Advanced Detection and Tracking in Medium PRF Radar

Evan Hughes, Mike Lewis
Cranfield University at The Defence Academy of the UK
Shrivenham, Swindon, SN6 8LA

Abstract

This paper describes an improved method of target tracking particularly applicable to littoral environments where a wide range of clutter characteristics are present. A light weight multiple hypothesis tracker based on multiple intelligent software agents is presented.

Introduction

In classic target detection methods, such as cell averaging CFAR systems and clutter maps, a small number of spatial or temporal samples is gathered from around the range-azimuth cell of interest in order to estimate the local clutter and noise statistics. A threshold level is then calculated against which the amplitude of the return in the cell of interest is compared in order to determine the presence or absence of a potential target.

The homogeneity and stationarity of sea clutter in the littoral environment is generally poor. If only a few samples are gathered, the resulting estimate of the mean will be poor with the result that the detection threshold must be set higher than the ideal to prevent excessive false alarms.

In Medium PRF radar systems that allow all-round measurements of both the range and Doppler of targets in high clutter environments to be made waveforms that are ambiguous in both range and Doppler are employed. Techniques that resolve these ambiguities require the number of detections input to the ambiguity resolution process to be kept to a small number, as otherwise the number of false correlations (‘ghosts’) becomes unworkably large. The higher than optimum threshold implies a consequent lower probability of detection of small and weak targets.

With low observable and low flying targets (where multi-path can cause significant fading), many returns will be below the detection threshold and there may be many missing detections along the track, resulting in targets being classified as noise if re-investigated, tracks never being initiated, tracks being deleted early or each track being maintained for an extended period. In order to increase the probability of detection of weak targets, the detection threshold must be lowered with a consequent increase in the number of false alarms.

As the information from the received signal is limited, a false alarm or a ‘ghost’ must be treated as a true target, until it can be established as false. A high false alarm rate causes problems with the association of returns with tracks and leads to an excessive number of false tracks being reported with the consequent risk of the tracking system becoming overwhelmed.

The Agent Based CFAR System

To overcome the problems described above a novel self-organising system based on the use of multiple intelligent software agents (MISA) has been developed and is an improved version of the system described in [1]. The agent based CFAR reacts to features in the environment according to simple rules and modifies the areas over which the statistics gathering processes are performed accordingly such that the spatio-temporal data gathering is more effective since the statistics are gathered over regions of homogenous clutter [2].

The CFAR is coupled to an agent-based pre-tracker which allows a depressed threshold to be used and therefore low-observable targets to be detected and tracked in a complex littoral environment whilst also extracting information on the location of fixed targets etc.

The Spatio-Temporal CFAR

The Temporal, or *T*, Level cells are arranged as elements of a range-azimuth map. Each cell contains two identical IIR filters that perform temporal integration of the amplitudes and their squares of successive target returns from the point represented by the co-ordinates. The IIR filter that calculates the mean is described by the following recurrence relationship

$$T_{\mu}(R,\theta,t) = \frac{0.9T_{\mu}(R,\theta,t-1) + I(R,\theta,t)}{1+0.9}$$ W

here $T_{\mu}(R,\theta,t)$ is the temporal mean at each range, azimuth and time, $I(R,\theta,t)$ is the new raw input data. The filters produce the sum of exponentially decaying contributions from previous radar returns.

A similar filter sums the squares of the input voltages thus the variance (and therefore standard deviation) may be estimated as $T_{\sigma}(R,\theta,t) - T_{\mu}(R,\theta,t)^2$.

The range-azimuth cells are also part of the Spatial layer the purpose of which is to perform a spatial integration across regions of homogenous clutter. A means of adapting the regions over which spatial integration is performed is incorporated within the layer.

Each range-azimuth cell has 4 intelligent agents around its borders, the bridging or *B* agents, shared with its neighbours, as shown in Figure 1. The *B* agents prevent the spatial integration from being disturbed by fixed targets. Each *B* agent monitors the $T_{\mu}(R,\theta,t)$ and $T_{\sigma}(R,\theta,t)$ values of the cells on either side of it, and if either $T_{\mu}(R,\theta t)$ or $T_{\sigma}(R,\theta,t)$ are consistently different, it switches to a blocking state and prevents spatial integration occurring across the boundary.

The state of the *B* agents surrounding each range-azimuth cell can also be used to infer which range-azimuth cells may be fixed targets or other discontinuities such as harbour walls, coastline etc.

A threshold is calculated based on the temporally-spatially gated data and used to threshold the input data in the central cell. To prevent moving targets from disrupting the mean and standard deviations, target detections are censored by preventing *T* level updates for any cells in which detections have been made.

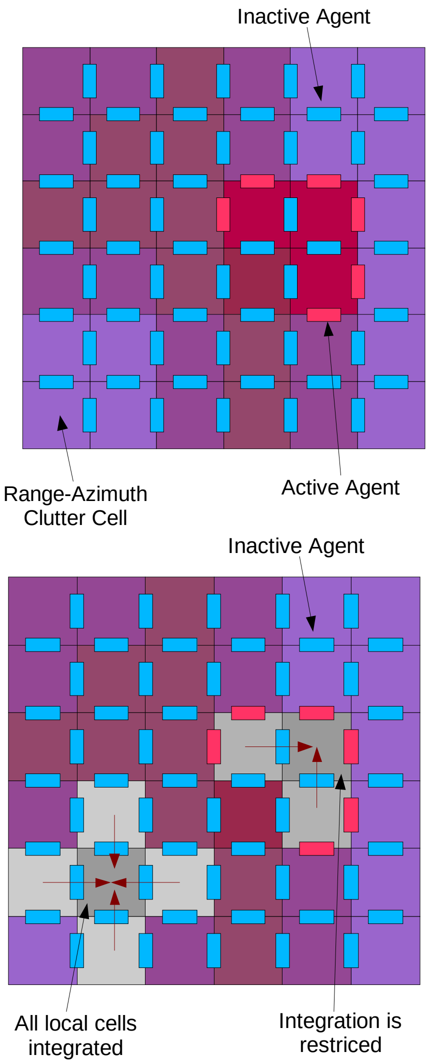

Figure 2: Layout of cells and agents

The controlled spatial integration allows more samples to be gathered and more stable and accurate estimates of mean and variance to be obtained with edges in the scene preserved as sharp discontinuities. This process allows accurate thresholds to be determined to within a few cells of features within the environment.

The edge preserving nature appears similar to filtering methods such as Beltrami flow, or median fitting, but importantly also provides temporal integration and exploits the temporal division also in identifying edges in the scene.

False Track Reduction

In MPRF radar systems range ambiguity means that for each range measurement along an azimuth spoke there are multiple potential targets at ranges, R_n , given by the expression

$$R_n = nR^u + \Delta R, n \in 0,1,\dots$$

where R^u is the maximum unambiguous range of the radar, in range bins, at the PRF in use and ΔR is the range as measured by the radar.

It is normal to employ several PRIs in order to resolve the ambiguities, thus the potential target ranges for the i^{th} PRI form a set of feasible solutions

$$\left\{R_0^{(i)},\dots,R_N^{(i)}\right\} = \bigcup_{n=0}^{N}\left\{nR_i^u + \Delta R_i\right\}$$

Since the set represents the set of feasible solutions for R it follows from the uniqueness property of the Chinese Remainder Theorem that the true target range R is the intersection of the sets of feasible solutions

$$\{R\} = \bigcap_{i=1}^{M}\left\{R_0^{(i)},\dots,R_N^{(i)}\right\}$$

This may also be represented by a Venn Diagram [3].

The Resolution of Ambiguities in the Presence of Multiple Targets

In the case of T targets on the same azimuth then T returns will be taken in each PRF. For the individual targets, t, the set of feasible ranges, $\{R_t\}$, is

$$\{R_t^{(i)}\} = \bigcup_{n=0}^{N}\{nR_i^u + \Delta R_t^{(i)}\}$$

For two targets and two PRIs there are four sets of congruencies to be solved and the First Chinese Remainder Theorem guarantees a solution to all these systems. It is thus not possible to determine unambiguously the range of two targets using only two PRIs.

Since the members of the solution set are simple combinations it is easy to show that the cardinality of the solution set is T^M

where M is the number of PRIs and T is the number of targets.

Since there are T true targets the number of ghosts is found by subtraction

$$T^M - T = T\left(T^{M-1} - 1\right)$$

The number of ghosts generated per scan is invariant and is a function of the number of targets on the same azimuth at any one time.

Given a set of PRIs, a reasonable estimate for the expected number of ghosts in the region of interest can be calculated (ignoring the possibility of ghost targets falling on top of each other). If the chosen PRI set results in an unambiguous range-Doppler region with on average K range-Doppler cells, and the region of interest has on average Q repeats of the unambiguous region, then an approximation to the probability of ghosts in an M of N system, where M out of N PRIs are required to be coincident can be made.

Assuming that there are T targets in the unambiguous region, and that in the Q repeats of the first PRI/PRF, images of all the targets are present without overlap, then in the second PRI/PRF, the probability of any one target cell overlaying a used cell in the first PRI/PRF is approximately Q/K. Once an overlap has occurred, subsequent PRIs have a probability of achieving an overlap of $1/K$ (there no longer being a free choice of Q ambiguous regions).

Thus an approximation for the expected number of ghosts in the region of interest, given a probability of detection of 100% is

$$E_G \approx \left(T^M - T\right)\left(\begin{array}{l} {}_{M-2}C_{N-2}\left(\dfrac{Q}{K}\right)\left(\dfrac{1}{K}\right)^{M-2}\left(1-\dfrac{1}{K}\right)^{N-M} \\ + \displaystyle\sum_{i=M-1}^{N-2} {}_{i}C_{N-2}\left(\dfrac{1}{K}\right)^{i}\left(1-\dfrac{1}{K}\right)^{N-i-2} \end{array}\right)$$

For a typical airborne fire control system with a 3 of 8 schedule, with K=2000 and Q=100, with T=8 targets, E_G=3 ghosts. With T=10, E_G=19 ghosts and with T=14, E_G=280 ghosts.

It is clear that the number of ghosts likely to be present increases very rapidly with only a small increase in the number of strong targets present.

Decorrelation of Ghost Tracks

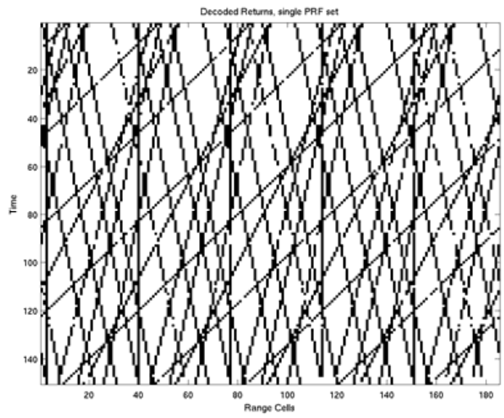

Figure 2. Ghost Tracks from 10 Targets with ambiguities resolved using two PRIs

Figure 2 shows the range-time plot from 10 targets viewed with a 2 PRI system. The targets are: two closing targets with equal velocities; four opening targets with equal velocities; three closing targets with differing velocities and one stationary target. The PRIs are such that the ambiguity is five times in range.

Severe ambiguity can clearly be observed and as all the ghosts are strong, it is very difficult to determine which tracks are from the real targets. As the probability of detection is 100%, some of the ghost tracks can be identified as they have brief breaks and can be dismissed, but this is a special case. In general, with targets in close formation, the ghosts will appear to move in a very ‘target-like’ manner.

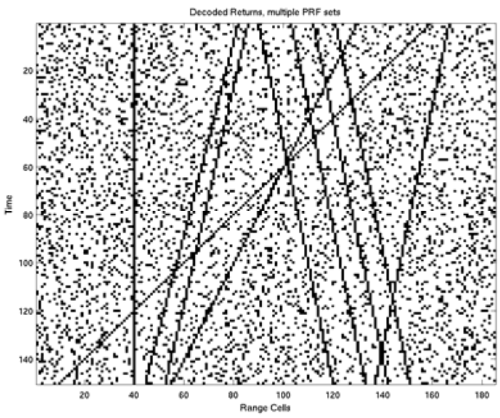

Figure 3. Effect of Scan to Scan PRF Change

fragments caused by ghosting. Although approximately the same number of ghosts is present, they occur in a different location for each PRI set, therefore the effect of the PRI changes has been to decorrelate the ghost tracks. shows the effect of changing the PRI set on a scan to scan basis. Five sets of two PRIs were cycled through. The true tracks are clearly visible against a background of track fragments caused by ghosting. Although approximately the same number of ghosts is present, they occur in a different location for each PRI set, therefore the effect of the PRI changes has been to decorrelate the ghost tracks.

Inspection indicates a clear set of true target tracks and suggests that a high score would be achieved on such SIAP metrics as accuracy, completeness, continuity and clarity. Unfortunately, the ghost returns must still be handled by the tracker, and so a tracking system that can handle a very high false alarm rate must be used.

Track Formation by 'Prediction on Demand'

The high level of false alarms and 'ghosts' presents a particular problem for the subsequent tracker as the information from the received signal is limited, a false alarm or a 'ghost' must be treated as a true target with the consequence that an excessive number of track hypotheses are generated.

Common trackers use predictive techniques such as the Kalman filter to associate new detections with existing tracks. Since a prediction has to be made for every hypothesis the computation load is high but the association rate is low since there are fewer detections than hypotheses.

The track association method used is based on retrodiction which on closer examination can be seen to be 'prediction on demand'.

Potential Track Formation, Intelligent Agents

The Intelligent Agent subsystem is a light weight multiple hypothesis tracker that assembles track fragments according to heuristic rules.

Intelligent agents are formed with each agent being associated with a target return. When an Intelligent Agent is created, it strives to form links with existing Intelligent Agents that represent *virtual* tracks within the multi-agent system.

The 'Agent is a detection' approach allows many track hypotheses to be formed for each return and many tracks could pass through each Intelligent Agent.

Hypothesis formation is conducted in a number of stages. Each new detection agent searches its immediate area to find any track fragments that are within a feasible distance to it based on knowledge of the apparent velocity from the change in distance with time.

Having found loose associations of detections and track hypotheses these loose associations are tested to determine if the speed and direction changes represented by the new detection are within the feasible region for that hypothesis. Explicit forward prediction of likely positions is not used, only reverse checks on link and agent feasibility are performed. The calculation of the feasible or reachable set for association of agents to allow links to be formed whilst keeping processing to an absolute minimum is one of the cornerstones of this research.

The final rule that is applied is that agents older than four scans are discarded. The result of setting agent life to a maximum of four scans allows up to four successive detections to be missed.

As the number of agents reaches the upper limit of the processing capability, the life of the agents can be managed to allow a maximum population size to be maintained, whilst performance is allowed to degrade gracefully. This contrasts with conventional track formation where track overload can be catastrophic.

Track fragments having a length equivalent to three scans are passed to the main tracker for formation into longer tracks.

The simple track fragment generation method here imposes a lower computational load than a Kalman filter. The Kalman filter will produce smooth interpolation between detections when detections are missing whereas the method described here merely 'joins the dots'. Since the subsequent tracker generally performs smooth interpolation when producing tracks this disadvantage is not considered to be significant.

Linking with Track Before Detect Methods

The subsystem described is a pre-tracker which removes the higher number of false alarms introduced by the spatio-temporal CFAR. A tracker is still required to form complete tracks from the track fragments.

The main processing methods, apart from Kalman filters, potentially available are Dynamic Programming [4], Hough Transforms [5] and Particle Filters [6].

In radar, Dynamic Programming is an optimisation process that tries to identify the single most likely track through each cell. An algorithm based on the Viterbi Algorithm and a Hidden Markov Model is described by Tonissen and Evans [7]. The algorithm relies on the assumption that a fragment of an optimal track is itself optimal. Therefore, if the single optimal track fragment through each cell can be identified, then a full optimal track can be constructed. Dynamic Programming works best when high resolution range-azimuth-Doppler data is available to reduce the size of the feasible space that a target could attain between track points. If low resolution , or no Doppler data is used, the computational complexity increases rapidly.

The Hough, and related Radon Transform, provides a means of integrating the returns from moving targets. The approach adopted has similarities to Multiple Hypothesis Tracking methods where a number of hypotheses are made on each new set of data received where the hypotheses are based on the probability of the return being true or false and whether the track is true or false, non-manoeuvring or manoeuvring. In the Hough Transform method the data is transformed according to a hypothesis on the track dynamics. The returns from a target with corresponding dynamics will be transformed into the same transform cell whilst false returns should spread over the transform domain.

Both Dynamic Programming and the Hough Transform method are computationally intensive, the time to perform the calculations being proportional to N^3 although fast approximate forms of the Hough transform where the time is proportional to $N^2 \log N$ [8] exist. In addition the Hough transform requires an extra step to re-associate returns with the set of possible tracks extracted from the transform.

Both techniques are limited as to the geometry of the tracks that can be handled. These transform methods are best suited for straight lines and circles.

With a simple straight-line track Radon Transform operating on (x,y) space only, the corresponding Radon space is also 2 dimensional, but clutter tracks are formed easily as no time correlations are accounted for. If time is also used, the input (*x,y,t*) space may be transformed into a 3 dimensional Radon space for radially inbound targets only. A 4 dimensional space is needed if crossing targets are to be considered too with a corresponding increase in the processing load.

The particle filter approach attempts to identify the "current state" of each target through generating many simple hypotheses as particles in each cell, i.e., states such as "is a target present?", location, velocity, intensity etc. The particles are propagated using Bayes rule and are capable of tracking highly manoeuvreable, weak targets through intense clutter.

Early attempts required massive numbers of particles for relatively small regions of interest and were slow however improvements in this area are being made. The key difficulty of the Particle Filter approach lies with the initial detection of targets without the use of excessive numbers of particles being needed. For tracking of very weak targets after detection by another process, the particle filter approaches are very promising indeed.

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