WiFi-RTT indoor positioning using particle, genetic and grid filters with RSSI-based outlier detection

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Biography

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Abstract

WiFi has vast infrastructure presence making it an ideal candidate for mobile indoor positioning. WiFi Fine Time Measurement (FTM), is a WiFi protocol that enables the time of flight (ToF) of a WiFi signal to be determined; referred to as WiFi Round Trip Timing (RTT). Providing a ToF based protocol has allowed ToF based positioning algorithms to be applied to WiFi signals which could provide an improvement over the current RSSI-fingerprinting state of the art. Non line of sight (NLOS) reception and multipath interference degrade WiFi RTT accuracy. The research in this paper explores the accuracy of WiFi RTT positioning in a variety of indoor environments by utilising filtering techniques and RSSI-based outlier detection. Four positioning algorithms are explored: Least squares, a particle filter, a genetic filter and a grid filter. 67% of trials resulted in sub-metre accuracy and 90.5% of trials had a RMSE below 2m, the accuracy was worst in environments with NLOS conditions where 38% of trials resulted in sub-metre accuracy whereas for environments with complete LOS conditions 95.2% of trials resulted in sub-metre accuracy. A method to mitigate NLOS error is RSSI-based outlier detection, this method detects anomalies between the RSSI and the measured RTT range and de-weights anomalous signals during filtering. This outlier detection performed well in environments with NLOS conditions, at its best providing an average improvement of 41.3% over no outlier detection across all algorithms in an environment. The Genetic Filter performed best overall with a mean improvement of 49.2% when compared to least squares, the particle filter performed achieved an average of 38%. For the particle filter, this can be attributed to poorer mitigation of particle degeneracy. The genetic filter was also the only algorithm to provide a performance improvement over least squares in all environments.

1 INTRODUCTION

WiFi is one of the primary tools to carry out mobile indoor positioning due to its vast infrastructure presence and typically static location. WiFi Fine Time Measurement (FTM), is a WiFi protocol enabled in routers and mobile devices that use chips compatible with 802.11mc (Google, 2022) and beyond; it enables the time of flight (ToF) of a WiFi signal to be determined, the system that applies this protocol is commonly referred to as WiFi RTT. This protocol is promising as providing a ToF based protocol has allowed ToF based positioning algorithms to be applied to WiFi signals, which could be a key step to unlocking more accurate and reliable indoor positioning than WiFi Residual Signal Strength Indicator RSSI-based positioning. Non line of sight (NLOS) reception and multipath interference are inevitable in complex indoor environments and degrade WiFi RTT accuracy, this paper presents a solution to these problems.

The research in this paper explores the accuracy, reliability and computational efficiency of WiFi RTT positioning in a variety of indoor environments and focuses on more efficient filtering techniques. Four positioning algorithms are explored: Least squares, a generic particle filter using sequential importance resampling, a new genetic filter that applies a genetic algorithm to the resampling step of a particle filter and a new grid filter. All methods were also augmented with a new environment-agnostic Residual Signal Strength Indication (RSSI) based outlier detection model, which detects NLOS signals and severe multipath interference by finding and accounting for inconsistencies between the RTT range measurement and the RSSI of the measurement. The paper will begin by providing a background of current literature, then an explanation of all the techniques explored in this paper will be provided, next the experimental methodology will be provided, finally the results of these experiments will be analysed.

2 BACKGROUND

Typically in research, WiFi-based indoor positioning is done with RSSI fingerprinting where the WIFI RSSI of the indoor environment is mapped, providing a database which is then used by a device that requires a location by comparing its current RSSI fingerprint with that of the database. However, this is potentially cumbersome and not deployable at scale as the survey step to construct the RSSI fingerprint requires a significant amount of data and time, moreover, it has been found that fingerprints have a tendency to change in changing environments such as underground stations (Ma, 2017), limiting their accuracy in certain locations where indoor positioning would be quite powerful. Currently, major companies such as Google, crowd source large amounts of WiFi data in order to construct models and predict the locations of APs in order to improve the accuracy of indoor positioning by having a larger and more detailed database. The issue with these methods are the intense data requirements and centralisation of data; with WiFi RTT this method could still be done but the accuracy would likely be better than RSSI with a given amount of data or the same accuracy with less data.

Google also believes in and led this vision given that all of their WiFi compatible devices now support WiFi RTT (Google, 2022) and they believe WiFi RTT can achieve sub-meter accuracy (Van Diggelen, 2018). In (Malkos, 2014), Malkos found that the Line-Of-Sight (LOS) error on calibrated devices were approximately 1m, up to a distance of 35m, this aligns with research conducted for this paper where the accuracy up to 10m for LOS scenarios was sub-metre when the instruments were correctly calibrated, it was however found that the Non-Line-Of-Sight (NLOS) error was greater than 1m on average and varied in magnitude depending on the scenario, thus introducing the necessity for positioning algorithms with more versatile error models and outlier detection methods.

WiFi RTT-based positioning has been explored by several different authors, in Gentner (Gentner, 2020) this paper reviewed the distribution of the WiFi-RTT distance estimation errors and developed a Gaussian mixture model since the error was non-Gaussian. This model was then utilised in a particle filter, in an experiment involving a person carrying the mobile device being tracked the average positioning error was found to be 0.93m which is an improvement of 0.45m over the model using a standard Gaussian measurement model. In addition Gentner also found there was a −1.3m mean bias between the measured distance and true distance, indicating some sort of instrument bias, this bias is also supported by research conducted as part of this paper where the instrument bias was measured at around −1m.

Guo et al opted for a different approach in (Guo, 2019) which revolved around a hybrid RSSI and RTT model. The model essentially used the RSSI of each RTT signal to determine whether the signal was from a LOS or NLOS signal, this was done by comparing the predicted distance based on the measured RSSI using a RSSI path loss model against the RTT measured range and if the two ranges were different by a certain margin then the RTT measurement would be de-weighted. A part of the paper compared RSSI finger-printing against a Kalman filter using WiFi RTT ranging data, the average accuracy of the fingerprinting was 3.41m whilst the Kalman filter had an accuracy of 2.04m for the same environment, when the RSSI outlier detection method was used the positioning accuracy of the RTT-based Kalman Filter improved to 1.435m. The inclusion of RSSI path loss ranging into the Kalman filter had the effect of identifying outliers as if there were a large disparity between the RSSI path loss range and the RTT range then the measurement would be removed from the solution. Sun et al. (Sun, 2020) integrated Pedestrian Dead Reckoning (PDR) (specifically step detection and length estimation) with WiFi RTT in an extended Kalman Filter. The model in this paper also used RSSI for outlier detection by determining the standard deviation of the RSSI and ranging data in one second, if the standard deviation was above a certain threshold, then the datapoint was removed from consideration for the positioning solution. This method achieved an RMSE of 1.1m. This is better than WiFi FTM trilateration without outlier detection which achieved an RMSE of 2.74m. In (Hashem, 2021) Hashem et al developed an algorithm called WiNar that combined WiFi RTT and RSSI fingerprinting using both measurements in a fingerprinting database, this paper found that combining WiFi RTT and RSSI fingerprinting into a single fingerprinting database provided a 50% improvement over RSSI fingerprinting alone and a 193% improvement over WiFi RTT multi-lateration with uncalibrated WiFi RTT measurement ranges. From Guo et al and Sun et al it is clear that the accuracy of WiFi RTT can be improved by developing algorithms that also take into the account RSSI.

Gentner developed a WiFi RTT Simultaneous Localisation and Mapping (SLAM) model (Gentner, 2021) that is one of the first papers that presents a WiFi RTT based positioning algorithm that does not assume prior knowledge of the environment such as the location of APs or a fingerprint database. This model follows a SLAM approach with a particle filter and fuses WiFi RTT ranging measurements with IMU data from the same mobile device; the model estimates the AP locations and the position of the mobile device simultaneously. The particle filter used is a Rao-Blackwellized particle filter based on the sequential importance resampling particle filter (Arulampalam, 2002). In this paper, Gentner highlights the importance of using a particle filter over a low complexity extended Kalman filter due to the non-linearity of the measurements. The estimated mobile device position using this method had a root mean square error below 1m.

In (Malkos, 2014) and (Gentner, 2021), Gentner explored WiFi RTT in combination with a particle filter. Aside from a few other papers that also use particle filters, not much research has been conducted on alternative filtering techniques, three filtering techniques will be explored in the following sections alongside a new RSSI-based outlier detection model.

3 FILTERING TECHNIQUES

3.1 Particle Filter

Particle Filters are a promising method for WiFi RTT positioning as they are better suited than standard Kalman filters for highly nonlinear problems (Arulampalam, 2002) (Gentner, 2020). WiFi RTT is a non-linear problem as the RTT measurements are not linear functions of the mobile device position and are non-Gaussian. This is mainly a result of NLOS reception errors and multipath effects. Due to the increasing computational capacity of mobile phones, more complex algorithms can be run. Thus the computational trade-off of a particle filter vs a Kalman filter is less of an inhibitor to the use of a particle filter for a better level of accuracy as more states and particles can be used, furthermore the computational load of a particle filter can be adjusted by reducing or increasing the number of particles allowing for greater flexibility across different platforms.

The process for the particle and genetic filters follow the diagram shown in Figure 1.

1. An initial position estimate is determined based on a rudimentary single epoch least squares algorithm.
2. Particle filter
    i. Initialisation – Creates N_p particles using the initial position estimate, $\mathbf{x_0}$, as the mean, the particles are randomly distributed around the initial position estimate to account for uncertainty, the standard deviation of the state distribution matches the uncertainty of the initial position estimate.
    ii. Prediction - Move the particles according to a control input, i.e. velocity with some noise (for the case of static positioning the velocity is simply 0 with some noise to prevent the filter from over-converging)
    iii. Update - Update the weightings of each particle by seeing how closely the measured ranges to each landmark match the particles distance to the landmarks. The model used for weighting is described in depth in Equations 1. Following this the weights are normalised.
    iv. Resampling – If Equation 2 evaluates to be true then carry out Sequential Importance Resampling (SIR) – take higher weighted particles, replacing lower weighted particles with them and then resetting weights
    v. Estimate – compute the mean and standard deviation of the states using the particle weights.

    Repeat steps ii – v for each epoch.

The update step for computing weightings is the step for determining how strongly a particle matches the measured state from state estimates. The Euclidean distance between each particle and the landmarks are computed, d_i^n, where n is the AP landmark being measured from and i represents the epoch which is then treated as the mean in a Normal distribution alongside a standard deviation, the standard deviation is assumed to be equal across all APs at this stage, this will be modified using RSSI-based outlier detection which is described in Chapter 4, specifically according to Equation 11. Once the normal distribution is determined, the PDF of the distribution at z_i^n, the measurement obtained for the distance between the AP, n, and the mobile device is calculated at epoch i, this gives the particle weight for that landmark. The weights for all landmarks for each epoch are then multiplied together to give a final weight for that particle, this process is repeated for all particles.

$$w = \frac{1}{\sigma_i^n\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{z_i^n - d_i^n}{\sigma_i^n})^2} \qquad (1)$$

The effective sample size, N_{eff}, is determined as shown in Equation 3 so long as Equation 2 evaluated as true. Where N_p is the number of particles and w_k^i is the normalised weight of the ith particle.

$$N_{eff} < \frac{N_p}{2} \qquad (2)$$

$$N_{eff} = \frac{1}{\sum_{i=1}^{N_p}\left(w_k^i\right)^2} \qquad (3)$$

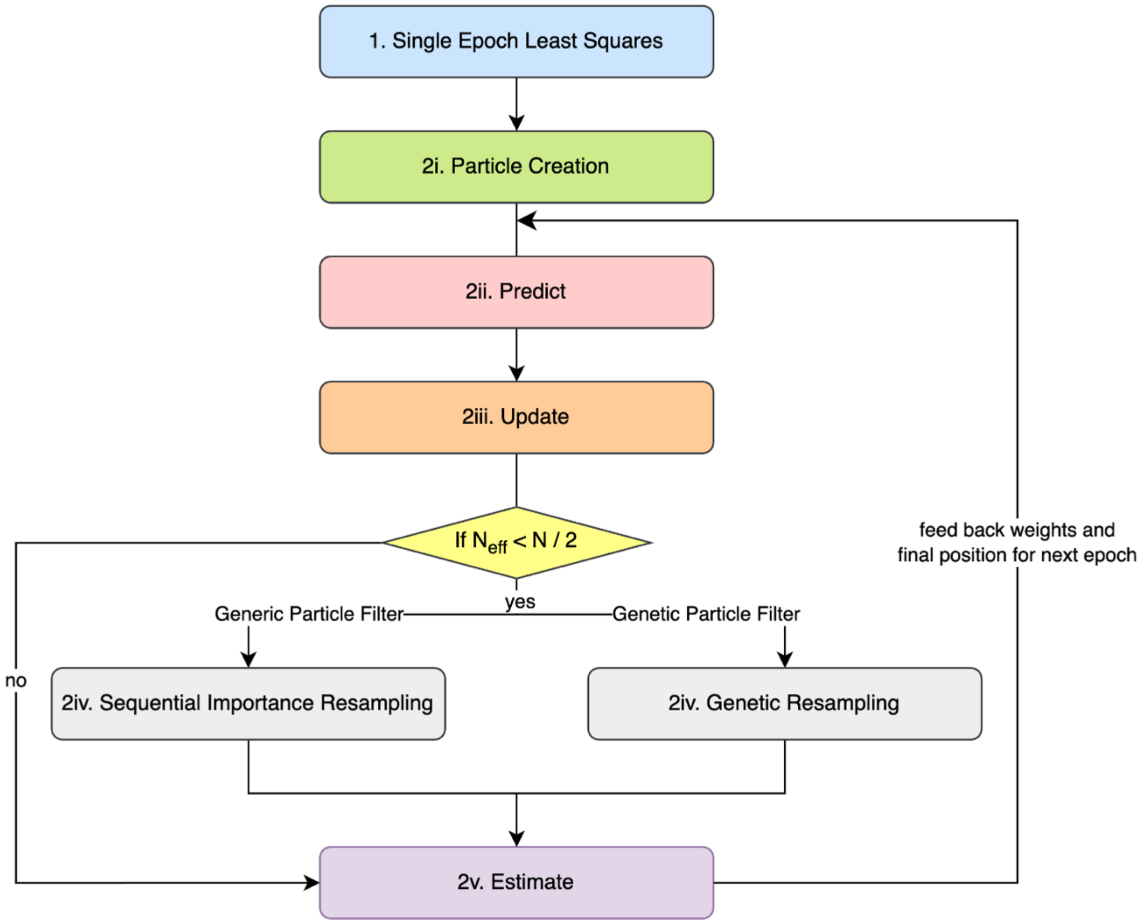

FIGURE 1 Generic Particle and Genetic Filter process

In most particle filters SIR is used (Arulampalam, 2002), where resampling is triggered because the number of effective particles is too low SIR essentially replicates higher weighted particles and deletes lower weighted particles. This is done is to mitigate particle degeneracy. As the algorithm progresses there will be particles that have very low weight and contribute nothing to the solution and are thus wasted computation. The resampling step essentially removes these low weighted particles in favour for the higher weighted particles such that more particles are being used to identify the position of the mobile device.

The particle filter used for this paper used 400 particles, had states of 2D position and velocity, the initial position uncertainty is 1m distributed following a gaussian distribution, the velocity is assumed to be 0, the noise used for the prediction step follows a gaussian distribution.

3.2 Genetic Filter

The genetic filter (Park, 2007) (Higuchi, 1997) offers an alternative to SIR at the resampling step; instead, the resampling follows a genetic algorithm. The intention of this method is to provide an alternative and potentially more effective way of mitigating particle degeneracy and increase the diversity of the particles during resampling than SIR, such that fewer particles could be used for the same level of accuracy. Mitigating particle degeneracy is important as it reduces the chance of the particles of a particle filter focusing on false positive too quickly. Essentially, the genetic filter enables the particles more opportunity to explore the search space to identify regions which could result in a higher weighting. A genetic filter has been applied to an ultrawideband (UWB) positioning solution in (Zhou, 2021).

The resampling step of a genetic filter is composed of 3 steps: classification, crossover and mutation. At the selection/classification step the algorithm gets a set of strongly weighted particles and a set of weakly weighted particles. Classification is the process of sorting the particles into mating pools to be used in the crossover step. The particles are sorted into ascending order based on weight. Then the particles are split into two particle sets, n, computed through Equation 4, represents the integer that is used as the index to split the ordered particle set, where the set with index 0 to n is the higher weighted set and the set with starting index n+1 to N_p is the lower weighted set. The higher weighted set will be denoted as X_H and the lower weighted set will be denoted as X_L.

$$nint(n) \leq N_{eff} < nint(n+1) \qquad (4)$$

For the crossover step, to summarise, each strongly weighted particle undergoes an arithmetic crossover with another strongly weighted particle to produce two offspring particles which will replace the two parent particles, then all weakly weighted particles undergo an arithmetic crossover with a strongly weighted parent particle and the new particles replace the original particles.

Crossover is the process of taking two random particles from the mating pools and exchanging information between them to construct a new particle (referred to as offspring), the crossover operation conducted for this algorithm is an arithmetic crossover. Equation 5 and 6 describe the arithmetic crossover conducted on the higher weighted set X_H, the two offspring particles are then used for the next epoch. The total number of particles remains the same. Equation 7 describes the arithmetic crossover conducted for the lower weighted particle set, X_L, in this version of the crossover instead of taking two parents from the same set, a particle from the higher weighted set is crossed over with a random particle from the lower weighted particle set, the parent particle used and the new offspring particle are then passed onto the next generation.

$$\begin{Bmatrix} x_k^{off,1} = \alpha_1 x_k^{par,1} + (1-\alpha_1) x_k^{par,2} \\ x_k^{off,2} = \alpha_2 x_k^{par,2} + (1-\alpha_2) x_k^{par,1} \end{Bmatrix} \qquad (5)$$

$$\begin{Bmatrix} \alpha_1 = \dfrac{w_k^{par,1}}{(w_k^{par,1} + w_k^{par,2})} \\ \alpha_2 = \dfrac{w_k^{par,2}}{(w_k^{par,1} + w_k^{par,2})} \end{Bmatrix} \qquad (6)$$

$$x_k^{off,L} = \beta x_k^{par,L} + (1-\beta) x_k^{par,H} \qquad (7)$$

Where β is a random number between 0 and $(N_p - N_{eff}) / N_p$.

For this algorithm, a mutation step was not implemented as noise is incorporated in the prediction step which achieves the same objective.

3.3 Grid Filter

The Grid filter differs to the genetic filter and particle filter in the initialisation, prediction and resampling steps. Instead of using particles the search space is split into grid squares. Each grid square intersection represents a candidate position of the mobile device and fundamentally, instead of particles moving around and each particle's weight being updated, weights are moved throughout the grid to represent the posterior distribution of the device's state. The process follows the following steps:

1. Initialisation - The search area is initialised as a square grid of the indoor environment being explored, (in larger environments the search area would be a subset of the environment this is not necessary for the environments used in the experiments in this paper), this is then split into 2D grid squares of dimensions, q, to form an array of dimensions N. N is determined based on the largest x or y dimension of the floor plan of the indoor environment being searched. This way you can adjust the size of the grid which is equivalent to the number of particles in the particle filter whilst still having a representation of each area of the search area. For this paper, q, was initialised as 1m.
2. Prediction - Move the weights in the grid according to a control input, i.e. velocity with some noise (for the case of static positioning the velocity is simply 0 with some noise to prevent the filter from over-converging)
3. Weighting – each grid square is weighted according to the distance of the upper left point of the square from all of the landmarks. The model used for the weighting is the same as the particle filter and genetic filter. This weight is multiplied

by the previous weight of that grid square. This weighting represents the likelihood that the device is in that grid square, the model for the particle and genetic filter are also used here. Following this, the weights are normalised.

4. Using the weights of each grid point the weighted average position is determined according to Equation 8. This represents the estimated position of the mobile device at that epoch.
   Repeat steps 2 to 4

$$x = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{8}$$

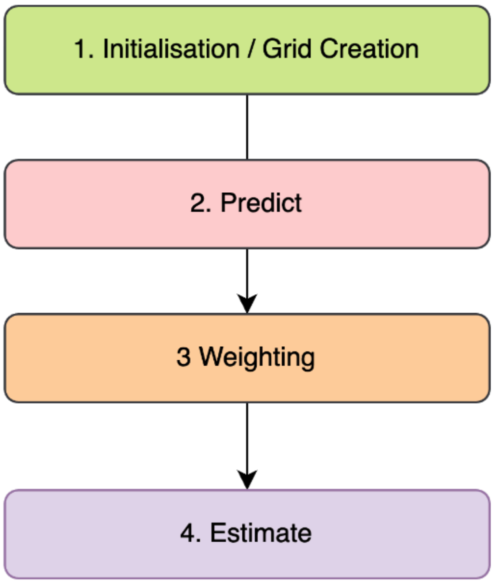

FIGURE 2 Grid Filter process

4 RSSI-BASED OUTLIER DETECTION

All positioning algorithms explored in this paper were also augmented with a new environment-agnostic Residual Signal Strength Indication (RSSI)-based outlier detection model, which detects NLOS signals and severe multipath interference by finding and accounting for inconsistencies between the RTT range measurement and the RSSI of the measurement. Guo et al and Sun et al have also used RSSI for outlier detection, however, these algorithms were optimised for the environments by conducting surveys of the RSSI path loss model and fingerprinting. The environment-agnostic RSSI-based outlier detection model proposed in this paper is as follows:

1. RSSI-threshold determination – take the median measured RTT range between an AP and the mobile device across 2 seconds worth of data (the sampling speed of the experiments was set to 200ms or 500ms). Then use Equation 9 for each access point to compute the expected RSSI given that distance, giving the RSSI threshold, $R_n^{threshold}$where n represents the epoch, $\bar{d}$ represents the median measured RTT distance and d_{min} is a minimum distance, below which RSSI-based outlier detection is not used. It was found during experimentation that the relationship between RSSI and RTT measurements below 4m was misleading, thus RSSI-based outlier detection is not conducted below a certain RTT range measurement. Equation 9 was derived from (Bensky, 2016) but modified slightly to account for its use as threshold detection by increasing the constant value, optimising these values for each specific environment is a potential research focus, but for the purpose of this paper this was not done to keep the model environment-agnostic.

$$\boldsymbol{R_n^{threshold}} = -(51.4 + 20 \log_{10}(\bar{d})) \quad where \quad d_{min} < \bar{d} < 8$$

$$\boldsymbol{R_n^{threshold}} = -(65.5 + 33 \log_{10}(\bar{d}) / 8) \quad where\ \bar{d} > 8 \tag{9}$$

2. During the filtering process, following the prediction step but before the update step. Go through each AP and compare the measured RSSI against the threshold of that AP, if the measured RSSI is lower than the threshold then this particle is treated with lower confidence and the absolute difference between the measured RSSI and threshold is taken, δ_{rssi}. For each epoch these differences are normalised to produce an RSSI-based weighting factor, ϵ_i^n, for AP, n and the epoch, i.
3. ϵ_i^n are then used during the update step as a multiple to the standard deviation of the measured distances, this increases the measurement noise of the measurements with an RSSI below the threshold with the magnitude of the difference creating greater measurement noise. The standard deviation computed in Equation 10 can then be used to obtain the standard deviation used in Equation 1 for all filters. For this paper, σ, was set at 1m.

$$\sigma_i^n = \sigma \times (1 + \epsilon_i^n) \qquad (10)$$

5 EXPERIMENTAL TESTS

5.1 Methodology

The experiments tested the algorithms across a diverse range of environments that aimed to recreate LOS and NLOS signal reception as well as multipath effects. Six environments were used, the diagrams of the environments are shown in Figure 5. Each environment used its own coordinate system; these are shown in Figure 6. Within all environments the devices were kept at the same z axis. The orientation of the mobile device, a Google Pixel 4a, is shown in Figure 3. All access points used Google Nest WiFi access points, shown in Figure 4. All data was collected via a custom mobile app that was able to collect RTT ranging data and RSSI data from all access points simultaneously. It was assumed that the location of all access points was known for all post-processing. All algorithms were tested with all datasets with and without RSSI-based outlier detection and the computation time was measured during post-processing of the positioning solution as opposed to real time. Additionally, for some APs there was an instrument bias, this was measured before each trial and removed during post processing.

FIGURE 3 Google Pixel 4a orientation - "texting mode”

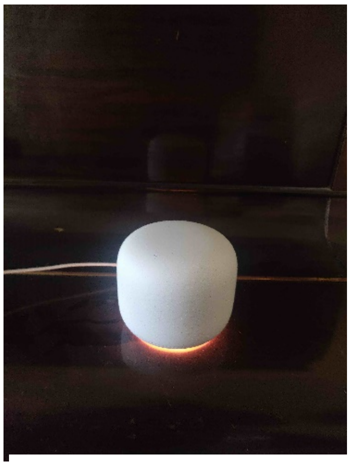

FIGURE 4 Google Nest WiFi Access point

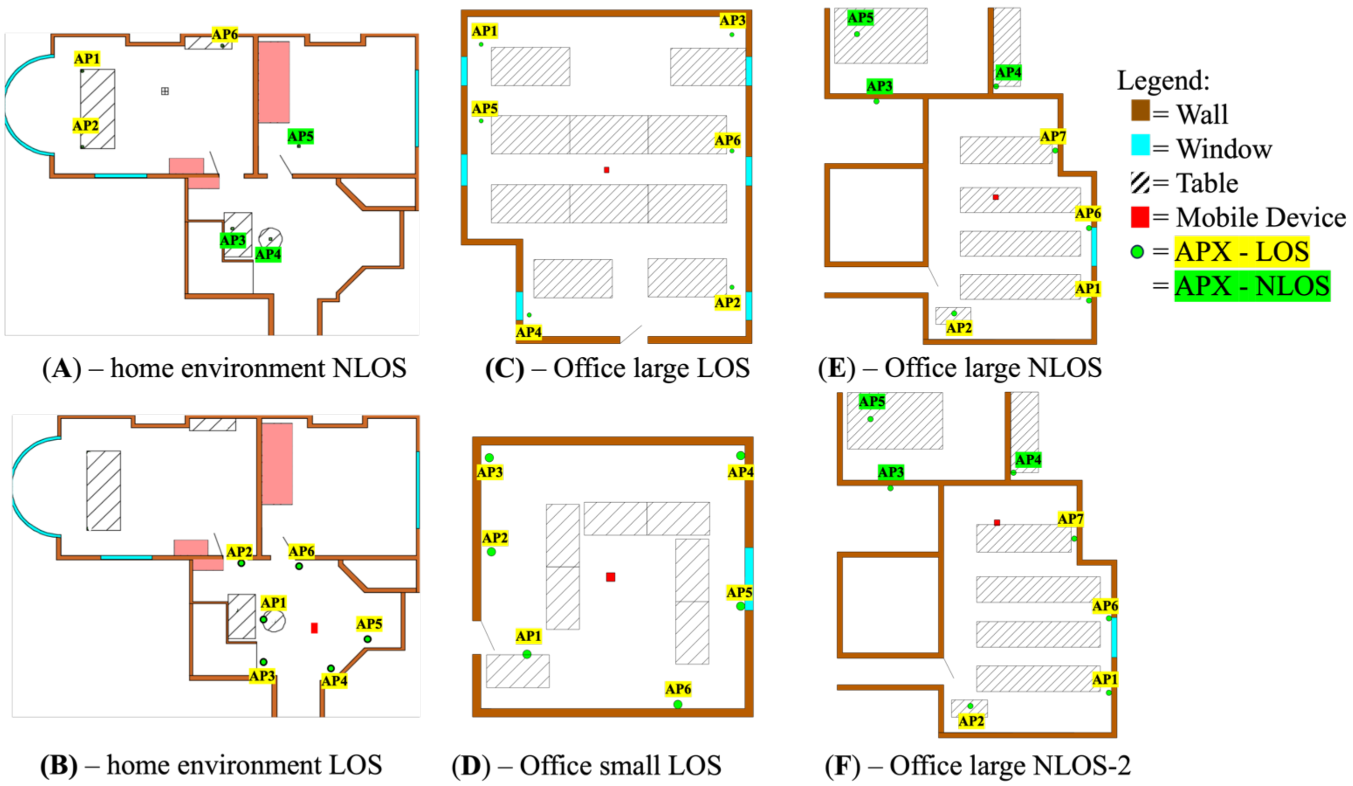

FIGURE 5 Experimental Environments

5.2 Experimental Results

The resulting measurements were then processed by all algorithms with and without RSSI-based outlier detection to determine a final position solution. First, all algorithms will be analysed against what WiFi RTT has been advertised to be capable of, then each algorithm will be compared against one another, then the algorithms will be compared with and without outlier detection. Finally, the computational efficiency of the algorithms will be explored.

TABLE 1 Positioning solution RMSE for each environment and algorithm configuration

	A RMSE (mm)	B RMSE (mm)	C RMSE (mm)	D RMSE (mm)	E RMSE (mm)	F RMSE (mm)
Single Epoch Least Squares	2193.6	1252.6	931.5	544.5	1261.4	1166.0
Particle Filter	1088.2	451.9	406.5	497.6	1533.1	1617.3
Particle Filter + outlier detection	714.6	455.5	297.2	467.3	1515.2	752.1
Genetic Filter	1176.3	442.0	282.1	488.5	1004.0	919.3
Genetic Filter + outlier detection	856.3	559.0	214.5	498.5	800.0	498.7
Grid Filter	795.4	275.0	611.2	214.1	4048.0	2640.7
Grid Filter + outlier detection	802.3	219.5	586.1	230.9	3005.8	1969.3

The root mean square error (RMSE) of the positioning solution for each environment is shown in Table 1. 28 out of 42 or 67% of tests produced sub-metre accuracy, 38 out of 42 or 90.5% trials had an RMSE below 2 metres, indicating there is a strong argument for WiFi RTT being able to produce sub-metre accuracy for positioning as pitched in (Google, 2022) as long as the

AP biases are calibrated. Environments B, C and D where all APs had a LOS to the mobile device produced sub-metre accuracy for 20 out of 21 trials, indicating that in optimal conditions (with calibration), WiFi RTT could provide a reasonable positioning solution for most pedestrian navigation use cases. In environments A, E and F where there were NLOS signals present only 8 out of 21 trials achieved sub-metre accuracy. This is to be expected as NLOS and multipath effects vary substantially from environment to environment and are a substantial error source for WiFi RTT positioning. As most indoor pedestrian navigation and tracking use cases will likely involve NLOS signals this needs to be improved. The filters and outlier detection provide an improvement. The worst performing environment and algorithm combination was the Grid filter on environments E and F. This is a complex environment, taking into account Figure 6E and 6F it appears that the filter seemed to quickly converge on an incorrect position, resulting in a RMSE over double the base line single epoch least squares. This could be attributed to the grid filter not using an initial position estimate. As the grid filter initialises with a uniform distribution of grid squares, every grid square intersect is treated as a candidate location, as opposed to the other filters which have a distribution around the initial position estimate, this results in potentially converging to an incorrect position. To test this hypothesis a sub-test was conducted where the particle and genetic filters were initialised with a uniform distribution and it was found that these filters performed similarly to the grid filter. This problem could be solved by using the initial position estimate to define the centre of the grid and reducing the size of the grid to a radius around the initial position estimate, as opposed to applying the grid to the entire environment, this will be explored in further research. In the case of the genetic filter's improvement over the particle filter the problem could be attributed to poor mitigation of particle degeneracy as the genetic filter has the most advanced particle degeneracy mitigations.

TABLE 2 Percentage decrease of RMSE against least squares for each environment and algorithm configuration

	A	B	C	D	E	F	Mean Percentage improvement
Single Epoch Least Squares	0%	0%	0%	0%	0%	0%	0%
Particle Filter	50%	64%	56%	9%	-22%	-39%	20%
Particle Filter + outlier detection	67%	64%	68%	14%	-20%	35%	38%
Genetic Filter	46%	65%	70%	10%	20%	21%	39%
Genetic Filter + outlier detection	61%	55%	77%	8%	37%	57%	49%
Grid Filter	64%	78%	34%	61%	-221%	-126%	-18%
Grid Filter + outlier detection	63%	82%	37%	58%	-138%	-69%	6%
Mean percentage improvement	59%	68%	57%	27%	-57%	-20%	

Overall the results are promising. Table 2 shows the percentage improvement of each algorithm combination against the baseline least squares algorithm with green indicating a better accuracy and red indicating a worse accuracy. Single-Epoch least squares was used as the control to compare the filters against, in 2 out of 6 environments sub-metre accuracy was achieved, both LOS environments (C and D). In these environments, all of the filters improved the positioning accuracy over least squares, this is also true for environment A and B. However, in environment E and F, the particle filter and grid filter perform worse than least squares. The Grid Filter with outlier detection producing the highest improvement of 82%. Whilst for environments E and F the algorithms only improved performance over least squares 5/12 times, the genetic filter with and without outlier detection performed the best for those trials, whereas the grid filter performed the worst as discussed previously. The algorithms provided the greatest mean improvement in Environment B; this is the simplest environment with the smallest distances between the APs and mobile devices and no LOS signals and would be expected to have the highest accuracy given there are fewer error sources when compared to more complex environments like E and F. The best performing algorithm on average across all environments was the genetic filter with and without outlier detection with 49.2% and 38.7% mean percentage improvement over single epoch least squares. This could be attributed to better handling of particle degeneracy as well as RSSI-based outlier detection, which provides a bonus 10.5% over the algorithm with no outlier detection. Furthermore, unlike the other algorithms the genetic filter only improved accuracy, in contrast, in environment E the other algorithms caused a decrease in accuracy when compared to single epoch least squares.

TABLE 3 Percentage decrease of RMSE comparing outlier detection against no outlier detection for each algorithm

	A (NLOS)	B (LOS)	C (LOS)	D (LOS)	E (NLOS)	F (NLOS)
Particle Filter	0%	0%	0%	0%	0%	0%
Particle Filter + outlier detection	34%	-1%	27%	6%	1%	53%
Genetic Filter	0%	0%	0%	0%	0%	0%
Genetic Filter + outlier detection	27%	-26%	24%	-2%	20%	46%
Grid Filter	0%	0%	0%	0%	0%	0%
Grid Filter + outlier detection	-1%	20%	4%	-8%	26%	25%
Mean percentage improvement	20%	-2.3%	18.3%	-1.3%	15.7%	41.3%

Table 3 focuses specifically on the improvement that RSSI-based outlier detection provided for each algorithm in each environment. For all of the environments where NLOS signals were present RSSI-based outlier detection provided an improvement on average. This is because the RSSI-based outlier detection model's purpose is to de-weight NLOS signals by identifying inconsistencies with the received RSSI and measured range as signals that are not direct will have weaker RSSIs due to signal reflection, building attenuation and multipath effects. All results produced by the genetic filter with outlier detection and 5 out of 6 of the results produced by the particle filter with outlier detection resulted in sub-metre accuracy, this is because the RSSI-based outlier detection is identifying and de-weighting NLOS signals successfully, thus prioritising stronger and more reliable RTT signals. In environment F, the mean improvement was 41.3% with the outlier detection providing a 53% improvement for the particle filter and a 46% improvement for the genetic filter. For environments B, C and D, RSSI-based outlier detection was less effective and in 4 out of 9 cases provided worse performance than no outlier detection. This is because the outlier detection model is best placed for identifying outliers from NLOS signals whereas in situations where LOS signals it is possible that the model will remove signals that have reliable ranges but have had reduced RSSI for other reasons such as noise or multipath effects. The model caused a 26% reduction in performance accuracy in environment B, the simplest environment with the least error sources, suggesting that the algorithm may need to be better refined for environments with LOS signals and smaller ranges. However, these environments are less common in real world use cases like pedestrian navigation and thus is not as important as getting a better method for dealing with NLOS signal reception error, additionally, any outlier detection algorithm will have false negatives if not properly tuned to a specific scenario.

The computational efficiency of all algorithms (ran with outlier detection) was compared and the results are shown in Table 4, showing the computation time per epoch and the mean accuracy improvement. It is worth noting that the code is currently not optimised and is written in Python and ran on a Macbook Pro 2021 (Apple M1 Pro) so these computation times could be reduced significantly. The computational efficiency is as expected; the genetic filter has more computation than the other algorithms and as expected has the longest total processing time. Positioning performance would seem to correlate with processing load.

TABLE 4 Computation time per epoch for each algorithm alongside mean accuracy improvement over least squares

Algorithm	Computation Time per epoch (ms)	Mean Accuracy Improvement
Least Squares	0.47	0%
Particle Filter (400 particles)	3.39	38.5%
Genetic Filter (400 particles)	5.52	49.2%
Grid Filter (400 grid intersects)	3.21	5.5%

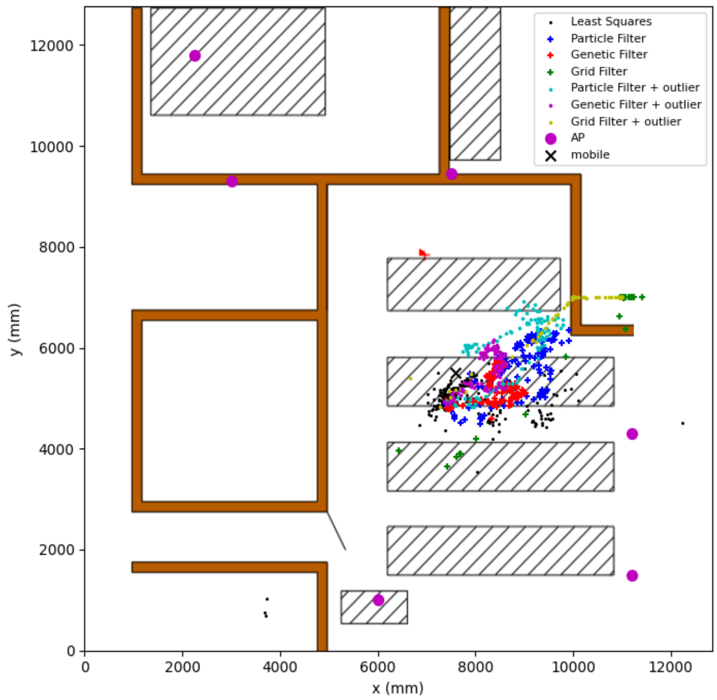

FIGURE 6E Environment E particle distribution diagram

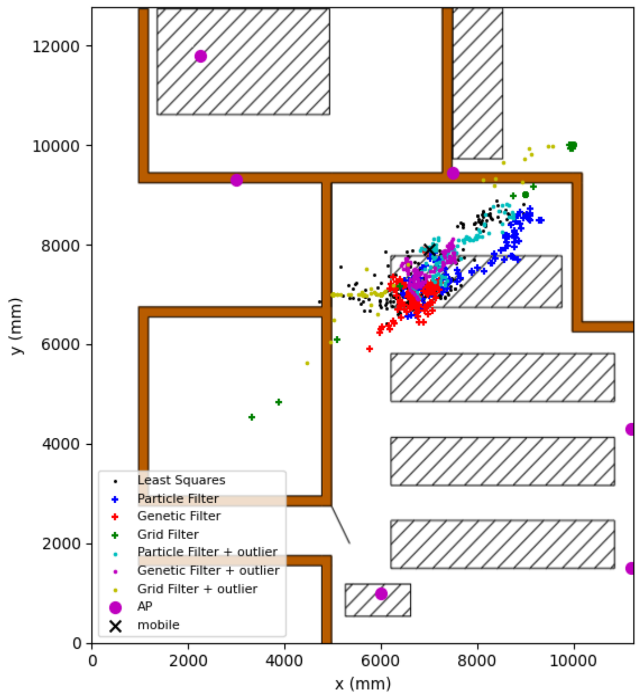

FIGURE 6F Environment F particle distribution diagram

6 CONCLUSION

Overall, the results suggest that for WiFi RTT-based positioning, filtering techniques provide a superior positioning solution to basic least squares for positioning and the addition of RSSI-based outlier detection provides an improved positioning solution in NLOS environments. The best performing algorithm on average was the Genetic Filter with outlier detection, with an average improvement of 49.2% over single-epoch least squares. This filter provided an improved method for handling particle degeneracy during the filtering process whilst the RSSI-based outlier detection enabled the removal of unreliable RTT signals caused by NLOS signal reception, an important characteristic for a viable commercial solution. Between the filters, the grid filter seemed to perform inaccurately in more complex environments such as environment E and F but very accurately in less complex environments such as B, C and D. In the case of the particle filter, this could be attributed to ineffective handling of particle degeneracy resulting in converging to a positioning solution too quickly. The grid filter appears to perform poorly overall but there is much that can be improved on the algorithm, such as using an initial position estimate to define a smaller grid, this aids with avoiding converging to an incorrect position.

Generally, the RSSI-based outlier detection was less effective for environments where all APs had a direct line of sight to the mobile device. This is expected from the algorithm as it can potentially remove reliable signals due to the RSSI path loss model not being calibrated to the environment resulting in an incorrect expected range estimation.

7 FUTURE WORK

Optimising the path loss model by calibrating it to the environment was not conducted in this paper as the objective was to create an environment agnostic outlier detection model, this is a potential opportunity for further work and has also been explored in (Sun, 2020).

The grid filter also requires additional work, as mentioned in the paper, the initial position estimate needs to be incorporated into the model, this could be done by using the initial position estimate to define a smaller search area within the environment which will represent the grid, this should improve computational efficiency further whilst also reducing the chance of the grid filter converging to an incorrect position estimate.

SLAM techniques for dynamic positioning and removing access point location assumptions will be explored in future papers and will build upon the work of Gentner et al's paper on WiFi RTT SLAM (Gentner, 2021). This removes the assumptions of static positioning and knowledge of the AP's locations which are important considerations for a viable commercial solution.

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