Digital Signal Processing 27 (2014) 1–11

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Multi-target tracking with PHD filter using Doppler-only measurements

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ARTICLE INFO

Article history:
Available online 30 January 2014

Keywords:
Random sets
Multi-target tracking
Probability hypothesis density filter
Doppler measurements
Gaussian mixture
Sequential Monte Carlo

ABSTRACT

In this paper, we address the problem of multi-target detection and tracking over a network of separately located Doppler-shift measuring sensors. For this challenging problem, we propose to use the probability hypothesis density (PHD) filter and present two implementations of the PHD filter, namely the sequential Monte Carlo PHD (SMC-PHD) and the Gaussian mixture PHD (GM-PHD) filters. Performances of both filters are carefully studied and compared for the considered challenging tracking problem. Simulation results show that both PHD filter implementations successfully track multiple targets using only Doppler shift measurements. Moreover, as a proof-of-concept, an experimental setup consisting of a network of microphones and a loudspeaker was prepared. Experimental study results reveal that it is possible to track multiple ground targets using acoustic Doppler shift measurements in a passive multi-static scenario. We observed that the GM-PHD is more effective, efficient and easy to implement than the SMC-PHD filter.

1. Introduction

Multi-static radar/sonar systems making use of cooperative/non-cooperative transmitters have attracted interest of researchers working in different fields [1]. Modern multi-static systems consist of multiple transmitter and receiver sites each collecting several independent target measurements, such as the time-of-arrival, direction-of-arrival and Doppler shift of the reflected signals. At the fusion center, these measurements are then combined to estimate the target state. For target surveillance, multi-static passive radar systems exploit illuminators of opportunity like FM radio transmitters, digital audio/video broadcasters, WiMAX systems and global system for mobile-communication (GSM) base stations [2–5]. Passive radar systems provide crucial advantages over active systems: no frequency allocation problem, receivers are hidden for a possible jamming, energy saving and much lower costs. Especially, GSM-based passive radar systems have attracted tremendous research interest and they are considered to be used practically for surveillance [5–7]. These systems have several distinct advantages. Firstly, GSM base stations provide global coverage. Secondly, multiple base stations can be utilized in a multi-static passive radar network to improve the overall performance and robustness. Although the GSM waveform has poor range resolution, it can achieve good Doppler resolution, which makes the GSM-based passive radar suitable for Doppler detection and tracking.

Localization and tracking of a moving target using only Doppler shift measurements is actually an old problem studied in different contexts [8–10]. However, analysis of multi-static passive systems that use Doppler-only measurement has not been fully investigated yet. Some of the studies in the literature mainly concentrate on the static estimation solutions, observability analysis of the target using Doppler-only measurements and optimal positioning of the passive system [11–15]. Moreover, recently, tracking of moving targets using a Doppler-shift measuring sensor network has gained interest from researchers and mostly considered in multi-static passive radar framework [16–19]. Two main reasons behind this interest is: firstly passive radar systems provide crucial advantages over active systems, secondly Doppler measuring sensors are inexpensive and no hardware array is required unlike the direction-of-arrival measuring arrays. However, tracking using Doppler-only measurements is not an easy problem due to several reasons: (1) since Doppler-only measurements are uninformative, target state remains unobservable before collecting at least three Doppler measurements from sensors with different locations,

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1051-2004/$ – see front matter
http://dx.doi.org/10.1016/j.dsp.2014.01.009

(2) since Doppler measurements are typically accurate and initially target state is unobservable, initial measurement updates are weighted significantly and, thus, low-complexity nonlinear filters diverge and also special care should be given to avoid sample impoverishment when using particle implementations, (3) mentioned two problems get worse if the prior distribution covers the whole surveillance volume (i.e. too big covariance values for location and velocity), which is the case in most of the practical applications, in the state space [20–22].

In this work, we propose to use the probability hypothesis density (PHD) filter, which is based on the random finite sets (RFS) framework [23,24]. The PHD filter, propagates the first-order statistical moment of the RFS of states in time and avoids the combinatorial data association problem. There are two implementations of the PHD filter; one is using sequential Monte Carlo (SMC) method other one is using Gaussian mixtures (GM). Each implementation method has its own pros and cons [23]. GM implementation is very popular because it provides a closed form analytic solution to PHD recursions under linear Gaussian target dynamics and measurement models. Moreover, contrary to SMC implementation, GM implementation provides reliable state estimates extracted from the posterior intensity in an easier and efficient way [25]. Alternatively, SMC implementation imposes no such restrictions and has the ability of handling nonlinear target dynamics and measurement models. It can be said that SMC implementation is a more general framework for PHD recursions. On the other hand, its performance is affected by different kind of problems in reality [26–28]. Therefore, in general, GM based approach is easier, effective and more intuitive.

The novelty of this work is twofold: first we present the performances of both the SMC-PHD and GM-PHD filters in tracking multiple non-cooperative targets using a passive Doppler-shift measuring sensor network. Clutter, missed detections and multi-static Doppler variances are incorporated into a realistic multi-target scenario. Second, additional to the simulation analysis, we provide a proof-of-concept study to show the feasibility of tracking multiple targets using a passive acoustic microphone network which provides Doppler shift measurements. For this purpose, an experimental setup consisting of three microphones and a loudspeaker (LS) was configured. Non-cooperative transmissions from the LS (i.e. illuminator of opportunity) are exploited by non-directional separately located microphones (i.e. Doppler measuring sensors). The LS is directed towards the road and continuously transmits pure sinusoids at a known certain frequency. Reflections from moving vehicles on the road are received by each microphone and microphone outputs are connected to a main storage unit through cables to be processed. Doppler shift measurements from each microphone are fed to the tracker.

The organization of the paper is as follows. Mathematical formulation of the problem and the measurement model are presented in Section 2. Section 3 presents RFS formulation of multi-target tracking and the PHD filter. Section 4 and 5 provide SMC-PHD and GM-PHD formulations, respectively. Simulation results are presented in Section 6. Details of the acoustic field trials and results are given in Section 7. Lastly, conclusion is given in Section 8.

2. Sensor and target model

The scenario in this work is as follows: An illuminator of opportunity (TX), constantly transmits signal with a known carrier frequency, f_c, as in Fig. 1. The transmitted signal is reflected from moving targets in the analyzed area. These reflections are received by each Doppler-shift measuring sensors. It is assumed that location of the transmitter and the sensors are known to the fusion center and each sensor sends its measurement to the fusion center. The state vector of a target, takes a value in the state space

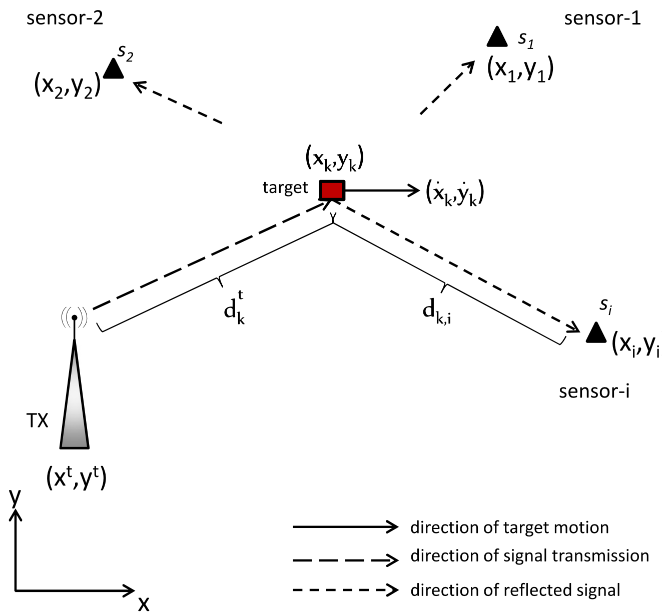

Fig. 1. Multi-static geometry. Transmitted signal from an illuminator of opportunity TX is reflected from a detected moving target and received by the each Doppler-shift measuring sensors (black triangles). s_i: $i = 1, \dots, N_s$.

$\mathcal{X} \subseteq \mathbb{R}^{n_\mathbf{x}}$, at time k is

$$\mathbf{x}_k = [x_k, y_k, \dot{x}_k, \dot{y}_k]^T, \tag{1}$$

where $[x_k, y_k]$ is the position, $[\dot{x}_k, \dot{y}_k]$ is the velocity of the target and T denotes transpose operation. The target dynamic is modeled by linear Gaussian constant velocity model [29]:

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{v}_k, \tag{2}$$

where $\mathbf{F}$ is the state transition matrix given as,

$$\mathbf{F} = \begin{bmatrix} \mathbf{I}_2 & \Delta\mathbf{I}_2 \\ \mathbf{0}_2 & \mathbf{I}_2 \end{bmatrix}, \tag{3}$$

$\mathbf{v}_k \sim \mathcal{N}(\mathbf{v}; \mathbf{0}, \mathbf{Q})$ is the white Gaussian process noise, $\mathbf{Q}$ is the process noise covariance given as,

$$\mathbf{Q} = \sigma_\mathbf{v}^2 \begin{bmatrix} \frac{\Delta^3}{3}\mathbf{I}_2 & \frac{\Delta^2}{2}\mathbf{I}_2 \\ \frac{\Delta^2}{2}\mathbf{I}_2 & \Delta\mathbf{I}_2 \end{bmatrix}, \tag{4}$$

Δ is the sampling interval, k is the discrete time index, $\sigma_\mathbf{v}$ is the standard deviation of the process noise, $\mathbf{I}_n$ and $\mathbf{0}_n$ denote $n \times n$ identity and zero matrices, respectively.

Bi-static Doppler shift measurements are collected by each sensor, $i = 1, \dots, N_s$, in the area. Motion components of the target in the directions of the transmitter and the receiver together cause Doppler shift. The measured bi-static Doppler shift, takes a value in the measurement space $\mathcal{Z} \subseteq \mathbb{R}^{n_z}$, by the i-th sensor located at $[\mathrm{x}_i, \mathrm{y}_i]$ is given by

$$z_{k,i} = h_i(\mathbf{x}_k) + \varepsilon_{k,i}, \tag{5}$$

where

$$h_i(\mathbf{x}_k) = -\left[\frac{\dot{d}_k^t}{\lambda} + \frac{\dot{d}_{k,i}}{\lambda}\right], \tag{6}$$

is the Doppler shift, λ is the wavelength of the transmitted signal and $\varepsilon_{k,i}$ is measurement noise in sensor i, $\varepsilon_{k,i} \sim \mathcal{N}(\varepsilon; 0, \sigma_\varepsilon^2)$. Distance between the transmitter and the target, d_k^t, at time k is defined as