Indoor Localisation of IoT Devices by Dynamic Radio Environment Mapping

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***Abstract*— Radiolocation within indoor environments is a challenge due to the dynamic variations caused by movement of objects and the complex multipath radio propagation. Therefore techniques that are suitable for indoor scenarios need to be robust to the multipath effects, which leads to additional power consumption and complexity. For instance, Ultra-wideband transmission can overcome multipath impact at the expense of requiring at least three access points in range with high bandwidth transmission. Such approaches are not feasible in commodity and low power IoT device tracking using legacy transmitter devices, such as WiFi or Bluetooth. Therefore, the proposed approach to address this problem is to selectively use Angle of Arrival (AoA) capabilities in access points, with the need for only two, to adaptively take measurements as compatible devices move around the environment in order to update radio maps used for optimising this process. In doing so important inferences about the dynamic environment can be exploited to adapt the measurement intervals to reduce the measurements and processing required and conserve power.**

***Keywords*— Radiolocation, REM, IoT device localisation**

I. Introduction

This paper investigates the problem of accurate radiolocation of commodity low power radio devices in indoor deployments, by exploitation of dynamic radio mapping. Indoor scenarios are affected by the movements of people and objects in the environment; creating significant variations in radio propagation that impact on performance. With better characterization of the propagation environment more accurate and simpler localisation of transmitters is possible. Hence, it is attractive to track the changes in the radio propagation environment in order to adapt the radiolocation approach.

Prior approaches to indoor radio mapping either rely on a detailed surveying process to form fingerprint databases, using specialist hardware with inertial or infrared / laser based navigation, being repeated each time significant changes occur which can be both time consuming and complex to perform. Alternatively, it can be performed by passively observing radio transmissions using standard terminals [1], such as by using minimization of drive test capabilities. However, such prior techniques are not attractive within indoor environments because of the problem of complex multipath propagation, the cost of specialist hardware and surveying or lack of accurate indoor localisation capabilities in commodity mobile devices. More accurate localisation is possible by using more anchor nodes (access points) and larger bandwidth transmissions, but as a consequence is more complex and consumes more power, which are undesirable in IoT scenarios. Therefore, our approach uses commodity WiFi radio transmissions received at two access points to create awareness of the environmental impact and reduce the power consumption by at least a factor of 20.

II. Background

There are many IoT scenarios in which there is a need to provide accurate real time indoor location information. This for instance can be for asset tracking in industrial, medical or retail sites. Alternatively, for monitoring and geo-fencing to protect human personnel from being injured in factories with autonomous robots present. In these scenarios there is a need for low power consumption on the target as they are mobile and hence battery powered. Conventional approaches in these scenarios either use optical or depth cameras, or exploit RSS trilateration or fingerprint databases. There is also recent interest in using combinations of Time of Arrival (TOA) and AoA techniques to increase robustness [3], but these require larger bandwidth transmission to achieve better performance and hence higher power consumptions and associated costs. The approaches relying on optical or depth image and AoA also have limitations as they rely on a Line of Sight (LOS) path to the targets which must also be uniquely identifiable, which often cannot be guaranteed. This motivates us to develop a solution that can adapt to the environment to improve performance even when there is obscuring of the LOS paths.

The proposed solution to this problem is to use standard radio infrastructure (such as WiFi access points) that also have AoA estimation capability. Then to track radio transmitters, such as commodity smart watches and phones or asset tags, using beamforming sounding packets, to update radio maps that are used to better understand and provide awareness of the changes in the environment. In this way the radio maps are formed without specialist hardware, modification, special applications or complex surveys. The maps are used to adapt the measurement intervals and localisation method by detecting when obstructed line of sight situations exist. The impact of the radio environment on radiolocation accuracy is determined in order to perform this adaptation. In this paper the proposed approach is evaluated in an indoor test environment and the potential power consumption reductions are estimated.

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III. Approach

A. Radio environment mapping

Radio environment maps are repositories of radio measurements and predictions obtained by using spatial interpolation or radio propagation and physical models [5][6]. Both of these approaches have limitations as they can be complex and time consuming or become outdated in dynamic environments. In particular detailed physical models of indoor propagation rely on complex knowledge of the environment. Also, spatial interpolation techniques rely on sufficient quantity and quality of geo-located measurements, which is currently difficult and time consuming to obtain. Hence, we propose selective tracking of commodity radio transmitters as they move under normal usage and update predictions about the radio environment using comparisons with models to reduce the amount of measurements required.

The benefit of forming radio environment maps is twofold. Firstly it permits a way of detecting Non-Line Of Sight (NLOS) situations and to adapt the measurement frequency when permitted, reducing the amount of complex calculations that need to be performed. Therefore, more devices can be accurately tracked for the same or lower computational cost and power consumption. Secondly, radio maps can be used for coarse localisation of transmitters to eliminate unfeasible candidates and also locate transmitters that do not support sounding packets required for AoA based localisation.

The radio environment mapping process is illustrated in Fig 1. Firstly, measurements are collected from the WiFi sensing devices (two access points in our case) which are used for localisation of the moving transmitters in the surrounding environment. Localisation is performed by calculating the AoA of beamforming sounding packets transmitted by the 802.11n compliant WiFi devices in response to sounding requests. Then the AoA intersection is computed and the measurements interpolated to obtain a complete radio map which can be used for subsequent fingerprint based localisation of other transmitters and for adapting the measurement interval. Filtering and clustering can also be applied to the map data to reduce error propagation.

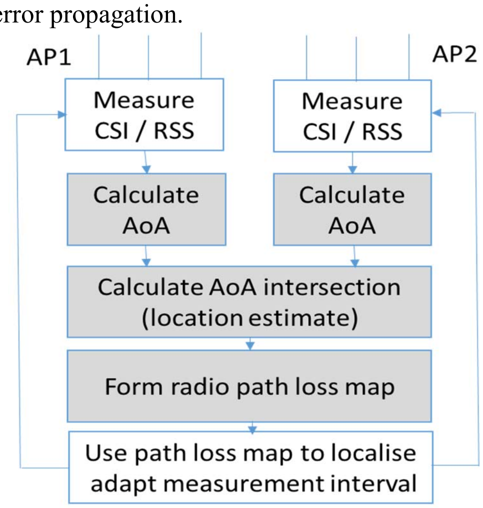

Fig 1 : Localisation approach using AoA and Radio map data

B. Localisation

The proposed localisation technique exploits the AoA estimation capabilities of the commodity access points by using multiple antennas (three are assumed). Typically, the number of antennas and their spacing (and geometry) determines the resolution of the angle estimation. However, size and cost considerations usually limit this and in practical access points 3 or 4 are normally a maximum. As a general rule for MUltiple SIgnal Classification (MUSIC) based algorithms, see [7], the number of elements determines how many signals or multiple paths can be distinguished. Even so, it is not easy to determine the correct paths when the environment is complex and dynamic and hence the performance degrades significantly when there are many multipath components and small bandwidths and NLOS situations [7]. Also, optical or depth image techniques cannot work in NLOS.

The SpotFi algorithm [2] exploits the Channel State Information (CSI) across multiple subcarriers within the WiFi transmission in order to create sub-arrays of sensors comprising of subsets of the CSI computed on 30 subcarriers for each of the three antenna elements. This permits a super-resolution process for resolving more paths than the number of antenna elements by taking advantage of the Time of Flight (ToF) differences inducing frequency dependent phase offsets. The AoA estimation algorithm has multipath countermeasure included; which involves the clustering with the combinations of candidate peak attributes (such as AoA, ToF, MUSIC peak magnitude and packet RSS) over a number of successive sounding packets *N*, after which the candidate AoA that minimises the expression in (1) is selected. However, errors in the AoA still exist in NLOS situations, as also shown in [2].

$$a.ToF - b.MUSIC\ Peak - c.Cluster\ size\ fraction \qquad (1)$$

Where *a,b* and *c* are weighting constants and cluster size fraction is the relative number of individual peaks observed in the path cluster compared to total peaks from all paths.

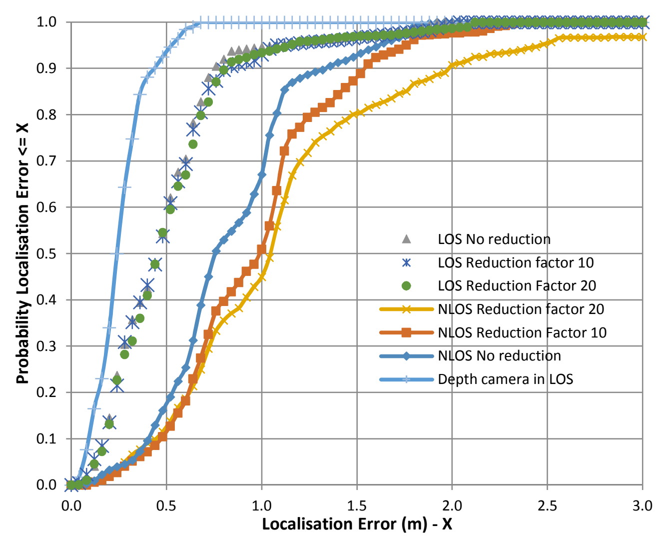

Fig 2 : CDF of Localisation Accuracy for Test Environment for LOS and NLOS cases with different measurement frequency reductions

In addition we see that adapting the measurement frequency also plays an important role in NLOS situations (see Fig 2). In this test, when one of the APs is in NLOS the localisation errors are heavily dependent on the measurement frequency of the NLOS AP. In contrast in LOS situations the measurement frequency can be reduced by a factor of 20 or more without any significant impact on the accuracy and the performance is close to that of the depth image based approach with LOS. Therefore, using higher frequency measurements permits the NLOS AoA estimates to be more easily filtered based on the closeness to the average of what is determined to be the best estimates over the sliding window interval of N packets. The depth image approach, used for comparison, utilises a Kinect™ V2 with OpenCV object tracking and the target object is ensured to be uniquely identifiable, see [10].

In order to achieve this accuracy, if AoA estimates diverge by more than an error threshold amount (5 degrees in our case) from the average over a sliding window of N packets then around 20% of packets in LOS and 50% in NLOS are discarded. By doing so the localisation errors obtained, for a moving transmitter in the test environment, are substantially improved. Even so the average errors in NLOS can still be a factor of two worse than those for LOS situations if the measurement frequency is low. However, it is not reliable to determine NLOS situations by just considering variation in AoA over successive packets as this can also be due to sudden changes in movement and when close to the AP. Therefore, it is proposed that measurement frequency is determined by exploiting a radio map to help indicate NLOS situations. The radio map is formed using measurements as described next.

C. Radio map formation

The aim of radio environment mapping is to obtain an accurate representation of the spatial radio environment, such as path loss or signal strength, with minimal measurements. Hence, spatial interpolation is used to achieve this goal. The purpose of spatial interpolation is to obtain estimates of the radio signal strength or path losses at locations where no measurements are available. This can be considered as essentially fitting a model of the spatial variations based on the measurements obtained. Direct techniques make some prior assumptions regarding the spatial distribution such as spatial stationarity. These techniques can over-simplify the radio propagation and hence may not converge to the best solution, particularly if there is an uneven geographic spread of measurements or significant outliers. Therefore, we utilize the Barnes surface interpolation approach, which is a successive error reduction technique, with two or more passes as described in the following steps.

For the first pass, the estimated value $\boldsymbol{E_g}$ at each grid point $\boldsymbol{g_{x,y}}$ is:

$$E_g = \sum(w_i * o_i) / \sum(w_i) \qquad (2)$$

where o_i is the value of the i'th observation point and w_i is the weight (decay function) value for the i'th observation point, defined as:

$$w_i = exp(- d_i^2 \ / \ L^2 C \ ) \qquad (3)$$

where d_i is the distance from the grid point to the i'th observation point and L is the length scale, which is determined by the observation spacing and the natural scale of the phenomena being measured. C is the convergence factor, which controls how much refinement takes place during each refinement step. In the first pass the convergence factor is 1. For subsequent passes a value in the range 0.2 - 0.3 is effective. During refinement passes the estimate at each grid point is re-computed using:

$$E'_g = E_g + \sum(w_i * (o_i - E_i)) / \sum(w_i) \qquad (4)$$

where E_i is the estimated value at the grid cell containing the i'th observation point.

D. Indirect radio map

Indirect radio map formation makes use of statistical or empirical propagation models that predict the spatial distribution. These techniques are useful for comparing with the maps obtained from the direct approach methods to detect NLOS situations or to adapt measurement frequency. For instance the typical path-loss model may be given by the following expression.

$$PL_{p,t} = 10\alpha \operatorname{Log}(d_{t,p}) + \Sigma[\ O_{t\to p}\ ] \qquad (5)$$

where $d_{t,p}$ is distance between the transmitter t and the spatial point p and α is the path loss attenuation exponent, with $O_{t\to p}$ representing the set of positive additional attenuation contributions caused by the presence of shadow fading on the path between t and p.

The path loss expression above can also be easily combined with directional antenna gain patterns if necessary, but in our case omni-directional antennas were used. Hence, our approach is to predict the positive $O_{t\to p}$ values corresponding to spatial points and hence detect the NLOS cases using the threshold condition in (6).

$$\Sigma[\ O_{t\to p}\ ] > PL_T, \qquad (6)$$

where PL_T is a threshold used to indicate NLOS between the AP at p and transmitter at t.

IV. Measurement Campaign

A. Storage

The radio map storage is implemented with a Postgis spatial database [3] to provide scalability for the many radio measurements collected over time. The database performs timestamping of the measurement updates, storage of the historical measurements and triggers operations on the data, such as computation of radio maps.

B. Localisation

Two APs are used each consisting of an Intel 5300 radio with three dipole antenna elements with 2.5cm spacing. CSI data is obtained using the tool in [8] and the AoA estimation utilises the SpotFi algorithm (implemented in C#) and a fuzzy-c-means clustering algorithm to determine the best two AoA candidates for each set of 4 channel sounding transmissions. The centre frequency of 5.67GHz is used with 40MHz bandwidth. The REM storage is also updated with the localised RSS measurements. In addition, comparison and evaluation is made with the recently introduced Bluetooth Low Energy (BLE) AoA techniques, see [9] and [11].

C. *Interpolation and Extrapolation*

The spatial interpolation function is implemented in C# and operates on the historical data within the REM storage. When sufficient measurements are available the interpolation creates a new spatial radio signal map. The resolution used is with grid cells of 5x5cm and a length scale of 30cm. The test environment size is 5x5m resulting in a 100x100grid. Three passes are used with a convergence factor of 0.2.

D. *Measurements*

In order to evaluate the ability of the radio map to detect NLOS situations a measurement campaign was conducted in a 5x5m test environment within an open plan office. The aim of performing the measurements is twofold, firstly to determine how many measurements are necessary to create an accurate spatial radio map using the direct approach and secondly to determine the benefit of indirect approach to reduce the number of measurements needed. In our case this involved placing a large electronic whiteboard within the test area, which is an example of a typical office object that can cause NLOS situations. The sets of measurements were taken with a moving transmitter in the test area, each set comprising of 1250 measurements corresponding to averaged path gain at different spatial points in the test area with a grid resolution of 10x10cm, hence only half of the grid cells having associated measurement.

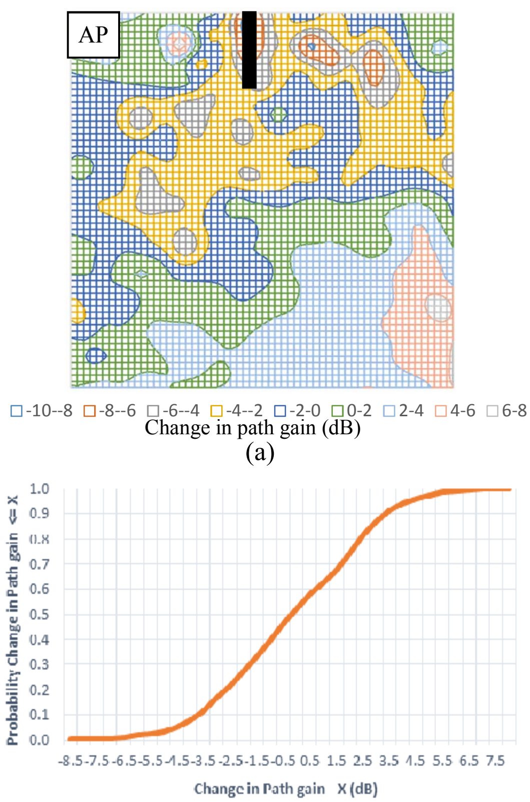

Fig 3 : Spatial variation of change in path gain caused by obstruction for AP1 (a) spatial map (b) CDF of path gain difference

The AoA location estimates were used to form the mapping of the estimated path gain data to the grid cells. The next step is to compute the variation in the spatially interpolated path gain over time (see Fig *3*), due to presence of obstructions or other variations in the environment. In this case Fig *3*a indicates the differential path gain, by spatial interpolation of the difference between values before and after an obstruction is moved. It highlights the fact that some areas observe a reduced path gain of up to 8.5dB (as would be expected) while others see a similar increase. The distribution of the change (in terms of a CDF) is shown in Fig *3*b. By applying PL_T =6dB we can determine the NLOS conditions, with a 94% confidence, but if PL_T = 4dB this reduces to 58%. This result also indicates that the simple path loss model can achieve a reasonable average accuracy even if it does not capture the local spatial fluctuations. The median absolute error being less than 1.7 and 1.2dB for the case of with and without obstruction present respectively. Note also that to achieve this level of similarity, with the direct approach, while reducing the number of measurements required is possible with a factor of 3 or less (i.e. 417 or more measurement points needed). It can also be seen by the difference between the direct radio signal maps, which is 2.3dB, that the indirect approach provides good approximation to both cases even without spatial estimation of $O_{t\to p}$. Furthermore, it is possible to determine an adaptive measurement frequency based on the observed accuracy and spatial autocorrelation of the model. For instance, the indirect path loss model error, without the $\Sigma[\ O_{t\to p}\ ]$ estimation, is shown in Fig *4*. Hence, this provides a means to determine the reliability of using a threshold PL_T placed on the estimate of $\Sigma[\ O_{t\to p}\ ]$ to detect NLOS. It indicates that if the PL_T of 6dB or larger is applied then there are less than 6% failure to detect NLOS, as also observed in Fig *3*a with the direct model. Also, as the difference between distributions can be approximated by the expression in (7), which is obtained by a regression fit, it is possible to derive an adaptive measurement frequency that depends on the previous path loss measurement, which is proportional to y.

$$y = -0.0005x^4 + 0.0125x^3 - 0.0975x^2 + 0.258x - 0.0706 \quad (7)$$

where x is the path loss difference between model and measurement (in dB) and y is the probability of occurrence difference between the obstruction and no obstruction cases.

Then with the above approach the potential performance improvement when adapting the measurement frequency is illustrated in Fig *5* and in Table *1*, indicating that slight benefit can be made in the accuracy of capturing the environment anomalies at the same time as reducing required measurements.

Table 1 : Comparison of average absolute difference between REMs

Direct REM comparison (with obstruction) vs	**Median absolute path loss difference(dB)**	**90th percentile path loss difference(dB)**
Indirect path loss model all measurements	0.8	2.0
Indirect path loss model adaptive measurement	0.7	2.1
Direct REM without obstruction	2.3	4.2

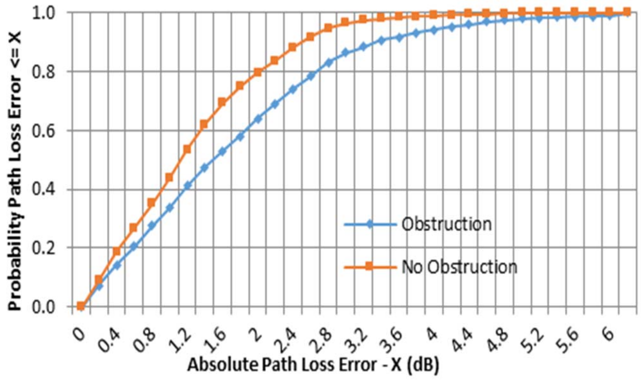

Fig 4 : CDF of path loss error for path loss model without predicting spatial variation of $O_{t\rightarrow p}$ (with and without obstruction)

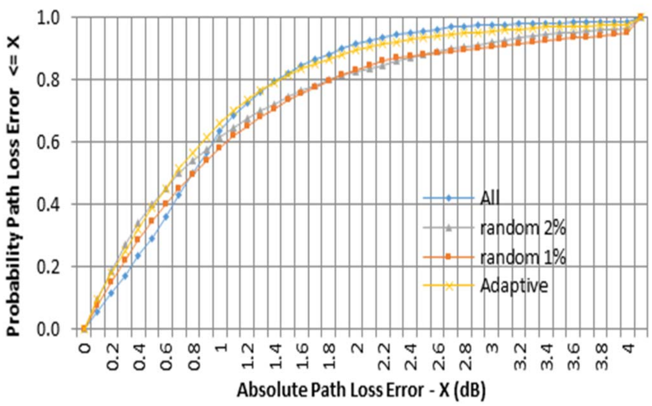

Fig 5 : Performance of indirect model for measurement reduction (where all is no reduction) compared with random frequency

E. *Evaluation of benefits*

The benefit of the proposed adaptive measurement frequency is realised in terms of the measurement reduction factor. Battery power saving is directly proportional to the reduction in the frequency of transmissions and computations that need to be performed. Therefore, a reduction in measurement frequency of a factor of 100 can equal the same reduction factor in terms of battery power consumption saving. This is an important consideration for asset tracking tags or smartphone / smartwatch tracking use cases where low power consumption and scalability are needed. If there is always a LOS with both APs, the adaptive measurement algorithm (7) results in a reduction factor of ~25 being utilised. Then in the same environment with the obstruction present, after the characterisation step, the reduction factor is close to unity for only the NLOS area. The average reduction factor for the NLOS AP, assuming transmitter devices are evenly spaced throughout the test area, is ~20. This is possible while still achieving a median localisation error <0.8m throughout the whole test area. Hence, the power consumption due to transmission and also computational complexity in the NLOS APs is also reduced by a factor of 20 and the LOS AP by a factor of 25.

It is also possible that the NLOS AP measurements are not used when NLOS is detected. In this case the set of measurements from the single LOS AP can provide the means to localise the transmitter. The way in which this is achieved is for the transmitter movement direction to be estimated and projected using (9).

$$x_i = \frac{1}{M}\sum_{m=1}^{M} \hat{x}_{i,m}\,,\ \hat{x}_{i,m} = \frac{y_{i-m}}{\tan\theta_i - \text{m}.\tan\emptyset} \text{ and } y_i = x_i.\tan\theta_i \quad (9)$$

where θ_i is the AoA at interval i and $\emptyset$ is the direction of movement, assuming that it remains constant over >*M* successive intervals with a constant unit speed.

Alternatively, the distance can be estimated based on the assumption that the transmitter lies on a known lower plane than the APs (see [9]). For instance, with six antennas, with three arranged horizontally and three at 45 degrees to vertical the distance and AoA can be calculated using the two sets of antennas.

If the direction $\emptyset$ and speed is constant for >*M* intervals, then the results provide a reasonable accuracy compared with the two AP case, see Fig *6*. However, as there is a dependency on detecting the change of direction of movement it is advantageous when they are large and infrequent (i.e. *M*>>1, such as 10). Estimating $\emptyset$ is performed by computing in (10).

$$arg\ min \sum_{m=1}^{M} |\ (x_i - \hat{x}_{i,m})^2 + (y_i - \hat{y}_{i,m})^2 | \quad (10)$$

Furthermore, the reduction in localisation error is 25% or 36%, for median and 95th percentile respectively, if the measurement frequency is adapted when the NLOS case is detected. Alternatively, if the distance method is selected then 30% and 9% for median and 95th percentile case respectively, or for the direction prediction there is no reduction in median error but the 95th percentile is also reduced by 36%. Hence, it is possible to observe that adapting the frequency of the measurements is the best strategy overall.

The overall summary of the localisation performance is shown in Table *2*. This highlights the fact that depth image tracking is superior to radio based techniques provided that the target can be uniquely identified and tracked and that the depth cameras have sufficient resolution and field of view to cover the deployment area. However, this is not always possible or realistic to achieve in practice. In such cases the use of commodity radio techniques is attractive and in this case the WiFi AoA approach is next best in terms of accuracy followed by BLE approach with four APs and using Machine Learning (ML) to train a neural network via a survey. In the case of WiFi RSS the radio map is used as the basis to perform a best match (i.e. lowest RSS error) lookup of the RSS measured from the two APs. In this case the NLOS error is significant and worse than the BLE AoA using triangulation, but in this case four BLE APs are used, instead of two; deployed at each corner of the test area. It is also possible to observe that BLE is less susceptible to NLOS conditions due to the use of four APs rather than two.

Table 2 : Overall absolute localisation error comparison (in m)

	LOS		**One AP in NLOS**	
	Median	**95th percentile**	**Median**	**95th percentile**
Depth image	0.24	0.52	0.24	0.52
WiFi AoA	0.46	1.00	0.76	1.64
BLE (ML)	0.45	1.20	0.60	1.50
WiFi RSS	1.15	2.40	1.52	3.20
BLE (AoA)	1.20	2.50	1.30	2.60

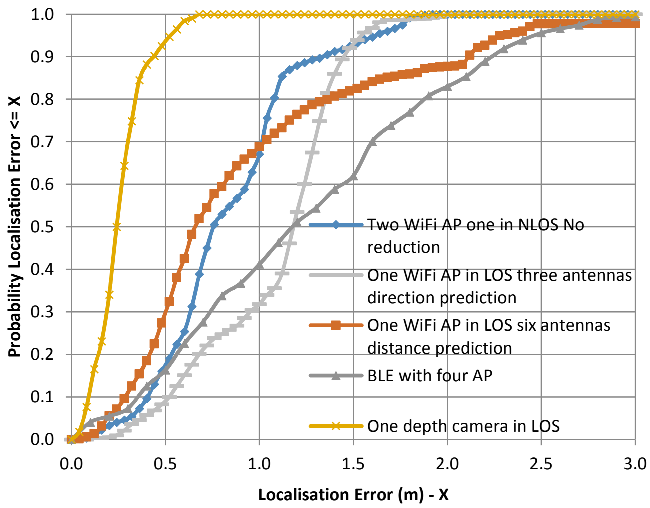

Fig 6 : CDF of localisation error with one AP in LOS (with either target distance or direction estimation) and comparison with depth image and BLE

V. Conclusions

Accurate indoor real time localisation and tracking requires significant amount of complex measurements to overcome the effect of multipath propagation and obscured line of sight, which causes spurious errors. However, for IoT scenarios the cost and power consumption are important considerations. Therefore, it is often not possible to deploy large amounts of infrastructure or specialist solutions that either require very frequent and high bandwidth transmissions or guaranteed line of sight with at least two APs. The proposed approach to solve these issues presented in this paper exploits commodity WiFi APs and builds up awareness of the environment. The radio environment awareness is used to reduce the complexity by adapting the measurement frequency to maintain high accuracy while reducing energy consumption. This is particularly beneficial within dynamic environments in which it is not possible to a priori determine the optimum configuration at deployment time. Hence, detection of NLOS situations using dynamic radio environment maps has been shown to be attractive and realisable.

The proposed approach to solve this problem has been evaluated in an indoor test scenario and results compared with prior techniques. The most similar prior techniques utilise radio surveys to form fingerprint databases or ML approaches to train neural networks for a particular deployment scenario. In such a case the model needs retraining with radio measurement data (such as geo-located AoA and RSS) via a repeat survey each time a change takes place. In contrast the proposed approach does not need surveys as the radio environment maps can be updated on the fly without training data but instead utilising direct spatial interpolation techniques.

The dynamic variations in the radio environment require significant numbers of measurement points and frequency of measurements to capture these changes. To acquire this without surveys the proposed solution uses target localisation exploiting AoA triangulation and adaptively takes measurements at a frequency that depends on the comparison of RSS with an indirect radio propagation model. In doing so fewer measurements are needed for obtaining a more accurate representation of the spatial radio environment with lower power consumption and complexity. This also permits selection of AoA measurement and computation frequency to reduce power consumption and complexity. Measurements conducted in an indoor test scenario indicate that, with an adaptive approach, a factor of 20 to 25 reduction in measurements and power consumption is possible with the same accuracy, or up to 36% greater accuracy than a fixed measurement frequency approach. This makes the approach suitable for low power IoT device localisation (e.g. for real time positioning and asset tracking) in complex radio environments.

In more dynamic industrial deployment scenarios the power consumption will increase, but as the proposed approach is adaptive it can still provide the necessary level of accuracy. In contrast repeat surveys can become very costly and inconvenient if they occur frequently. Further work is needed to extend the proposed approach to high reliability dynamic geo-fencing applications in which there is a need to constantly adapt to the changing environment. It is expected that the exploitation of phase fingerprints, (see [12]), with radio mapping could permit better environment awareness with fewer measurements, which opens up new possibilities for low cost, low power consumption applications.

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