Progress In Electromagnetics Research, PIER 97, 373–389, 2009

TARGET TRACKING WITH LINE-OF-SIGHT IDENTIFICATION IN SENSOR NETWORKS UNDER UNKNOWN MEASUREMENT NOISES

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Abstract—Tracking a target is a fundamental and crucial problem in wireless sensor networks. It is well known that non-line-of-sight (NLOS) propagation will significantly degrade the tracking accuracy if its effects are ignored. In this paper, a line-of-sight (LOS) identification approach for range-based tracking systems is developed to discard the NLOS measurements. Based on L_p-norm LOS identification strategy, a novel target tracking method is devised with the use of cost-reference particle filter, which does not require the knowledge of the measurement noise distribution. Computer simulations are included to verify the effectiveness of the proposed approach under different noise distributions.

1. INTRODUCTION

The research topic of wireless sensor network (WSN) has attracted much attention over the past few years. WSNs have wide applications in environmental, medical, food-safety and habitat monitoring, assessing the health of machines, vehicles and civil engineering structures, energy management, inventory control, home and building automation, homeland security and military initiatives [1, 2]. An important problem in WSNs is to track the position of a target. Due to reflection and diffraction, non-line-of-sight (NLOS) error which may occur in urban environments, will lead to unreliable tracking results if its effects are not taken into account. Usually, the line-of-sight (LOS) identification step is carried out, and then the identified LOS measurements are used for target tracking. Assuming that prior knowledge of NLOS-induced error and measurement noise is

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available, a NLOS mitigation algorithm is proposed in [3]. In [4], a non-parametric probability density estimation technique is employed to approximate the distribution of measurements based on complete knowledge of measurement noise. A simple hypothesis test problem is utilized to detect NLOS error in [5]. However, neither NLOS-induced error nor measurement noise distribution is available in practice.

In this work, we tackle the target tracking problem in NLOS environment using the particle filter (PF) approach. PF [6, 7] has emerged as an important sequential state estimation method for stochastic nonlinear and/or non-Gaussian state-space models, for which it provides a powerful tool in signal processing and other communities. However, one of the problems with PF is that the noise distribution is needed for algorithm development. When there is no prior information about the noise distributions, the PF cannot be effectively utilized. A modification to PF is cost-reference particle filter (CRPF) [8, 9]. It is also based on the principle of exploring the state-space by drawing particles but it does not require noise distribution information. As with all particle-based filters, choosing the importance function is an important issue of CRPF in the implementation. The most popular choice is transition prior because of its simplicity and this corresponds to the so-called bootstrap filter. Since the transition prior does not utilize the latest measurements to generate new particles, this filter usually leads to unsatisfactory performance. On the other hand, extended Kalman filter (EKF) [6] and unscented Kalman filter (UKF) [10] generate new particles with the use of latest measurements for performance enhancement. In this paper, we will tackle two major issues that deteriorate the tracking performance in sensor networks, namely, NLOS propagation and unknown measurement noise. First, we propose to use L_p-norm as a criterion to identify LOS measurements under unknown noise distributions. According to L_p-norm, the quality of each measurement is calculated, which can be seen as a probability of measurement being under LOS propagation, and then the identified LOS measurements are selected. Second, using the identified LOS measurements, target tracking is accomplished with use of CRPF, in which we propose to use L_p-norm to calculate the particles' cost without measurement noise information. The main novelty of this paper is that a LOS identification algorithm is developed based on L_p-norm in target tracking under different noise distributions with use of the CRPFs.

The rest of the paper is organized as follows. The problem formulation of target tracking with NLOS propagation is presented in Section 2. Three types of noise distributions used in this paper are introduced in Section 3. A brief introduction of PF and CRPF is given in Section 4. In Section 5, our LOS identification approach is proposed to perform tracking using CRPFs. In Section 6, simulation results for evaluating the tracking performance of the developed algorithms are provided. Finally, conclusions are drawn in Section 7.

2. PROBLEM FORMULATION

The model-based methods for tracking applications generally require two models: The state model, denoted by $\mathbf{x}_t$, describes the evolution of the state with time, and the measurement model, denoted by $\mathbf{z}_t$, defines the relationship between noisy observations and the state. In case of two-dimensional (2D) target tracking, let $\mathbf{x}_t = [x_t, y_t, \dot{x}_t, \dot{y}_t]^T$ be state vector that contains the coordinates and velocities of a moving target at time t. In this paper, linear state and nonlinear measurement models are considered [2]:

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}) + \mathbf{v}_t = \mathbf{F}\mathbf{x}_{t-1} + \mathbf{v}_t \tag{1}$$

and

$$\mathbf{z}_t = g(\mathbf{x}_t) + \mathbf{w}_t \tag{2}$$

where

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

and $g(\cdot)$ is a nonlinear measurement function. The T_s is the sampling interval, $\mathbf{v}_t$ is a 4×1 independent and identically distributed (i.i.d.) process noise vector with $\mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$, where $\mathbf{0}$ is a zero vector and $\mathbf{Q}$ is the covariance matrix of the form of $\mathbf{D}\text{diag}(\sigma_x^2, \sigma_y^2)\mathbf{D}^T$, with σ_x^2 and σ_y^2 are the variances in x-coordinate and y-coordinate, and $\mathbf{D}$ is given as

$$\mathbf{D} = \begin{bmatrix} T_s^2/2 & 0 \\ 0 & T_s^2/2 \\ T_s & 0 \\ 0 & T_s \end{bmatrix}$$

In our study, time-of-arrival (TOA) measurements under possibly NLOS propagation are used. By multiplying the TOAs with the known propagation speed, the observed distance measurement at time t of the jth sensor is [3]:

$$z_{t,j} = d_{t,j} + \phi_{t,j}\eta_{t,j} + w_{t,j}, \quad t = 1, 2, \ldots, \quad j = 1, 2, \ldots, M \tag{3}$$

where $d_{t,j} = \sqrt{(x_t - x_j)^2 + (y_t - y_j)^2}$, M is the total number of sensors in the WSN, (x_j, y_j) denotes the known coordinates of jth sensor, $w_{t,j}$ is measurement noise, $\eta_{t,j}$ is NLOS-induced error and $\phi_{t,j}$ is the NLOS existence variable of the jth sensor at time t. The distance measurement corresponds to LOS and NLOS propagation when $\phi_{t,j} = 0$ with probability $q_{t,j}$ and $\phi_{t,j} = 1$ with probability $1-q_{t,j}$, respectively. The NLOS-induced error $\eta_{t,j}$ is assumed a large positive random variable which is valid particularly in open areas [11, 12]. In the next section, three types of measurement noise distributions are introduced, which will be used in Section 6 to evaluate the performance of proposed method.

3. NOISE DISTRIBUTIONS

Even though most engineering systems in control, communication and signal processing are devised under the assumption of Gaussian noise, many physical environments can be modeled more accurately as non-Gaussian rather than Gaussian observation channels. Examples include, atmospheric noise, lightning spikes, electronic devices and relay switching noise [13]. Therefore, it is important to develop a tracking algorithm for LOS identification under non-Gaussian noise case. Prior to the tracking algorithm development, we will introduce three different types of measurement noises, namely, Gaussian, Gaussian mixture and α-stable process since they are popular and widely used in the fields of communications and signal processing.

3.1. Gaussian Noise

The Gaussian noise [14, 15] is the most popular choice used in many areas, such as image processing, communications, and acoustics. It is justified by the central limit theorem, which says that the distribution of infinite numbers of i.i.d. random variables with finite variance is Gaussian. Another reason for its popularity is that the Gaussian distribution has closed-form probability density function (PDF) expression, which leads to simple closed-form solutions in many problems. The scalar Gaussian distribution for a random variable w is given as follows:

$$f_w(w) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(w-\mu)^2}{2\sigma^2}\right) \qquad (4)$$

where μ and σ^2 are the mean and variance, respectively.

3.2. Gaussian Mixture Noise

In communication channels, the observation noise exhibits non-Gaussian property due to impulsive noise and/or co-channel interference. In fact, many types of non-Gaussian noise can be modelled as a Gaussian mixture [16, 17]. The scalar Gaussian mixture distribution is given as follows:

$$f_w(w) = \sum_{l=1}^{N_m} \frac{\lambda_l}{\sqrt{2\pi\sigma_l^2}} \exp\left(-\frac{(w-\mu_l)^2}{2\sigma_l^2}\right) \tag{5}$$

where λ_l denotes the probability that w is chosen from the lth model in the mixture PDF, with $\sum_{l=1}^{N_m} \lambda_l = 1$, N_m is the number of models, μ_l and σ_l^2 are the mean and variance in the lth model, respectively. This model will also be used to approximate α-stable distribution in the Appendix.

3.3. α-stable Noise

Theoretical justification for using stable distribution as a statistical modeling tool comes from the generalized central limit theorem in stable case [18–20]. It states that if the sum of i.i.d. random variables with or without finite variance converges to a distribution by increasing the number of variables, the limit distribution must belong to the family of stable laws. The main difference between the stable and Gaussian distributions is that the tails of the stable density are heavier than those of the Gaussian density. This characteristic of the stable distribution is one of the main reasons why it is suitable for modeling impulsive noise. In addition, the stable distribution is very flexible because it has a parameter α ($0 < \alpha \leq 2$), called the characteristic exponent, that controls the heaviness of its tails. As the value of α becomes smaller, the impulsiveness becomes more severe. Specially, when $\alpha = 2$, the stable distribution is the Gaussian distribution. In general, there is no closed-form expression for the PDF of stable distributions. The most convenient way to define them is to use the characteristic function

$$\varphi(t) = \exp\left\{jat - \gamma|t|^\alpha \left[1 + j\beta \text{sign}(t)\omega(t,\alpha)\right]\right\} \tag{6}$$

where

$$\omega(t,\alpha) = \begin{cases} \tan\alpha\pi/2, & \text{if } \alpha \neq 1 \\ 1/\alpha \log|t|, & \text{if } \alpha = 1 \end{cases}$$

$$\text{sign}(t) = \begin{cases} 1, & \text{if } t > 0 \\ 0, & \text{if } t = 0 \\ -1, & \text{if } t < 0 \end{cases}$$

The meanings of α, γ, β and a are:

- α $(0 < \alpha \leq 2)$ is the characteristic exponent. It is the most important parameter as it determines the shape of the distribution. It controls the heaviness of the tails of the density function. A small value of α indicates severe impulsiveness.
- γ $(\gamma > 0)$ is the dispersion parameter. It determines the spread of the density. It acts in a similar way to the variance of the Gaussian density, and it is, in fact, equal to half of the variance for the Gaussian case.
- β $(-1 \leq \beta \leq 1)$ is the symmetry parameter, and $\beta = 0$ corresponds to symmetric α-stable (SαS) distribution, that is symmetric about a.
- a $(-\infty < a < \infty)$ is the location parameter. It is the mean when $1 < \alpha \leq 2$ and the median when $0 < \alpha < 1$ for SαS distributions.

The algorithm development in this paper is based on PF. Therefore, in the next section, the details of PF are introduced.

4. PARTICLE FILTER

PF has been successfully applied in many nonlinear and/or non-Gaussian problems. It is a sequential Monte Carlo approach using particles and associated weights to approximate the posterior distribution of interest [6, 21–24]. In PF, two essential steps recursively proceed: prediction according to properly designed importance function, and update using latest measurements to evaluate particles' weights. The steps of PF are summarized in Table 1 and more information on the PF mechanism can be found in [21, 22].

We clearly see that one makes an assumption about the prior knowledge of measurement noise distributions in developing PF. However, there is a risk of degraded performance if the assumed distribution is mismatched with the real case. For those situations, robust approach without prior noise information is proposed in [8, 9], called CRPF. The main idea of CRPF is to use a cost function to evaluate particle quality without measurement noise distribution information to track the target. In this paper, we utilize the CRPF to perform tracking. To cope with different measurement noises, L_p-norm is adopted to compute the particle cost. The steps on CRPF are summarized in Table 2 and the interested reader is referred to [8, 9] for comprehensive readings on CRPF.

The above algorithm does not consider NLOS propagation case. To track the target in that case, in the following section, we develop a

Table 1. Particle filtering algorithm.

(i) **Initialization**:
For $i = 1, \ldots, N$, sample the state particle $\mathbf{x}_0^i \sim p(\mathbf{x}_0)$
(ii) **Prediction of particles**:
For $i = 1, \ldots, N$, draw particles
$\mathbf{x}_t^{(i)} \sim q\left(\mathbf{x}_t \vert \mathbf{x}_{t-1}^{(i)}, \mathbf{z}_{1:t}\right)$
where $q(\cdot)$ is an importance function,
$\mathbf{z}_{1:t} = \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_t\}$ denotes all the observations up to the current time t and $\mathbf{z}_t = [z_{t,1}, \ldots, z_{t,M}]^T$.
(iii) **Update**:
For $i = 1, \ldots, N$, evaluate the importance weight:
$w_t^{(i)} \propto w_{t-1}^{(i)} \times \frac{p\left(\mathbf{z}_t \vert \mathbf{x}_t^{(i)}\right) p\left(\mathbf{x}_t^{(i)} \vert \mathbf{x}_{t-1}^{(i)}\right)}{q\left(\mathbf{x}_t \vert \mathbf{x}_{t-1}^{(i)}, \mathbf{z}_{1:t}\right)}$
For $i = 1, \ldots, N$, normalize the importance weight:
$\tilde{w}_t^i = w_t^i / \sum_{j=1}^N w_t^j$
(iv) **Resampling step**: (if necessary)
Eliminate samples with low importance weights and multiply samples with high importance weights.
For $i = 1, \ldots, N$, set $w_t^i = 1/N$.
(v) **Estimation step**:
The minimum mean square error estimate of state is obtained as:
$\hat{\mathbf{x}}_t \approx \sum_{i=1}^N w_t^{(i)} \mathbf{x}_t^{(i)}$

LOS identification algorithm with the use of L_p-norm under different noise distributions.

5. LINE-OF-SIGHT IDENTIFICATION

NLOS error is one of the major sources that deteriorates tracking performance. In our study, we perform LOS identification prior to target tracking. Our LOS identification idea is to calculate the quality of each measurement, which can be seen as a probability of measurement whether it is under LOS propagation or not. Then, we

Table 2. Cost-reference particle filtering algorithm.

(i) **Initialization**:
For $i = 1, \ldots, N$, sample the state particle $\mathbf{x}_0^i \sim p(\mathbf{x}_0)$, and set costs $s_0^i = 0$
(ii) **Prediction of particles**:
For $i = 1, \ldots, N$, draw particles
$\mathbf{x}_t^{(i)} \sim q\left(\mathbf{x}_t | \mathbf{x}_{t-1}^{(i)}, \mathbf{z}_{1:t}\right)$
where $q(\cdot)$ is an importance function,
$\mathbf{z}_{1:t} = \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_t\}$ denotes all the observations up to the current time t and $\mathbf{z}_t = [z_{t,1}, \ldots, z_{t,M}]^T$.
(iii) **Cost calculation**:
For $i = 1, \ldots, N$, evaluate the cost:
$s_t^i = \tau s_{t-1}^i + \Delta s_t^i$
where $\Delta s_t^i = \left\|\mathbf{z}_t - \hat{\mathbf{z}}_t^i\right\|_p$, $\hat{\mathbf{z}}_t^i = g\left(\mathbf{x}_t^i\right)$, $\|\cdot\|$ is L_p-norm.
Then, calculate the corresponding weight by $w_t^i = 1/s_t^i$
(iv) **Resampling step**: (if necessary)
(v) **Estimation step**:
The minimum mean square error estimate of state is obtained as:

$$\hat{\mathbf{x}}_t \approx \sum_{i=1}^{N} w_t^{(i)} \mathbf{x}_t^{(i)}$$

select three most qualified measurements to perform tracking using CRPFs because the risk of deciding a NLOS measurement as a LOS measurement will be minimized in an intuitive sense while unique positioning is guaranteed in the 2D scenario. Of course, a threshold can be set to select the LOS measurements, but it is difficult to determine and the tracking performance is sensitive to the threshold. First we assume that the measurement noise $\mathbf{w}_t$ is distributed as $\mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I})$, where $\mathbf{I}$ is the identity matrix and σ^2 is known. It serves as a starting point for the algorithm development. As mentioned earlier, the NLOS-induced error is a large positive random variable, which means that the signal residue of the NLOS measurement is larger than that of LOS measurement. As a result, we calculate the quality of each measurement as follows

$$\varphi_{t+1,j} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(z_{t+1,j} - d_{t+1,j})^2}{2\sigma^2}\right), \ j = 1, 2, \ldots, M \tag{7}$$

The larger value means the higher chance of the measurement is under LOS propagation. One problem is that the true distance $d_{t+1,j}$ is not available at time $(t + 1)$. Fortunately, based on CRPF, the prediction of distance is achieved using $\overline{x}_{t+1} = 1/N \sum_{i=1}^{N} x_{t+1}^i$ and $\overline{y}_{t+1} = 1/N \sum_{i=1}^{N} y_{t+1}^i$, where $(x_{t+1}^i, \ y_{t+1}^i)$ is prediction of position in the CRPF. The prediction of distance is calculated as $\overline{d}_{t+1,j} = \sqrt{(\overline{x}_{t+1} - x_j)^2 + (\overline{y}_{t+1} - y_j)^2}$. In practice, instead of (7), we employ:

$$\varphi_{t+1,j} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(z_{t+1,j} - \overline{d}_{t+1,j})^2}{2\sigma^2}\right), \ j = 1, 2, \ldots, M \tag{8}$$

The above calculation needs the value of the noise variance, which may be unknown. Moreover, the assumption of Gaussian distributed noise may not be valid as well [16, 23]. In fact, the exact value of probability is not necessary to select LOS measurements. That is, we essentially only need a measure under a certain criterion to indicate the measurement quality. Based on this idea, we propose to use L_p-norm to calculate the quality of each measurement without knowledge of noise distribution and NLOS-induced error. In mathematical expression, the calculation of signal residue $c_{t+1,j}$ and measurement quality $\varphi_{t+1,j}$ is given as follows

$$\begin{aligned} c_{t+1,j} &= \|z_{t+1,j} - \overline{d}_{t+1,j}\|_p \\ \varphi_{t+1,j} &= 1/c_{t+1,j}, \ j = 1, 2, \ldots, M \end{aligned} \tag{9}$$

In the same manner, we pick the three most qualified measurements inf the CRPFs.

In summary, the pseudo-code of the two major steps for LOS identification with CRPFs are given in Table 3.

Table 3. Particle filters with LOS identification.

(i) **LOS identification**: –Based on (8) when the noise is known and Gaussian distributed or (9) when the noise distribution is not available. (ii) **CRPF**: — Use identified LOS measurements to perform tracking in CRPFs.

6. SIMULATION RESULTS

Computer simulations have been conducted to evaluate the tracking performance of the proposed methods by comparing to posterior Cramer-Rao lower bound (PCRLB) [6] and [3] when the measurement is Gaussian distributed. The main purpose here is to test the proposed method under different measurement noise scenarios. In the α-stable noise case, the PCRLB is calculated by using the estimated Gaussian mixture model (GMM) parameters in the Appendix. CRPF schemes with transition prior, EKF and UKF as importance functions are denoted by CRPF, CRPF-EKF and CRPF-UKF, respectively. The mean square error (MSE) is chosen as the performance measure. Unless stated otherwise, we assume that there are $M = 10$ sensors randomly deployed on a 2D WSN of dimension $500 \times 500\,\mathrm{m}^2$, and the initial state vector of the target is $[50\,\mathrm{m},\ 40\,\mathrm{m},\ 7\,\mathrm{m/s},\ 6\,\mathrm{m/s}]^T$. The sampling time is $T_s = 1\,\mathrm{s}$. The number of particles is $N = 100$. The $\tau = 0$ is used in the CRPFs. The NLOS-induced error $\eta_{t,j}$ is generated by exponential distribution with mean $100\,\mathrm{m}$. The PF is randomly initialized around the true values. All results provided are averages of 2000 independent runs. The results of three noise distributions are illustrated separately as follows.

6.1. Gaussian Noise

In the first test, the validity of proposed approach is investigated. The measurement noise is Gaussian distributed with variance $\sigma^2 = 1$. The value of $p = 2$ is used when no knowledge of noise distribution is available. Three sensors out of 10 sensors are under LOS condition while other seven sensors are under NLOS propagation with probability $q_{t,j} = 0.5$. In doing so, at least three sensors being under LOS propagation is guaranteed. In Figure 1, the MSEs of the CRPFs are plotted. The LOS identification carried out by (8) is denoted by CRPFs (Congzhuang), which means that the noise variance information is used as in [3]. The LOS identification calculated by (9) is denoted by CRPFs (unknown), which means that the noise variance is not utilized. It is seen that the performance of the proposed methods using (9) is similar to that of the ones using (8), which proves the effectiveness of the proposed approach. The performance of the CRPF-UKF and CRPF-EKF is superior to that of the CRPF. Notice that we also plot the performance of the proposed method with $M = 20$. From Figure 1, we can see that the performance of the proposed method does provide the same level of performance for two densities of sensors in the network. However, the performance in general will be improved as the sensor network becomes denser since the mean distance between the target and sensor is smaller. Due to the limited measurements, the performance of CRPFs cannot approach PCRLB.

In the second test, we test the performance of proposed method under different NLOS probability $q_{t,j}$. We assume that all measurements are under NLOS propagation with certain probability while other settings remain as in the first test. In this test, three most qualified measurements are selected without noise distribution information and CRPF-UKF is examined. In Figure 2, the MSEs of CRPFs are plotted for different $q_{t,j}$. For sufficiently small probability $q_{t,j}$, it is very likely that there are three LOS measurements. As the probability $q_{t,j}$ increases indicating the more severe NLOS propagation, the performance becomes more degraded.

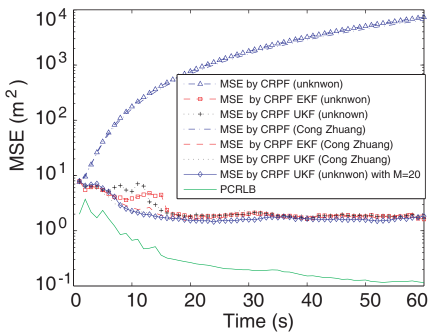

Figure 1. Mean square error under Gaussian noise.

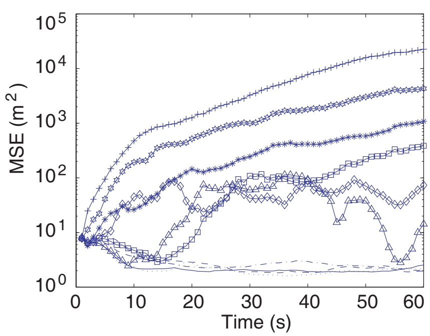

Figure 2. Mean square error versus different values of $q_{t,j}$ for CRPF-UKF. — for $q_{t,j} = 0.05$. - · - for $q_{t,j} = 0.1$. −− for $q_{t,j} = 0.15$. $\cdots$ for $q_{t,j} = 0.2$. $\triangle$ for $q_{t,j} = 0.25$. $\Box$ for $q_{t,j} = 0.3$. $\Diamond$ for $q_{t,j} = 0.35$. $\star$ for $q_{t,j} = 0.4$. $\bigtriangledown$ for $q_{t,j} = 0.45$. $+$ for $q_{t,j} = 0.5$.

6.2. Gaussian Mixture Noise

In this test, the proposed method under the Gaussian mixture measurement noise is investigated. The other settings remain as in the first test. Specifically, two Gaussian components are used: $w_{t,j} \sim 0.5\mathcal{N}(0,1) + 0.5\mathcal{N}(0,0.01)$. Since the finite moment still exists, $p = 2$ is used in this case. The MSEs are plotted in Figure 3. It is observed that the proposed approach works well under the GMM noise case. Since the UKF approximates the posterior distribution better than the EKF, it is observed that the performance of the CRPF-UKF is superior to that of the CRPF-EKF.

6.3. α-stable Noise

In this test, the α-stable process is assigned as the measurement noise. The $\alpha = 1.5$, $\sigma = 1$, $\beta = 0$, $\mu = 0$ are used to generate α-stable process.

First, the algorithm in Appendix is utilized to approximate the α-stable process with 1000 samples. The value of N_m starts at 20 in GMM. The parameters in GMM are calculated finally as $\{(\hat{\mu}_1 = 0.5168,\ \hat{\sigma}_1^2 = 18.3144,\ \hat{\lambda}_1 = 0.1603),\ (\hat{\mu}_2 = -0.7159,\ \hat{\sigma}_2^2 = 1.3685,\ \hat{\lambda}_2 = 0.3590),\ (\hat{\mu}_3 = 0.5530,\ \hat{\sigma}_3^2 = 1.5978,\ \hat{\lambda}_3 = 0.1697),\ (\hat{\mu}_4 = -1.7912,\ \hat{\sigma}_4^2 = 802.7704,\ \hat{\lambda}_4 = 0.011)\}$.

Second, in Figure 4, the MSEs of the CRPFs are plotted under the α-stable noise. The $p = 1$ is used in L_p-norm. The CRPF-UKF gives the best performance. The PCRLB is calculated by the parameters computed according to the approximated GMM.

Third, the effect of the different values of p in L_p-norm is examined in Figure 5. The value of p must be less than the value of α in the case

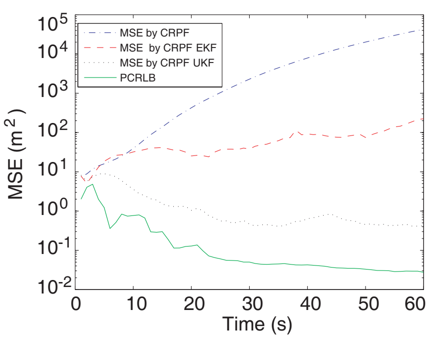

Figure 3. Mean square error under Gaussian mixture noise.

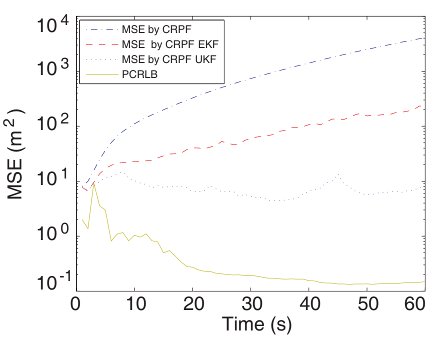

Figure 4. Mean square error under α-stable noise.

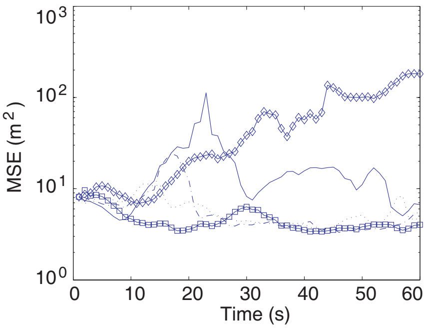

Figure 5. Mean square error under different values of p for CRPF-UKF. — for 2-norm. - · - for 1.5-norm. $\cdots$ for 1-norm. □ for 0.5-norm. ◊ for ∞-norm.

of stable process to assure the existence of the fractional moments of order p. This is verified by the results in Figure 5. It is seen that the performance is more degraded when $p \geq \alpha$ compared with that when $p < \alpha$. All the lower order moments give similar performance since they are equivalent for a stable process.

7. CONCLUSION

Target tracking with the use of cost-reference particle filter is proposed to handle non-line-of-sight (NLOS)-induced error under different measurement noise distributions. According to the L_p-norm criterion, the quality of each measurement being line-of-sight (LOS) propagation is calculated. Then, the most qualified LOS measurements are selected to be utilized in tracking. Computer simulation results demonstrate the validity of the proposed methods.

APPENDIX A.

Since the α-stable distributions do not share closed-form expressions of PDFs, it will be very convenient if we can model them with a closed-form distribution much like Gaussian thanks to its analytical characteristic. Mixture models are able to represent arbitrarily complex PDFs, specially, GMM is the most commonly used so far. Therefore, GMM is a natural option. The standard method used to fit finite mixture models to the observed data is the expectation-maximization (EM) algorithm [19], which is a maximum-likelihood estimator to estimate the parameters of GMM iteratively. However, it is sensitive to initialization and needs to know the number of components in mixture models *a priori*, which usually is hard to obtain in practice. Due to the above mentioned drawbacks of the EM algorithm, a clustering algorithm proposed in [26] is adapted to approximate the α-stable distribution using GMM in this paper. Consider a α-stable distribution is approximated by GMM as follows:

$$p_\alpha(y) \approx p(y|\boldsymbol{\theta}) = \sum_{l=1}^{N_m} \lambda_l p\left(y|\mu_l, \sigma_l^2\right) \tag{A1}$$

where $p_\alpha(\cdot)$, $p(\cdot)$ represent the α-stable distribution and Gaussian distribution, respectively, $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_{N_m}, \lambda_1, \ldots, \lambda_{N_m}\}$ is the set of the Gaussian distribution parameters to be estimated to approximate the α-stable distribution, where $\boldsymbol{\theta}_l = \{\mu_l, \sigma_l^2\}$. According to the minimum message length criterion, the optimization problem to estimate the parameters is given as follows [26]:

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \mathcal{Y}) \tag{A2}$$

with

$$\mathcal{L}(\boldsymbol{\theta}, \mathcal{Y}) = \frac{N_d}{2} \sum_{l,\lambda_l>0} \log\left(\frac{n\lambda_l}{12}\right) + \frac{k_n}{2} \log \frac{n}{12} + \frac{k_n(N_d+1)}{2} - \log p(\mathcal{Y}|\boldsymbol{\theta}) \tag{A3}$$

where $\mathcal{Y} = \{y_1, \ldots, y_n\}$, $k_n \in \{1, 2, \ldots, N_m\}$, N_d is the dimensionality of $\boldsymbol{\theta}_l$. For this cost function, the EM algorithm has following E-step and M-step:

• **E-Step**: Compute the conditional expectation of the complete log-likelihood, given $\mathcal{Y}$ and the current estimate $\hat{\boldsymbol{\theta}}(k)$ with missing data $\mathcal{Z} = \{\mathbf{z}^1, \ldots, \mathbf{z}^n\}$ indicating which component produces each sample and each component is a binary vector $\mathbf{z}^q = [z_1^q, \ldots, z_{N_m}^q]$. The conditional expectation of element of $\mathcal{Z}$ is given by:

$$w_l^q = E\left[z_l^q|\mathcal{Y}, \hat{\boldsymbol{\theta}}(k)\right] = \frac{\hat{\lambda}_l(k) p\left(y_q|\hat{\boldsymbol{\theta}}_l(k)\right)}{\sum_{m=1}^{N_m} \hat{\lambda}_m(k) p\left(y_q|\hat{\boldsymbol{\theta}}_m(k)\right)} \tag{A4}$$

• **M-Step**: Update the parameter estimates according to:

$$\hat{\lambda}_l(k+1) = \frac{\max\left\{0, \left(\sum_{q=1}^n w_l^q\right) - \frac{N_d}{2}\right\}}{\sum_{m=1}^{N_m} \max\left\{0, \left(\sum_{q=1}^n w_m^q\right) - \frac{N_d}{2}\right\}} \quad l = 1, 2, \ldots, N_m \tag{A5}$$

$$\hat{\mu}_l(k+1) = \left(\sum_{q=1}^n w_l^q\right)^{-1} \sum_{q=1}^n y_q w_l^q \tag{A6}$$

$$\hat{\sigma}_l^2(k+1) = \left(\sum_{q=1}^{n} w_l^q\right)^{-1} \sum_{q=1}^{n} (y_q - \hat{\mu}_l(k+1))^2 w_l^q \tag{A7}$$

This procedure starts with $k_n = N_m$ and repeats until $k_n = 1$. The algorithm produces a sequence of estimates $\{\hat{\boldsymbol{\theta}}(k),\ k = 0, 1, 2, \ldots\}$ through applying the above two steps until convergence, i.e., when the relative difference in $\mathcal{L}(\hat{\boldsymbol{\theta}}(k), \mathcal{Y})$ is less than a threshold of 10^{-6}. Finally, the parameters that give the minimum value of $\mathcal{L}(\boldsymbol{\theta}, \mathcal{Y})$ will be the estimates.

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