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# Bearings-only multi-target tracking using an improved labeled multi-Bernoulli filter

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ABSTRACT

Most classical bearing-only target tracking algorithms model the measurement likelihood by one Gaussian distribution. The effectiveness of one Gaussian distribution model relies heavily on the accuracy of the predicted target position. However, due to the high nonlinearity of the bearing-only measurement, the predicted target position is mostly inaccurate before the target state observability is established. As a consequence, some classical nonlinear filters become not applicable for tracking bearing-only targets, especially when the measurements of multiple targets and clutter are present. The published bearings-only multiple-target tracking algorithms suffer from either the estimation inaccuracy or lack of track trajectories. Motivated by the problems mentioned above, we propose an improved labeled multi-Bernoulli filter for the goal of reducing estimation error under the premise that track trajectories are guaranteed. The proposed method divides the bearing measurement uncertainty into several measurement components that the measurement likelihood can be approximated by a Gaussian mixture. By assigning each track a unique label, the previous scan estimations and current scan measurements are associated and the track trajectories become available. Simulation results show that the proposed method considerably reduces estimation error. Further, various scenario parameters are investigated to validate the effectiveness of the proposed method.



## 1. Introduction

The problem of bearing-only tracking (BOT) [1] can be referred to as target motion analysis (TMA) [2] and has been widely studied for decades. This problem is crucial for a variety of surveillance systems such as mobile platforms equipped with passive sonar that detects the radiated signals from moving objects or aircrafts using an electronic warfare device [3,4]. The bearing-only tracking problem is essential due to two features: measurement nonlinearity and lack of system observability [5]. The extended Kalman filter (EKF) [6] has been generally applied for target tracking with nonlinear measurements. The EKF linearizes the measurement nonlinearity around the predicted target position through first-order approximation, which holds when the predicted target position is accurate enough but can introduce large estimation errors or even divergence in the presence of inaccuracy [7]. Instead of linearizing the measurement nonlinearity, the unscented Kalman filter (UKF) [7] utilizes the unscented transform to sample and propagate the probability density function by sigma points, while the particle filter (PF) [8] uses a large number of weighted random (Monte Carlo) samples. When only the bearing information is provided, the distance between a passive observer and a target is not available, which leads to the system state observability problem for the BOT problem. Due to the unknown distance, the target of interest cannot be distinguished from the other targets of that direction (bearing). Thus, the observer must ‘outmaneuver’ the target to satisfy the observability condition to recognize the target of interest, i.e., the observer motion model must be at least one derivative higher than that of the target [9].

For practical applications, a filter structure such as the EKF, the UKF and the PF cannot be directly applied for tracking bearing-only targets in cluttered environments. One has to resort to the data association algorithms to account for the measurement origin uncertainty due to the presence of multiple targets and clutter measurements. In addition, due to the limited prior information of the surveillance region, real target tracking systems usually utilize the received measurements for track initiation. The received measurements can either originate from the true targets or clutter such that both true tracks (initialized by target measurements) and false tracks (initialized by clutter measurements) are generated. The false tracks that follow wrong or not existing targets are subjected to termination. Then, a metric of evaluating track quality

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**Nomenclature**

*A. List of acronyms*

| | |
|---|---|
| BOT | Bearing-only tracking |
| TMA | Target motion analysis |
| EKF | Extended Kalman filter |
| UKF | Unscented Kalman filter |
| PF | Particle filter |
| GMM | Gaussian mixture measurement |
| GMM-ITS | Gaussian mixture measurement integrated track splitting |
| MTT | Multi-target tracking |
| MHT | Multiple hypothesis tracking |
| JIPDA | Joint integrated probabilistic data association |
| GMM-JITS | Gaussian mixture measurement joint integrated track splitting |
| HPRF | High pulse repetition frequency |
| RFS | Random finite set |
| CBMeMBer | Cardinality balanced multi-target multi-Bernoulli |
| $\delta$-GLMB | $\delta$-generalized labeled multi-Bernoulli |
| LMB | Labeled multi-Bernoulli |
| SLAM | Simultaneous localization and mapping |
| LMB-GMM | Labeled multi-Bernoulli with Gaussian mixture measurements |
| SMC | Sequential Monte Carlo |
| SIR | Sequential importance resampling |
| RPF | Regularized particle filter |
| OSPA | Optimal sub-pattern assignment |
| LMB-EKF | Labeled multi-Bernoulli with extended Kalman filter |
| LMB-UKF | Labeled multi-Bernoulli with unscented Kalman filter |
| LMB-SMC | Labeled multi-Bernoulli with sequential Monte Carlo implementation |

*B. List of symbols*

| | |
|---|---|
| $x_k$ | Single-target state at scan $k$ |
| $X_k$ | Multi-target state at scan $k$ |
| $Z_k$ | Multi-target observation at scan $k$ |
| $Z^k$ | Sequence of measurement sets up to scan $k$ |
| $\mathbb{X}$ | Target state space |
| $\mathbb{Z}$ | Measurement space |
| $\mathbb{L}$ | Label space |
| $\pi_k(X_k\|Z^k)$ | Multi-target state density $X_k$ given measurement sequence $Z^k$ |
| $r$ | Target existence probability |
| $\ell$ | Track label |
| $p(x, \ell)$ | Probability density function of track with label $\ell$ |
| $\boldsymbol{x}$ | Labeled single-target state |
| $\boldsymbol{X}$ | Labeled multi-target state |
| $\Delta(\boldsymbol{X})$ | Distinct label indication to ensure labels in $\boldsymbol{X}$ are distinct |
| $\mathcal{L}(\boldsymbol{X})$ | The set of labels of $\boldsymbol{X}$ |
| $\omega(L)$ | Weight of the hypothesis that $L$ is the set of track labels |
| $\sigma_\phi$ | Sensor noise standard deviation |
| $A_k$ | The number of Gaussian measurement components generated by one bearing measurement |
| $a$ | Gaussian measurement component index |
| $\bar{L}_{k,a}$ | The mean range of interval $a$ |
| $\Delta L_{k,a}$ | The length of range interval $a$ |
| $y_k^a$ | Mean of Gaussian measurement component $a$'s probability density function at scan $k$ |
| $R_k^a$ | Covariance of Gaussian measurement component $a$'s probability density function at scan $k$ |
| $\gamma_k^a$ | Weight of Gaussian measurement component $a$ at scan $k$ |
| $z_{k,i}$ | The $i$th measurement in $Z_k$ |
| $p_{x,k}^{(s)}$ | Sensor position in $x$ axis |
| $T_{k,i}$ | Rotation matrix of measurement $z_{k,i}$ |
| $\lambda_k$ | Coordinate transformation factor at scan $k$ |
| $c$ | Track component index |
| $C_k$ | The number of track components at scan $k$ |
| $\xi_k(c)$ | Track component probability |
| $p(x, \ell\|c, Z)$ | Probability density function of track component $c$ in track $\ell$ |
| $x_c$ | Mean of track component $c$'s probability density function |
| $P_c$ | Covariance of track component $c$'s probability density function |
| $\boldsymbol{X}_+$ | Predicted LMB RFS |
| $\boldsymbol{W}$ | The survival LMB RFS |
| $\omega_{+,S}(L)$ | Weight of the hypothesis that $L$ is the label set of survival tracks |
| $r_{+,S}^{(\ell)}$ | Predicted target existence probability of survival track with label $\ell$ |
| $p_{+,S}^{(\ell)}$ | Predicted probability density function of survival track with label $\ell$ |
| $p_S(x, \ell)$ | State-dependent target survival probability |
| $\bar{x}$ | Predicted single-target state |
| $\boldsymbol{Y}$ | The newborn LMB RFS |
| $\omega_B(L)$ | Weight of the hypothesis that $L$ is the label set of newborn tracks |
| $r_B^{(\ell)}$ | Initial target existence probability of newborn track with label $\ell$ |
| $p_B^{(\ell)}$ | Initial probability density function of newborn track with label $\ell$ |
| $\boldsymbol{X}_+^{(i)}$ | The $i$th group of the predicted LMB RFS |
| $\theta$ | Measurements-to-tracks association |
| $\theta(\ell)$ | The measurement index associated to track $\ell$ under $\theta$ |
| $\mathcal{F}(L)$ | The collection of finite subsets of $L$ |
| $\Theta$ | The space of measurements-to-tracks association |
| $\omega^{(I_+,\theta)}$ | Updated weight of the hypothesis that the predicted track labels in set $I_+$ are associated with measurements under $\theta$ |
| $g(z_{k,i}\|x, \ell)$ | The measurement likelihood of measurement $z_{k,i}$ with respect to track $\ell$ |
| $p_D(x, \ell)$ | State-dependent target detection probability |
| $p_G$ | Gating probability that the true measurement falls in the gate |
| $\kappa(z_{k,i})$ | Poisson clutter intensity at measurement $z_{k,i}$ |
| $p^{(\theta)}(x, \ell\|Z^{k+1})$ | Updated single-target probability density function of track $\ell$ under $\theta$ |
| $p^{(\theta)}(x, \ell\|c, a, Z^{k+1})$ | Probability density function of the new track component generated by measure- |