INDIVIDUAL AOA MEASUREMENT DETECTION ALGORITHM FOR TARGET TRACKING IN MIXED LOS/NLOS ENVIRONMENTS

Lili Yi[⋆] *Sirajudeen Gulam Razul*[†] *Zhiping Lin*[⋆] *Chong-Meng See*[†∗]

[⋆]School of EEE Nanyang Technological University, Singapore
[†]Temasek Laboratories@NTU, Singapore
[∗] DSO National Laboratories, Singapore

ABSTRACT

In this paper, a novel individual angle-of-arrival (AOA) measurement detection method and extended Kalman filter (EKF) based tracking algorithm is proposed. The detection method is used to detect whether an individual AOA measurement is line-of-sight (LOS) or non-line-of-sight (NLOS). After the measurement detection, the selected LOS AOA measurements are then used into an dynamic EKF to track a moving target in mixed LOS/NLOS environments. Different from some traditional NLOS error detection methods, which determine the estimation result of a set of AOA measurements collected at every time step is LOS or not, the proposed method detects each AOA measurement one by one at one time step. This algorithm makes good use of LOS AOA measurements and greatly improves the tracking accuracy of the EKF in mixed LOS/NLOS environments. Simulations implemented under different NLOS percentage scenarios demonstrates the improvement of the classical EKF with the assistance of the proposed measurement detection method for AOA measurement.

Index Terms— Non-line-of-sight mitigation, measurement detection, target tracking, angle-of-arrival, extended Kalman filtering

1. INTRODUCTION

Research topic of target tracking consists several different branches, such as target motion analysis (TMA) with bearing-only or Doppler-bearing measurements [1, 2], target tracking with state constraints or road constraints [3, 4], target tracking in cluster and multi-target tracking using probability data association (PDA) techniques [5, 6], target tracking with time-difference-of-arrival (TDOA) and frequency-difference-of-arrival (FDOA) [7, 8], target tracking in mixed line-of-sight/non-line-of-sight (LOS/NLOS) [9, 10, 11] and so on.

Target tacking in mixed LOS/NLOS environments has been of considerable interest over the past decades. Several algorithms have been proposed to improve the tracking accuracy. In [9], a semi-parameter modified residual algorithm is proposed. This algorithm has been greatly improve the tracking performance of the extended Kalman filter (EKF) while additional computational cost is introduced. In [10], an EKF with individual time-of-arrival (TOA) measurement detection (EKF-IMD) algorithm is proposed to improve the tracking accuracy without introducing much more additional computational cost into the tracking strategy. In [11], the individual measurement detection method based on the probability density function of the LOS noise is used into the TDOA techniques. Together with the known road constraint, the performance of the EKF is also improved.

In this paper, the individual measurement detection (IMD) approach proposed in [10] for TOA measurement technique is now expanded to AOA measurement. The proposed IMD approach can efficiently select LOS AOA measurements from mixed LOS/NLOS measurements. Then, the selected LOS AOA measurements are reformulated as a dynamic measurement vector and used into the EKF to track the moving target. When the number of selected LOS AOA measurements is less than 2, the prediction state of the moving target obtained from the state evolution equation is used to instead.

The rest of this paper is organized as follows. Section 2 briefly describes the system model adopted in the tracking problem based on AOA measurements. Section 3 presents how to calculate the geometrical estimate position from an individual AOA measurement and how to detect the pseudo-position is LOS or not. Section 4 gives the tracking algorithm based on the dynamic EKF and the proposed IMD algorithm. Section 5 shows simulation results implemented under different percentage of NLOS errors. Section 6 draws the conclusion of this paper.

2. PROBLEM STATEMENT

Here, we consider a dynamic system contains one moving target in a 2-D plane and M stationary or moving sensors to collect AOA measurements $\boldsymbol{\beta}_k$. The state of the moving target at time step k is denoted as $\mathbf{x}_k = \left[\begin{array}{cccc} x_k & y_k & \dot{x}_k & \dot{y}_k \end{array}\right]^T$, containing the instantaneous position (x_k, y_k) and the instantaneous speed $(\dot{x}_k, \dot{y}_k)$, where $k \in \mathbb{Z}^+$. Sensors are located at $\left(x^S_{m,k}, y^S_{m,k}\right), m = 1, \cdots, M$.

To analyze and make inferences about the dynamic system, the state-space model, which consists of a state evolution equation and a measurement equation, is required. The state evolution equation describes the evolution of the target's state over time and the measurement equation represents the relationship between the state and the measured data. The state space model of our dynamic system is defined as

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{u}_{k-1}, \tag{1}$$

$$\boldsymbol{\beta}_k = \mathbf{h}(\mathbf{x}_k) + \boldsymbol{\eta}_k, \tag{2}$$

where $\mathbf{F}$ is the state transition matrix and defined as

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

T_s in matrix $\mathbf{F}$ is the sampling time interval. The Gaussian random vector $\mathbf{u}_{k-1} = \begin{bmatrix} u_{k-1,x} & u_{k-1,y} & u_{k-1,\dot{x}} & u_{k-1,\dot{y}} \end{bmatrix}^T$ is the process noise with corresponding covariance matrix $\mathbf{Q}_u$. The non-linear function vector $\mathbf{h}(\cdot) = \begin{bmatrix} h_1(\mathbf{x}_k) & \cdots & h_M(\mathbf{x}_k) \end{bmatrix}^T$ is the mapping function vector. $\boldsymbol{\eta}_k = \begin{bmatrix} \eta_{k,1} & \ldots & \eta_{k,M} \end{bmatrix}^T$ is the mixture LOS/NLOS measurement noise vector. The probability density function for $\eta_{k,m}$ is

$$p(\eta_m) = (1-\varepsilon_m)p_{\text{LOS}}(w_{k,m}) + \varepsilon_m p_{\text{NLOS}}(\delta_{k,m}), m = 1, \cdots, M \tag{3}$$

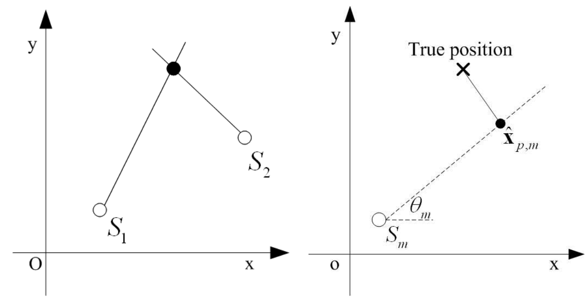
where $\varepsilon_m \in [0, 1]$ is the degree of contamination by NLOS errors at sensor m. The noise is effectively a mixture of LOS and NLOS noise where $p_{\text{LOS}}(w_{k,m})$ is a zero mean Gaussian noise and $p_{\text{NLOS}}(\delta_{k,m})$ is typically a mean-shifted Gaussian or exponentially distributed noise [10, 11].

3. MEASUREMENT ESTIMATION AND DETECTION

In this section, we propose a novel individual measurement estimation and detection approach to detect whether an AOA individual measurement is LOS or not. To implement the detection, we first estimate a raw position from an individual AOA measurement. Next, the hypotheses test is used to carry out the IMD. Details of individual measurement estimation and detection are given as follows.

3.1. Individual measurement estimation

AOA involves measurements of the angle a signal arrives at a sensor or a base station. Measuring AOA requires the system to be equipped with an antennae array. The AOA measurements can be obtained using algorithms such as the MUSIC and ESPRIT [12] [13]. In traditional tracking algorithms, such as EKF, the minimum number of AOA measurements is 2.



(a) AOA (b) Estimate

Fig. 1. Individual measurement estimate.

In the absence of noise, an accuracy estimation of the position of the target can be obtained using geometric equations. For AOA, each measurement points out a direction i.e. an angle to x axis or to y axis, so a line can be drawn starting from the stationary sensor with the given angle as gradient. The intersection point of two or more lines indicates the estimate position of the target. The localization geometry relationship between the measurements and the position of the moving target is shown in Fig. 1-(a).

One individual AOA measurement determines a set of points $\mathbf{x}_{k,m}^p$ on a straight line determined by the sensor's position and the measured angle as follows

$$\bar{\beta}_{k,m} = \arg\tan\frac{y_k - y_{k,m}^S}{x_k - x_{k,m}^S}, \tag{4}$$

where $\mathbf{x}_k^p = (x_k, y_k)$ stands for the true position of the moving target.

When the true position of the moving target is known, the best estimate pseudo-position from an individual AOA measurement can be obtained

$$\hat{\tilde{\mathbf{x}}}_{k,m}^p = \underset{\tilde{\mathbf{x}}_{k,m}^p}{\arg\min} \left\| \tilde{\mathbf{x}}_{k,m}^p - \mathbf{x}_k^p \right\|_{l_2}. \tag{5}$$

The pseudo-measured position defined in equation (5) is the position which minimize the distance between the true position of the moving and the pseudo-measured position.

Utilizing the cost function (5) and the geometrical relationship between the true position and the measured angle, the estimate position can be easily determined. For AOA measurements, the estimate position of the target is given by the cross point of two straight line perpendicular to each other, one starting from $(x_{S,m}, y_{S,m})$ with an angle of $\beta_{k,m}$ and the other starting from the true position of the moving target, as shown in Fig. 1-(b).

However, in practice, the true position of the moving target is unavailable. To obtain an estimate position from an individual AOA measurement, we use the predicted position $\mathbf{x}_{k,m}^{p,-}$ to replace the true position.

3.2. Individual measurement detection

After obtaining the estimate position of the moving target from an individual AOA measurement, the detection algorithm is introduced to identify the estimate position is LOS or not. It is easy to know that, for LOS Gaussian noise, all estimate positions must be very close to the predicted position of the moving target. When the NLOS error occurs, the measured AOA measurement is contaminated, correspondingly the estimate position. Based on this property, the individual measurement detection algorithm is proposed.

To identify whether the estimate position by each measurement is LOS or not, a confidence region is defined as

$$v_{k,m}(\gamma) = \left\{ \left(\hat{\hat{\mathbf{x}}}_{k,m}^{p} - \mathbf{x}_{k,m}^{p,-}\right)^T \left(\mathbf{P}_k^{p,-}\right)^{-1} \left(\hat{\hat{\mathbf{x}}}_{k,m}^{p} - \mathbf{x}_{k,m}^{p,-}\right) \leq \gamma \right\} \tag{6}$$

where $\mathbf{P}_k^{p,-}$ is a part of the matrix $\mathbf{P}_k^- = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^T$, the predicted position error covariance of the moving target which defined as

$$\mathbf{P}_k^p = \begin{bmatrix} \sigma_{x,k}^2 & 0 \\ 0 & \sigma_{y,k}^2 \end{bmatrix} \tag{7}$$

$\sigma_{x,k}$ and $\sigma_{y,k}$ are the standard deviations of the position on x axis and y axis, respectively.

As the position of the moving target $\mathbf{x}_k^p$ is two dimensional, the volume of the confidence region is

$$\begin{aligned} V_k &= c_2 \left|\gamma \mathbf{P}_k^{p,-}\right|^{\frac{1}{2}} = \pi\gamma \left|\mathbf{P}_k^{p,-}\right|^{\frac{1}{2}} \\ &= \pi\gamma^{\frac{1}{2}}\sigma_x\sigma_y. \end{aligned} \tag{8}$$

given a threshold γ, the span of the confidence region can be determined.

If the estimate position from individual AOA measurement fall into the confidence region, it is considered as LOS and vice versa. Only these AOA measurements corresponding to LOS estimate positions are retained and used into a modified dynamic EKF to track the moving target. The LOS AOA measurement vector is denoted as $\beta_k^L = \{\beta_k\}_1^{n_k}$, where n_k is the dynamic dimension of the selected LOS AOA measurements.

4. TRACKING ALGORITHM

Since $\mathbf{h}(\cdot)$ in equation (2) is a nonlinear measurement function, the standard KF cannot be applied and the EKF or other nonlinear filtering algorithms must be applied. Here, a simple but efficient EKF algorithm is adopted. To fit for the dynamic LOS measurement vector, the EKF is also modified as dynamic.

For AOA measurements, the nonlinear measurement function is now rewritten as

$$\mathbf{h}(\mathbf{x}_k) = \begin{bmatrix} \arctan\left(\frac{y_k - y_{S,1}}{x_k - x_{S,1}}\right) \\ \vdots \\ \arctan\left(\frac{y_k - y_{S,n_k}}{x_k - x_{S,n_k}}\right) \end{bmatrix}. \tag{9}$$

The EKF linearizes the nonlinear measurement function using a Taylor expansion. At time step k, $\mathbf{h}(\mathbf{x}_k)$ is approximated around the predicted state $\mathbf{x}_k^- = \mathbf{F}\hat{\mathbf{x}}_{k-1}$ as follows

$$\mathbf{h}(\mathbf{x}_k) = \mathbf{h}\left(\mathbf{x}_k^-\right) + \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}}\Big|_{\mathbf{x}=\mathbf{x}_k^-} \cdot \left(\mathbf{x}_k - \mathbf{x}_k^-\right). \tag{10}$$

The partial derivatives of $\mathbf{h}(\cdot)$ with respect to variable $\mathbf{x}$ denotes the Jacobian matrix

$$\begin{aligned} \mathbf{H}(\mathbf{x}_k) &= \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}} \\ &= \begin{bmatrix} \frac{\partial h_{1,k}(\mathbf{x})}{\partial x}\big|_{\mathbf{x}=\mathbf{x}_k} & \frac{\partial h_{1,k}(\mathbf{x})}{\partial y}\big|_{\mathbf{x}=\mathbf{x}_k} & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial h_{n_k,k}(\mathbf{x})}{\partial x}\big|_{\mathbf{x}=\mathbf{x}_k} & \frac{\partial h_{n_k,k}(\mathbf{x})}{\partial y}\big|_{\mathbf{x}=\mathbf{x}_k} & 0 & 0 \end{bmatrix}. \end{aligned} \tag{11}$$

The linearized measurement model is obtained

$$\boldsymbol{\beta}_k = \mathbf{h}\left(\mathbf{x}_k^-\right) + \mathbf{H}\left(\mathbf{x}_k^-\right) \cdot \left(\mathbf{x}_k - \mathbf{x}_k^-\right) + \mathbf{e}_k. \tag{12}$$

Note that, in mixed LOS/NLOS environments, the number of selected LOS measurements by the IMD is different at each time step, which leads to the dimension of the reconstructed LOS AOA measurement vector being dynamic. All the dimensions of related vectors and matrices are brought into correspondence with the reconstructed LOS measurement vector. If at some time steps, there are fewer than two LOS AOA measurements, i.e. the dimension of the reconstructed LOS measurement vector is less than two, the predicted state calculated by the state evolution equation (1) will be used as the estimate position.

5. SIMULATION RESULTS AND DISCUSSION

For comparison, the classical extended Kalman filter (EKF), the robust EKF (EKF-Hc)[9] and the EKF combined with the IMD algorithm (EKF-IMD) are implemented. Simulations are repeated over 100 Monte Carlo trails and each filter is performed over $k = 1000$ measurements. The sampling frequency is $5Hz$. The initial state $\hat{\mathbf{x}}_0$ of the moving target is set as a Gaussian random vector with a standard deviation of $50m$ for the positions and a standard deviation of $4m/s$ for the velocities, around the true initial state $\mathbf{x}_0 = \begin{bmatrix} 4300m & 4300m & 2m/s & 2m/s \end{bmatrix}^T$. The sensors are located at ($x_{S,1} = 2$km, $y_{S,1} = 7$km), ($x_{S,2} = 12$km, $y_{S,2} = 7$km),

$(x_{S,3} = 7\text{km}, y_{S,3} = 12\text{km})$, $(x_{S,4} = 7\text{km}, y_{S,4} = 2\text{km})$, $(x_{S,5} = 7\text{km}, y_{S,5} = 7\text{km})$. The NLOS noise is a mean shifted Gaussian pdf characterized by
$(\mu_{G,\eta}, \sigma_{G,\eta}) = (1rad, 0.5rad)$. The LOS noise is assumed to be zero mean Gaussian pdf with standard deviation $\sigma = 0.2rad$. Simulations are done under three different NLOS percentage scenarios:
Scenario C0: $\boldsymbol{\varepsilon} = \left[\begin{array}{ccccc} 0 & 0 & 0 & 0 & 0 \end{array}\right]$
Scenario C1: $\boldsymbol{\varepsilon} = \left[\begin{array}{ccccc} 0 & 0.25 & 0 & 0.25 & 0 \end{array}\right]$
Scenario C2: $\boldsymbol{\varepsilon} = \left[\begin{array}{ccccc} 0 & 0.25 & 0.1 & 0.75 & 0 \end{array}\right]$

To evaluate the performance of each tracker, the average mean error distance (MED) of each tracker are summarized in Table 1. The LOS root mean square error (RMSE) bound, which is calculated using all LOS measurements, and the RMSEs of each tracker under simulation scenario C1 with mean-shifted Gaussian NLOS error are shown in Fig. 2.

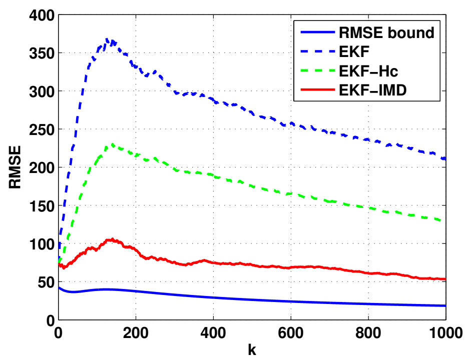


Fig. 2. LOS RMSE bound and RMSEs of each tracker at NLOS scenario C1.

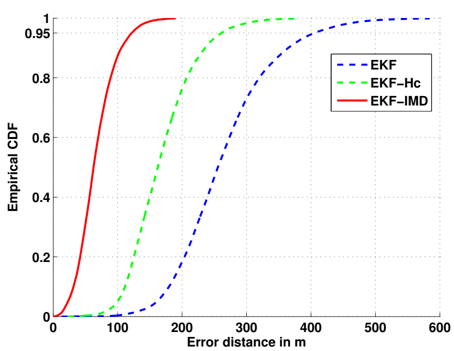


Fig. 3. Cumulative distribution functions of different trackers for Scenario C1.

From Table 1, it can be observed that in LOS environment, the EKF-IMD performs as well as the classical EKF. In mixed LOS/NLOS environments, the robust EKF performs better than the EKF. However, the EKF-IMD performs best than both the EKF and the robust EKF in all mixed LOS/NLOS scenarios. It is also easily to see the same conclusion from Fig. 2.

The cumulative error distribution of the localization error for the same example, shown in Fig. 3 indicates that the 95-percentile of the EKF-IMD is less than $150m$ whereas for the robust EKF and EKF the 95-percentile increases to more than $250m$ and $350m$ respectively.

Table 1. Mean over time MEDs of each tracker with mean shifted Gaussian NLOS errors.

Algorithms	C0	C1	C2
EKF	18.2788	264.0519	605.7763
EKF-Hc	20.8149	167.0978	425.3690
EKF-IMD	18.2788	**44.5998**	**101.9992**

6. CONCLUSION

In this paper, we have proposed an approach to improve the tracking accuracy in mixed LOS/NLOS environments based on individual measurement detection for angle-of-arrival technique. Utilizing the individual measurement detection algorithm, most LOS AOA measurements can be correctly selected from mixed LOS/NLOS AOA measurements. Then the dynamic EKF has been implemented to track the moving target. Simulation results have demonstrated the improved performance of the proposed EKF-IMD tracker.

7. REFERENCES

[1] K.C. Ho and Y.T. Chan, "An asymptotically unbiased estimator for bearings-only and doppler-bearing target motion analysis," *IEEE Transactions on Signal Processing*, vol. 54, no. 3, pp. 809–822, Mar. 2006.

[2] K. Becker, "Three-dimensional target motion analysis using angle and frequency measurements," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 41, no. 1, pp. 284–301, Jan. 2005.

[3] T. Kirubarajan, Y. Bar-Shalom, K.R. Pattipati, and I. Kadar, "Ground target tracking with variable structure imm estimator," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 36, no. 1, pp. 26–46, Jan. 2000.

[4] K.R.S. Kodagoda, S.S. Ge, W.S. Wijesoma, and A.P. Balasuriya, "IMMPDAF approach for road-boundary

tracking," *IEEE Transactions on Vehicular Technology*, vol. 56, no. 2, pp. 478–486, Mar. 2007.

[5] T. Kirubarajan and Y. Bar-Shalom, "Probabilistic data association techniques for target tracking in clutter," *Proceedings of the IEEE*, vol. 92, no. 3, pp. 536–557, Mar. 2004.

[6] Y. Bar-Shalom, T. Kirubarajan, and X. Lin, "Probabilistic data association techniques for target tracking with applications to sonar, radar and eo sensors," *IEEE Aerospace and Electronic Systems Magazine*, vol. 20, no. 8, pp. 37–56, Aug. 2005.

[7] K. C. Ho and Wenwei Xu, "An accurate algebraic solution for moving source location using TDOA and FDOA measurements," *IEEE Transactions on Signal Processing*, vol. 52, no. 9, pp. 2453–2463, Sep. 2004.

[8] K. C. Ho, Xiaoning Lu, and L. Kovavisaruch, "Source localization using TDOA and FDOA measurements in the presence of receiver location errors: Analysis and solution," *IEEE Transactions on Signal Processing*, vol. 55, no. 2, pp. 684–696, Feb. 2007.

[9] U. Hammes, E. Wolsztynski, and A.M. Zoubir, "Robust tracking and geolocation for wireless networks in NLOS environments," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 5, pp. 889–901, Oct. 2009.

[10] Lili Yi, S.G. Razul, Zhiping Lin, and Chong-Meng See, "Target tracking in mixed los/nlos environments based on individual toa measurement detection," in *2010 IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM)*, Oct. 2010, pp. 153 –156.

[11] Lili Yi, Sirajudeen Gulam Razul, Zhiping Lin, and Chong-Meng See, "Road-constraint assisted target tracking in mixed los/nlos environments based on tdoa measurements," in *Proceedings of 2012 IEEE International Symposium on Circuits and Systems (ISCAS)*, May 2012, pp. 2581–2584.

[12] R. Klukas and M. Fattouche, "Line-of-sight angle of arrival estimation in the outdoor multipath environment," *IEEE Transactions on Vehicular Technology*, vol. 47, no. 1, pp. 342–351, Feb. 1998.

[13] H. Miao, M. Juntti, and Kegen Yu, "2-d unitary esprit based joint AOA and AOD estimation for MIMO system," in *IEEE 17th International Symposium on Personal, Indoor and Mobile Radio Communications*, Sep. 2006, pp. 1–5.