

Mobile Location Tracking Scheme for Wireless Sensor Networks with Deficient Number of Sensor Nodes

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1. Introduction

A wireless sensor network (WSN) consists of sensor nodes (SNs) with wireless communication capabilities for specific sensing tasks. Among different applications, wireless location technologies which are designated to estimate the position of SNs (Gezici et al., 2005) (Hara et al., 2005) (Patwari et al., 2005) have drawn a lot of attention over the past few decades. There are increasing demands for commercial applications to adopt location tracking information within their system design, such as navigation systems, location-based billing, health care systems, and intelligent transportation systems. With emergent interests in location-based services (Perusco & Michael, 2007), location estimation and tracking algorithms with enhanced precision become necessitate for the applications under different circumstances.

The location estimation schemes have been widely proposed and employed in the wireless communication system. These schemes locate the position of a mobile sensor (MS) based on the measured radio signals from its neighborhood anchor nodes (ANs). The representative algorithms for the measured distance techniques are the Time-Of-Arrival (TOA), the Time Difference-Of-Arrival (TDOA), and the Angle-Of-Arrival (AOA). The TOA scheme measures the arrival time of the radio signals coming from different wireless BSs; while the TDOA scheme measures the time difference between the radio signals. The AOA technique is conducted within the BS by observing the arriving angle of the signals coming from the MS.

It is recognized that the equations associated with the location estimation schemes are inherently nonlinear. The uncertainties induced by the measurement noises make it more difficult to acquire the estimated MS position with tolerable precision. The Taylor Series Expansion (TSE) method was utilized in (Foy, 1976) to acquire the location estimation of the MS from the TOA measurements. The method requires iterative processes to obtain the location estimate from a linearized system. The major drawback of the TSE scheme is that it may suffer from the convergence problem due to an incorrect initial guess of the MS's position. The two-step Least Square (LS) method was adopted to solve the location estimation problem from the TOA (Wanget al., 2003), the TDOA (Chen & Ho, 1994), and the hybrid TOA/TDOA (Tseng & Feng, 2009) measurements. It is an approximate

realization of the Maximum Likelihood (ML) estimator and does not require iterative processes. The two-step LS scheme is advantageous in its computational efficiency with adequate accuracy for location estimation.

In addition to the estimation of a MS's position, trajectory tracking of a moving MS has been studied. The Extended Kalman Filter (EKF) scheme is considered the well-adopted method for location tracking. The EKF algorithm estimates the MS's position, speed, and acceleration via the linearization of measurement inputs. The Kalman Tracking (KT) scheme (Nájar & Vidal, 2001) distinguishes the linear part from the originally nonlinear equations for location estimation. The linear aspect is exploited within the Kalman filtering formulation; while the nonlinear term is served as an external measurement input to the Kalman filter. The Cascade Location Tracking (CLT) scheme (Chen & Feng, 2005) utilizes the two-step LS method for initial location estimation of the MS. The Kalman filtering technique is employed to smooth out and to trace the position of the MS based on its previously estimated data.

With the characteristics of simplicity and high accuracy, the range-based positioning method based on triangulation approach is considered according to the time-of-arrival measurements. The location of a MS can be estimated and traced from the availability of enough SNs with known positions, denoted as anchor nodes ANs. In general, at least three ANs are required to perform two-dimensional location estimation for an MS. However, enough signal sources for location estimation and tracking may not always happen under the WSN scenarios. Unlike the regular deployment of satellites or cellular base stations, the ANs within the WSN are in general spontaneously and arbitrarily deployed. Even though there can be high density of SNs within certain area, the number of ANs with known position can still be limited. Moreover, the transmission ranges for SNs are comparably shorter than both the satellite-based (Kuusniemi et al., 2007) and the cellular-based (Zhao, 2002) systems. Therefore, there is high probability for the node deficiency problem (i.e., the number of available ANs is less than three) to occur within the WSN, especially under the situations that the SNs are moving. Due to the deficiency of signal sources, most of the existing location estimation and tracking schemes becomes inapplicable for the WSNs.

In this book chapter, a predictive location tracking (PLT) algorithm is proposed to alleviate the problem with insufficient measurement inputs for the WSNs. Location tracking can still be performed even with only two ANs or a single AN available to be exploited. The predictive information obtained from the Kalman filtering technique (Zaidi & Mark, 2005) is adopted as the virtual signal sources, which are incorporated into the two-step least square method for location estimation and tracking. Persistent accuracy for location tracking can be achieved by adopting the proposed PLT scheme, especially under the situations with inadequate signal sources. Numerical results demonstrate that the proposed PLT algorithm can achieve better precision in comparison with other location tracking schemes under the WSNs.

2. Preliminaries

2.1 Mathematical Modeling

In order to facilitate the design of the proposed PLT algorithm, the signal model for the TOA measurements is utilized. The set r_k contains all the available measured relative distance at

the k^{th} time step, i.e., $\mathbf{r}_k = \{ r_{1,k}, r_{2,k}, \dots, r_{i,k}, \dots, r_{N_k,k} \}$, where N_k denotes the number of available ANs. The measured relative distance ($r_{i,k}$) between the MS and the i^{th} AN (obtained at the k^{th} time step) can be represented as

$$r_{i,k} = c \cdot t_{i,k} = \zeta_{i,k} + n_{i,k} + e_{i,k} \tag{1}$$

Where $t_{i,k}$ denotes the TOA measurement obtained from the i^{th} AN at the k^{th} time step, and c is the speed of light. $r_{i,k}$ is contaminated with the TOA measurement noise $n_{i,k}$ and the NLOS error $e_{i,k}$. It is noted that the measurement noise $n_{i,k}$ is in general considered as zero mean with Gaussian distribution. On the other hand, the NLOS error $e_{i,k}$ is modeled as exponentially-distributed for representing the positive bias due to the NLOS effect (Lee, 1993). The noiseless relative distance $\zeta_{i,k}$ in (1) between the MS's true position and the i^{th} AN can be obtained as

$$\zeta_{i,k} = [(x_k - x_{i,k})^2 + (y_k - y_{i,k})^2]^{1/2} \tag{2}$$

where $\mathbf{x}_k = [x_k, y_k]$ represents the MS's true position and $\mathbf{x}_{i,k} = [x_{i,k}, y_{i,k}]$ is the location of the i^{th} AN for $i = 1$ to N_k . Therefore, the set of all the available ANs at the k^{th} time step can be obtained as $\mathbf{P}_{AN,k} = \{ \mathbf{x}_{1,k}, \mathbf{x}_{2,k}, \dots, \mathbf{x}_{i,k}, \dots, \mathbf{x}_{N_k,k} \}$.

2.2 Two-Step LS Estimator

The two-step LS scheme (Chen & Ho, 1994) is utilized as the baseline location estimator for the proposed predictive location tracking algorithms. It is noticed that three TOA measurements are required for the two-step LS method in order to solve for the location estimation problem. The concept of the two-step LS scheme is to acquire an intermediate location estimate in the first step with the definition of a new variable β_k , which is mathematically related to the MS's position, i.e., $\beta_k = x_k^2 + y_k^2$. At this stage, the variable β_k is assumed to be uncorrelated to the MS's position. This assumption effectively transforms the nonlinear equations for location estimation into a set of linear equations, which can be directly solved by the LS method. Moreover, the elements within the associated covariance matrix are selected based on the standard deviation from the measurements. The variations within the corresponding signal paths are therefore considered within the problem formulation.

The second step of the method primarily considers the relationship that the variable β_k is equal to $x_k^2 + y_k^2$, which was originally assumed to be uncorrelated in the first step. Improved location estimation can be obtained after the adjustment from the second step. The detail algorithm of the two-step LS method for location estimation can be found in (Chen & Ho, 1994) (Cong & Zhuang, 2002) (Wang et al., 2003).

3. Architecture overview of proposed PLT algorithm

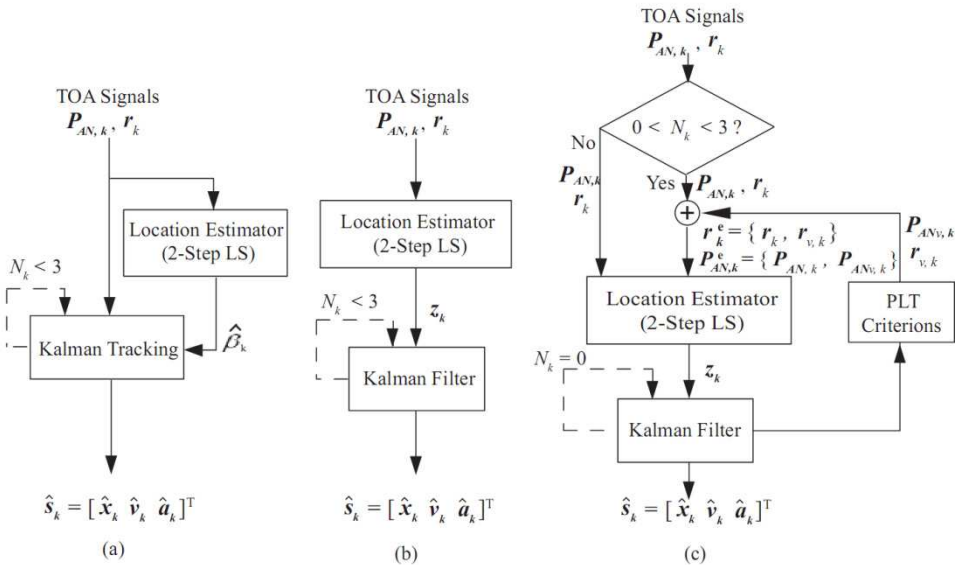


Fig. 1. The architecture diagrams of (a) the KT scheme; (b) the CLT scheme; and (c) the proposed PLT scheme.

The objective of the proposed PLT algorithm is to utilize the predictive information acquired from the Kalman filter to serve as the assisted measurement inputs while the environments are deficient with signal sources. Fig. 1 illustrates the system architectures of the KT (Nájjar & Vidal, 2001), the CLT (Chen & Feng, 2005) and the proposed PLT scheme. The TOA signals (r_k in (1)) associated with the corresponding location set of the ANs ($P_{AN,k}$) are obtained as the signal inputs to each of the system, which result in the estimated state vector of the MS, i.e. $\hat{s}_k = [\hat{x}_k \hat{v}_k \hat{a}_k]^T$ where $\hat{x}_k = [\hat{x}_k \hat{y}_k]$ represents the MS's estimated position, $\hat{v}_k = [\hat{v}_{x,k} \hat{v}_{y,k}]$ is the estimated velocity, and $\hat{a}_k = [\hat{a}_{x,k} \hat{a}_{y,k}]$ denotes the estimated acceleration.

Since the equations (i.e., (1) and (2)) associated with the location estimation are intrinsically nonlinear, different mechanisms are considered within the existing algorithms for location tracking. The KT scheme (as shown in Fig. 1.(a)) explores the linear aspect of location estimation within the Kalman filtering formulation; while the nonlinear term (i.e., $\hat{\beta}_k = \hat{x}_k^2 + \hat{y}_k^2$) is treated as an additional measurement input to the Kalman filter. It is stated within the KT scheme that the value of the nonlinear term can be obtained from an external location estimator, e.g. via the two-step LS method. Consequently, the estimation accuracy of the KT algorithm greatly depends on the precision of the additional location estimator. On the other hand, the CLT scheme (as illustrated in Fig. 1.(b)) adopts the two-step LS method to acquire the preliminary location estimate of the MS. The Kalman Filter is utilized to smooth out the estimation error by tracing the estimated state vector \hat{s}_k of the MS.

The architecture of the proposed PLT scheme is illustrated in Fig. 1.(c). It can be seen that the PLT algorithm will be the same as the CLT scheme while $N_k \geq 3$, i.e. the number of available ANs is greater than or equal to three. However, the effectiveness of the PLT schemes is revealed as $1 \leq N_k < 3$, i.e. with deficient measurement inputs. The predictive state information obtained from the Kalman filter is utilized for acquiring the assisted information, which will be fed back into the location estimator. The extended sets for the locations of the ANs (i.e., $\mathbf{P}_{AN,k}^e = \{\mathbf{P}_{AN,k}, \mathbf{P}_{AN_v,k}\}$) and the measured relative distances (i.e., $\mathbf{r}_k^e = \{\mathbf{r}_k, \mathbf{r}_{v,k}\}$) will be utilized as the inputs to the location estimator. The sets of the virtual ANs' locations $\mathbf{P}_{AN_v,k}$ and the virtual measurements $\mathbf{r}_{v,k}$ are defined as follows.

Definition 1 (Virtual Anchor Nodes). Within the PLT formulation, the virtual Anchor Nodes are considered as the designed locations for assisting the location tracking of the MS under the environments with deficient signal sources. The set of virtual ANs $\mathbf{P}_{AN_v,k}$ is defined under two different numbers of N_k as

$$\mathbf{P}_{AN_v,k} = \begin{cases} \{\mathbf{x}_{v1,k}\} & \text{for } N_k = 2 \\ \{\mathbf{x}_{v1,k}, \mathbf{x}_{v2,k}\} & \text{for } N_k = 1 \end{cases} \quad (3)$$

Definition 2 (Virtual Measurements). Within the PLT formulation, the virtual measurements are utilized to provide assisted measurement inputs while the signal sources are insufficient. Associating with the designed set of virtual ANs $\mathbf{P}_{AN_v,k}$, the corresponding set of virtual measurements is defined as

$$\mathbf{r}_{v,k} = \begin{cases} \{\mathbf{r}_{v1,k}\} & \text{for } N_k = 2 \\ \{\mathbf{r}_{v1,k}, \mathbf{r}_{v2,k}\} & \text{for } N_k = 1 \end{cases} \quad (4)$$

It is noticed that the major task of the PLT scheme is to design and to acquire the values of $\mathbf{P}_{AN_v,k}$ and $\mathbf{r}_{v,k}$ for the two cases (i.e. $N_k = 1$ and 2) with inadequate signal sources. In both the KT and the CLT schemes, the estimated state vector $\hat{\mathbf{s}}_k$ can only be updated by the internal prediction mechanism of the Kalman filter while there are insufficient numbers of ANs (i.e., $N_k < 3$ as shown in Fig. 1.(a) and 1.(b) with the dashed lines). The location estimator (i.e., the two-step LS method) is consequently disabled owing to the inadequate number of the signal sources. The tracking capabilities of both schemes significantly depend on the correctness of the Kalman filter's prediction mechanism. Therefore, the performance for location tracking can be severely degraded due to the changing behavior of the MS, i.e., with the variations from the MS's acceleration.

On the other hand, the proposed PLT algorithm can still provide satisfactory tracking performance with deficient measurement inputs, i.e., with $N_k = 1$ and 2. Under these circumstances, the location estimator is still effective with the additional virtual ANs $\mathbf{P}_{AN_v,k}$ and the virtual measurements $\mathbf{r}_{v,k}$, which are imposed from the predictive output of the Kalman filter (as shown in Fig. 1.(c)). It is also noted that the PLT scheme will perform the same as the CLT method under the case with no signal input, i.e., under $N_k = 0$. The virtual ANs' location set $\mathbf{P}_{AN_v,k}$ and the virtual measurements $\mathbf{r}_{v,k}$ by exploiting the PLT formulation are presented in the next section.

4. Formulation of PLT algorithm

The proposed PLT scheme will be explained in this section. As shown in Fig. 1.(c), the measurement and state equations for the Kalman filter can be represented as

$$\mathbf{z}_k = \mathbf{M} \cdot \hat{\mathbf{s}}_k + \mathbf{m}_k \quad (5)$$

$$\hat{\mathbf{s}}_k = \mathbf{F} \cdot \hat{\mathbf{s}}_{k-1} + \mathbf{p}_k \quad (6)$$

where $\hat{\mathbf{s}}_k = [\hat{\mathbf{x}}_k \hat{\mathbf{v}}_k \hat{\mathbf{a}}_k]^T$. The variables \mathbf{m}_k and \mathbf{p}_k denote the measurement and the process noises associated with the covariance matrices \mathbf{R} and \mathbf{Q} within the Kalman filtering formulation. The measurement vector $\mathbf{z}_k = [\hat{\mathbf{x}}_{1s,k} \hat{\mathbf{y}}_{1s,k}]^T$ represents the measurement input which is obtained from the output of the two-step LS estimator at the k^{th} time step (as in Fig. 1.(c)). The matrix \mathbf{M} and the state transition matrix \mathbf{F} can be obtained as

$$\mathbf{M} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \quad (7)$$

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & \Delta t & 0 & 0.5\Delta t^2 & 0 \\ 0 & 1 & 0 & \Delta t & 0 & 0.5\Delta t^2 \\ 0 & 0 & 1 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & 1 & 0 & \Delta t \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (8)$$

where Δt denotes the sample time interval. The main concept of the PLT scheme is to provide additional virtual measurements (i.e., $\mathbf{r}_{v,k}$ as in (4)) to the two-step LS estimator while the signal sources are insufficient. Two cases (i.e. the two-ANs case and the single-AN case) are considered in the following subsections.

4.1 Two-ANs case

As shown in Fig. 2, it is assumed that only two ANs (i.e., AN_1 and AN_2) associated with two TOA measurements are available at the time step k in consideration. The main target is to introduce an additional virtual AN along with its virtual measurement (i.e., $\mathbf{P}_{\text{AN}_v,k} = \{\mathbf{x}_{v1,k}\}$ and $\mathbf{r}_{v,k} = \{r_{v1,k}\}$) by acquiring the predictive output information from the Kalman filter. Knowing that there are predicting and correcting phases within the Kalman filtering formulation, the predictive state can therefore be utilized to compute the supplementary virtual measurement $r_{v1,k}$ as

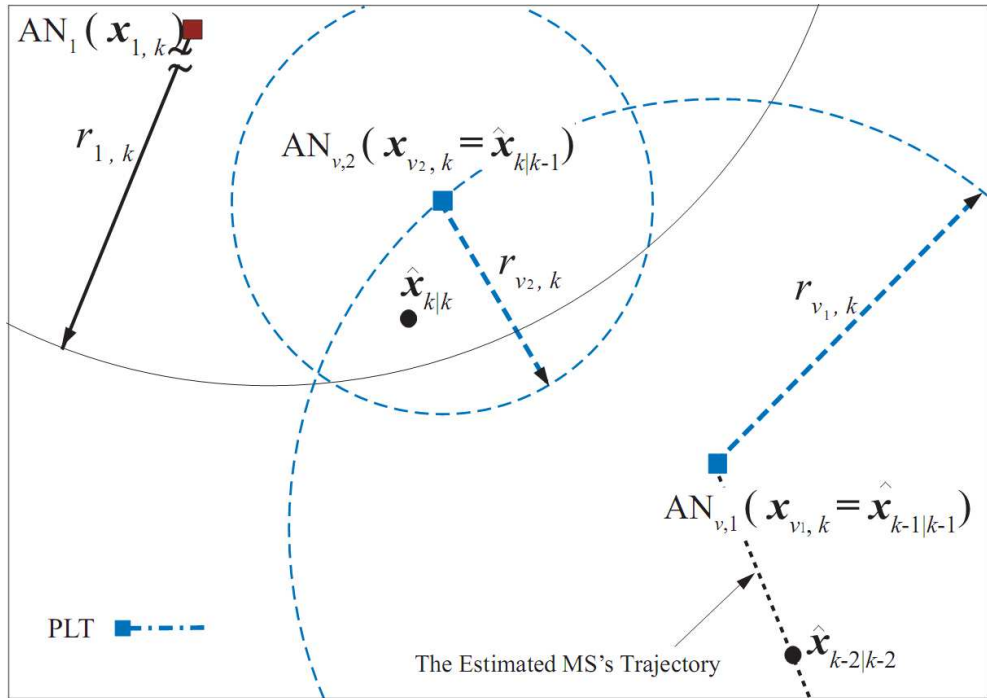


Fig. 2. The schematic diagram of the two-ANs case for the proposed PLT scheme.

$$\begin{aligned}
 r_{v1,k} &= \|\hat{\mathbf{x}}_{k|k-1} - \hat{\mathbf{x}}_{k-1|k-1}\| \\
 &= \|\mathbf{M} \cdot \mathbf{F} \cdot \hat{\mathbf{s}}_{k-1|k-1} - \hat{\mathbf{x}}_{k-1|k-1}\|
 \end{aligned}
 \tag{9}$$

where $\hat{\mathbf{x}}_{k|k-1}$ denotes the predicted MS's position at time step k ; while $\hat{\mathbf{x}}_{k-1|k-1}$ is the corrected (i.e., estimated) MS's position obtained at the $(k - 1)^{\text{th}}$ time step. It is noticed that both values are available at the $(k - 1)^{\text{th}}$ time step. The virtual measurement $r_{v1,k}$ is defined as the distance between the previous location estimate ($\hat{\mathbf{x}}_{k-1|k-1}$) as the position of the virtual AN (i.e., $\text{AN}_{v1}: x_{v1,k} \triangleq \hat{\mathbf{x}}_{k-1|k-1}$) and the predicted MS's position ($\hat{\mathbf{x}}_{k|k-1}$) as the possible position of the MS as shown in Fig. 2. It is also noted that the corrected state vector $\hat{\mathbf{s}}_{k-1|k-1}$ is available at the current time step k . However, due to the insufficient measurement input, the state vector $\hat{\mathbf{s}}_{k|k}$ is unobtainable at the k^{th} time step while adopting the conventional two-step LS estimator. By exploiting $r_{v1,k}$ (in (9)) as the additional signal input, the measurement vector \mathbf{z}_k can be acquired after the three measurement inputs $r_k^e = \{r_{1,k}, r_{2,k}, r_{v1,k}\}$ and the locations of the ANs $\mathbf{P}_{\text{AN},k}^e = \{x_{1,k}, x_{2,k}, x_{v1,k}\}$ have been imposed into the two-step LS estimator. As \mathbf{z}_k has been obtained, the corrected state vector $\hat{\mathbf{s}}_{k|k}$ can be updated with the implementation of the correcting phase of the Kalman filter at the time step k as

$$\hat{\mathbf{s}}_{k|k} = \hat{\mathbf{s}}_{k|k-1} + \mathbf{P}_{k|k-1} \mathbf{M}^T [\mathbf{M} \mathbf{P}_{k|k-1} \mathbf{M}^T + \mathbf{R}]^{-1} (\mathbf{z}_k - \mathbf{M} \hat{\mathbf{s}}_{k|k-1})
 \tag{10}$$

where

$$\mathbf{P}_{k|k-1} = \mathbf{F}\mathbf{P}_{k|k-1}\mathbf{F}^T + \mathbf{Q} \tag{11}$$

and

$$\mathbf{P}_{k-1|k-1} = [\mathbf{I} - \mathbf{P}_{k-1|k-2}\mathbf{M}^T(\mathbf{M}\mathbf{P}_{k-1|k-2}\mathbf{M}^T + \mathbf{R})^{-1}\mathbf{M}] \cdot \mathbf{P}_{k-1|k-2} \tag{12}$$

It is noted that $\mathbf{P}_{k|k-1}$ and $\mathbf{P}_{k-1|k-1}$ represent the predicted and the corrected estimation covariance within the Kalman filter. \mathbf{I} in (12) is denoted as an identity matrix. As can be observed from Fig. 2, the virtual measurement $r_{v1,k}$ associating with the other two existing measurements $r_{1,k}$ and $r_{2,k}$ provide a confined region for the estimation of the MS's location at the time step k , i.e., $\hat{\mathbf{x}}_{k|k}$. Based on (9), the signal variation of $r_{v1,k}$ is considered as the variance of the predicted distance $\|\hat{\mathbf{x}}_{k|k-1} - \hat{\mathbf{x}}_{k-1|k-1}\|$ between the previous ($k-1$) time steps. Therefore, the variance of virtual noise $n_{v1,k}$ is regarded as $\sigma_{n_{v1,k}}^2 = \text{Var}(\|\hat{\mathbf{x}}_{k|k-1} - \hat{\mathbf{x}}_{k-1|k-1}\|)$.

4.2 One-AN case

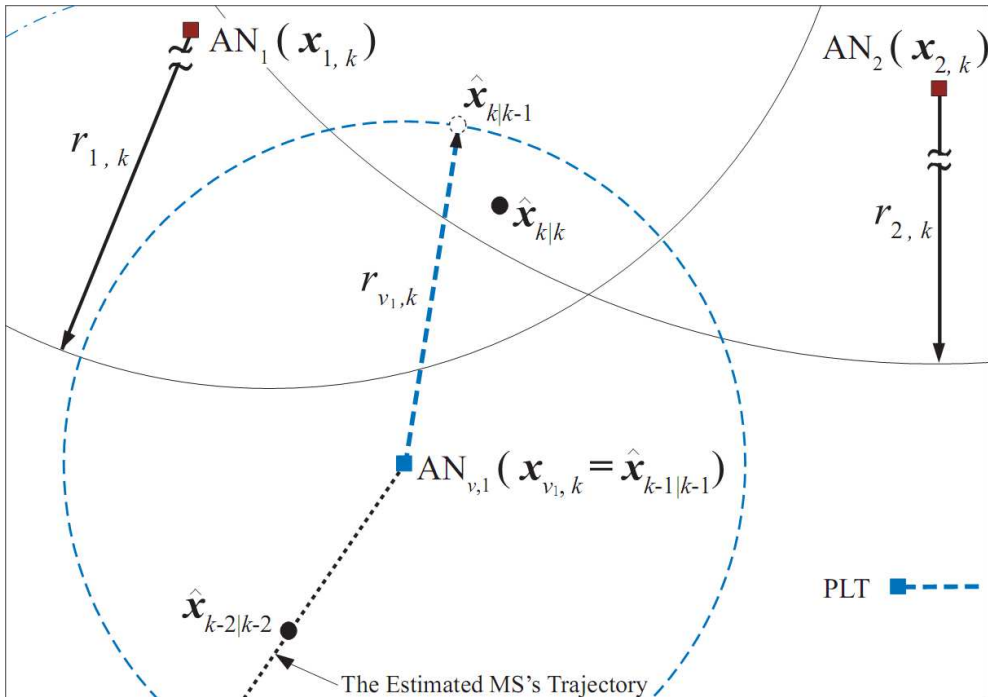


Fig. 3. The schematic diagram of the one-AN case for the proposed PLT scheme.

In this case, only one AN (i.e., AN_1) with one TOA measurement input is available at the k^{th} time step (as shown in Fig. 3). Two additional virtual ANs and measurements are required

for the computation of the two-step LS estimator, i.e., $\mathbf{P}_{AN_v,k} = \{\mathbf{x}_{v1,k}, \mathbf{x}_{v2,k}\}$ and $\mathbf{r}_{v,k} = \{r_{v1,k}, r_{v2,k}\}$. Similar to the previous case, the first virtual measurement $r_{v1,k}$ is acquired as in (9) by considering $\hat{\mathbf{x}}_{k-1|k-1}$ as the position of the first virtual AN (i.e., $\mathbf{x}_{v1,k} = \hat{\mathbf{x}}_{k-1|k-1}$) with the predicted MS's position (i.e., $\hat{\mathbf{x}}_{k|k-1}$) as the possible position of the MS. On the other hand, the second virtual AN's position is assumed to locate at the predicted MS's position (i.e., $\mathbf{x}_{v2,k} \triangleq \hat{\mathbf{x}}_{k|k-1}$) as illustrated in Fig. 3. The corresponding second virtual measurement $r_{v2,k}$ is defined as the average prediction error obtained from the Kalman filtering formulation by accumulating the previous time steps as

$$r_{v2,k} = \frac{1}{k-1} \sum_{i=1}^{k-1} \|\hat{\mathbf{x}}_{i|i} - \hat{\mathbf{x}}_{i|i-1}\| \tag{13}$$

It is noted that $r_{v2,k}$ is obtained as the mean prediction error until the $(k-1)^{\text{th}}$ time step. In the case while the Kalman filter is capable of providing sufficient accuracy in its prediction phase, the virtual measurement $r_{v2,k}$ may approach zero value. Associating with the single measurement $r_{v1,k}$ from AN₁, the two additional virtual measurements $r_{v1,k}$ (centered at $\hat{\mathbf{x}}_{k-1|k-1}$) and $r_{v2,k}$ (centered at $\hat{\mathbf{x}}_{k|k-1}$) result in a constrained region (as in Fig. 3) for location estimation of the MS under the environments with insufficient signal sources. Similarly to two-ANs case, the variance of virtual noise $n_{v1,k}$ is regarded as $\sigma_{n_{v1,k}}^2 = \text{Var}(\|\hat{\mathbf{x}}_{k|k-1} - \hat{\mathbf{x}}_{k-1|k-1}\|)$. On the other hand, the signal variation of the second virtual measurement $r_{v2,k}$ is obtained as the variance of the averaged prediction errors as

$$\begin{aligned} n_{v2,k} &= r_{v2,k} - \zeta_{v2,k} \\ &= \frac{1}{k-1} \sum_{i=1}^{k-1} \|\hat{\mathbf{x}}_{i|i} - \hat{\mathbf{x}}_{i|i-1}\| - \|\hat{\mathbf{x}}_{k|k} - \hat{\mathbf{x}}_{k|k-1}\| \end{aligned} \tag{14}$$

The associated variance of virtual noise $n_{v2,k}$ can also be regarded as $\sigma_{n_{v2,k}}^2 = \text{Var}(r_{v2,k})$. It is noted that the variances will be exploited as the weighting coefficients within the formulation of the two-step LS estimator.

5. Performance evaluation

Simulations are performed to show the effectiveness of the proposed PLT scheme under different numbers of ANs, including the scenarios with deficient signal sources. The noise models and the simulation parameters are illustrated in Subsection 5.1. The performance comparison between the proposed PLT algorithm with the other existing location tracking schemes, i.e., the KT and the CLT techniques, are conducted in Subsection 5.2.

5.1 Noise model

Different noise models (Chen, 1999) for the TOA measurements are considered in the simulations. The model for the measurement noise of the TOA signals is selected as the Gaussian distribution with zero mean and 5 meters of standard deviation, i.e. $n_{i,k} \sim \mathcal{N}(0,25)$. On the other hand, an exponential distribution $p_{e_i,k}(\tau)$ is assumed for the NLOS

noise model of the TOA measurements as

$$p_{e_i,k}(v) = \begin{cases} \frac{1}{\lambda_{i,k}} \exp\left(-\frac{v}{\lambda_{i,k}}\right) & v > 0 \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

where $\lambda_{i,k} = c \cdot \tau_{i,k} = c \cdot \tau_m (\zeta_{i,k})^\varepsilon \rho$. The parameter $\tau_{i,k}$ is the RMS delay spread between the i^{th} AN to the MS. τ_m represents the median value of $\tau_{i,k}$, which is selected as 0.1 in the simulations. ε is the path loss exponent which is assumed to be 0.5. The shadow fading factor ρ is a log-normal random variable with zero mean and standard deviation σ_ρ chosen as 4 dB in the simulations. The parameters for the noise models as listed in this subsection primarily fulfill the environment while the MS is located within the rural area in (Chen, 1999). It is noticed that the reason for selecting the rural area as the simulation scenario is due to its similarity to the channel condition of WSNs. The transmission range of the AN is set as 100 meter. Moreover, the sampling time Δt is chosen as 1 sec in the simulations.

5.2 Simulation Results

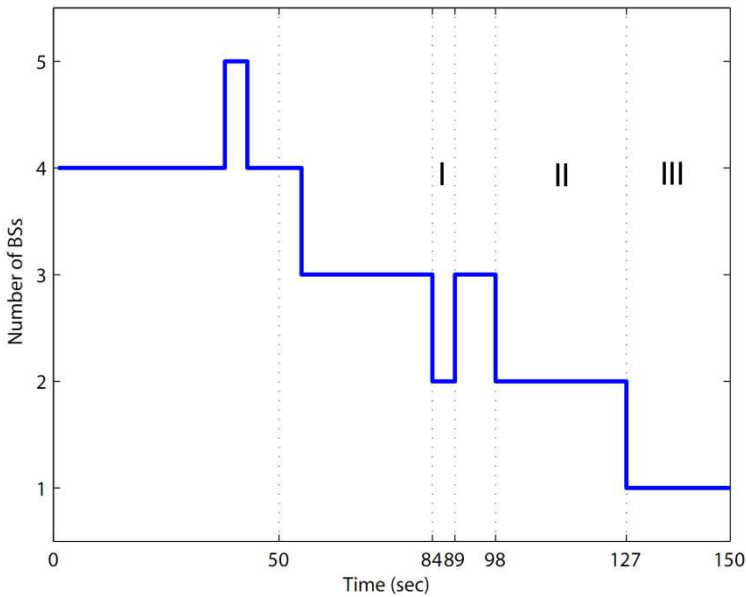


Fig. 4. Total number of available ANs (N_k) vs. simulation time (sec).

The performance comparisons between the KT scheme, the CLT scheme, and the proposed PLT algorithm are conducted under the rural environment. Fig. 4 illustrates the scenario with various numbers of ANs (i.e. the N_k values) that are available at different time intervals. It can be seen that the number of ANs becomes insufficient (i.e. $N_k < 3$) from the time interval of $t = 84$ to $t = 89$ and $t = 98$ to $t = 150$ sec. The region I marked in Fig. 4 denotes for the time period

$t=84$ to 89 when the number of available AN is two (i.e., $N_k=2$); the region II represents for the time period $t=98$ to 126 when $N_k=2$; while the region III stands for $t=127$ to 150 when $N_k=1$. The total simulation interval is set as 150 seconds.

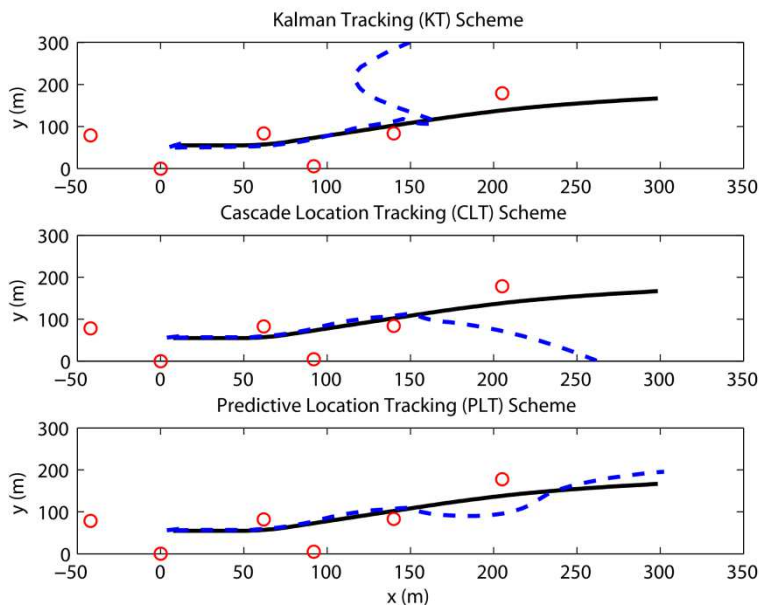


Fig. 5. Performance comparison of MS tracking. (Dashed lines: estimated trajectory; Solid lines: true trajectory; Red empty circles: the position of the ANs).

Fig. 5 illustrates the performance comparison of the trajectory using the three algorithms. The estimated values obtained from these schemes are illustrated via the dashed lines; while the true values are denoted by the solid lines. The locations of the ANs are represented by the red empty circles as in Fig. 5. The acceleration is designed to vary at time $t = 1, 40, 55, 100,$ and 120 sec from $\mathbf{a}_k = (\mathbf{a}_{x,k}, \mathbf{a}_{y,k}) = (0.05, 0), (-0.01, 0.075), (0, 0), (0.025, 0),$ to $(0.05, -0.1)$ m/sec². The corresponding velocity of MS is lied between $[0,5]$ m/sec. It is noted that the MS experiences third (i.e., region I and II), fourth (i.e., region II) and fifth (i.e. region III) acceleration change when the number of ANs becomes insufficient.

By observing the starting time interval between $t = 0$ and 83 sec (where the number of ANs is sufficient), the three algorithms provide similar performance on location tracking as shown in the x-y plots in Fig. 5. During the time interval between $t = 98$ and 150 sec with inadequate signal sources, it can be observed that only the proposed PLT scheme can achieve satisfactory performance in the trajectory tracking. The estimated trajectories obtained from both the KT and the CLT schemes diverge from the true trajectories due to the inadequate number of measurement inputs.

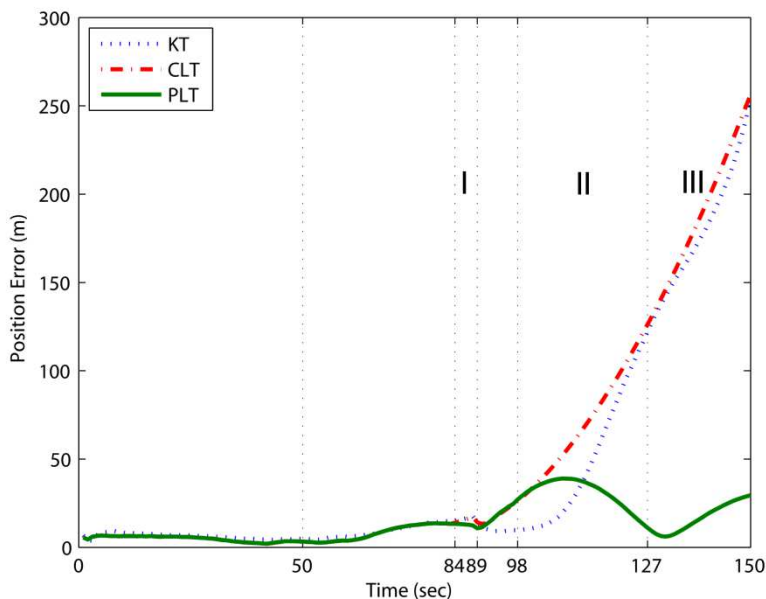


Fig. 6. The position error(m) vs. the simulation time (sec)

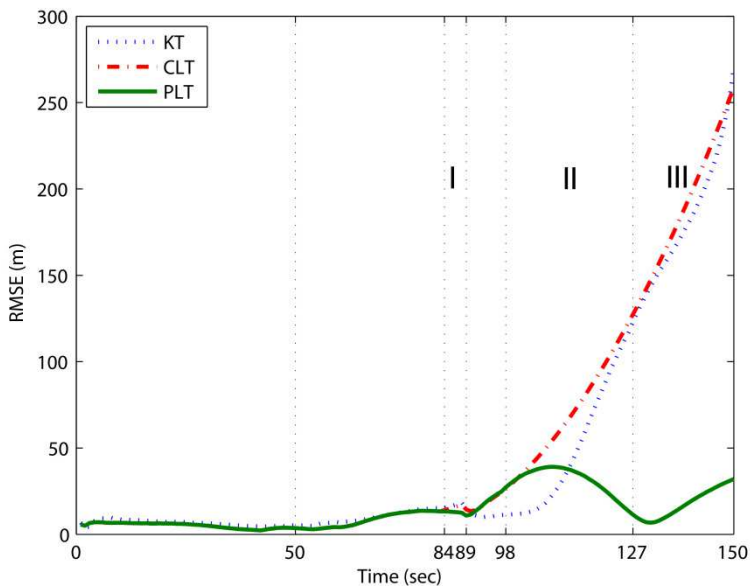


Fig. 7. The RMSE (m) vs. the simulation time (sec).

Moreover, Figs. 6 and 7 illustrate the position error and the Root Mean Square Error (RMSE)(i.e., characterizing the signal variances) for location estimation and tracking of the

MS. It is noted that the position error (Δx_k) are computed as: $\Delta x_k = [\|\hat{x}_k - x_k\|]/N_r$, where $N_r = 100$ indicates the number of simulation runs. On the other hand, it is noted that the RMSE is computed as: $RMSE = \{[\sum_{i=1}^{N_r} \|\hat{x}_k - x_k\|^2]/N_r\}^{1/2}$. The three location tracking schemes are compared based on the same simulation scenario as shown in Fig. 5. It can be observed from both plots that the proposed PLT algorithms outperform the conventional KT and CLT schemes. The main differences between these algorithms occur while the signal sources become insufficient within the region I, II, and III. The proposed PLT schemes can still provide consistent location estimation and tracking; while the other two algorithms result in significantly augmented estimation errors. The major reason is attributed to the assisted information that is fed back into the location estimator while the signal sources are deficient.

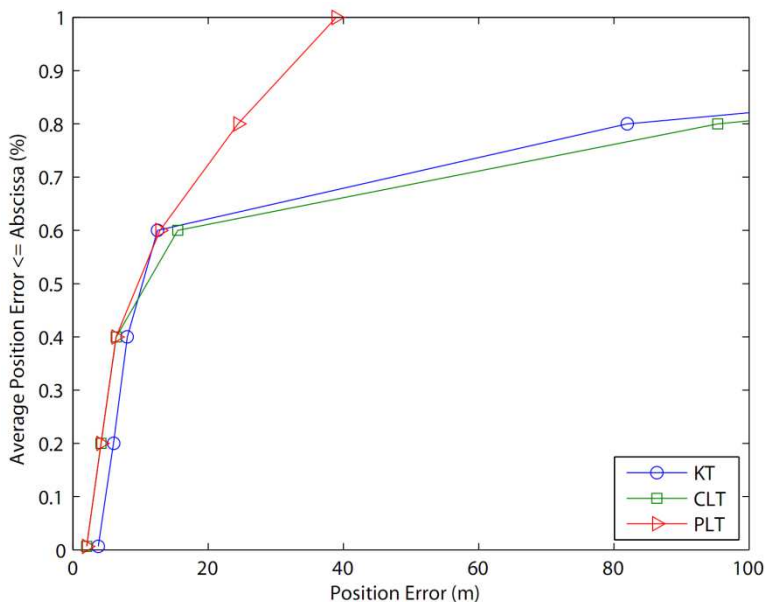


Fig. 8. Performance comparison between the location tracking schemes.

Fig. 8 shows the sorted position errors based on the same simulation results as shown in Fig. 6. Since the PLT algorithm is essentially the same as the CLT scheme while the number of ANs is adequate, both schemes perform the same under 50% of position errors. The performance of the CLT scheme becomes worse after 60% of position errors due to the deficiency of signal sources; while the proposed PLT algorithm can still provide feasible performance for location tracking. Moreover, the performance obtained from the KT scheme is similar to the CLT which is comparably worse than the PLT algorithm.

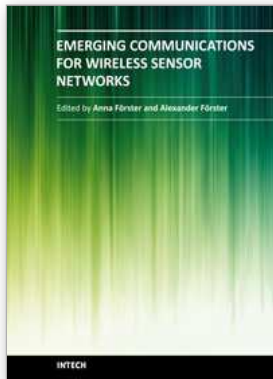
6. Conclusion

In this book chapter, the Predictive Location Tracking (PLT) scheme is proposed. The predictive information obtained from the Kalman filtering formulation is exploited as the additional measurement inputs for the location estimator. With the feedback information,

sufficient signal sources become available for location estimation and tracking of a mobile device. It is shown in the simulation results that the proposed PLT scheme can provide consistent accuracy for location estimation and tracking even with insufficient signal sources.

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