WiFi-RTT Posterity SLAM for Pedestrian Navigation in Indoor Environments

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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). This has allowed ToF based positioning algorithms to be applied to WiFi signals which could provide an improvement over the established RSSI-based positioning. A common assumption in WiFi RTT research is prior knowledge of the access point locations in an environment. The research in this paper explores the accuracy of WiFi RTT positioning in an indoor environment by utilising a FastSLAM algorithm applied to WiFi RTT that improves over time with the benefit of previous SLAM maps of the environment, this is known as Posterity SLAM. This specific version of the algorithm presents a positioning solution that has sub-two-metre accuracy for the mobile device without the need for a dedicated survey step. In some cases the final horizontal position error of the mobile device was sub-metre. The algorithm was effective at improving the accuracy of landmark estimates for shorter trials 100% of the time. For the landmark estimates, Posterity SLAM achieved sub-two-metre accuracy 78% of the time improving on regular SLAM which achieved sub-two-metre accuracy 61% of the time. The landmark position accuracy was sub-metre 42% of the time for Posterity SLAM and 28% of the time for regular SLAM.

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.

A common pattern in indoor positioning research is the necessity of a survey step or some prior knowledge of the environment. For most solutions the assumption is some knowledge of the location of the access points or landmarks of an environment. Alternatively, in the case of fingerprinting solutions such as RSSI-based fingerprinting a lengthy survey step is required to collect the fingerprints at each grid point in the given environment. Given the number and diversity of indoor environments this solution is not scalable. In addition, access points can be moved around and indoor environments have dynamic obstacles which can change the properties of the environment (Ma, 2017). A solution that is able to reliably position a user to sub-metre accuracy without significant cost of setup is an ideal and scalable solution for indoor positioning. WiFi RTT and Simultaneous localisation and mapping (SLAM) techniques have potential to enable this solution (Faragher, 2012) (Gentner, 2021). SLAM algorithms do not require prior knowledge of an environment as by definition the algorithm is locating the user and landmarks at the same time, in real time. Furthermore, the solution can improve over time with more users as more data can be collected. A flavour of this method is likely adopted by large technology companies such as Apple or Google who have access to vast amounts of position data and a large network of mobile devices. However, it is not possible to verify the nature of these algorithms or whether WiFi RTT is used as this is proprietary information.

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The research in this paper explores the accuracy and reliability of WiFi RTT Posterity SLAM for positioning a mobile device and all access points in a single environment over several paths. This extends work done presented at the ENC 2023 conference. The posterity SLAM algorithm works with a FastSLAM algorithm (Montmerlo, 2003) and takes advantage of previous SLAM maps of the same environment to improve the landmark position estimates and mobile device position estimate over time. All methods were also augmented with an 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 this was also presented in (Raja, 2023). 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

Simultaneous Localisation and Mapping (SLAM), first discovered by John Leonard and Hugh Durrant-Whyte (Leonard, 1991), is a procedural method to build a map of an unknown environment while at the same time navigating that environment using the map. SLAM uses sensors within the device being positioned, such as IMUs, visual data, signal data etc. This section will focus on the application of SLAM to mobile devices where WiFi is a key component of creating the map of the WiFi AP locations in an environment. SLAM is a solution to the problem of requiring previous knowledge of the environment in order to carry out positioning. SLAM can enable mobile devices to position themselves in any building where the signals that it uses to construct a map of the environment are present.

A paper by Faragher et al (Faragher, 2013) demonstrated WiFi SLAM. A positioning technique for an indoor environment where an initial GPS position fix was used then WiFi signals and IMU data was used in combination with SLAM. The IMU in the device was used for step detection (accelerometer) and as a compass (magnetometer). Using an assumed step length it is possible to roughly calculate the distance moved and heading of a device. However, in this experiment the step length for each particle was randomly assigned within a range to account for different step lengths and noise was applied at each epoch to account for changes in minor changes in step length. Then various other signals were polled every second including WiFi RSSI, GNSS and cellular measurements. As with most SLAM systems, a particle filter was used for navigation and mapping. A particle filter, based on sequential Monte Carlo can be used to estimate the position of a mobile device. The algorithm takes a number of particles to represent a distribution of likely states. Whenever the device moves the algorithm predicts the new state based on the movement (deliberately adding noise during the process) and then compares this prediction with the measured state to determine how well they correlate. The weighted average of all particles should be a good estimate of the actual position of the device. In this paper, the particle filter is initialised using a GPS position, its associated uncertainty, the average step length and compass bias. As the device moves from the starting point the position solution from the IMU becomes less accurate. This is because error in the IMU measurement will affect the predicted state which will affect the predicted state of the next IMU measurement and so on. Essentially over time the error in predicted state increases if left uncorrected. However, the position solution corrects itself when the device passes a location it has better certainty on, either from a more reliable GNSS signal or because the device has already been at that position (thus the WiFi signal signatures at that location match). Loop closure (or a device returning to a location it has previously visited) is a key part of SLAM it is the primary way to remove the drift accumulated from the IMU errors that accumulate over time. By returning to a previously travelled reference point it is possible to reset the position of a device and also adjust the rest of the map to account for the drift error. For this method, over a 15 minute walking period the final position error was 4 metres compared to an 86m error for an uncorrected particle filter solution. Given that the SLAM solution has no prior knowledge of the environment, this is a good result, especially since the final position error is not reflective of the position error throughout the positioning phase which was lower but not measured in the experiment.

A paper by Ferris et al. (Ferris, 2007) also explored WiFi SLAM. The results of this paper yielded an average position error of 3.97m with a standard deviation of 0.59m. This model however used a Gaussian Process Latent Variable Model, a technique used for mapping high-dimensional data (signal strength information for all WiFi APs in the environment in this case) to a low-dimensional latent space (a two-dimensional latent space in this case [xy coordinates] (Lawrence 2003). A paper by Liu et al. (Liu, 2020) focused on WiFi SLAM that integrated visual methods through Google's Tango (now known as ARCore (Google, 2024)). This tool enables mobile devices to combine visual input from the Tango's camera which had better optical sensors than an ordinary phone camera with IMU data to track the movement of the device. This paper used a particle filter as the positioning engine and ran two experiments. The first experiment used WiFi RSSI and step-detection-based PDR and the second experiment used WiFi RSSI and Tango-based PDR using visual inertial odometry. The Tango-based-PDR required the user to hold the phone upright such that the phone's camera could view the environment to conduct visual inertial odometry. The Tango-based-PDR and WiFi SLAM yielded a average positioning error of 0.6m which is better when compared to step-detection-PDR and WiFi SLAM which yielded an average positioning error of 4.76m. The results of the Tango/visual-based model are impressive and has its benefits for specific mobile positioning tasks. However, in most cases of mobile pedestrian navigation it is unlikely that a user will be holding their phone upright with the camera on, especially considering the power requirements.

WiFi RTT SLAM has not been explored in much depth at the time of writing. WiFi RTT SLAM was explored by Gentner and Avram (Gentner, 2021) in 2021. This positioning solution used WiFi RTT signals and IMU data (gyroscope and accelerometer) processed using a particle filter. As a mobile device moves around an environment it is possible to narrow down the location of each AP to a specific area, thus enabling map creation. The WiFi RTT SLAM positioning algorithm used in this paper yielded an average positioning error under 1m. This is an improvement on WiFi SLAM when compared to WiFi RSSI SLAM and a good positioning performance. This paper is a great proof of concept for WiFi RTT SLAM and more research on this technique to explore alternative filter methods, outlier detection models and more sensor fusions would advance the field significantly.

3 FASTSLAM ALGORITHM

Fast SLAM 2.0 (Montmerlo, 2003) conceptually follows a similar flow to a Particle filter as it is made up of several particle filters. The particle filters used are described in (Raja, 2023). In addition to the particle filter of the mobile device state estimates; each landmark has their own particle filter state with their own state estimates. This means that the estimated position of the landmarks are actually variable and the location estimate is determined as the mobile device moves through the environment. During the earlier epochs of the SLAM process, the algorithm is more akin to odometry. Due to the uncertainty around the landmark locations, the algorithm relies more heavily on the motion sensors in the earlier epochs. Furthermore, by using particles, the mobile device and landmark states can scale more efficiently whilst dealing with a more complex distribution. This is a general benefit of Monte-Carlo based filters. This means that FastSLAM is well suited for positioning during operation as the number of particles can be altered to accommodate for computational requirements. Admittedly, this will have an effect on positioning accuracy.
The algorithm used in this paper follows the process shown in Figure 1. The particle filter follows the model described in (Raja, 2023).

1. The initial mobile device position and heading are assumed to be known. The landmark/access point coordinates are initialised based on a uniform distribution in the environment, where each access point will have its own particle filter. This initialisation occurs when each access point is observed.
2. The PDR model is applied during the prediction step. In this step the mobile device particles are moved according to the PDR model with noise distributed on a normal distribution. The PDR follows the algorithm described in (Raja, 2023).
3. For the access point update step, the particles of each access point are weighted against the distance between the particle and the estimated mean coordinates of the mobile device using equation 1. The update step for computing weightings is the step for determining how strongly a particle state matches the state suggested from measurements.

$$w_{k+1}^{j} = w_{k}^{j} \prod_{i=1}^{n} \frac{1}{\sigma_{k}^{i}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{z_{k}^{i} - d_{k}^{j,i}}{\sigma_{k}^{i}}\right)^{2}} \qquad \text{Equation 1}$$

   The Euclidean distance, $d_k^{j,i}$, between each particle, j, and the landmarks is computed using Pythagoras' theorem, where i is the AP landmark being measured from, n is the number of APs and k represents the epoch. This distance is then treated as the mean in a Gaussian distribution alongside a standard deviation. This standard deviation is modified using RSSI-based outlier detection which is described in (Raja, 2023). Once the gaussian distribution is determined, the PDF of the distribution of z_k^i, the measurement obtained of the distance between the AP, i, and the mobile device is calculated using Pythagoras' theorem at epoch k. This gives the particle weight for that landmark. The weights for all landmarks for each epoch are then multiplied together and the previous weight of that particle, w_k^j, to give a final weight for that particle, w_{k+1}^j. This process is repeated for all particles.
4. The particles of the mobile device are weighted against their distance from each estimated access point position, the estimate is based on the mean coordinates of each access point particle filter. The weighting follows Equation 1.
5. The particles for both the mobile device and access points go through Sequential Importance Resampling (SIR) (Arulampalam, 2002) (Doucet, 2024) (Raja, 2023) if the particle degeneracy limit is exceeded.
6. Finally, the position estimate of the mobile device and all access points is calculated using the weighted average of the particle positions.

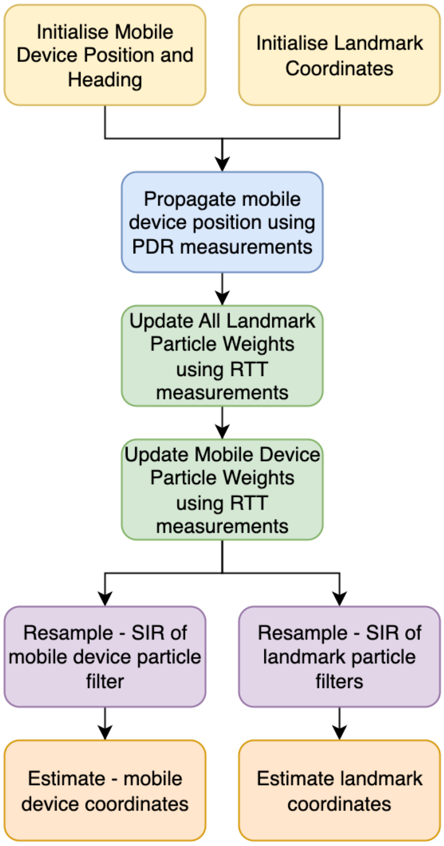

FIGURE 1 WiFi RTT FastSLAM algorithm

3.1 Posterity SLAM

The posterity SLAM algorithm is similar to the regular FastSLAM 2.0 algorithm with one key difference. During the initialisation step of the landmark particles, instead of using a uniform distribution throughout the environment, each landmark's particles are initialised with a Gaussian distribution around the final landmark coordinates of the previous SLAM trial. The standard deviation of each access point particle filter of the previous trial is taken to initialise the standard deviation of the Gaussian distribution of the access point particle filters for the new trial. This essentially allows each SLAM trial to benefit from previous SLAM trials improving the overall positioning solution over time whilst being aware of potential uncertainty in those estimates. Posterity SLAM is a form of cooperative SLAM as it takes advantage of multiple cooperative mobile devices to map a given environment.

4 EXPERIMENTAL TESTS

4.1 Methodology

The methodology for testing the SLAM algorithm involved moving through a route both forward and in reverse in an environment. These routes were designed to enable NLOS signal reception to occur. The routes and environment explored are shown in Figure 2. A Google Pixel 4a was used as the mobile device and 3 Google Nest routers, 2 Google WiFi Points and 1 Google WiFi Router was used for the access points. The trials involved a pedestrian holding the smartphone and walking on top of fixed step markers placed on the ground along the route of the trial. The markers were approximately 670mm apart, the location of each marker was measured against the reference points in the environment to generate the step marker's ground truth coordinates. In order to align the ground truth data with the measured data, the trials were filmed. The timestamps of the steps from the video were used to determine the expected position of a device at a given time, allowing the analysis to have an accurate comparison point at each step.

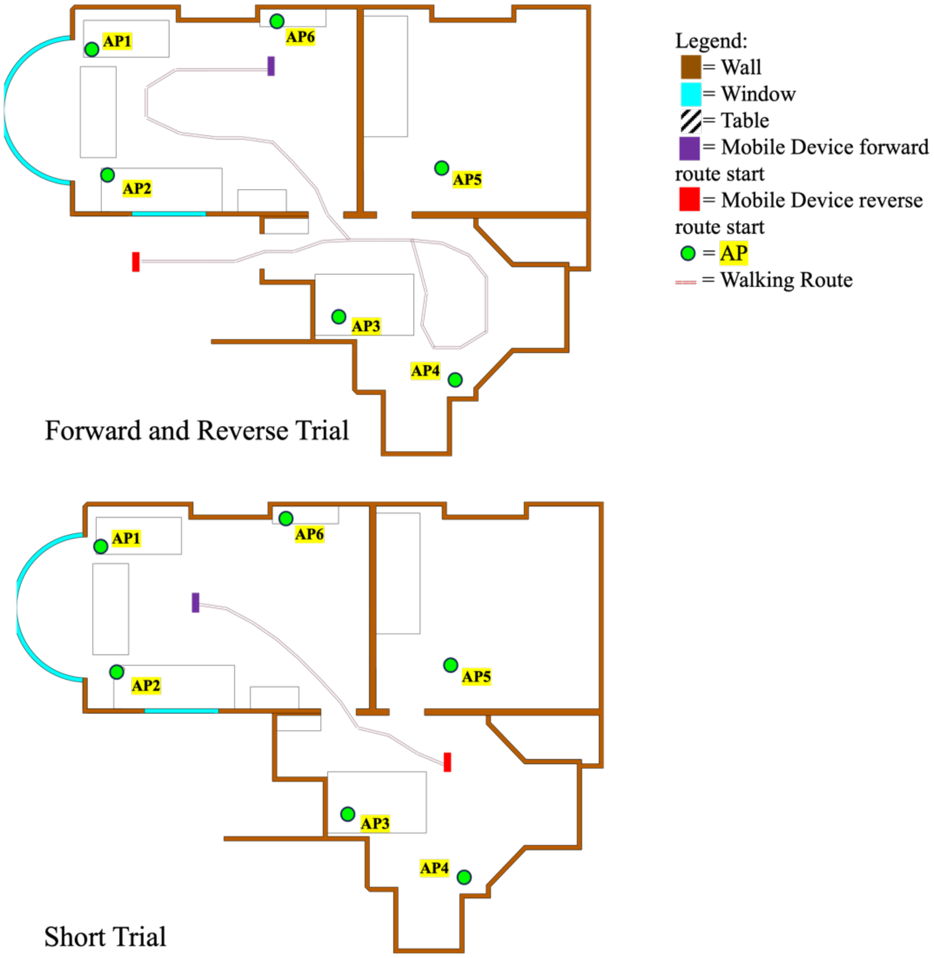

FIGURE 2 Experimental Environments

The standard deviation of the step length assuming white noise, used to determine the noise applied during the prediction step was calibrated as follows. A pedestrian carrying the mobile device walks 20 steps in a straight line 10 times, the real distance travelled is measured and the estimated distance travelled is calculated using the PDR model, the standard deviation of the difference is computed and this is divided by the number of steps to give the standard deviation of a step. All data was collected simultaneously using a custom mobile app. RTT and RSSI measurements were received at 100ms intervals and IMU data was collected at approximately 20ms intervals. The locations of the access points were also calculated and these were used to test the effectiveness of the SLAM algorithm landmark predictions.

For this set of experiments the parameters were set up as shown in Table 1.

TABLE 1 Experimental Configuration

Number of Particles in the mobile device particle filter	50000
Number of Particles in each landmark particle filter	10000
Initial Position Error	0.1m
Initial Heading Error	0.03 radians
Mikov constant	0.6
Sensor Heading Error	0.3 radians
Step Length Error	0.1m
Landmark Measurement Error	2m
Mobile Device Measurement Error	1m

4.2 Experimental Results

This section will explore the use of SLAM-determined landmark coordinates to initialise the landmark coordinates for new SLAM trials. All combinations of the forward, reverse and short trials are shown, these include: forward using reverse, reverse using forward, forward using short, short using forward, reverse using short and short using reverse. For example, with forward using reverse, the trial is the forward trial using the landmark position estimates from the reverse trial.

The positioning metrics of the forward using reverse and reverse using forward trials can be seen in Table 2 alongside the trials on their own. Posterity SLAM improved the final horizontal error of the mobile device from 1.55m for the reverse trial to 0.8m from 1.55m for the reverse using forward trial, providing sub-metre accuracy to the positioning solution. The mean horizontal error improved from 1.78m to 1.14m, whilst the median improved from 1.96m to 1.05m. However, in the case of forward using reverse whilst the final horizontal error was lower by 0.04m the maximum horizontal error increased by 0.62m and the mean horizontal error increased to 1.06m from 0.92m. The change in horizontal error per step for the forward path trials can be seen in Figure 3. The forward using reverse trial begins well but its position estimates degrade during the loop section of the path. The change in horizontal error per step for the reverse trials can be seen in Figure 4. Posterity SLAM demonstrates that the mobile device can be more consistently accurately positioned than regular SLAM.

TABLE 2 Statistics for the mobile device position estimates for the Forward and Reverse Trial

	Forward Trial	Reverse Trial	Reverse Using Forward	Forward Using Reverse
Maximum Horizontal Error (m)	2.76	2.45	2.47	3.38
Mean Horizontal Error (m)	0.92	1.78	1.14	1.06
Standard Deviation (m)	0.58	0.56	0.57	0.86
Median Horizontal Error (m)	0.87	1.96	1.05	1.06
Final Horizontal Error (m)	0.89	1.55	0.80	0.85

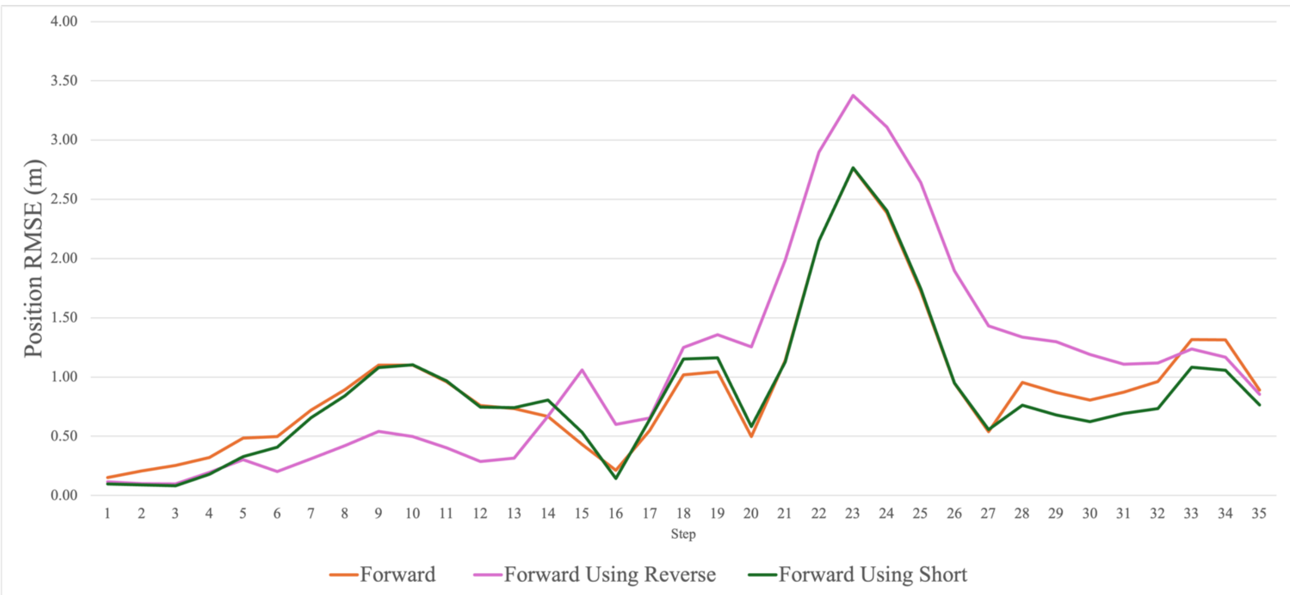

FIGURE 3 Forward Path posterity SLAM horizontal error per step

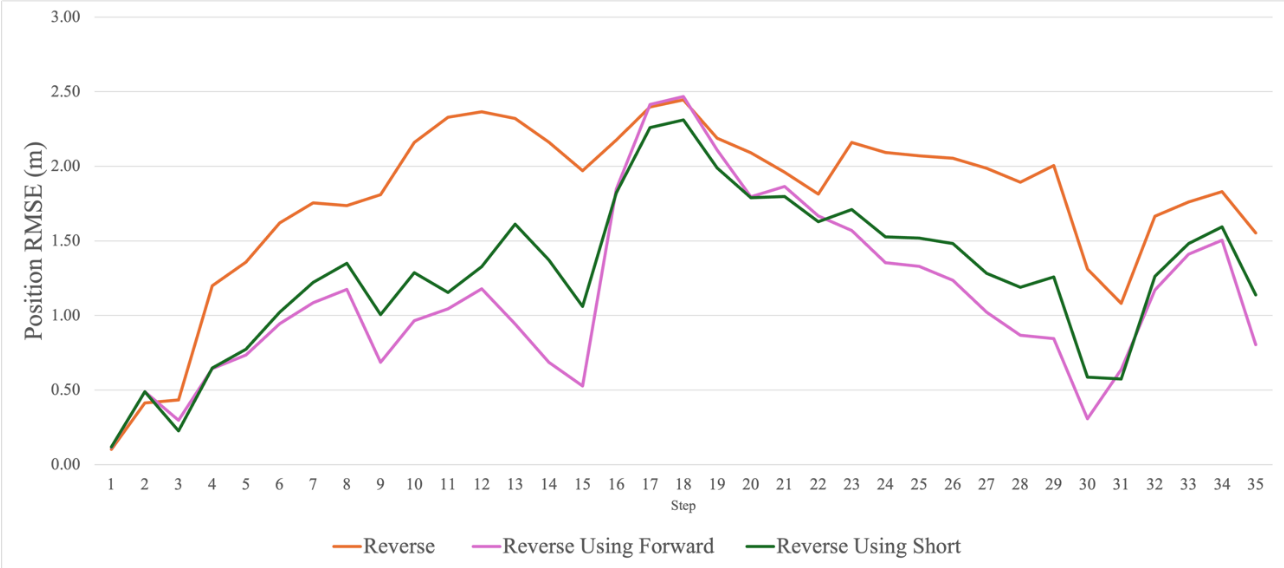

FIGURE 4 Reverse Path posterity SLAM horizontal error per step

The final horizontal position error for all APs for the forward-reverse trials are shown in Table 3. The final horizontal position error of the landmarks for the reverse using forward trial improved for 4 out of 6 access points when compared to the reverse trial. All landmarks were positioned to sub two metre accuracy. The most substantial improvement was in AP3 which improved from 2.69m to 1.6m. Comparing the AP horizontal errors of the reverse using forward trial to the forward trial on their own shows that 4 out of 6 AP positions improved. Comparing the forward and reverse using forward data, the best improvement was 0.88m on AP1. The largest decrease in accuracy was on AP3 with a decrease of 0.76m. However, this is in contrast to a 1.09m improvement when comparing the reverse using forward to the reverse trial alone. This is somewhat undesirable. An ideal outcome would be able to take the best of both datasets.

TABLE 3 Statistics for the landmark position estimates for the Forward and Reverse Trial

	Forward Trial	Reverse Trial	Forward Using Reverse	Reverse Using Forward
AP1 Final Horizontal Position Error (m)	1.43	1.44	1.11	0.55
AP2 Final Horizontal Position Error (m)	2.43	1.83	1.51	2.0
AP3 Final Horizontal Position Error (m)	0.84	2.69	2.11	1.60
AP4 Final Horizontal Position Error (m)	0.79	0.97	0.83	1.1
AP5 Final Horizontal Position Error (m)	0.76	0.95	1.06	0.75
AP6 Final Horizontal Position Error (m)	0.57	1.3	0.93	0.25

In the forward using reverse data also shown in Table 2, the landmark horizontal error only improved for 2 APs when compared to the forward trial alone. The greatest improvement being 0.92m on AP2 and the greatest decrease in accuracy being 1.27m on AP3. Comparing the forward using reverse trial to the reverse trial alone showed that posterity SLAM improved the horizontal error for 5 out of 6 APs. The mean horizontal error across all APs were 1.06m, 1.26m, 1.14m and 1.53m for the reverse using forward, forward using reverse, forward and reverse trials respectively. This demonstrates that posterity SLAM can improve the average AP horizontal error. This can be seen in Figures 5 and 6 which shows the AP position error per epoch for the reverse using forward trial and the forward using reverse trial respectively. Posterity SLAM allows the second trial to have a better starting point for the landmark estimates, enabling a better set of landmark position estimates. There is an opportunity for the most accurate landmark estimates to be picked over time as more trials occur, thus improving the overall positioning solution. This opportunity has not been explored in this paper and represents scope for future work.

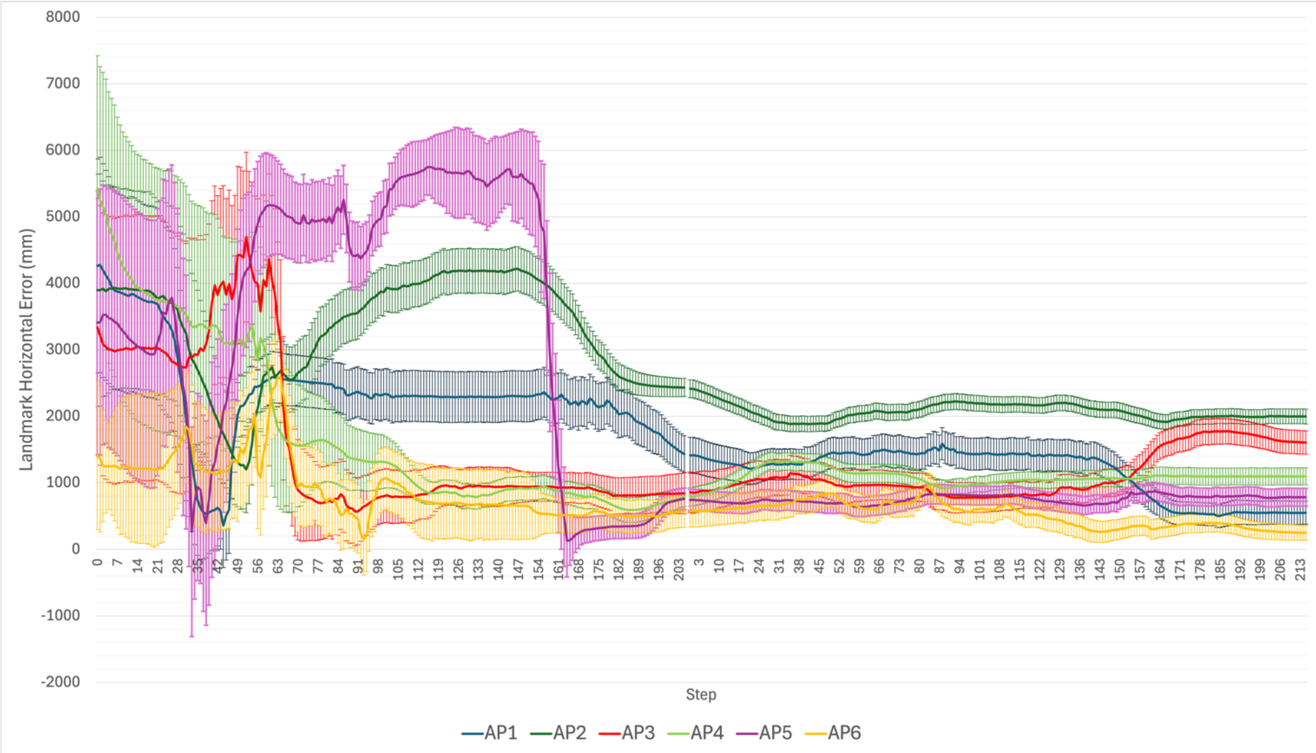

FIGURE 5 Forward then Reverse AP position error per step. The white cut-off in the centre of the chart represents the switch from the forward trial to the reverse trial. The error bars represent the standard deviation of each landmark particle filter.

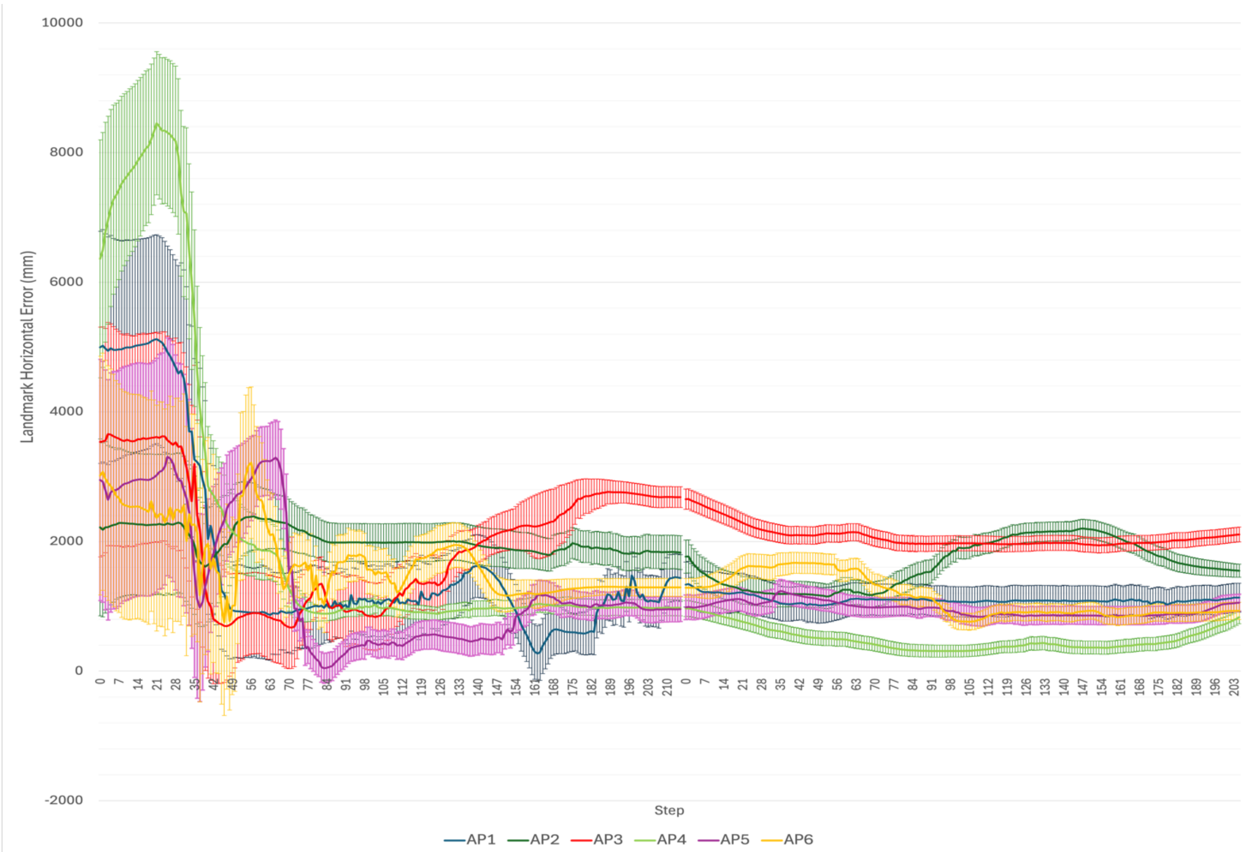

FIGURE 6 Reverse then Forward AP position error per step. The white cut-off in the centre of the chart represents the switch from the reverse trial to the forward trial. The error bars represent the standard deviation of each landmark particle filter

The Short Trial dataset was used to demonstrate the poor performance of the algorithm on shorter paths with fewer turns, more specifically poor performance for the AP positions. The reason that a shorter path would have poorer performance for determining landmark positions is that the algorithms have less time to allow the landmark particle filters to converge to a strong landmark position estimate, so essentially the algorithm relies heavily on odometry for the positioning solution. Furthermore, it is possible that observing landmarks from a range of different directions also has an impact on the landmark positioning accuracy. Theoretically this scenario is where posterity SLAM can provide a significant improvement to the positioning solution as more reliable landmark position estimates can be used.

The mobile device positioning metrics for the short and forward trials are shown in Table 4 and the metrics for the short and reverse trials are shown in Table 5. The Short trial final positioning error was 1.42m. Using posterity SLAM, this improved to 0.82m when the forward trial landmark position estimates were used and 0.96m when the reverse trial landmark position estimates were used. The improvement can be seen by comparing Figure 7 which shows the short path without posterity SLAM and Figure 8 which shows the short path when the landmark position estimates of the forward trial are used to initialise the short SLAM trial.

TABLE 4 Statistics for the mobile device position estimates for the Short and Forward Trials

	Forward Trial	Short Trial	Short Using Forward	Forward Using Short
Maximum Horizontal Error (m)	2.76	1.42	0.84	2.77
Mean Horizontal Error (m)	0.92	0.42	0.40	0.87
Standard Deviation (m)	0.58	0.41	0.26	0.60
Median Horizontal Error (m)	0.87	0.24	0.37	0.75
Final Horizontal Error (m)	0.89	1.42	0.84	0.77

TABLE 5 Statistics for the mobile device position estimates for the Short and Reverse Trials

	Reverse Trial	Short Trial	Short Using Reverse	Reverse Using Short
Maximum Horizontal Error (m)	2.45	1.42	0.96	2.31
Mean Horizontal Error (m)	1.78	0.42	0.49	1.28
Standard Deviation (m)	0.56	0.41	0.33	0.51
Median Horizontal Error (m)	1.96	0.24	0.43	1.29
Final Horizontal Error (m)	1.55	1.42	0.96	1.14

The AP final horizontal position error for the short and reverse trial combinations can be seen in Table 6. The short trial landmark position errors are on average 2.78m with a maximum horizontal error of 5.57m for AP2. 1 out of 6 APs were positioned sub two metre accuracy. When posterity SLAM using the reverse trial is incorporated, the errors improve to 4 out of 6 being sub-metre with all 6 AP positions improving. In the case of the short using reverse trial, in 5 out of 6 trials the landmark position accuracy improved compared to the reverse trial alone. This is interesting as posterity SLAM clearly demonstrates an improvement in the landmark position estimates. Additionally, the landmark position estimates improved for 4 out of 6 trials for the reverse trial when the short landmark estimates were used when compared to the reverse trial alone. Despite the poor performance of the short trial, it was still useful in providing a more accurate set of landmark position errors for the reverse trial. The final mobile device horizontal error for the reverse using short trial improved to 1.14m from 1.55m for the reverse trial. This trend of improvement in AP position accuracy per step can be seen in Figures 9 and 10 which show the short using reverse and reverse using short trials respectively.

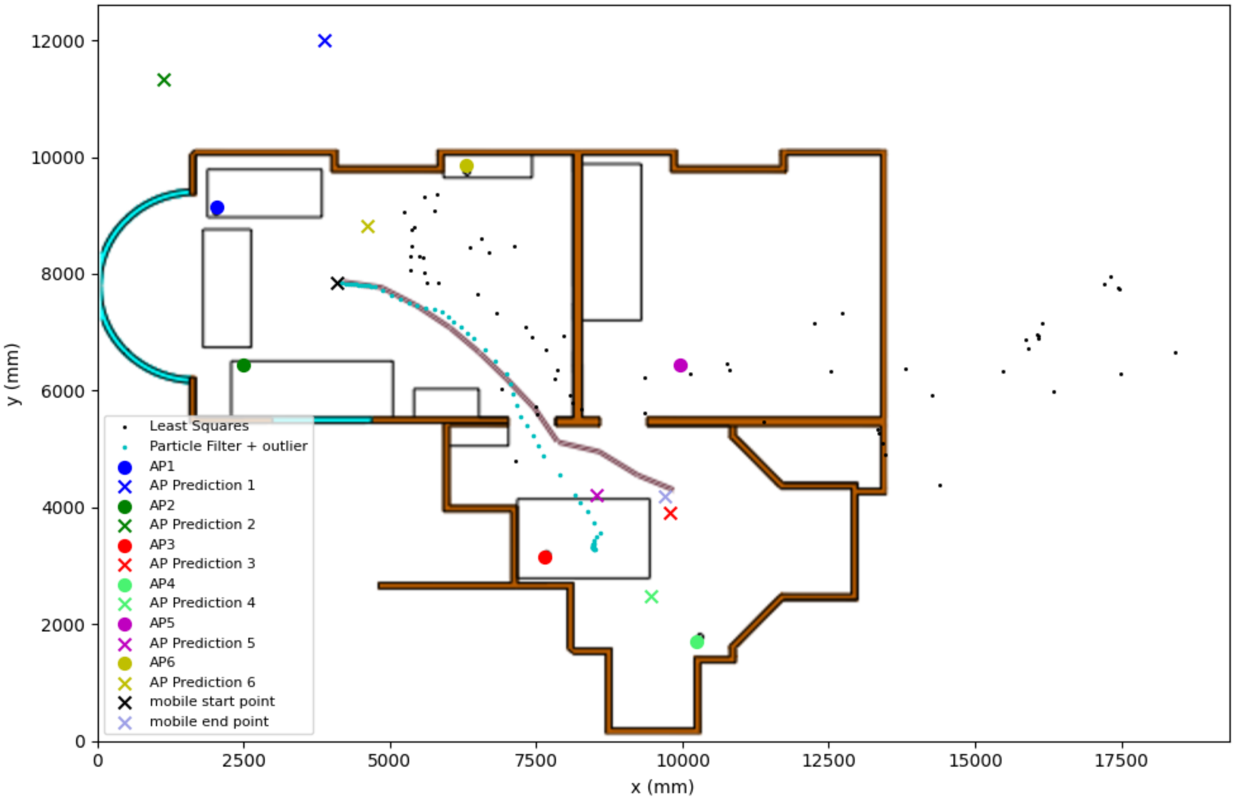

FIGURE 7 Short Path regular SLAM position estimate and landmark estimates

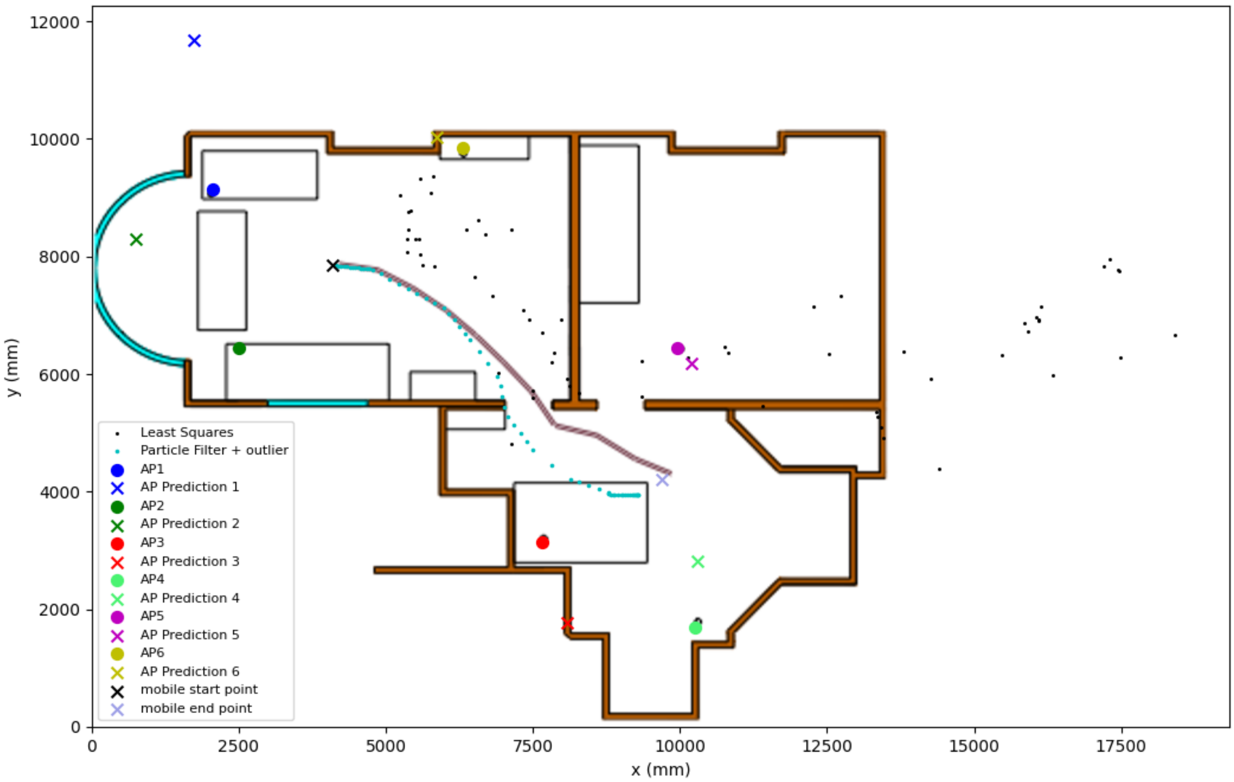

FIGURE 8 Short using Forward Path posterity SLAM position estimate and landmark estimates

TABLE 6 Statistics for the landmark position estimates for the Short and Reverse Trial

	Reverse Trial	Short Trial	Reverse Using Short	Short Using Reverse
AP1 Final Horizontal Position Error (m)	0.83	2.79	1.61	0.75
AP2 Final Horizontal Position Error (m)	1.86	5.57	2.70	2.40
AP3 Final Horizontal Position Error (m)	2.79	2.30	2.38	2.05
AP4 Final Horizontal Position Error (m)	1.11	1.27	0.15	0.58
AP5 Final Horizontal Position Error (m)	1.01	2.72	1.0	0.94
AP6 Final Horizontal Position Error (m)	1.23	2.05	0.75	0.77

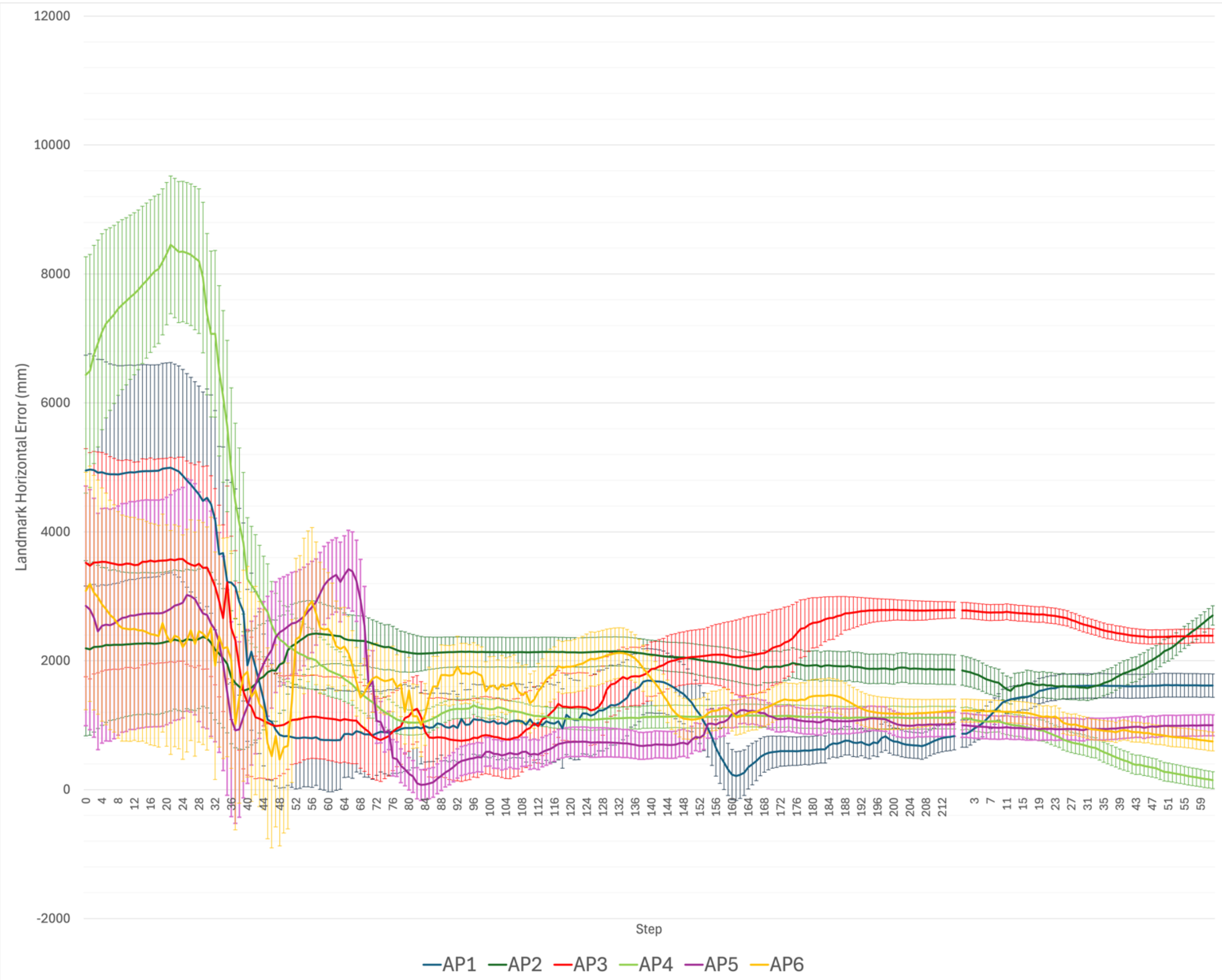

FIGURE 9 Reverse then Short AP position error per step. The white cut-off in the centre of the chart represents the switch from the reverse trial to the short trial. The error bars represent the standard deviation of each landmark particle filter

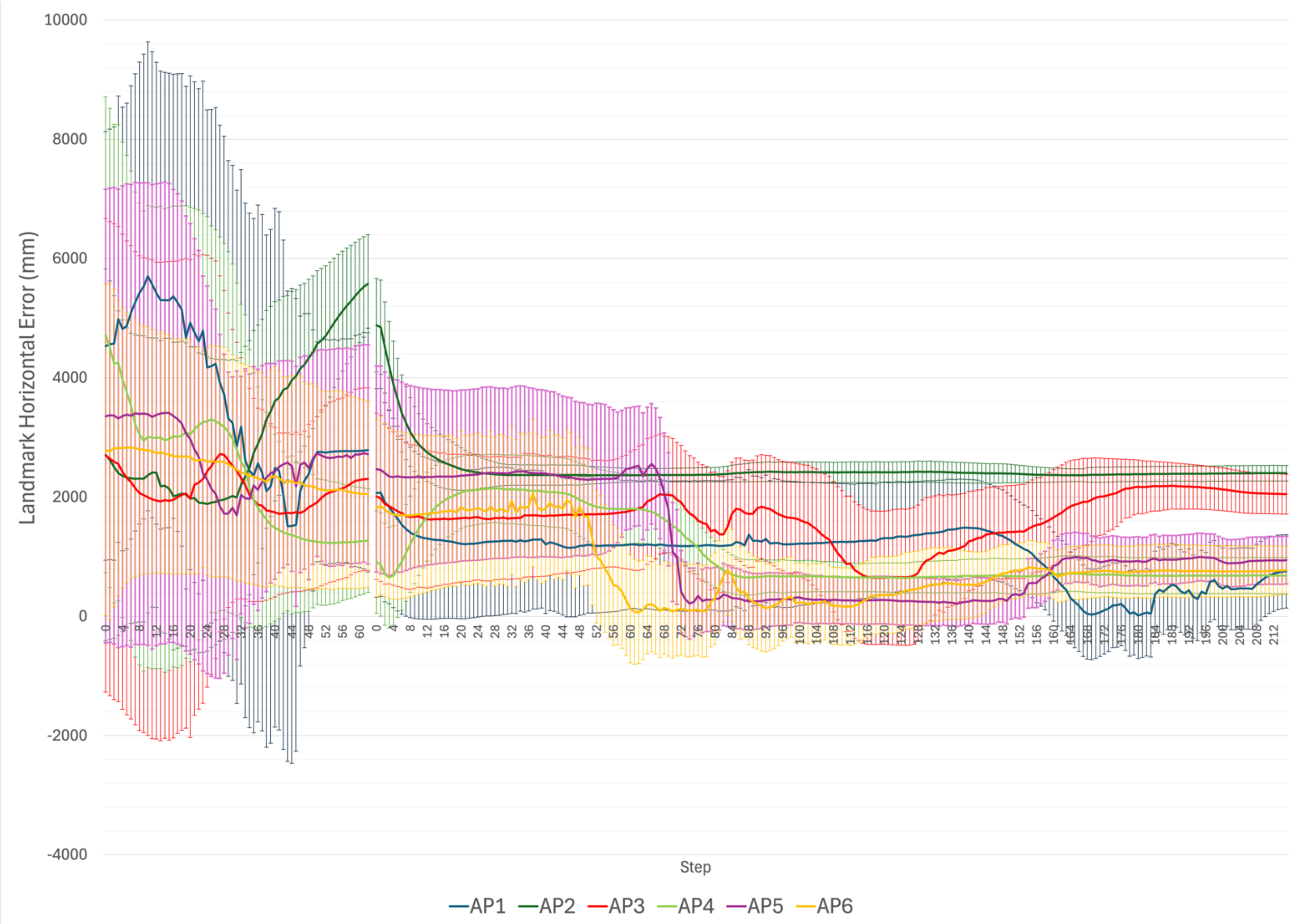

FIGURE 10 Short then Reverse AP position error per step. The white cut-off in the centre of the chart represents the switch from the short trial to the reverse trial. The error bars represent the standard deviation of each landmark particle filter

The trend of results for the landmark position estimates is mostly similar for the short and forward trial combinations shown in Table 7. The short trial landmark position error improved for 6 out of 6 APs when the forward trial landmarks were used for initialisation. However, when the short trial landmark estimates were used for the forward trial, 5 out of 6 AP position errors increased when compared to the forward trial alone.

TABLE 7 Statistics for the landmark position estimates for the Short and Forward Trial

	Forward Trial	Short Trial	Forward Using Short	Short Using Forward
AP1 Final Horizontal Position Error (m)	1.83	2.66	1.86	2.58
AP2 Final Horizontal Position Error (m)	2.64	5.56	3.31	2.89
AP3 Final Horizontal Position Error (m)	0.83	2.16	1.08	1.23
AP4 Final Horizontal Position Error (m)	0.99	1.33	1.25	1.03
AP5 Final Horizontal Position Error (m)	0.77	2.30	1.08	0.48
AP6 Final Horizontal Position Error (m)	0.57	2.05	0.55	0.60

Posterity SLAM benefits the overall positioning solution as data from trials can be shared meaning that over time the system can have a better estimate of the landmark positions due to more data. This specific version of the algorithm presents a positioning solution that has sub two metre accuracy without the need for a dedicated survey step, as previous SLAM paths essentially conduct the survey steps automatically. Furthermore, it has been shown that landmark position estimate accuracy is normally lower for shorter paths. This impacts the positioning solution as the particle filter is not able to weight paths correctly because the individual particle weights are less reliable. Posterity SLAM offers a solution to this problem as the landmark estimates of longer trials can be used to improve the positioning solution for shorter paths.

5 CONCLUSION

Posterity SLAM benefits the overall positioning solution as data from trials can be shared meaning that over time the system can have a better estimate of the landmark positions due to more data. This specific version of the algorithm presents a positioning solution that has sub two metre accuracy for the mobile device without the need for a dedicated survey step, as previous SLAM paths essentially conduct the survey steps automatically. The number of improved landmark estimates due to posterity SLAM was greater than or equal to 50% for all but one trial. The one trial were posterity SLAM made the landmark estimates overall worse was when a shorter trial was used to initialise the landmark filters for a longer trial. The landmark positioning for shorter trials was very poor with only one landmark being positioned to sub-two-metre accuracy. When the short trial takes advantage of SLAM maps from longer trials the landmark position accuracy improves for all APs. Posterity SLAM achieved sub-two-metre accuracy 78% of the time improving on regular SLAM which achieved sub-two-metre accuracy 61% of the time. The landmark position accuracy was sub-metre 42% of the time for Posterity SLAM and 28% of the time for regular SLAM. This clearly demonstrates that posterity SLAM offers a solution to the performance of SLAM on shorter paths as the landmark estimates of longer trials can be used to improve the positioning solution. A limitation of this algorithm is the potential error that can be caused by using poor position estimates. However, it would be expected that with more data this error would reduce over time.

6 FUTURE WORK

This paper did not apply GraphSLAM to WiFi RTT SLAM. The application of GraphSLAM to WiFi RTT would be interesting and could outperform FastSLAM.. The posterity SLAM algorithms had an issue where while the accuracy of the landmark position estimates would improve for some APs, for other APs the landmark position accuracy would reduce. This is potentially problematic as over-time these errors could grow. This problem could be solved with more data. More SLAM maps will be constructed as more users traverse an environment. These SLAM maps can be compared to identify outliers in landmark position estimates. Additionally, with every SLAM trial a set of new SLAM maps can be constructed based on the posterity of other SLAM maps or a combination of SLAM maps. This means that with every new SLAM map the number of landmark position estimates that can be constructed based on the SLAM data will grow very fast. With this method, overtime the system will have a better estimate of the landmark positions as with more trials the APs will be ranged from more angles, meaning a higher likelihood for APs to be more accurately positioned.

Multiple devices traversing multiple paths can be used simultaneously to construct SLAM maps. This could be particularly practical in large venues where there will be a large number of mobile devices. Multiple mobile devices contributing to the construction of a single SLAM map at the same time would allow for more geometries to each AP to be determined. By having more geometries to each AP it would be expected that the AP position estimates would be better. This improvement in AP position estimate would allow for a better indoor positioning system in a shorter amount.

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