4.1 *Target association*

1. Variation of ambiguity function
2. PHD filtering and tracking

Variation of ambiguity function

We have seen that the ambiguity performance in PBR depends on :

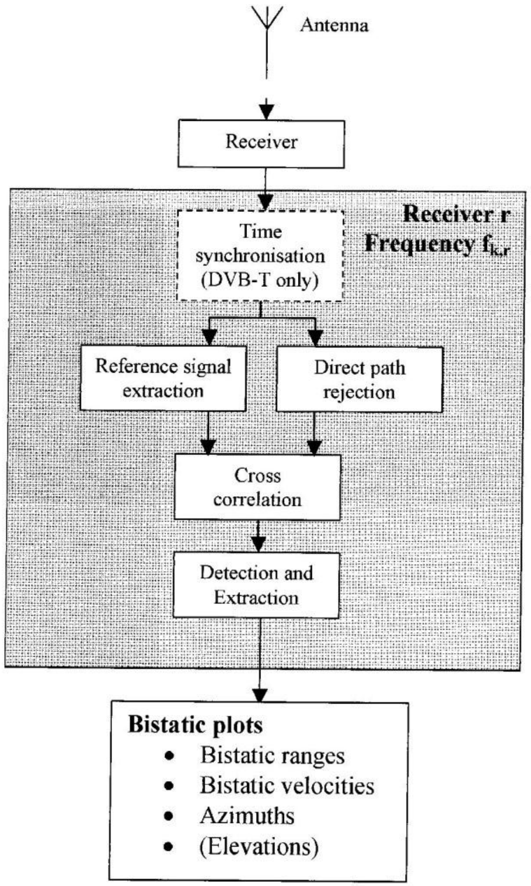
- The waveform: for analogue modulation formats this depends on the nature of the programme content (speech or music …), and will be time-varying, whilst for digital modulation formats it will be more favourable – it does not depend on the programme content and it will not be time-varying.

- The bistatic geometry, so for targets close to the bistatic baseline, the ambiguity performance will be poor, no matter what the waveform.

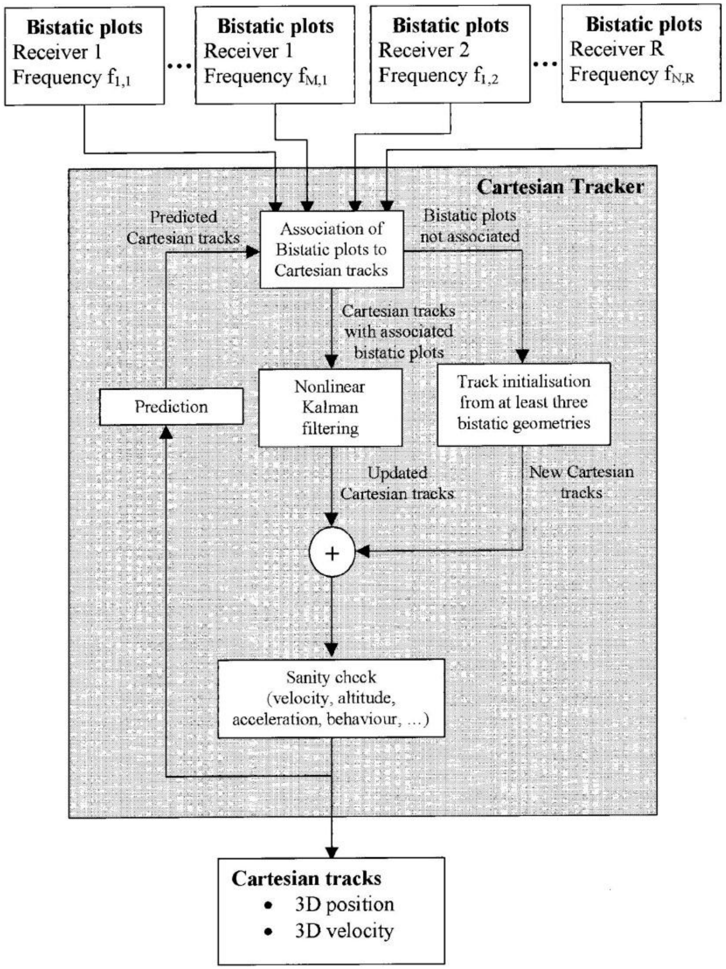
- Both of these effects are deterministic, so it should be possible, for a given target, to dynamically select and use just those transmissions which give favourable ambiguity performance.

Griffiths, H.D. and Baker, C.J., 'Measurement and analysis of ambiguity functions of passive radar transmissions', Proc. *RADAR 2005* Conference, Washington DC, IEEE Publ. No. 05CH37628, pp321–325, 9–12 May 2005.

Processing



signal processing architecture



tracking architecture

Klein, M. and Millet, N., ‘Multireceiver passive radar tracking’, *IEEE AES Magazine*, Vol.27, No.10, pp26–36, 26 October 2012.

PHD filtering and tracking

Tobias and Lanterman tackled the problem of ghost excision and target state estimation using the Probability Hypothesis Density (PHD) approach, which was originally developed by Mahler. The PHD is defined as being any function that, when integrated over any given area, specifies the expected number of targets present in the area.

They use the particle filter implementation of the update equations in which the PHD is represented by a collection of particles and their corresponding weights. Using the same notation as Tobias and Lanterman, at time-step *k* each particle in the filter is a vector of the form

$$\xi_i = \left[x_i \ y_i \ \dot{x}_i \ \dot{y}_i \right]^T$$

and has a weight $w_{i,k}$, where $(x_i \ y_i)$ specify the location of the particle and $(\dot{x}_i \ \dot{y}_i)$ specify its velocity components.

Tobias, M.; Lanterman, A.D. Probability Hypothesis Density-based multitarget tracking with bistatic range and Doppler observations, *IEE Proc. Radar, Sonar and Navigation*, **152** (3), 195–205, June 2005..

Mahler, R.P.S Multitarget Bayes filtering via first-order multitarget moments, *IEEE Trans. Aerospace and Electronics Systems*, **39** (4), 1152–1178, 2003.

PHD filtering and tracking

As per the defining property of the PHD:

$$\tilde{N} = E\left[no.\,of\ targets\right] = \left[N_{k|k}\right]_{nearest\ integer}$$

where

$$N_{k|k} = \sum_{i} w_{i,k}$$

Specifically, the PHD is expected to (a) automatically estimate the number of targets, (b) resolve ghost targets, and (c) fuse sensor (i.e. bistatic transmit–receive pair) data without the need for any explicit report-to-track association.

Results were presented from a simulation using three bistatic transmit–receive pairs measuring first range and then range/Doppler on two aircraft targets flying in the Washington DC area. The transmitters were three local VHF FM stations and the receiver was based on that used by Lockheed Martin’s Silent Sentry™, located 30–50 km from the transmitters. The simulations assumed adequate target visibility, overlapping coverage, and no multipath, and calculated SNRs ranged from 12.2 dB to 32.5 dB.

PHD filtering and tracking

In its simplest form, the simulation began by independently and randomly assigning the particles’ two-dimensional position and velocity components to fall within the FOV of each transmit–receive pair. Particle weights were initially set to zero. These particles were then propagated forward in one-second steps. Birth particles with random positions and velocities were added at each time step to model new targets. One new target and hence one birth particle was assumed to appear at each step.

The PHD then assigned (and updated) particle weights $w_{i,k+1}$ at each time step by incorporating range/Doppler observations, calculated probability of detection, Poisson-distributed false alarms, and a single-target likelihood function.

Finally, the expected number of targets in the FOV was calculated by means of equation (18). The locations of the N expected targets were found by extracting the N highest peaks from the PHD represented by these weights.

PHD filtering and tracking

The results of these preliminary simulations were described as ‘encouraging’. It was observed that in areas of low SNR the number of targets was overestimated.

Subsequently an improved method was developed which removed the need to restrict particles to areas of high SNR, though at the expense of greater computational load.

This also had the effect of reducing the number of particles needed from a few thousand to a few hundred.