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# SLAM using LTE Multipath Component Delays

Junshi Chen[†*], Meifang Zhu[*], Fredrik Tufvesson[†]
[†]Dept. of Electrical and Information Technology, Lund University, Lund, Sweden
[*]Terranet AB, Lund, Sweden
Email: {junshi.chen, fredrik.tufvesson}@eit.lth.se, meifang.zhu@terranet.se

***Abstract*—Cellular radio based localization can be an important complement or alternative to other localization technologies, as base stations continuously transmit signals of opportunity with beneficial positioning properties. In this paper, we use the long term evolution (LTE) cell-specific reference signal for this purpose. The multipath component delays are estimated by the ESPRIT algorithm, and the estimated multipath component delays of different snapshots are associated by global nearest neighbor with a Kalman filter. Rao-Blackwellized particle filter based simultaneous localization and mapping (SLAM) is then applied to estimate the position of user equipment and that of the base station and virtual transmitters. In a measurement campaign, data from one base station was logged, and the analysis based on the data shows that, at the end of the measurement, the SLAM performance is 11 meters better than that with only inertial measurement unit (IMU).**

***Index Terms*—MPC delay, SLAM, positioning, particle filter, LTE, CRS.**

## I. Introduction

Reliable and accurate location information is a critical requirement of safety and traffic efficiency applications for intelligent transport systems (ITS). Global navigation satellite systems (GNSS) are the most common systems used for positioning in the world. However, sub-meter level accuracy is not yet available with any mass market GNSS technology. In addition, in critical environments, such as urban canyons or indoors, the position accuracy using GNSS can be drastically reduced. There is a variety of systems that can be used to support GNSS in such challenging scenarios. Those include radar or lidar, as well as camera based systems. However different weather and daylight conditions pose severe challenges to such systems. IMU is not sensitive to weather or daylight conditions, but it has accumulated error, so a stand alone IMU is not suitable for long time localization. Hence, in order to achieve robust and precise localization, a combination of different sensors with complementary properties should eventually be used. Since wireless signals, such as LTE and 5G NR, are insensitive to weather and daylight conditions and have no accumulated error, they can be used as complementary signals for localization.

There are some challenges of using wireless signals for positioning. For example, in urban canyons and tunnels, multipath effects, low received signal power and non line-of-sight (NLoS) propagation reduce the positioning accuracy. Exploiting multipath propagation instead of mitigating the multipath effect is attracting a great deal of research interests. The authors of [1], and [2] interpret the effect of an electromagnetic wave reflected on a surface as a signal emitted from a virtual transmitter (VT), and based on this interpretation, multipath component (MPC) delays can be used not only to estimate the trajectory of the receiver but also to estimate the surrounding features by employing a simultaneous localization and mapping (SLAM) algorithm. Some additional information from the vehicle, such as the heading and speed information from an IMU, can be used as the control input of the SLAM algorithm to further improve the performance.

There are many studies that have investigated the positioning algorithms using wireless signals. The paper [3] uses the estimation of signal parameters via rotational invariance technique (ESPRIT) algorithm to estimate the delay of the first arrival path, and tracks the path delay from one snapshot to the next. However, the study only considers the first arrival path, and does not take advantage of the multipath information. The paper [4] exploits all the multipath information and considers them as signals transmitted from synchronous VTs, which can further increase the positioning accuracy. The authors use the Kalman enhanced super resolution tracking (KEST) algorithm to estimate and track the MPCs, but this algorithm still has high computational complexity compared with the ESPRIT algorithm. The paper [5] develops a belief propagation (BP) algorithm for feature-based SLAM with probabilistic data association (DA) using MPC parameters extracted from radio signals as input measurements, it has good performance but it is rather complex. In this paper, a low complexity algorithm only exploitting the MPC delays is developed to verify the idea of wireless SLAM with commercial LTE signals. Single antenna LTE cell-specific reference signal (CRS) transmitted from commercial base station is logged by a single antenna user equipment (UE) for positioning.

The structure of the paper is as follows. Section II introduces the system model. Section III describes the super resolution algorithm (SRA) to estimate the multipath delays in each snapshot. Section IV explains the data association based on global nearest neighbor (GNN) with a Kalman filter. Section V explains the Rao-Blackwellized particle filter (RBPF) based SLAM used to estimate the trajectory of UE and the positions of BS and VTs. Section VI presents the measurement campaign logged data analysis results based on the proposed algorithm. Finally, section VII summarizes the paper.

*Notation*: Matrices and vectors are denoted as uppercase and lowercase boldface letters, respectively, e.g., $\mathbf{A} \in \mathbb{C}^{M\times N}$ and $\mathbf{a} \in \mathbb{C}^{M}$. $\mathbf{I}^P$ is the $P \times P$ identity matrix, $\mathbf{0}^{P\times Q}$ is an $P \times Q$ all-zero matrix, and $\mathbf{0}^P$ is a length $P$ all-zero vector. The operators $(\cdot)^T$, $(\cdot)^H$, $(\cdot)^{-1}$, and $(\cdot)^\dagger$ denote the transpose,

the Hermitian transpose, the inverse, and the Moore-Penrose pseudoinverse of a matrix, respectively. $\mathbb{E}[\cdot]$ is the expected value of a random variable (RV). $|\cdot|$ and $arg(\cdot)$ are the absolute value and the argument of a complex number, respectively. $\|\cdot\|$ denotes the norm of a vector. $c \simeq 3 \cdot 10^8$ m/s is the speed of light.

## II. System Model

In the LTE system, the baseband signal is an orthogonal frequency division multiplexed (OFDM) signal described as:

$$\begin{aligned} s^p(t) = & \sum_{k=-N_{sc}/2}^{k=-1} S^p[k+N_{sc}/2] e^{j2\pi k \Delta f t} \\ & + \sum_{k=0}^{k=N_{sc}/2-1} S^p[k+N_{sc}/2] e^{j2\pi (k+1) \Delta f t}, \\ & t \in [-T_{CP}, T_s], \end{aligned} \tag{1}$$

where $S^p[k], k \in [0, N_{sc}-1]$ is the transmitted signal at the $k$-th subcarrier and the $p$-th antenna port, where $p \in [1, \ldots, 4]$ is the antenna port number for CRS, and $N_{sc}$ is the number of the subcarrier to be transmitted. Further, $t$ denotes the continuous time variable, $T_{CP}$ is the duration of the cyclic prefix (CP), $T_s = 1/\Delta f$ is the duration of the actual OFDM symbol, and $\Delta f$ is the subcarrier spacing. For more details about parameter settings, please refer to [6] and [7].

The multipath channel is modeled as the following channel impulse response (CIR) and channel frequency response (CFR)

$$h(t) = \sum_{l=0}^{L-1} h_l \delta(t - \tau_l), \tag{2}$$

$$H(f) = \sum_{l=0}^{L-1} h_l e^{-j2\pi f \tau_l}, \tag{3}$$

where $\delta(\cdot)$ denotes the Dirac delta function, $h_l \in \mathbb{C}$ is the complex channel gain associated to the $l$-th path, $\tau_l$ is the corresponding delay, with $\tau_0 < \cdots < \tau_{L-1}$, and $L$ is the number of multipath components. It should be noted that we have neglected dense multipath components (DMC) for simplicity, though this has shown to affect positioning performance in a negative way. The received signal at the UE side is the convolution of the transmitted signal $s^p(t)$ and the CIR $h(t)$. After synchronization and removal of CP, the received signal is transformed into the frequency domain with fast Fourier transform (FFT), and represented as:

$$R_t^p[k] = H_t^p[k] \cdot S^p[k] + n_t[k], k \in [0, N_{sc}-1], \tag{4}$$

where $n_t[k]$ is complex white Gaussian noise with zero mean and variance of $\sigma_n^2/2$. For the CRS signal, the transmitted signal $S^p[k]$ is known at UE side, and the CFR at CRS subcarriers can be acquired through least squares (LS) estimation as:

$$\hat{H}_t^p[k] = R_t^p[k]/S^p[k]. \tag{5}$$

## III. Super resolution algorithm based MPC delay estimation

In [3] the authors use a super resolution algorithm to estimate the delay of the first arriving path form many BSs to localize the UE, however, it is possible to estimate the delays of many MPCs from a single BS, and use them to locate the UE, BS and VTs.

The CFR estimates $\hat{H}_t^p[k]$ are arranged in length $M$ snapshots $\hat{\mathbf{x}}_t^p[k]$, which are used to build the so-called data matrix $\hat{\mathbf{X}}_t^p$, i.e.,

$$\hat{\mathbf{X}}_t^p = \frac{1}{\sqrt{N}} [\hat{\mathbf{x}}_t^p[0], ..., \hat{\mathbf{x}}_t^p[N-1]] \in \mathbb{C}^{M \times N}, \tag{6}$$

$$\hat{\mathbf{x}}_t^p[k] = \left[\hat{H}_t^p[k], ..., \hat{H}_t^p[k+M-1]\right]^T \in \mathbb{C}^M, \tag{7}$$

where $N = 2N_{tot} - M + 1$ is the number of stacked columns, $2N_{tot}$ is the number of CRS subcarriers in one symbol, which is 200 for the LTE system with 20 MHz bandwidth. $M$ is a design parameter of the SRA. $M$ is usually chosen as $M = \bar{m} 2N_{tot}$, with $\bar{m} \in [0, 1]$ being a parameter subject to empirical tuning.

A singular value decomposition of the data matrix $\hat{\mathbf{X}}_t^p$ is computed as $\hat{\mathbf{X}}_t^p = \mathbf{U} \cdot \Sigma \cdot \mathbf{V}^H$, with the matrices $\mathbf{U} \in \mathbb{C}^{M \times M}$ and $\mathbf{V} \in \mathbb{C}^{N \times N}$ being unitary, and $\Sigma \in \mathbb{C}^{M \times N}$ being a diagonal matrix with the singular values $\sigma_1 \geq ... \geq \sigma_M$ in the main diagonal. This permits the evaluation of the parameters $\sigma_m^2, \ m = 1, ..., M$, which are the eigenvalues of the autocorrelation matrix $\hat{\mathbf{R}}_x = \hat{\mathbf{X}}_t^p \cdot \hat{\mathbf{X}}_t^{pH} \in \mathbb{C}^{M \times M}$. Since vehicle speeds are fairly low at urban areas, the vehicle position not change much over a short time interval, e.g., it changes 0.1 m in 10 ms for a vehicle with speed of 10 m/s, and $\hat{\mathbf{R}}$ can be averaged over $n$ ms, such that

$$\tilde{\mathbf{R}}_x = \frac{1}{n} \sum_{t=1}^{n} \hat{\mathbf{X}}_t^p \cdot \hat{\mathbf{X}}_t^{pH}, \tag{8}$$

Here $n$ is the number of subframes used for averaging, which depends on the vehicle speed and channel condition.

In [3], the minimum description length (MDL) criterion is used to estimate the number of multipath components $\hat{L}$. Here we use another method that decides the number of multipath components based on an SNR threshold, i.e., the number of multipath components equals the maximum index $m$ that satisfies the following criteria:

$$10log10 \left( \frac{\sigma_m^2}{2/M \sum_{m=M/2}^{M} \sigma_m^2} \right) > SNR_{thr}, \tag{9}$$

where $SNR_{thr}$ is a predefined SNR threshold.

After the eigenvalues of $\Psi$ are found, a classical ESPRIT approach is used to estimate multipath delays based on the

following matrix manipulations:

$$\mathbf{U}_s = \mathbf{U} \cdot \begin{bmatrix} \mathbf{I}_{\hat{L}} & \mathbf{0}_{\hat{L}\times(M-\hat{L})} \end{bmatrix}^T \in \mathbb{C}^{M\times\hat{L}}, \tag{10a}$$

$$\mathbf{U}_{s,1} = [\mathbf{I}_{M-1} \quad \mathbf{0}_{M-1}] \cdot \mathbf{U}_s \in \mathbb{C}^{(M-1)\times\hat{L}}, \tag{10b}$$

$$\mathbf{U}_{s,2} = [\mathbf{0}_{M-1} \quad \mathbf{I}_{M-1}] \cdot \mathbf{U}_s \in \mathbb{C}^{(M-1)\times\hat{L}}, \tag{10c}$$

$$\Psi = \mathbf{U}_{s,1}^{\dagger} \cdot \mathbf{U}_{s,2} \in \mathbb{C}^{\hat{L}\times\hat{L}}. \tag{10d}$$

Finally, the $\hat{L}$ eigenvalues $\psi_0, ..., \psi_{\hat{L}-1}$ of $\Psi$ are computed and then used to evaluate the multipath delay as:

$$\hat{\tau}_l = -\frac{1}{2\pi\Delta f_{mCRS}} arg\{\psi_l\}, \quad l = 0, ..., \hat{L}-1, \tag{11}$$

where $\Delta f_{mCRS}$ is the subcarrier spacing between two adjacent CRS subcarriers. The estimated MPC delay is converted into estimated MPC propagation distance by

$$\hat{d}_l = \hat{\tau}_l \cdot c, \tag{12}$$

where $c$ denotes the speed of light. If the BS and UE are not perfectly synchronized in reality, then the estimated MPC delay also includes the synchronization error.

## IV. Data association based on global nearest neighbor with a Kalman filter

The estimated MPC delays of different snapshots have to be associated to each other to achieve continuous trajectories, which represent how the distance between the vehicle and the BS or VTs change with the movement of the vehicle. The Kalman filter is used to predict and update the states of MPC delays. The method used here is similar to the one described in the paper [8], but with the MPC delay estimates.

The state equation is written as

$$\theta_l^{(n)} = \Phi\theta_l^{(n-1)} + \mathbf{w}_l^{(n)}, \tag{13}$$

where $\theta_l^{(n)} = \begin{bmatrix} \tilde{d}_l^{(n)} & v^{(n)}\Delta T \end{bmatrix}^T$, $\tilde{d}_l^{(n)}$ is the updated delay of the $l$-th MPC, $v^{(n)}$ is the velocity of the vehicle, and $\Delta T$ is the sampling interval between snapshots. Further, $\mathbf{w}_l^{(n)}$ denotes the state noise with covariance matrix $\mathbf{Q}_l$, and $\mathbf{\Phi}$ is the state transition matrix given by

$$\mathbf{\Phi} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, \tag{14}$$

The observation model is written as

$$\hat{d}_l^{(n)} = \mathbf{F}\theta_l^{(n)} + u_l^{(n)}, \tag{15}$$

where $\hat{d}_l^{(n)}$ is the estimated MPC delay from previous section, $\mathbf{F}$ is given by

$$\mathbf{F} = \begin{bmatrix} 1 & 0 \end{bmatrix}, \tag{16}$$

and $u_l^{(n)}$ denotes the observation noise with covariance $r_l$. The derivation of the Kalman filter is straightforward and leads to the following prediction and update equations

**Prediction:**

$$\theta_l^{(n|n-1)} = \Phi\theta_l^{(n-1|n-1)}, \tag{17a}$$

$$\mathbf{M}_l^{(n|n-1)} = \Phi\mathbf{M}_l^{(n-1|n-1)}\Phi^T + \mathbf{Q}_l, \tag{17b}$$

**Update:**

$$\mathbf{K}_l^{(n|n)} = \mathbf{M}_l^{(n|n-1)}\mathbf{F}^T(\mathbf{F}\mathbf{M}_l^{(n|n-1)}\mathbf{F}^T + r_l)^{-1}, \tag{17c}$$

$$\theta_l^{(n|n)} = \theta_l^{(n|n-1)} + \mathbf{K}_l^{(n|n)}(\hat{d}_l^{(n)} - \mathbf{F}\theta_l^{(n|n-1)}), \tag{17d}$$

$$\mathbf{M}_l^{(n|n)} = (\mathbf{I} - \mathbf{K}_l^{(n|n)}\mathbf{F})\mathbf{M}_l^{(n|n-1)}. \tag{17e}$$

There is an association problem between the predictions of the Kalman filter and the MPC delay estimates. In the area of multitarget tracking (MTT), many methods have been developed to solve the data association problem, such as the joint probabilistic DA (JPDA) filter [9], the joint integrated probabilistic DA (JIPDA) filter [10], and the belief propagation based data association algorithm [5], these methods are effective but also have high complexity. Here we apply a simple global nearest neighbor data association method that could be sufficient for the LTE system with a single receiver antenna. It will be interesting to investigate the performance of data association with these advanced algorithms in the future.

## V. Rao-Blackwellized particle filter based SLAM

After associating all the MPC delay estimates, RBPF based SLAM algorithm is used to find out the trajectory of the vehicle and the positions of the BS and VTs. Here only 2-dimensional positioning is considered, but it can be extended to 3-dimensional straightforwardly. For each time instant $t_k$, the relevant MPC delay estimates are condensed as the vector $\tilde{\mathbf{d}}(t_k)$ with

$$\tilde{\mathbf{d}}(t_k) = \left[\tilde{d}_0(t_k), ..., \tilde{d}_{N(t_k)-1}(t_k)\right]^T, \tag{18}$$

where the number of VTs at time $t_k$ is denoted by $N(t_k)$.

In order to use the VTs for positioning, their states have to be estimated during the receiver movement. Hence, the state vector $\mathbf{y}(t_k)$ at time instant $t_k$ is defined by

$$\mathbf{y}(t_k) = \left[\mathbf{y}_u(t_k)^T, \mathbf{y}_{VT,0}(t_k)^T, ..., \mathbf{y}_{VT,N(t_k)-1}(t_k)^T\right]^T, \tag{19}$$

with the receiver state

$$\mathbf{y}_u(t_k)^T = \left[\mathbf{r}_u(t_k)^T, \mathbf{v}_u(t_k)^T, b_u(t_k), \rho_u(t_k)\right]^T, \tag{20}$$

where $\mathbf{r}_u(t_k)$ is the receiver position, $\mathbf{v}_u(t_k)$ is the receiver velocity, $b_u(t_k)$ and $\rho_u(t_k)$ is the receiver's clock bias and drift, respectively. The parameters representing the VT of the $i$-th MPC are defined as

$$\mathbf{y}_{VT,i}(t_k) = \left[\mathbf{r}_{VT,i}(t_k)^T, d_{VT,i}(t_k)\right]^T, \tag{21}$$

where $\mathbf{r}_{VT,i}(t_k)$ is the position of the $i$-th VT and $d_{VT,i}(t_k)$ is its additional propagation distance. For solving the SLAM problem, i.e., estimating the state vector at time steps 0 to $k$ of

$\mathbf{y}(t_{0:k})$, a recursive Bayesian filtering approach is followed. In general, recursive Bayesian filtering provides a methodology to optimally estimate parameters in non-stationary conditions [11]. It consists of two steps, the prediction step and the update step. As illustrated in [12], assuming a first-order Markov model and independence among the measurements for the single VT, the transition prior can be expressed here as

$$p(\mathbf{y}(t_k)|\mathbf{y}(t_{k-1}) = p(\mathbf{y}_u(t_k)|\mathbf{y}_u(t_{k-1}) \prod_{i=0}^{N(t_k)-1} p(\mathbf{y}_{VT,i}(t_k)|\mathbf{y}_{VT,i}(t_{k-1}). \quad (22)$$

As mentioned in [12], the positions of the VTs are considered time-invariant. Hence, it can obtain for the $i$-th MPC

$$p(\mathbf{y}_{VT,i}(t_k)|\mathbf{y}_{VT,i}(t_{k-1}) = \delta(\mathbf{y}_{VT,i}(t_k) - \mathbf{y}_{VT,i}(t_{k-1})). \quad (23)$$

For the transition prior probability density function (PDF) of the user state $\mathbf{y}_u(t_k)$, $p(\mathbf{y}_u(t_k)|\mathbf{y}_u(t_{k-1})$, velocity information from IMU is included. The receiver position $\mathbf{r}_u(t_k)$ is calculated as

$$\mathbf{r}_u(t_k) = \mathbf{r}_u(t_{k-1}) + (t_k - t_{k-1})\mathbf{v}_u(t_k), \quad (24)$$

where the receiver velocity is modeled as:

$$\mathbf{v}_u(t_k) = [v_x(t_k) \;\; v_y(t_k)]^T + [n_x(t_k) \;\; n_y(t_k)]^T, \quad (25)$$

where $v_x(t_k)$ and $v_y(t_k)$ are the x-axis and y-axis velocities, $n_x(t_k)$ and $n_y(t_k)$ are the noise of x-axis and y-axis, which are from the noise of accelerometer and gyroscope. The modeling of IMU from [13] is adopted here.

Assuming the elements of $\tilde{\mathbf{d}}(t_k)$ to be independent Gaussian distributed, the PDF $p(\tilde{\mathbf{d}}(t_k)|\mathbf{y}(t_k)$ for the update step of the Bayesian filter can be expressed as

$$p(\tilde{\mathbf{d}}(t_k)|\mathbf{y}(t_k) = \prod_{i=0}^{N(t_k)-1} \frac{1}{\sqrt{2\pi}\sigma_{d,i}(t_k)} e^{-\frac{(\tilde{d}_i(t_k)-d_i(t_k))^2}{2\sigma^2_{d,i}(t_k)}}, \quad (26)$$

where $\sigma^2_{d,i}(t_k)$ denotes the corresponding noise variance of the distance measurement. The predicted propagation distances $d_i(t_k)$ are calculated as

$$d_i(t_k) = \|\mathbf{r}_u(t_k) - \mathbf{r}_{VT,i}(t_k)\|_F + d_{VT,i}(t_k) + b_u(t_k) \cdot c, \quad (27)$$

where $\|\cdot\|_F$ is the Frobenius norm.

## VI. Measured Data Analysis

A data logging system based on the LabVIEW Communications LTE Application Framework was developed for USRP 2953R to log the LTE signal from a commercial base station. The measurement campaign was conducted in Gothenberg, Sweden. The base station is to the south of the origin in fig. 2 around 500 meters away, and it transmits a 20 MHz LTE signal with a center frequency of 2.63 GHz and cell ID of 104. During the measurement, an OXTS Initial+ was used to record the vehicle trajectory with centimeter-level accuracy and used as the vehicle ground truth. The IMU data is used as the control input of SLAM, which is modeled from the ground truth with accelerometer noise density of 0.0053 $m/s^2/\sqrt{Hz}$ and gyroscope noise density of 0.0240 $°/s/\sqrt{Hz}$.

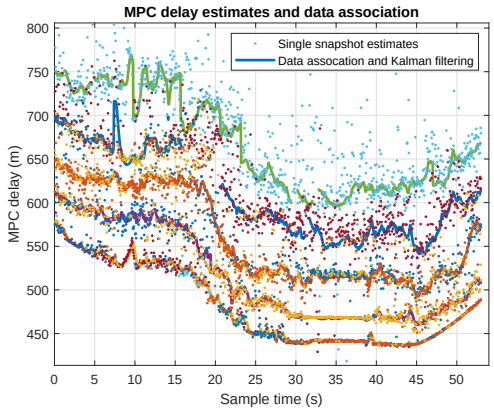


Fig. 1. MPC delay estimates and data association.

The estimated MPC delays from the CFR before data association, and after data association with the Kalman filter are shown in fig. 1. Different MPC trajectories are shown in the figure. The trajectory with the shortest MPC distance is the LOS component from the BS, and the other trajectories are from the VTs. The LOS component has the highest SNR, and is more stable and has less fluctuation than the other trajectories. While the trajectory with the largest distance has the worst SNR and is the most unstable.

The MPC delay estimates after data association are fed into RBPF based SLAM to estimate the trajectory of the vehicle and the positions of the BS and VTs. Both the number of particle for the vehicle and the BS or VTs are set to 2000. Since no angular information is used in the system, the initial positions of the BS and VTs are set as circles with radii equal to corresponding MPC distances of first snapshot and standard deviations of 20 meters. The estimated trajectory of UE by SLAM and by IMU only, as well as the ground truth of the vehicle are shown in fig. 2, and their absolute errors to ground truth are shown in fig. 3. We can see from the figures that the

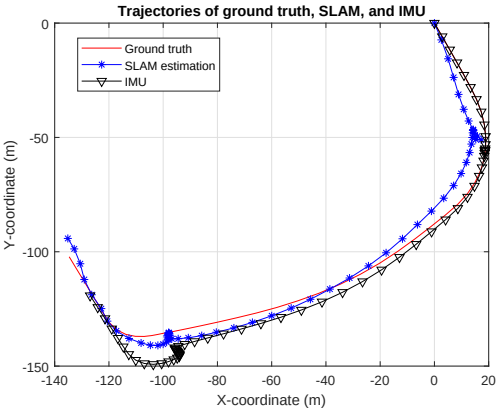


Fig. 2. Trajectories of ground truth, SLAM, and IMU.

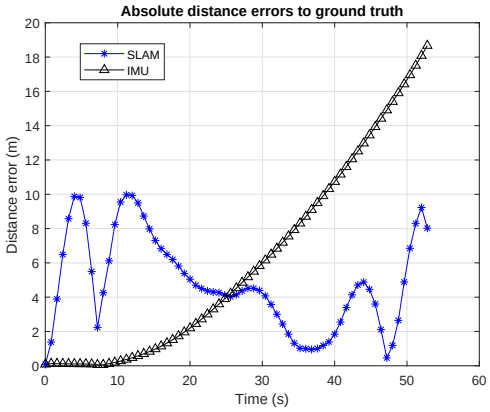


Fig. 3. Absolute distance errors to the ground truth.

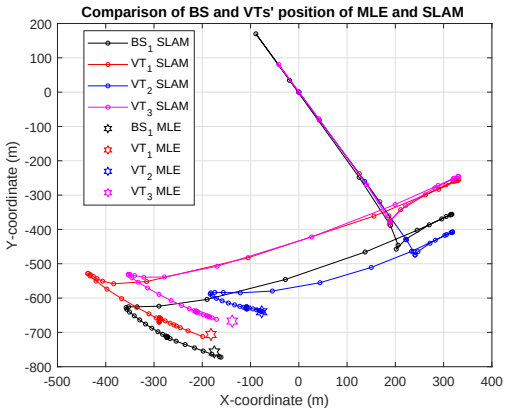


Fig. 4. Comparison of BS and VTs' positions of MLE and SLAM.

SLAM error is 11 meters smaller than that of IMU only at the end of the measurement. Since the SLAM is not convergent at the beginning of the measurement, it has bigger error than that of IMU only.

Since the true positions of the VTs are not available, the positions of VTs estimated by maximum likelihood estimation (MLE) are compared with the SLAM estimates. In the MLE, we use the ground truth vehicle trajectory $\mathbf{r}_{u,GT}(t_k)$ and the estimated MPC delays to estimate the positions of BS and VTs, which reach the minimum of the following cost function:

$$\arg\min_{\mathbf{r}_{VT,i}} \sum_{k=1}^{K} \| \|\mathbf{r}_{u,GT}(t_k) - \mathbf{r}_{VT,i}\|_F - \tilde{d}_i(t_k)\|_F^2. \qquad (28)$$

Figure 4 shows the comparison between the estimated positions of the BS and VTs from MLE and mean values from the SLAM. From the figure, we can see the SLAM estimates converge to that of the MLE gradually. At the end of the measurement, the position difference between the MLE and the mean of SLAM for the BS is 2.7 meters, and the position differences for the VTs vary from 14 to 30 meters.

## VII. Summary

In this paper, a low complexity LTE MPC delay based SLAM framework is introduced. It estimates the MPC delays with the CRS signal and the ESPRIT algorithm, associates the MPC delays of different snapshots to each other by the GNN algorithm and a Kalman filter, then exploits the Rao-Blackwellized particle filter based SLAM to estimate the vehicle trajectory and positions of the BS and VTs. Measured data shows improved performance compared with IMU only case. The next step is to explore the performance of the SLAM system with angular information, and investigate how accurate angular information can help to improve the localization accuracy.

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