Passive Detection and Tracking of Maneuvering Targets with Particle Filter Techniques Using DVBT Broadcasting

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***Abstract*— We present a complete and practical particle filter-based scheme to detect, classify and track multiple maneuvering targets using DVBT-based passive radar. As in the conventional radar signal processing, the proposed technique first detects the target Doppler and bi-static range considering the outputs of long-term correlation matched filters whose level exceeds an adaptive threshold. The detections are then followed by a bank of particle based-filters. Each filter tracks a detected target and estimates its position and velocity from the analysis of short-term correlations.**

I. Introduction

Particle filters show great promise in solving nonlinear and/or non-Gaussian filtering problems, and have recently become popular for object tracking due to their flexibility and ease of implementation. In passive radar systems, Particle Filtering gives interesting performance for detecting and tracking one single target in presence of maneuvers even at low signal-to-noise ratio. However, it is still difficult to exploit the interest of Particle Filtering (PF) in a multi-targets mode by using the correlation outputs directly as observations without a maxima grid-scheme with Doppler and bi-static range extraction. This is due to the resampling step included in the PF, which leads the particles to be redistributed close to the existing targets. This makes the detection of new upcoming targets very difficult.

A proposed solution to solve this problem consists in using the extraction of Doppler shift and bi-static range by considering the outputs of long-term correlations whose level exceeds an adaptive threshold, as in the conventional Radar techniques. These Doppler-range extractions are used to initialize parallel particle filters. Each filter is matched to a detected track.

Once detected and estimated the initial position, velocity and phase, we can initialize each filter by covering with particles a part of state space corresponding to the detected location of the target. To estimate the new state, the filter uses the output of correlators matched to the zero Doppler frequency shift, at chosen instants corresponding to the detected bi-static range. The first role of PF in this case is to reduce the estimation error, but it also brings interesting performance by filtering the false alarms, resulting from the detection scheme. The proposed method is exploited on a passive radar that processes signals coming from non-cooperative DVBT Broadcasting signals transmitters.

II. Particle Filter

A general nonlinear and non-Gaussian system can be represented by:

$$\begin{cases} \mathcal{X}_k = f(\mathcal{X}_{k-1}) + \varepsilon_k \\ \mathcal{Y}_k = h(\mathcal{X}_k) + \eta_k \end{cases} \tag{1}$$

where $\mathcal{X}_k \in \mathbb{R}^{N_x}$ represents the continuous state of the system at the time-step k, ε_k the associated Gaussian process noise with covariance matrix Q_k, f the system dynamic function, $\mathcal{Y}_k \in \mathbb{R}^{N_y}$ the vector of measurement, η_k the associated Gaussian measurement noise with covariance matrix R_k and h the measurement function.

The recursive Bayesian estimation problem is formulated as a time-update and a measurement-update for the posterior probability density function [1]. The PF gives a good approximation of the optimal solution of the Bayesian filtering problem, when the number of particles gets close to infinity [2]. The PF approximates the distribution $p(\mathcal{X}_k \mid \mathcal{Y}_{1:k})$ by a large set of N_s samples $\left\{\mathcal{X}_k^i\right\}_{i=1}^{N_s}$ called particles; each particle representing one possible system state, PF also assigns a weight w_k^i to each particle. The location and weight of each particle reflect the value of the probability density in that region of state space. The posterior distribution is approximated as:

$$p(\mathcal{X}_k \mid \mathcal{Y}_{1:k}) = \sum_{i=1}^{N_s} w_k^i \delta(\mathcal{X} - \mathcal{X}_k^i) \tag{2}$$

The first stage in a particle filter is to take N_s samples from initial distribution, which is assumed to be unknown and supposed therefore uniform. However, asymptotically the approximated pdf converges to the real one. In order to determine the location of the state at time-step k, we generate N_s particles according to the importance density denoted $q(\mathcal{X}_k \mid \mathcal{X}_{1:k-1}^i, \mathcal{Y}_{1:k})$. In case of Sampling Importance Resampling (SIR) filter, we use the transition prior density $p(\mathcal{X}_k \mid \mathcal{X}_{k-1}^i)$ as importance function. The update of the current weights is made according to the weight equation which involves the likelihood, the kinematics model and the importance density. For SIR filter, the weight update equation reduces to:$w_k^i = w_{k-1}^i \times p\left(\mathcal{Y}_k \mid \mathcal{X}_k^i\right)$. The likelihood function is taken as normal distribution centered at the measurement calculated using the current state.

To avoid divergence of the filter, an auxiliary step is necessary; it consists in resampling the particles so that the

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