TDOA-Based Localization Using Interacting Multiple Model Estimator and Ultrasonic Transmitter/Receiver

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TDOA based Localization using Interacting Multiple Model Estimator and Ultrasonic Transmitter/Receiver

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***Abstract*—This paper presents a wireless network infrastructure based localization system using ultrasonic transmitter and receiver for obtaining accurate TDOA measurements and Interacting Multiple Model (IMM) estimator for calculating the actual position of the target by running two filters, i.e. extended Kalman filter (EKF) and robust extended Kalman filter (REKF), which offers the protection against the noise in both line-of-sight (LOS) and non-line-of-sight (NLOS) environments. The experiment results showed that the system utilized the advantages of EKF and REKF for different environments and thus was able to provide a localization solution with high accuracy.**

***Index Terms*—Kalman filter, Ultrasonic, Interacting Multiple Model (IMM), M-estimator, TDOA,**

I. Introduction

Although localization is becoming available to the general public and businesses via widespread use of GPS receivers, GPS signal can be blocked by high buildings, canyons or forests among others. It can be a significant problem in certain situations to provide accurate position estimate of mobile station (MS).

Network-based location systems are systems using existing wireless communication network infrastructures for determining the geographical location of an MS. Mobile positioning using network-based location system is used to provide various location-based services (LBS), such as hostage rescue, emergency service, location-based billing, fleet management and intelligent transport systems. The MS can be located by measuring the parameters of its signals received at a fixed set of base stations (BSs). In order to achieve the accuracy standard and performance requirement by the FCC, different measurement approaches such as angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), received signal strength (RSS) or the combination of these methods can be utilized [1]. In this study, we focus mainly on TDOA, since only receivers need to be synchronized when the transmitter is on MS side.

If line-of-sight (LOS) path exists between the MS and the BSs, high accuracy can be achieved in location estimates. However, LOS path may not be available since the signal can be hidden or reflected by obstacles such as buildings in urban areas. Therefore, the non-line-of-sight (NLOS) path can be much longer than the LOS path resulting in a bias in the TDOA measurements or no TDOA measurements received. Thus, accurate location estimation can not be achieved due to the existence of NLOS propagation. Hence, finding techniques that alleviate the NLOS error is very important.

In this study, a novel localization system based on TDOA measurements provided by ultrasonic transmitter and receiver using interacting multiple model (IMM) estimator is presented. The experiment results showed that the system was able to track the true trajectory of an MS and overcome the influence of NLOS interference.

II. Geometric Description of TDOA Estimation

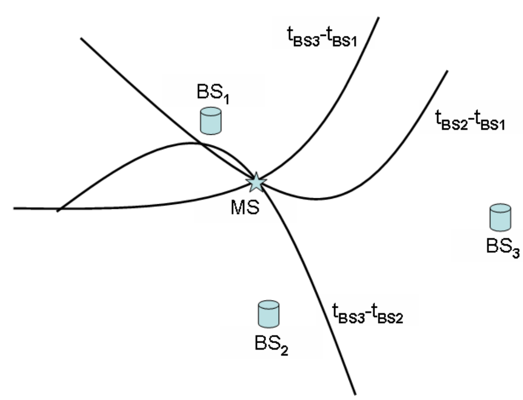


Fig. 1. TDOA Hyperbolic Positioning

TDOA is an observer measuring the time difference of arrival [2], later converted to distance difference by multiplying the speed of ultrasound v_{us}. For stationary MS approaches at least 3 BSs are required for computation of the MS's position. If one BS is used as reference BS, at least 4 BSs are required if there is no prior knowledge available. TDOA measurements

h_{ij} $(i,j = 1,2,3.\ i \neq j)$ between BS_i and BS_j can be calculated by

$$\begin{aligned} h_{ij} &= \sqrt{(x_{BSi}-x_{MS})^2+(y_{BSi}-y_{MS})^2}+v_i \\ &- \sqrt{(x_{BSj}-x_{MS})^2+(y_{BSj}-y_{MS})^2}-v_j \\ &= v_{us}\times(t_{BSi}-t_{BSj}) \end{aligned} \tag{1}$$

From equation (1), the difference of two TOA measurement noises v_i $(i = 1,2,3)$ is considered to be the TDOA measurement noise. If the measured distance of reference BS and the measured distance of rest BSs have identical bias, there is no bias existed in TDOA measurement and better performance can be achieved [3]. Note that any BS can be the reference BS.

III. Extended Kalman Filter for Tracking an MS using TDOA Estimates

The Kalman filter (KF) has been widely studied and applied in positioning due to its low computational complexity which is well suited to small mobile devices. The KF is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of process, meanwhile minimize the mean of the squared error [4]. Since we focus on TDOA estimate, the measurement equation is nonlinear. Thus, the extended Kalman filter (EKF) is used to estimate the state by linearizing the measurement equation. The signal model consists of two equations:

Process equation

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{G}\mathbf{w}_{k-1} \tag{2}$$

Measurement equation

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k \tag{3}$$

The state vector being estimated $\mathbf{x}_k = [x_k \quad y_k \quad v_{x,k} \quad v_{y,k}]^T$, contains the position and the velocity of the MS. $\mathbf{z}_k$ is the measurement vector at the time step k, $\mathbf{w}_k$ and $\mathbf{v}_k$ are the process and measurement noise. The process noise is assumed to be independent, white Gaussian random variable.

$$\mathbf{w} \sim \mathcal{N}(0, \mathbf{Q}), \tag{4}$$

where $\mathbf{Q}$ is the process noise error covariance. In LOS environment, measurement noise $\mathbf{v}_k$ is assumed to be normal distributed.

$$\mathbf{v}_k \sim \mathcal{N}(0, \mathbf{R}_{LOS}), \tag{5}$$

The matrices in (2) are given by

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \ \mathbf{G} = \begin{bmatrix} dt^2/2 & 0 \\ 0 & dt^2/2 \\ dt & 0 \\ 0 & dt \end{bmatrix}, \tag{6}$$

where dt is the sample period.

The function $h(\mathbf{x}_k)$ can be approximated using first order Taylor approximation about the predicted state estimate $\hat{\mathbf{x}}_k^-$, given in (8) [5].

$$h(\mathbf{x}_k) = h(\hat{\mathbf{x}}_k^-) + \frac{\partial h(\hat{\mathbf{x}}_k^-)}{\partial \mathbf{x}}(\mathbf{x}_k - \hat{\mathbf{x}}_k^-) = h(\hat{\mathbf{x}}_k^-) + \mathbf{H}_k(\mathbf{x}_k - \hat{\mathbf{x}}_k^-), \tag{7}$$

where $\mathbf{H}_k$ is the the Jacobian matrix of the partial derivatives of h with respect to $\mathbf{x}$ at time step k.

EKF equations are shown below, consisting of two groups, one for time update, the other one for measurement update.

EKF time update equations

$$\hat{\mathbf{x}}_k^- = \mathbf{A}\hat{\mathbf{x}}_{k-1} \tag{8}$$

$$\mathbf{P}_k^- = \mathbf{A}\mathbf{P}_{k-1}\mathbf{A}^T + \mathbf{G}\mathbf{Q}_{k-1}\mathbf{G}^T, \tag{9}$$

where $\mathbf{P}_k^-$ and $\mathbf{P}_k$ are a priori (predicted) and a posteriori error covariances.

EKF measurement update equations

$$\mathbf{K}_k = \mathbf{P}_k^-\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_k^-\mathbf{H}_k^T + \mathbf{R}_k)^{-1} \tag{10}$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k(\mathbf{z}_k - h(\hat{\mathbf{x}}_k^-)) \tag{11}$$

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_k^- \tag{12}$$

$\mathbf{R}_k$ is the measurement noise covariance. The term $\mathbf{z}_k - h(\hat{\mathbf{x}}_k^-)$ is called innovation. The Kalman gain $\mathbf{K}$ is the innovation weighting coefficient which determines the influence of the innovation in updating the estimate [4].

IV. Robust Extended Kalman Filter for Tracking an MS using TDOA Estimates

Since EKF is accurate for problems with small nonlinearities and nearly Gaussian noise statistics, it can perform very badly when these conditions are not fulfilled. However, in practical positioning, large nonlinearities and large outliers can be caused due to the multipath and NLOS signals. In order to improve the robustness of EKF, the weighted least squares regression form of Kalman filter using Huber's M-estimate are presented.

A. EKF in Regression

In order to enhance the performance of the conventional EKF and add robustness manner, the equations (8)-(9) and (10)-(12) are rewritten as follows.

Recall the linearization of $h(\cdot)$ and rewrite (2) and (3) as

$$\begin{bmatrix} \mathbf{I} \\ \mathbf{H}_k \end{bmatrix} \mathbf{x}_k = \begin{bmatrix} \hat{\mathbf{x}}_k^- \\ \hat{\mathbf{z}}_k \end{bmatrix} + \mathbf{E}_k, \tag{13}$$

where $\hat{\mathbf{z}}_k$ is defined by

$$\hat{\mathbf{z}}_k = \mathbf{z}_k - h(\hat{\mathbf{x}}_k^-) + \mathbf{H}_k\hat{\mathbf{x}}_k^- \tag{14}$$

and $\mathbf{E}_k$ is given by

$$\mathbf{E}_k = \begin{bmatrix} \mathbf{A}(\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}^-) + \mathbf{G}\mathbf{w}_k \\ -\mathbf{v}_k \end{bmatrix} \tag{15}$$

$$E\left\{\mathbf{E}_k\mathbf{E}_k^T\right\} = \begin{bmatrix} \mathbf{P}_k^- & 0 \\ 0 & \mathbf{R} \end{bmatrix} = \mathbf{S}_k\mathbf{S}_k^T, \tag{16}$$

where $\mathbf{P}_k^-$ is given by (9) and $\mathbf{S}$ can be obtained by Cholesky decomposition [6]. Multiplying (13) by $\mathbf{S}_k^{-1}$, then we get

$$\mathbf{Y}_k = \mathbf{N}_k \mathbf{x}_k + \boldsymbol{\xi}_k, \tag{17}$$

where

$$\mathbf{N}_k = \mathbf{S}_k^{-1}\begin{bmatrix} \mathbf{I} \\ \mathbf{H}_k \end{bmatrix}, \quad \boldsymbol{\xi}_k = -\mathbf{S}_k^{-1}\mathbf{E}_k, \quad \mathbf{Y}_k = \mathbf{S}_k^{-1}\begin{bmatrix} \hat{\mathbf{x}}_k^- \\ \hat{\mathbf{z}}_k \end{bmatrix}. \tag{18}$$

Now equation (17) is in the form of standard linear least squares regression problem with $E\left\{\boldsymbol{\xi}_k \boldsymbol{\xi}_k^T\right\} = \mathbf{I}$.

The least squares estimator is given by

$$\hat{\mathbf{x}}_k = (\mathbf{N}_k^T \mathbf{N}_k)^{-1} \mathbf{N}_k^T \mathbf{Y}_k. \tag{19}$$

B. Huber's M-Estimator

The least squares estimates can behave badly when the error distribution is not normal, particularly when the errors are heavy-tailed. $M-estimator$ is used here to solve (19) in a robust manner. Note that for simplicity in the notations we do not use the time index k with $\mathbf{x}$, $\mathbf{N}$ and $\mathbf{Y}$, even though they are in fact different at each time step. The general $M-estimator$ minimizes the objective function J_n:

$$\hat{\mathbf{x}} = arg\min J_n, \;\; J_n = \sum_{i=1}^{n} \rho(e_i), \tag{20}$$

where $e_i = y_i - \mathbf{n}_i^T \hat{\mathbf{x}}$ and function $\rho(\cdot)$ gives the contribution of each e_i to the objective function, y_i is the ith element of $\mathbf{Y}$ and $\mathbf{n}_i^T$ is the ith row of $\mathbf{N}$. n is the dimension of $\mathbf{Y}$ in (17).

Let $\psi(\cdot) = \rho'(\cdot)$, the influence function, be the derivative of ρ. Differentiating the objective function with respect to the coefficients, e_i, and setting the partial derivative to 0

$$\sum_{i=1}^{n} \mathbf{n}_i^T \psi(e_i) = 0 \tag{21}$$

Define the weight function $w(e_i) = \frac{\psi(e_i)}{e_i}$. Then,

$$\sum_{i=1}^{n} \mathbf{n}_i^T w(e_i) = 0. \tag{22}$$

Here redescending function is chosen for REKF in order to suppress the impact of noise with heavy-tailed distributions efficiently in NLOS environments. Its influence function is defined by

$$\psi_{HR}(e_i) = \begin{cases} e_i & , \quad |e_i| < a \\ c \cdot \mathsf{tanh}[\frac{c(b-x)}{2}] & , \quad a \leq |e_i| < b \\ 0 & , \quad |e_i| \geq b \end{cases} \tag{23}$$

The value a and b for is called clipping point and c is determined so that ψ_{HR} is continuous. Smaller values of a and b lead to more robust estimation, but at the expense of lower efficiency when the errors are normal distributed. Generally the clipping point is picked to give reasonably high efficiency in the normal distributed case. However, in our case, REKF will be only used to minimize the impact of the NLOS propagation, smaller values are chosen for clipping points: $a = 1\sigma$, $b = 4\sigma$ (where σ is the standard deviation of the errors). Detail can be found in [7].

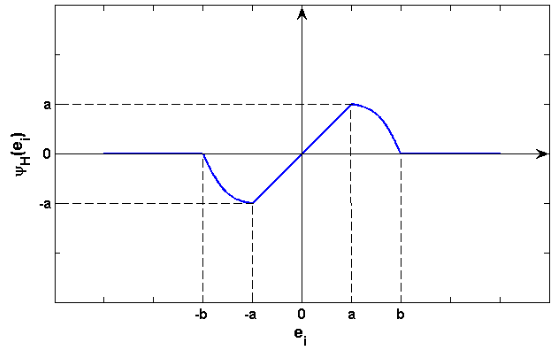


Fig. 2. Huber's Minimax Redescending

In practice, we need an estimate of the standard deviation of the errors to use these results. Usually a robust measure of scale is preferred for the standard deviation of e_i. For example, a common approach is to take $\hat{\sigma} = \mathsf{MAD}/0.6745$, where $\mathsf{MAD} = \mathsf{median}_i(|e_i - \mathsf{median}_j(e_j)|)$ is median absolute deviation.

Now the weighted least squares solution of (17) is

$$\hat{\mathbf{x}} = (\mathbf{N}^T \boldsymbol{\Omega} \mathbf{N})^{-1} \mathbf{N}^T \boldsymbol{\Omega} \mathbf{Y}, \tag{24}$$

where $\boldsymbol{\Omega} = \mathsf{diag}\left\{w(e_i), ..., w(e_n)\right\}$, with the diagonal matrix $\mathsf{diag}(\cdot)$. Then repeat the steps above until the state estimate converges to a stable value.

V. Interacting Multiple Model Algorithm

From the previous section, EKF can only follow the true trajectory in the LOS environment, to the contrary, the REKF can cope with some NLOS interference by choosing a smaller clipping point for the price of losing performance in the LOS environment. It is affirmative that a better result can be achieved if these two methods are combined [8].

The multiple model algorithm is based on the fact that the behavior of the MS can not be characterized at all time by a single model. One of the schemes is called Generalized Pseudo-Bayesian (GPB) method and the other one is the Interacting Multiple Model (IMM) algorithm. The general structure of these algorithm consists of more than one filter matched to different models. The IMM algorithm being conceptually similar to the second-order GPB and performing nearly as well as second-order GPB with less computations as the first-order GPB is suboptimal hybrid filter shown to achieve an excellent compromise between performance and complexity [10]. The detail of GPB is given in [9].

In this section, we only focus on the IMM algorithm. Two modes are considered in our case: LOS mode and NLOS mode. EKF is matched for tracking an MS for the LOS case and REKF for the NLOS case. Since REKF is not matched for the LOS case, a redescending score function with smaller clipping points can be chosen for REKF in order to alleviate the noise impact efficiently in NLOS situations.

The structure of the IMM algorithm consists of five components, which are mixing probability calculation, interaction, mode-matched filtering, mode probability update and combination [11].

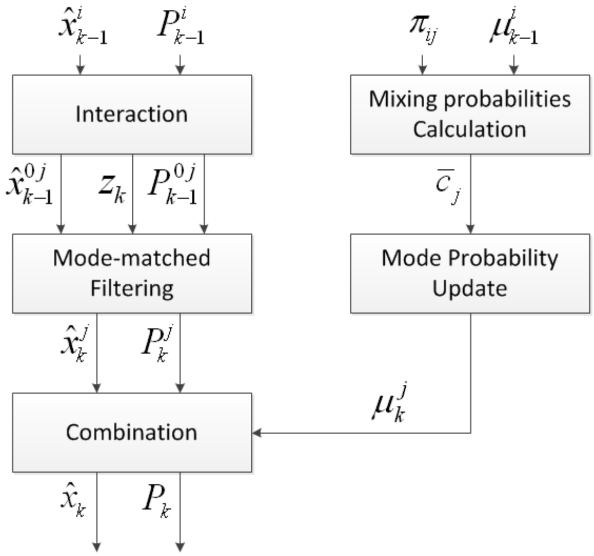


Fig. 3. IMM structure

The algorithm is as follows.

1 *Calculation of the mixing probabilities* $(i, j = 1, 2)$
According to Bayes' formula

$$\mu^{i|j}_{k-1} = \frac{1}{\bar{c}_j}\pi_{ij}\mu^i_{k-1}, \tag{25}$$

where the normalizing constants are

$$\bar{c}_j = \sum_i \pi_{ij}\mu^i_{k-1} \tag{26}$$

and π_{ij} is the transition probability from mode i to mode j and μ^i_{k-1} is probability of the ith mode at time step $k-1$.

2 *Interaction* $(j = 1, 2)$
In this step, the mixing initial conditions $\hat{\mathbf{x}}^{0j}_{k-1}$ and $\mathbf{P}^{0j}_{k-1}$ for each mode-matched filter are calculated in order to prevent from 2^2 parallel filtering as the second-order GPB. [9].

$$\hat{\mathbf{x}}^{0j}_{k-1} = \sum_i \hat{\mathbf{x}}^i_{k-1}\mu^{i|j}_{k-1}. \tag{27}$$

$$\tilde{\mathbf{x}}^{ij}_{k-1} = \hat{\mathbf{x}}^i_{k-1} - \hat{\mathbf{x}}^{0j}_{k-1}. \tag{28}$$

$$\mathbf{P}^{0j}_{k-1} = \sum_i \mu^{i|j}_{k-1}\left\{\mathbf{P}^i_{k-1} + \tilde{\mathbf{x}}^{ij}_{k-1}(\tilde{\mathbf{x}}^{ij}_{k-1})^T\right\}. \tag{29}$$

3 *Mode-matched Extended Kalman Filtering* $(j = 1, 2)$
In this step, the two mixing state estimates and their corresponding covariances are the inputs of our two mode-matched filters: EKF and REKF.

Within the filtering, the likelihood functions corresponding to two filters are computed by.

$$\Lambda^1_k = \mathcal{N}(\mathbf{e}^1_k; 0, \mathbf{S}_{LOS,k}), \tag{30}$$

$$\Lambda^2_k = \mathcal{N}(\mathbf{e}^2_k; 0, \mathbf{S}_{NLOS,k}), \tag{31}$$

where $\mathbf{e}^1_k$ and $\mathbf{e}^2_k$ being the innovations for mode 1 and mode 2 are given by,

$$\mathbf{e}^j_k = \mathbf{z}_k - h(\hat{\mathbf{x}}^{0j}_{k|k-1}), \quad j = 1, 2 \tag{32}$$

where $\hat{\mathbf{x}}^{0j}_{k|k-1} = \mathbf{A}\hat{\mathbf{x}}^{0j}_{k-1}$.

$\mathbf{S}_{LOS,k}$ and $\mathbf{S}_{NLOS,k}$ are calculated according to the equations below.

$$\mathbf{S}_{LOS,k} = \mathbf{H}^1_k\mathbf{P}^{01}_{k|k-1}(\mathbf{H}^1_k)^T + \mathbf{R}_{LOS,k}, \tag{33}$$

$$\mathbf{S}_{NLOS,k} = \mathbf{H}^2_k\mathbf{P}^{02}_{k|k-1}(\mathbf{H}^2_k)^T + \mathbf{R}_{NLOS,k}. \tag{34}$$

Here multivariate normal probability density function is used as the likelihood function for both modes.

4 *Mode Probability Update*$(j = 1, 2)$
In this step, the new mode probabilities are computed.

$$\mu^j_k = \frac{1}{c}\Lambda^j_k\bar{c}_j, \tag{35}$$

where the normalization constant for (35) is

$$c = \sum_j \Lambda^j_k\bar{c}_j. \tag{36}$$

$\bar{c}_j$ is the expression from (26) and Λ^j_k is the likelihood computed in step 3.

5 *Combination*$(j = 1, 2)$
In this step, the combination of the estimates and corresponding covariances of two modes is executed according to the mixture equations below. The combination result is only used for output purposes, and it will not be the input for next time step.

$$\hat{\mathbf{x}}_k = \sum_j \hat{\mathbf{x}}^j_k\mu^j_k \tag{37}$$

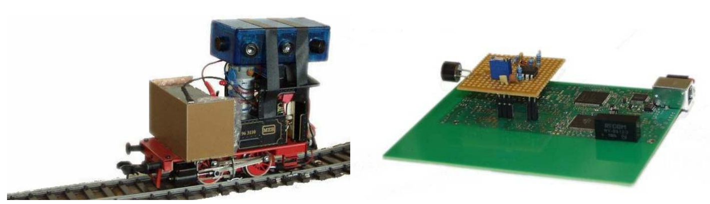
$$\mathbf{P}_k = \sum_j \mu^j_k\left\{\mathbf{P}^j_k + \tilde{\mathbf{x}}^j_k(\tilde{\mathbf{x}}^j_k)^T\right\}, \tag{38}$$

where $\tilde{\mathbf{x}}^j_k$ is

$$\tilde{\mathbf{x}}^j_k = \hat{\mathbf{x}}^j_k - \hat{\mathbf{x}}_k. \tag{39}$$

The derivation of the IMM algorithm is given in [9].

VI. Experiment Result



(a) Model locomotive with transmitter (b) Receiver

Fig. 4. Ultrasonic transmitter and receiver [13]

To validate the absolute position accuracy as well as the repeat accuracy of the system, a model railway is used. The track if the railway is about $1.75m$ times $3.85m$ of rectangular shape wit rounded corners and has a length of $10.35m$. The track is placed in a rectangular measurement area of 10 times $12m^2$ within a factory building [12], as shown in Fig. 5. The ultrasonic transmitter fixed on the model locomotive and the receiver fixed on the table or chair are shown in Fig. 4.

Fig. 5. Experiment environment [13]

The reason to use our self-built ultrasonic transmitter and receiver is that: firstly, multipath propagation can be detected due to the slow speed of ultrasound; secondly, the ultrasound is more robust to the noise interruption due to its particular frequency; thirdly, comparing with other ultrasound positioning systems, e.g., Cricket system, only receiver need to be synchronized when using TDOA measurements and no other wireless signals are needed to send trigger. Beside, our transmitter is able to cover direction of 360 degrees, thus only one transmitter is needed [14].

The speed of ultrasound is about $343m/s$ and the frequency of ultrasound is about $40kHz$. The time step duration dt is $0.3s$. Since process of movement is no more a line, smaller $\mathbf{R}$ and bigger $\mathbf{Q}$ should be chosen comparing with normal random walk case. $\mathbf{R}_{NLOS} = 2 \cdot \mathbf{R}_{LOS}$.

In our case, the strength of NLOS interference is estimated by the number of invalid receivers i.e., sometimes the path between the transmitter and receiver might be blocked by some obstacles and not all the receivers are able to receive ultrasonic signal from transmitter.

From Fig. 9 we can see clearly that in most of the time EKF mode dominates the performance of IMM estimator since NLOS interference is not very high, i.e., in most of time, the functional receivers are able to provide enough measurements for tracking the model locomotive. Therefore, EKF estimator performs better than REKF estimator which are shown in Fig. 6 and 7, as REKF estimator is tuned to handle NLOS interference. However, if too many receivers become non-functional, i.e., NLOS interference becomes large, REKF mode is going to dominate the performance of IMM estimator, as shown in Fig. 10. The probability of REKF mode is going to become higher if two receivers keep experiencing NLOS propagation and become invalid continually for some time or more than two receivers are experiencing NLOS propagation and become invalid. In these time durations, EKF estimator tuned to handle LOS situation is not capable of tracking the

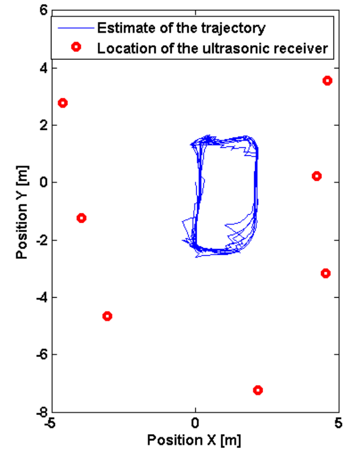


Fig. 6. Railway track estimated by EKF

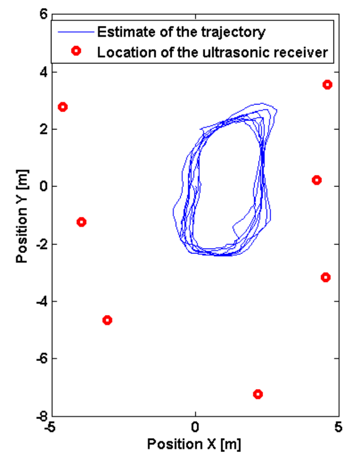


Fig. 7. Railway track estimated by REKF

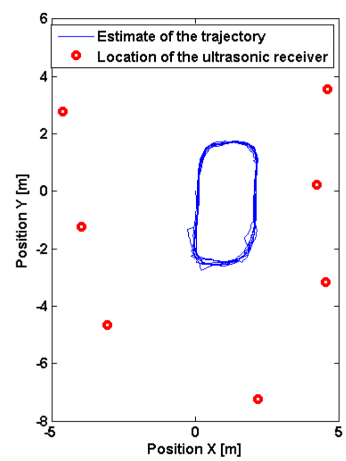


Fig. 8. Railway track estimated by IMM

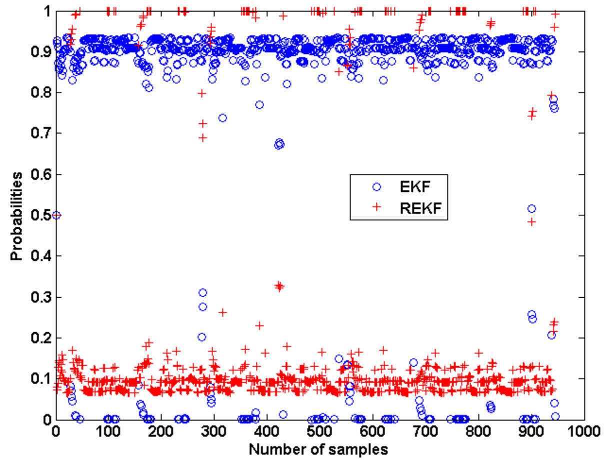


Fig. 9. Probability comparson of two modes inside IMM estimator

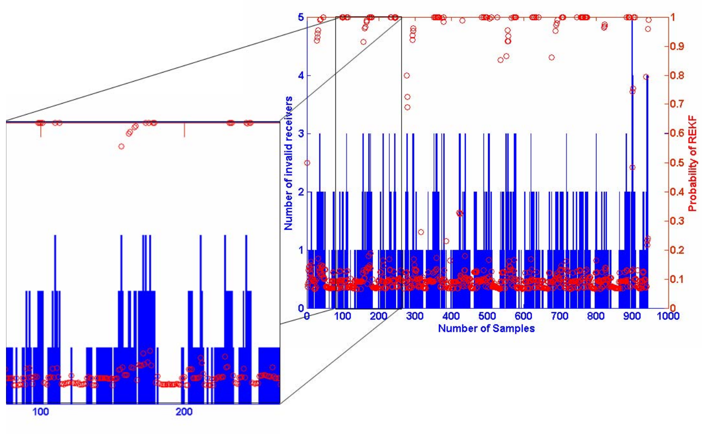


Fig. 10. Number of the invaild receivers V.S. Probabilities of REKF mode

true trajectory and results some errors as shown in Fig. 6. Comparing with EKF or REKF only estimator, IMM estimator is able to switch between the internal modes to take the advantages of each mode, hence, provides a robust and stable estimation in both LOS and NLOS environments, which can be seen in Fig. 8.

VII. Conclusion

This paper presented a wireless network infrastructure based localization system using TDOA measurements and IMM estimator. Comparing with conventional radio signal, ultrasonic signal is more robust and stable when being located in noisy environments [15], thus the recording of time of arrival is more accurate. IMM estimator runs EKF and REKF estimators parallelly and combines their results by calculating the probabilities of each estimator, in order to achieve a higher accuracy positioning for different noise scenarios.

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References

[1] F. Gustafsson and F. Gunnarsson, *Mobile positioning using wireless networks: possibilities and fundamental limitations based on available wireless network measurements*, IEEE, Signal Processing Magazine, vol. 22, no. 4, pp. 4153, 2005.

[2] M. Najar and J. Vidal, *Kalman tracking based on tdoa for umts mobile location*, in Personal, Indoor and Mobile Radio Communications, 2001 12th IEEE International Symposium on, vol. 1, pp. B45-B49, 2001.

[3] A. Muhammad, *Evaluation of tdoa techniques for position location in cdma systems*, Master thesis, Virgnina Polytechnic Institute and State University, 1997.

[4] W. Greg and B. Gary, *An introduction to the kalman filter*, IEEE Computer Graphic and Applications, 2006.

[5] A. Francine, *Tracking of a mobile station in non-line-of-sight environments using network infrastructure*, Master thesis. TU Darmstadt, Germany, 2008.

[6] T. Perala and R. Piche, *Robust extended kalman filtering in hybrid positioning applications*, in 4th Workshop on, Positioning, Navigation and Communication, 2007, pp. 5563, 2007.

[7] J. Fox and S. Weisberg. *An R Companion to Applied Regression*. Sage, Thousand Oaks, CA, second edition, 2011.

[8] R. Zhang, *Wireless Network-based Positioning of a Mobile Station in Non-Line-Of-Sight Environment*, Master thesis. TU Darmstadt, Germany, 2009.

[9] Y. Bar-Shalom, X. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation, Theory Algorithms And Software*, John Wiley & Sons, Inc., New York, 2001.

[10] E. Mazor, A. Averbuch, Y. Bar-Shalom and J. Dayan, *Interacting multiple model methods in target tracking: a survey*, Aerospace and Electronic Systems, IEEE Transactions on, vol. 34, no. 1, pp. 103123, 1998.

[11] C. Fritsche, U. Hammes, A. Klein, A. M. Zoubir, *Robust mobile terminal tracking in nlos environments using interacting multiple model algorithm*, IEEE International Conference on Acoustics, Speech and Signal Processing ICASSP 09, 2009.

[12] M. Sippel, *Localization of Mobile Objects with Embedded Microsystems*, Phd Dissertation. Albert-Ludwigs-Universität Freiburg, Germany, 2010.

[13] J. Wendeberg, F. Höflinger, C. Schindelhauer, and L. Reindl, *Anchor-free TDOA Self-Localization*. In Proceedings of 2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN 2011), 2011.

[14] B. Nissanka, Priyantha, A. Chakraborty and H. Balakrishnan, *The Cricket Location-Support System*.In Proc. 6th ACM MOBICOM, Boston, MA, 2000.

[15] F. Höflinger, R. Zhang, and L. M. Reindl, *Wireless Access to Numerous Destinations (WAND)-Pointer for museums*, Proc. of 2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN'2011), Guimaräes, Portugal, 2011.