Tracking Atmospheric Ducts Using Radar Clutter: II. Surface-based Duct Tracking Using Multiple Model Particle Filters

Caglar Yardim*, Peter Gerstoft, and William S. Hodgkiss
University of California, San Diego
La Jolla, CA 92093–0238, USA

Introduction

This paper addresses the problem of high variability in tracking surface-based ducts in marine and coastal environments. The method tracks the evolution of the range and height-dependent index of refraction using the radar sea clutter. A split-step fast Fourier transform (FFT) based parabolic equation (PE) approximation to the wave equation is used to compute the clutter return in complex environments with varying index of refraction. The summary of the problem and evaporation duct tracking has been introduced in [1].

In previous studies, atmospheric refractivity has been inverted using genetic algorithms (GA), Markov chain Monte Carlo (MCMC) samplers and a hybrid GA–MCMC method [2–4]. Tracking surface-based ducts was also analyzed using extended Kalman filters (EKF), unscented Kalman filters (UKF), particle (PF) filters [5]. This paper uses multiple model particle filters (MMPF) in addition to these filters to improve tracking performance in highly fluctuating environments.

Formulation and Filter Comparisons

The same framework used in refractivity from clutter (RFC) tracking [1] has been used here with the difference that the range and height dependent M-profile is calculated using the tri-linear surface-based duct profile instead of the evaporation duct profile. A tri-linear profile requires four parameters: slope and thickness of base (c_1, h_1) and inversion layers (c_2, h_2). Top layer slope is taken constant as 0.118 M-units/m. For range-dependent profiles, the M-profile parameters are defined at n_r range intervals and the values at other ranges are calculated using a cubic fit. Hence, the number of state parameters $n_x = 4n_r$. The 2-D M-profile is calculated using the following procedure:

$$\mathbf{x}_k = \left[\mathbf{m}_1^{\mathrm{T}}\ \mathbf{m}_2^{\mathrm{T}}\ \ldots\ \mathbf{m}_{n_r}^{\mathrm{T}}\right]^{\mathrm{T}} \tag{1}$$

$$\mathbf{m}_i = \left[c_1(r_i)\ c_2(r_i)\ h_1(r_i)\ h_2(r_i)\right]^{\mathrm{T}} \quad i = 1, \ldots, n_r \tag{2}$$

$$M(z,r) = M_0 + \begin{cases} \tilde{c}_1 z & \text{if } z \le \tilde{h}_1 \\ \tilde{c}_1\tilde{h}_1 + \tilde{c}_2(z - \tilde{h}_1) & \text{if } \tilde{h}_1 \le z \le \tilde{h}_2 \\ \tilde{c}_1\tilde{h}_1 + \tilde{c}_2\tilde{h}_2 & \text{if } z \ge \tilde{h}_2 \\ \quad +0.118(z - \tilde{h}_1 - \tilde{h}_2), & \end{cases} \tag{3}$$

where M_0 is the base refractivity usually taken as 330 M-units/m, $\mathbf{m}_i$ represent the trilinear profiles at n_r different ranges defined in the state vector, $\tilde{c}_1$, $\tilde{c}_2$, $\tilde{h}_1$, and $\tilde{h}_2$ are cubic fitted parameters at range r. One problem with the previous

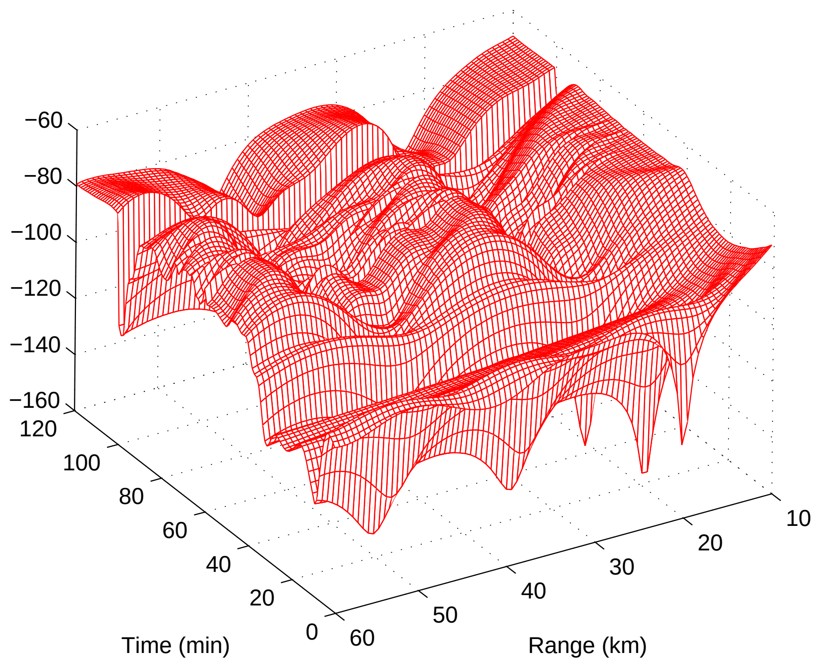

Figure 1: Evolution of the highly nonlinear radar clutter $\mathbf{y}_k$ computed for the true environment without $\mathbf{w}_k$.

tracking algorithms is that, they used a fixed environmental model and as long as the environment behaves as described in that model these algorithms worked fine. However, from previous experiments such as the Variability of Coastal Atmospheric Refractivity (VOCAR) [6], it is known that spatial and temporal duct variability are strong functions of region, season, time of the day and mesoscale atmospheric processes. For example, experiments indicate that Santa Ana-induced SBDs typically have higher spatial variability than the subsidence-induced SBDs. It is also known that duct parameters such as the duct height can stay stable for days, followed by rapid fluctuations [7]. Spatial variability also has similarly challenging and dynamic patterns as shown during Wallops'2000 experiment [8]. To mitigate this problem, [5] proposed increasing the process noise. However, using a high process noise results in highly fluctuating estimates even if the environment is stable. Moreover, due to these high fluctuations Kalman filters showed significant divergence as process noise is increased beyond a limit. Hence, different models may be necessary for different applications or regions. These different models can be incorporated into the particle filter structure using the multiple model particle filter [9].

MMPF used in this paper is based on the Sequential Importance Resampling (SIR) used in our previous PF algorithms. The difference is that MMPF introduces one extra parameter into the state equation.

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, r_{k-1}) + \mathbf{v}_{k-1}(r_{k-1}) \tag{4}$$

$$\mathbf{y}_k = \mathbf{h}\left(\mathbf{x}_k\right) + \mathbf{w}_k \tag{5}$$

where r_k represents an extra parameter appended to the state vector and all others

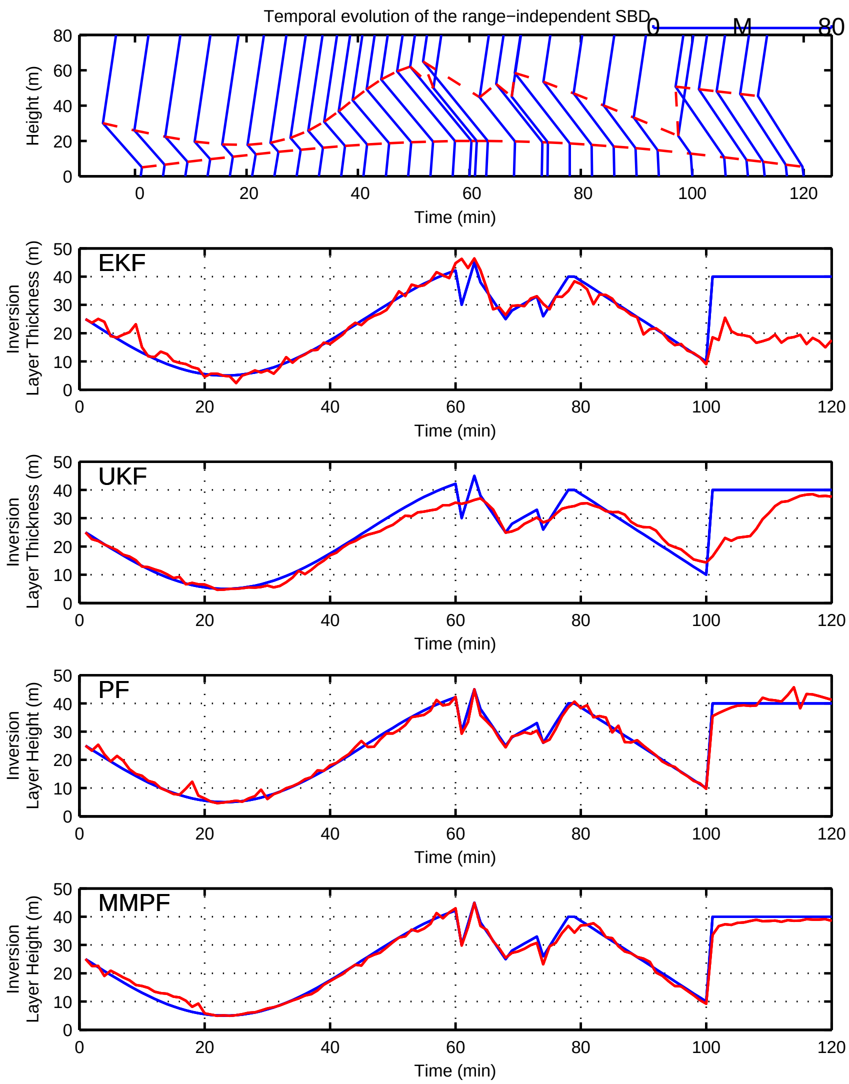

Figure 2: Temporal evolution of the tri-liner SBD. Tracking performances of EKF, UKF, PF and MMPF. True values (blue) and filter estimates (red).

values are defined in [5]. This extra parameter is called the regime parameter and it determines which regime model the PF should be using at a given step index k. Then a regime-conditioned SIR is used to track the environmental particles along with the regime parameter. Hence, MMPF effectively first estimates the environmental conditions, then uses the appropriate model for this regime to predict and correct the environmental parameters and the regime at the next step index. This flexibility enables MMPF to improve its tracking performance, especially in cases where environmental conditions are unpredictable.

The example given here shows tracking of a simple range-independent tri-linear surface-based duct (SBD). The example is designed so that the inversion layer height trajectory has 3 different phases. It first changes slowly for an hour and then it starts to fluctuate and finally it undergoes an sudden 30 m jump within 1 minute. All four algorithms are used to track this artificially created environment. The results can be seen in Fig. 1–2. Fig. 1 shows the high nonlinearity of the tracking problem. This is the main reason for track divergences in Kalman filters. On the other hand PF can handle these, however they need orders of magnitude more computation with respect to Kalman filters. The PF used here uses a high process noise in order to track sudden fluctuations. MMPF, on the other hand, uses 3 different regimes designated as highly fluctuating regime, normal regime and the smooth regime where the environment is very stable. MMPF provides accurate results in all regimes and adapts to regime changes. Notice how PF track is still noisy after the big jump at k =100 min. since PF uses a high process noise to track the sudden jump that leads to high fluctuations. Compare it with the smooth response of MMPF. During the jump MMPF uses a highly fluctuationg regime and after the jump it recognizes that the parameter is very stable and switches to a stable model where the parameters change smoothly so it is not noisy in this region as PF.

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