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ICT Express 5 (2019) 115–119
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3D moving target tracking with measurement fusion of TDoA/FDoA/AoA

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Received 30 April 2018; accepted 9 July 2018
Available online 18 August 2018

Abstract

In this paper, we investigate the tracking of the 3D moving target when multiple measurements are available. We propose a particle filter-based 3D target tracking algorithm with measurement of time difference of arrival (TDoA), frequency difference of arrival (FDoA), and angle of arrival (AoA). We analyze the performance of the proposed scheme by MATLAB simulations and show the efficiency of the particle filter for 3D moving target tracking with various types of measurements.

Keywords: 3D mobility tracking; AoA; FDoA; TDoA; Particle filter

1. Introduction

Accurate and reliable 3D target tracking/localization is becoming very important for current and future industrial applications. Location-based services (LBS) are being applied in various fields such as emergency responses, tracking systems, surveillance, mobile marketing, entertainments, gaming, etc. [1]. It is generally believed that the most accurate wireless positioning system is *global navigation satellite system* (GNSS) (e.g., GPS—USA, Galileo—Europe, GLONASS—Russia, and Beidu—China) which implements a form of *trilateration*, but the GNSS signal is not always available when operating under radio frequency interference or anomalous ionospheric conditions [2]. To simply and accurately perform the location estimate, many localization techniques without GNSS have been developed and proposed [3].

Geolocation technique-based localization methods are introduced [4]. The time difference of arrival (TDoA) has an advantage that can solve time synchronization problem by eliminating the clock bias, which causes localization error in time of arrival (ToA) measurements. The angle of arrival is determined by the array vector of the received signal, which can be a quite good measurement for the location-awareness communications [5]. The signal of a moving target can provide the frequency difference of arrival (FDoA) measurement which represents the difference of the Doppler frequency. Target tracking with TDoA, FDoA [6] have been developed.

In a scenario where the state or the measurements are nonlinear, the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) can be used for tracking the target. However, EKF has an unavoidable error in the linearization of the nonlinear model. In addition, EKF and UKF are designed for Gaussian models, leading to errors when the filters are applied to estimate non-Gaussian distribution.

In this paper, we propose the particle filter (PF)-based 3D target tracking algorithm with measurement collaboration of TDoA, FDoA, and AoA. It can be used for tracking the location of moving unmanned vehicles in real time. It can be also adapted to problems of tracking unmanned vehicles or people in distress where vehicles or people can be identified from the satellites. We show the performance enhancement in the

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Peer review under responsibility of The Korean Institute of Communications and Information Sciences (KICS).

https://doi.org/10.1016/j.icte.2018.07.003
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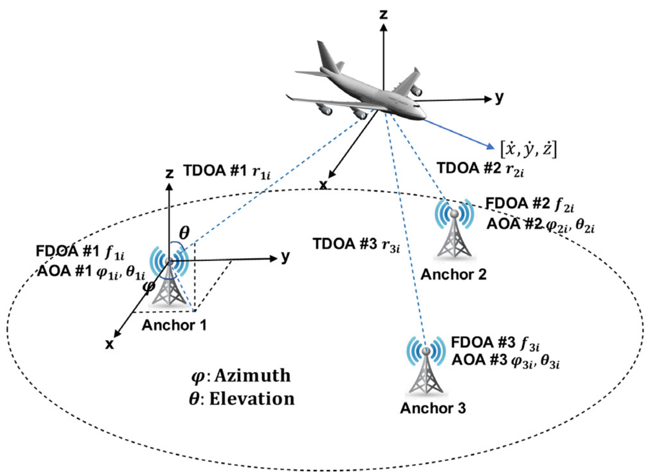

Fig. 1. Scenario of 3D target tracking with measurement collaboration of TDoA/FDoA/AoA.

localization accuracy of the proposed algorithm compared to the results of EKF-based target tracking and without the AoA measurement.

2. System model

2.1. Mobility model

We considered the mobility model [7] for defining the 3D movement of the target. The state vector of the moving target at time instant t is denoted by

$$\mathbf{x}_t = [x_t, \dot{x}_t, \ddot{x}_t, y_t, \dot{y}_t, \ddot{y}_t, z_t, \dot{z}_t, \ddot{z}_t]^{\mathrm{T}}, \tag{1}$$

where x_t, y_t, and z_t are the position of target, $\dot{x}_t$, $\dot{y}_t$, and $\dot{z}_t$ represent the velocity of target, $\ddot{x}_t$, $\ddot{y}_t$, and $\ddot{z}_t$ indicate the acceleration of target in the x, y, z directions in 3 dimension. The movement of the target can be described by

$$\mathbf{x}_t = \mathbf{A}(T, \alpha)\mathbf{x}_{t-1} + \mathbf{B}_u(T)u_t + \mathbf{B}_w(T)w_t, \tag{2}$$

where T is a discrete time step, α is a reciprocal of the maneuver time constant, and $\mathbf{w}_t$ is a noise of mobility model. More details of mobility model is given in [7].

2.2. Measurement model

Fig. 1 shows the scenario for 3D target tracking considered in this paper. We assume that TDoA/FDoA/AoA measurements are available at each anchor from the received signals of the 3D target and the other anchor nodes. In this scenario, an anchor node 1 acts as a reference node and the TDoA/FDoA/AoA measurements are defined as

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

where the function $h(\mathbf{x}_t)$ is denoted by

$$h(\mathbf{x}_t) = [r_{12}, r_{13}, \ldots, r_{1i}, f_{21}, f_{31}, \ldots, f_{i1}, \psi_1, \theta_1, \ldots, \psi_i, \theta_i]^{\mathrm{T}}, \tag{4}$$

where the location parameters are defined in Section 2.3. $\mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t)$ is the measurement noise vector, in which $\boldsymbol{\Sigma}_t$ is assumed to be diagonal matrix.

2.3. Location parameter

The TDoA between a reference anchor 1 and the anchor i is given by

$$r_{1i} \triangleq r_1 - r_i = (t_1 - t^0)c - (t_i - t^0)c = (t_1 - t_i)c, \tag{5}$$

where t^0 is the clock time, t_i is the time of arrival (ToA) between the anchor node i and the target, c is the speed of light.

FDoA [8] of the two received signals between the target and the anchor node i is denoted by

$$f_{i1} \triangleq \frac{f_c}{c}\left(\frac{(\dot{\mathbf{p}}_t - \dot{\mathbf{s}}_{t,1})^T(\mathbf{p}_t - \mathbf{s}_{t,1})}{|\mathbf{p}_t - \mathbf{s}_{t,1}|} - \frac{(\dot{\mathbf{p}}_t - \dot{\mathbf{s}}_{t,i})^T(\mathbf{p}_t - \mathbf{s}_{t,i})}{|\mathbf{p}_t - \mathbf{s}_{t,i}|}\right), \tag{6}$$

where $\mathbf{p}_t, \dot{\mathbf{p}}_t \in \mathbb{R}^3$ are the position and velocity of the target, and $\mathbf{s}_{t,i}, \dot{\mathbf{s}}_{t,i} \in \mathbb{R}^3$ are the position and velocity of the anchor node i, at time instant t respectively.

The azimuth and the elevation of AoA from the target to the anchor node i are respectively defined as

$$\phi_i = \arctan\frac{y_{t,i} - y_t}{x_{t,i} - x_t}, \quad \theta_i = \arccos\frac{\sqrt{(x_{t,i} - x_t)^2 + (y_{t,i} - y_t)^2}}{|\mathbf{p}_t - \mathbf{s}_{t,i}|}. \tag{7}$$

3. Particle filter-based target tracking with measurement collaboration

Unlike the KF, which do not guarantee optimum solution, we employ the use of PF for target tracking with the measurement collaboration given in (3) [9]. Furthermore, we adopt the Markov chain Monte Carlo (MCMC)-based resampling method for estimating the more accurate posterior distribution of the target state, [10,11].

Given the samples $\{\mathbf{x}_t^n, w_t^n\}_{n=1}^N$, the particle evolution is defined as

$$\mathbf{x}_t^n = \mathbf{A}(T, \alpha)\mathbf{x}_{t-1}^n + \mathbf{B}_u(T)\mathbf{u}_t^n + \mathbf{B}_w(T)\mathbf{w}_t, \quad \forall n \in \Omega_N, \tag{8}$$

where Ω_N is set of N particle samples.

The posterior distribution of the target state at time t is approximated by

$$p(\mathbf{x}_t|\mathbf{z}_t) \approx \sum_{n=1}^{N} w_t^n \delta(\mathbf{x}_t - \mathbf{x}_t^n), \tag{9}$$

where w_t^n is the nth particle weight and can be computed by

$$w_t^n \propto w_{t-1}^n p(\mathbf{z}_t|\mathbf{x}_t^n). \tag{10}$$

The likelihood function of measurements $p(\mathbf{z}_t|\mathbf{x}_t^n)$ is given by

$$p(\mathbf{z}_t|\mathbf{x}_t^n) = \frac{1}{\sqrt{(2\pi)^k|\boldsymbol{\Sigma}_t|}}\exp\left(-\frac{[\mathbf{z}_t - h(\mathbf{x}_t^n)]^{\mathrm{T}}\boldsymbol{\Sigma}_t^{-1}[\mathbf{z}_t - h(\mathbf{x}_t^n)]}{2}\right). \tag{11}$$

Table 1
Simulation parameters.

Parameter	Value	Parameter	Value
MC	100	σ_{TDoA}	10 [m]
Iteration	400 [s]	$CP_{X,Y}$	5, 15, 25, 30 [m/s^2]
N_p	2500, 5000	CP_Z	3, 8, 21, 25 [m/s^2]
σ_{state}	0.1 [m/s^2]	α	0.6
σ_{FDoA}	10 [Hz]	T	1
σ_{AoA}	1,3,5 [°]	Network size	5000 × 5000 × 400 [m^3]

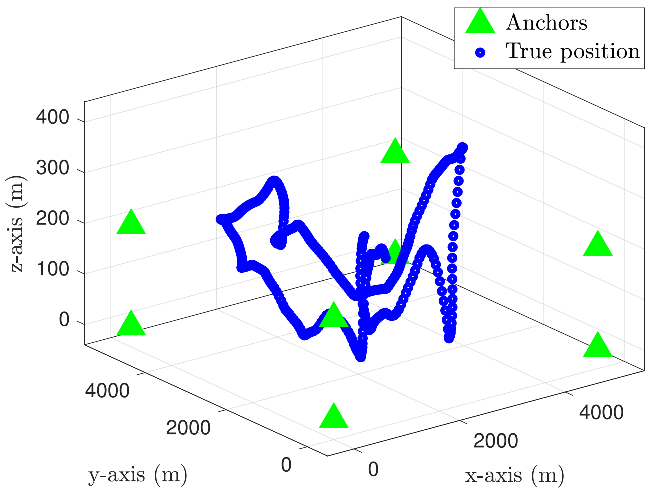

Fig. 2. Trajectory of moving target.

4. Simulation results

4.1. Simulation environment

To do tracking, we first need to know the existence of the target. There are many kinds of methods to detect the target, and this field has been studied much [12,13]. In this paper, we assume that the detection of the target is accurate.

In our simulation, we will track the position of one target. By using measurements, we can estimate the position of the target with particles. The number of anchor nodes used are 4 and 8. Regardless of N_{eff} (threshold value) the resampling process is performed every iteration. We summarize the simulation parameters in Table 1. The FDoA performance is affected by the velocity of the target rather than the noise, so we analyzed it according to the average velocity. And the AoA performance is analyzed according to the noise level. The performance about anchor nodes was analyzed according to the number and arrangement.

4.2. Performance analysis

Fig. 2 gives an illustration of the exemplary trajectory of the moving target. There are 8 anchors and the target moves in the network based on the mobility model. Fig. 3 shows the CDF of positioning errors using PF with FDoA (red line), PF without FDoA (black line) and EKF (blue line) where the average velocity is about 30 [m/s^2] and the number of anchors is 8 (4 anchors are placed on the ground and 4 anchor nodes are placed on $z = 200$). It can be observed that when the average velocity of a target is relatively slow, the use of the FDoA measurements does not help to improve the tracking performance. But, when the average velocity of a target is relatively fast, the use of the FDoA measurements can be helpful for tracking the position of a target. Fig. 4 shows the CDF of positioning errors using PF with FDoA (red line, green line) and PF without FDoA (black line, blue line) where the average velocity is about 40 [m/s^2] and about 50 [m/s^2].

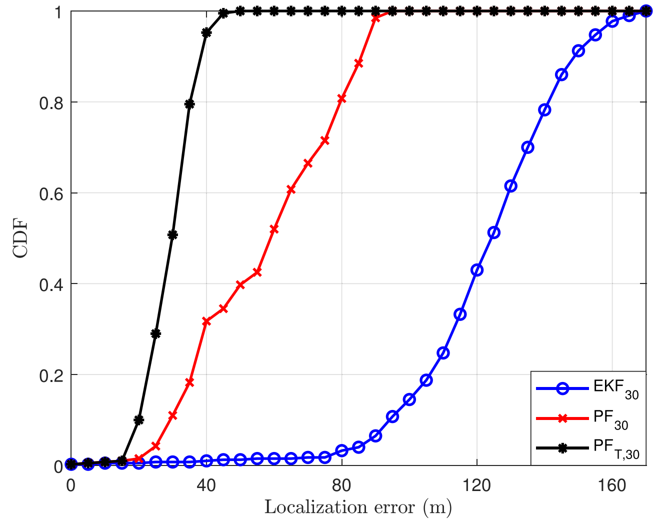

Fig. 3. CDF of positioning error according to Filters when average velocity of target is about 30 [m/s^2]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

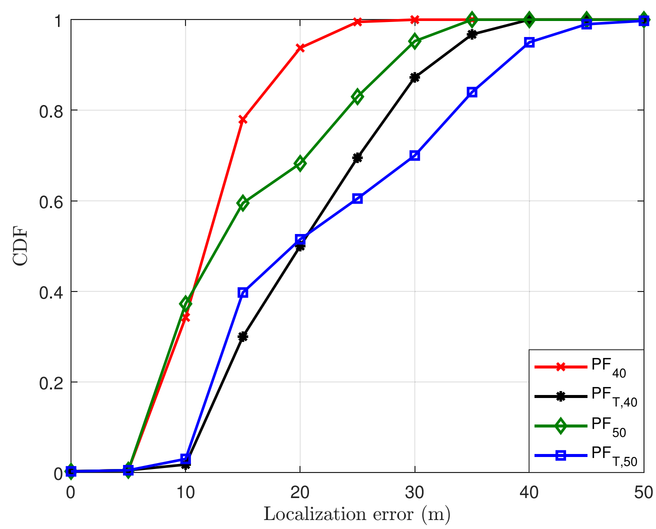

Fig. 4. CDF of positioning error according to Filters when average velocity of target is about 40 and 50 [m/s^2]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 5 shows the CDF of positioning errors where 4 anchors are placed on the ground and 4 anchors are placed on $z = 200$. When the AoA measurement is considered with noise error 5 degrees (blue line) are considered, the performance is lower than when the AoA measurement is not used (red

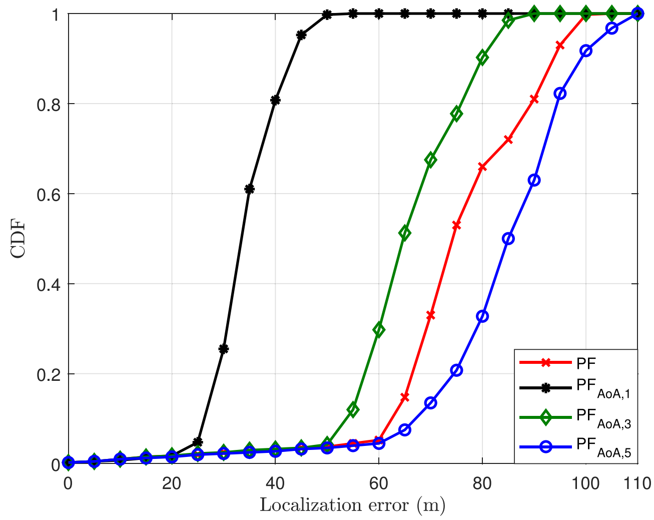

Fig. 5. CDF of positioning error according to AoA noise. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

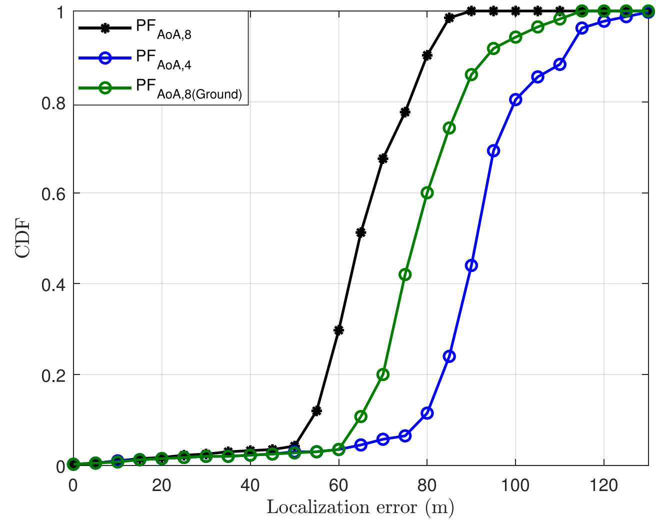

Fig. 6. CDF of positioning error according to the number and arrangement of anchors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

line). However, when the AoA measurement noise is 1 degree (black line) and 3 degrees (green line), the PF achieves a higher performance. From the results, it can be deduced that the use of AoA measurement with TDoA/FDoA can improve the performance of the system if the AoA measurement has an error less than 3 degree.

The CDF of positioning error according to the number and arrangement of anchors is shown in Fig. 6. When the number of anchor nodes is 4 and all four anchor nodes are placed on the ground (i.e. $z = 0$), the PF with AoA measurement (blue line) shows the worst tracking performance. If the number of anchor nodes is increased to 8 and all anchors are still placed on the ground (i.e. $z = 0$), some performance improvement (green line) occurs due to the increase in the number of anchors. On the other hand, if the number of anchor nodes is 8 (4 anchors are placed on the ground and 4 anchor nodes are placed on $z = 200$), better tracking performance (black line) can be obtained as compared to when all the 8 anchors are placed on the ground. This is because if all anchors are placed on the ground, the position estimation performance about the z coordinate is degraded.

5. Conclusions

In this paper, we investigate the tracking of the 3D moving target when multiple measurements are available. The results show that in a nonlinear scenario, the PF performance is superior to EKF with similar measurement models are used. Additionally, we confirmed the effect of FDoA and AoA measurement on tracking performance according to the velocity of a target and noise level of AoA measurement. From the results, when the average velocity of a target is relatively slow, the FDoA measurement interferes the tracking performance. When the average velocity of a target is relatively fast, the FDoA measurement is helpful for tracking. Also, when the AoA measurement error is more than 4 degrees, not using the AoA measurement is more helpful to the tracking performance. Using the AoA measurement only when the error of AoA measurement is lower than 3 degree helps to improve the positioning performance when 4 anchors are located on the ground while the other 4 anchors are located on $z = 200$. It is shown that when all the anchors are placed on the ground, it is difficult to obtain good positioning performance.

In our future work, optimal anchor node arrangement will be studied when moving objects are tracked. Also, further studies on tracking techniques using fewer anchor nodes, high performance positioning algorithm using a small number of particles, and new methodologies other than particle filtering will be investigated in our future work.

Acknowledgment

This work has been supported by the National GNSS Research Center program of Defense Acquisition Program Administration and Agency for Defense Development, Republic of Korea.

Conflict of interest

The authors declare that there is no conflict of interest in this paper.

References

[1] A.D. Lahe, P. Kulkarni, Location privacy preserving using semi-TTP server for LBS users, in: 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information Communication Technology, RTEICT, 2017, pp. 605–610. http://dx.doi.org/10.1109/RTEICT.2017.8256668.

[2] J. Lee, Y.T.J. Morton, J. Lee, H. Moon, J. Seo, Monitoring and mitigation of ionospheric anomalies for gnss-based safety critical systems: A review of up-to-date signal processing techniques, IEEE Signal Process. Mag. 34 (5) (2017) 96–110. http://dx.doi.org/10.1109/MSP.2017.2716406.

[3] N. Patwari, J.N. Ash, S. Kyperountas, A.O. Hero, R.L. Moses, N.S. Correal, Locating the nodes: cooperative localization in wireless sensor networks, IEEE Signal Process. Mag. 22 (4) (2005) 54–69.

[4] F. Gustafsson, F. Gunnarsson, Mobile positioning using wireless networks: possibilities and fundamental limitations based on available wireless network measurements, IEEE Signal Process. Mag. 22 (4) (2005) 41–53.

[5] R. Di Taranto, S. Muppirisetty, R. Raulefs, D. Slock, T. Svensson, H. Wymeersch, Location-aware communications for 5G networks: How location information can improve scalability, latency, and robustness of 5G, IEEE Signal Process. Mag. 31 (6) (2014) 102–112.

[6] G. Wang, S. Cai, Y. Li, N. Ansari, A bias-reduced nonlinear WLS method for TDOA/FDOA-based source localization, IEEE Trans. Veh. Technol. 65 (10) (2016) 8603–8615. http://dx.doi.org/10.1109/TVT.2015.2508501.

[7] Z. Yang, X. Wang, Joint mobility tracking and handoff in cellular networks via sequential Monte Carlo filtering, IEEE Trans. Signal Process. 51 (1) (2003) 269–281.

[8] X. Zhong, W.P. Tay, M. Leng, S.G. Razul, C.M.S. See, TDOA-FDOA based multiple target detection and tracking in the presence of measurement errors and biases, in: 2016 IEEE 17th International Workshop on Signal Processing Advances in Wireless Communications, SPAWC, 2016, pp. 1–6, http://dx.doi.org/10.1109/SPAWC.2016.7536786.

[9] A. Isaac, P. Willett, Y. Bar-Shalom, Quickest detection and tracking of spawning targets using monopulse radar channel signals, IEEE Trans. Signal Process. 56 (3) (2008) 1302–1308. http://dx.doi.org/10.1109/TSP.2007.908982.

[10] P.M. Djuric, J.H. Kotecha, J. Zhang, Y. Huang, T. Ghirmai, M.F. Bugallo, J. Miguez, Particle filtering, IEEE Signal Process. Mag. 20 (5) (2003) 19–38. http://dx.doi.org/10.1109/MSP.2003.1236770.

[11] B. Ristic, S. Arulampalam, N. Gordon, Beyond the Kalman filter: Particle filters for tracking applications, 2004.

[12] J.A. Bhatti, T.E. Humphreys, B.M. Ledvina, Development and demonstration of a TDOA-based GNSS interference signal localization system, in: Proceedings of the 2012 IEEE/ION Position, Location and Navigation Symposium, 2012, pp. 455–469, http://dx.doi.org/10.1109/PLANS.2012.6236915.

[13] D. Egea-Roca, G. Seco-Granados, J. López-Salcedo, Comprehensive overview of quickest detection theory and its application to GNSS threat detection, Gyroscopy Navigation 8 (1) (2017) 1–14.