangle$	(0.6, 1.4)	$1.5\,\mathrm{m}$
without D	$+$	(-0.2, 1.0)	$1.0\,\mathrm{m}$

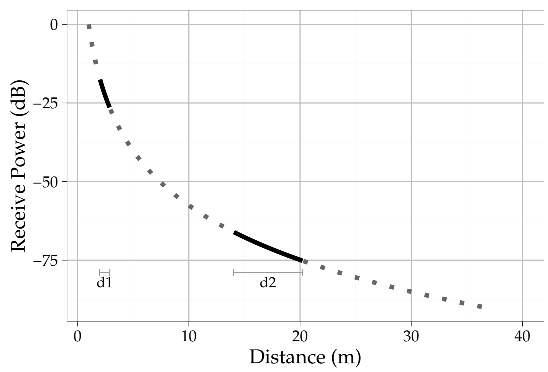

Fig. 3: Effects of RSSI measurement noise on distance estimates. The regions indicated by the darker line segments illustrate the effect of the same change in noise ($4\,\mathrm{dB}$) at different distances ($2\,\mathrm{m}$ and $14\,\mathrm{m}$) from the transmitter ($x = 0$). The closer to the transmitter the less effect the variation of measurements has on the distance estimate.

C. Filtering Algorithm

The issue now becomes how to determine the distinction between 'near' and 'far'. According to the LDPL model, the rate of change in the RSSI is faster when the anchor node is closer. Therefore, we can use the rate of change in the RSSI as an indicator for 'near' and 'far'. To get the rate of change, we differentiate (1) and obtain (2).

$$\frac{\mathrm{d}P}{\mathrm{d}x} = \frac{10}{\ln 10}\frac{\gamma}{x} \tag{2}$$

$$cn \leq \frac{10}{\ln 10}\frac{\gamma}{x} \tag{3}$$

$$x \leq \frac{10}{\ln 10}\frac{\gamma}{cn} \tag{4}$$

$$T_x = \frac{10}{\ln 10}\frac{\gamma}{cn} \tag{5}$$

Assuming n is the average variation of RSSI measurements, to relate n to the distance threshold determining the distinction between 'near' and 'far', we use (3) and (4) to find the cut-off threshold distance T_x as shown in (5), where c is a factor for adjusting out confidence in the threshold, its impact will be discussed in our experimental evaluation. The reason why we relate the variation of RSSI measurements n to the calculation of the distance threshold for 'near' and 'far' is that, when n is large in a noisy environment the threshold should be small to guarantee localisation accuracy. For each distance estimate between the query node and the anchor node, if it is smaller than T_x we include it; otherwise we ignore it. Note that both the value of γ and n are dependent on the environment such as building material that the signal is propagated through and must be measured. This approach is adaptable to other models where the derivative $\frac{dP}{dd}$ can be calculated.

Since the above distance threshold T_x has considered environmental factors such as noise level and path loss, it is adaptive to different environments and thus our filtering method is suitable for general use.

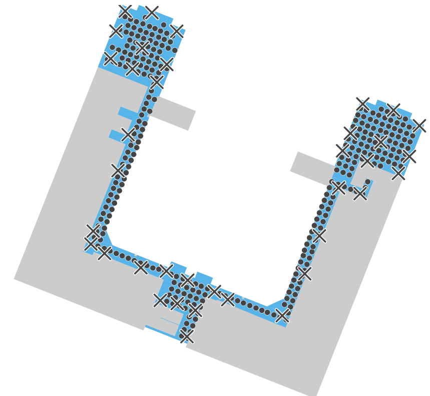

Fig. 4: The Owheo building anchor node and sample point layouts, orientated so north is at the top of the image. The dots mark sample locations, while crosses mark anchor nodes.

IV. Experimental Method

In this section we present the experimental method for comparing Emender with other filtering techniques using single query.

A. Experimental Setup

The data for our experiments was collected on the first floor of the Owheo Building, covering an area of $2496\,\mathrm{m}^2$ ($52\,\mathrm{m}$ by $48\,\mathrm{m}$). In Figure 4 the grey areas indicates private offices that are not accessible and the void in the centre is open to courtyard below, so we have a sample area of $339\,\mathrm{m}^2$). We collected data from a $1\,\mathrm{m}$ by $1\,\mathrm{m}$ grid as shown in Figure 4, using TelosB sensor motes on 802.15.4 radio channel 20.

Our RSSI measurements were obtained by broadcasting 50 requests (containing a unique serial number) from the query node at the maximum transmission power at each point in the grid. When the anchor node receives this message it responds with a copy at each of the 29 available power levels supported by the radio hardware. This is done for two reasons, firstly, so that we are able to use the Transmission Power filtering method; and secondly, we are able to collect more data from each of the sample points, up to a maximum of 300 responses. The more data available, the better the model fitting performs. On receipt of the responses the query node measures the RSSI and passes it to the application. This dataset is then split randomly into two sets (per point, based on the serial numbers), $80\,\%$ for training the model and $20\,\%$ for testing the localisation. To test the localisation methods, we iterate over all the data points in the test set performing a single localisation query. The error is the Euclidean distance between the resultant position estimate and the ground truth. The time is the computation time, excluding the time for I/O requests. Since the time for I/O requests is the same for all other techniques, we only compare the computation time of the filtering techniques as it indicates their performance.

The LDPL model was fitted to the data using the linear least squares technique. We also tested with RANSAC and found no difference between approaches. As each anchor node is treated independently, we fit the γ and P_0 terms of (1) from the training data set, (P_l, d) tuples, where d is the Euclidean distance between the grid points and the anchor node. All the geometric methods use distance estimates obtained from the same radio propagation models. Emender is designed to be

TABLE IV: Mean error (m) for localisation of queries.

	Boxes	Circles	Geo-n	Heron
Emender	3.7	3.8	2.6	3.6
Transmission Power	6.5	5.5	4.1	6.4
Static Distance (7 m)	4.7	5.3	3.3	5.2
Static Distance (53 m)	14.6	8.3	4.0	5.3
None	13.3	7.9	4.2	5.3

geometry agnostic, so we chose a variety of geometries to assess the performance of Emender. The geometries chosen are either representative of the state of the art (Geo-n and Heron-Bilateration) or simple (Circles and Bounding-Boxes).

B. *Evaluation of Filtering Techniques*

Though previously we discussed a range of filtering techniques, for fair comparison, we only choose those techniques using a single query since our focus in this work is on fast filtering techniques using a single query. For this reason, we use Transmission Power and Static Distance filters as a base line for comparison, while the other filters mentioned in Section III-A depend on multiple queries.

To estimate the variability of RSSI, n, we took 500 measurements in each of three rooms in our building. We then computed the standard deviation and selected the largest across these three rooms. We then set $n = 4.48$, three times the measured standard deviation to cover the $99\,\%$ confidence interval, and thus c to the interval $(0, 1]$ (if $c < 0$, the resulting threshold would be negative, if $c = 0$, the threshold becomes undefined, if $c > 1$ then we allow more noise through the filter). Emender generates a threshold, T_x, for each anchor node independently, and in our deployment, they range from $0.98\,\mathrm{m}$ to $2.74\,\mathrm{m}$ with a mean of $1.92\,\mathrm{m}$.

V. Experimental Evaluation

We evaluate the performance of Emender using the different combinations of geometries and filtering techniques, unless otherwise stated $c = 1$, though other values of c are also discussed.

A. *Accuracy*

We first discuss the accuracy of the localisation estimates. We measure the Euclidean distance between the location estimate and the real location of the query. In Table IV, we show the effects of the different filtering techniques on the localisation methods under test. We can see that Emender decreases the error for all of the geometries under test by $72\,\%$, $52\,\%$, $38\,\%$ and $32\,\%$ when compared to no filtering. It is apparent from these results that the Emender filter allows more accurate distance estimates through to participate in the localisation regardless of the geometry being used. From Table IV we see that the combination of Geo-n and Emender produces the lowest error across all filters and geometries.

Compared with Emender, the other filters, Static Distance and Minimum Transmit Power, do not improve the performance significantly.

B. *Timing*

We measure the time taken for the algorithms to produce a location estimate. The results are presented in Table V. Compared with no filtering, in all cases, Emender decreases the time taken by $73\,\%$, $90\,\%$, $99\,\%$ and $82\,\%$ for Boxes, Circles, Geo-n and Heron-Bilateration respectively. Geo-n takes the longest of the geometries (in the worst case around $1\,\mathrm{min}\ 30\,\mathrm{s}$ but on average approximately $26\,\mathrm{s}$ with no filtering). If we use Emender with Geo-n, the time taken to localise drops by two orders of magnitude (worst case $21.4\,\mathrm{s}$, average approximately $0.2\,\mathrm{s}$). From these results we see that, for the best performing geometry and filter combination – Geo-n and Emender, which has the highest localisation accuracy, we are able to decrease the execution time by two orders of magnitude on average. Within the same geometric localisation method, using Emender results in quicker location estimates than the other filtering techniques.

TABLE V: Mean times (s) for localisation of queries. The exponents appear in parentheses.

	Boxes (10^{-4})	Circles	Geo-n	Heron (10^{-3})
Emender	0.5	0.03	0.2	0.8
Transmission Power	0.9	0.07	6.0	1.3
Static Distance (7 m)	1.2	0.1	7.1	1.4
Static Distance (53 m)	1.9	0.3	24.9	1.8
None	1.9	0.3	26.1	4.0

TABLE VI: Emender's mean error (m) for localisation of queries with different c values.

	Boxes	Circles	Geo-n	Heron
$c = 1$	3.7	3.8	2.6	3.6
$c = 1/2$	4.5	5.1	3.1	5.4
$c = 1/3$	5.3	5.9	3.3	5.6
$c = 1/4$	6.2	6.2	3.6	5.6

C. *Tuning of c*

Table VI presents the effects of tuning Emender by adjusting confidence in the noise estimate through c. From the table, we can see that increasing the value of c leads to a decrease in the localisation error. Moreover, Table VII shows that in all cases increasing the value of c deceases the time taken to perform the localisation, in some cases by more than an order of magnitude. Geo-n shows a marked improvement for larger c. According to our experiments, when c is smaller, the localisation accuracy starts to drop.

TABLE VII: Emender's mean time (s) for localisation of queries with different c values.

	Boxes (10^{-4})	Circles	Geo-n	Heron (10^{-3})
$c = 1$	0.5	0.03	0.2	0.7
$c = 1/2$	1.1	0.12	4.1	1.2
$c = 1/3$	1.3	0.14	7.2	1.3
$c = 1/4$	1.5	0.15	9.1	6.0

D. Discussion

From the above results we can see that Emender is very effective for improving localisation accuracy. Though the absolute errors are relatively large compared with some hardware assisted methods (see Section VI), the contribution of this paper is the improvement for RSSI-based indoor localisation. Since Emender is a general filtering method which is adaptive to environment factors and independent of localisation techniques, we believe it will still improve accuracy in situations where special hardware is used and the absolute errors are small.

VI. Related Work

In this section we briefly discuss localisation techniques that use sensor modalities other than RSSI which are orthogonal to our work, but included here for completeness. Numerous solutions exist for indoor localisation, covering techniques such as triangulation, trilateration, and fingerprinting Gowami provides a general overview of the general principles of localisation technologies [2]. Briefly, the techniques include Time of Arrival (TOA) and Time Difference of Arrival (TDOA) approaches to trilateration (or more generically Time of Flight (TOF)). TOA is method that, using an absolute time source, measures the difference between when a signal was transmitted to when it was received. Knowing the propagation rate, the distance can be calculated, and we can derive an estimate of the location. The canonical example of such as system is GPS. TDOA is related to TOA in that it also measures the time taken for a signal to propagate. The difference here is that cooperating, geographically distributed, anchor nodes record when they observed the signal arriving. The stations, knowing their own positions and the propagation rate of the signal, can then cooperatively compute the distance the signal travelled. Typically, these TOF methods require specialised hardware. For example, highly accurate clocks are needed in order to measure the flight time of radio signals. Sonic-based systems are more pragmatic, however they still require hardware capable of detecting the frequencies in use (e.g. ultrasound distance sensors accurate to $9\,\mathrm{cm}$ [17]). Triangulation is a closely related approach to trilateration based around the use of angles. These approaches use Angle of Arrival (AOA) compute the position of the anchor nodes from the query nodes (e.g. used in surveying). In radio positioning systems, typically this requires the use of an antenna array – an additional hardware element not available in commodity mobile devices.

However, these techniques are not practical for ubiquitous mobile devices because they require specialised hardware often not available on commodity mobile devices.

VII. Conclusions

We have proposed a novel approach, Emender, that uses the parameters of the LDPL radio propagation model and the variability of RSSI measurements to exclude poor distance estimates that would otherwise decrease the accuracy of the location estimate. Since this approach is adaptive to environmental factors such as path loss and variability of RSSI measurements and independent of localisation methods, it is suitable for general use. Our comprehensive experiments conducted in a real-world environment show, with single queries, decreases in error (by at least 32%) and time (by approximately 70% or more, and in some cases by two orders of magnitude) for localisation across multiple state-of-the-art geometries and filtering techniques. While the absolute error remains relatively high, we anticipate that when Emender is integrated with better methods for the various other phases of trilateration, this absolute error will decrease significantly.

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