Cognitive Airborne Maritime Surveillance Radar: Towards Autonomous Sensors

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***Abstract*—This paper deals with the optimization of operational tasks in the case of airborne radar for maritime surveillance. The first step of the process is to learn the environment using a given waveform and associated processing. The objective of this learning is to provide a map of what can be detected or not, considering the analysis of the mixture of sea clutter and noise. In the case of a manned system, the result can be presented to the operator. In a second step, the proposed method aims at suggesting to the operator the mode or waveform that would be the most suitable for performing a given task. When appropriate, the most suitable platform altitude or the best horizontal viewing point is suggested to the crew. These recommendations are obtained by inferring the attainable performances with another waveform or another processing or another point of observation, etc. from the learning carried out in the first stage. This inference is based on a modelling of the mixture of sea-clutter and noise. The last step is to apply these recommendations. On a stand-alone platform, this will be done automatically by acting at the level of radar management and, when appropriate, at the level of the platform autopilot. In the longer term, this concept paves the way for autonomy: sensors or platforms capable of autonomous decision making without an operator being in the decision loop; and therefore without the need for a permanent high-speed bidirectional data link between the ground control and the platform(s).**

Keywords: Cognitive radar; Maritime Surveillance; Sea-clutter modelling; Sensor Autonomy.

I. Introduction

Modern airborne radars for maritime surveillance have many modes for detecting and tracking the marine targets. Each of them is designed to be optimal facing a given target class. Indeed, for technological problems, but also for physical limitations, it is not possible to have a single mode capable of detecting optimally any type of target in any condition. Today, the selection of the most appropriate mode must therefore be carried out with care by a qualified radar operator. In addition, the performances enhancement of new radars involves more complex signal processing than in the past. This increasing complexity associated with many modes makes it difficult for an operator to predict the effective capability of the sensor in a given environment, for example from the examination of the raw video. Finally, manual optimization is hardly conceivable in the case of radars on-board UAS (Unmanned Air System) because of the high demands for RF (Radio-Frequency) data-link that would be required. Hence, a process of automatic optimization (choice of transmitted waveforms, radar modes, signal processing, etc.) is desirable. Such a concept falls within the framework of cognitive systems.

II. Cognitive Radar

Cognitive Radar has been the object of many researches over the last fifteen years [1]-[5]. Cognition is the set of major functions of the mind related to knowledge (perception, memory, reasoning and action). Thus, a cognitive sensor periodically runs an optimization loop comprising these functions related to knowledge (Fig. 1). The processes used in cognitive radar should not be confused with those used in adaptive processing. Indeed, in the latter case, there is neither intelligence nor external information added to the processing: the adaptive processing merely performs optimal filtering according to a priori assumptions on received signals.

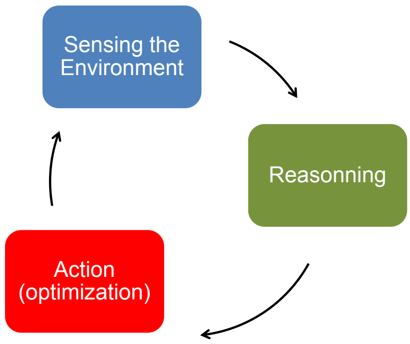

Fig. 1. Optimization Loop.

The aim of this article is to present cognitive mechanisms that optimize operational tasks in the particular case of airborne maritime surveillance radar. We assume in the following that the objective is to detect targets, in a given area, whose RCS (Radar Cross Section) is less than a given threshold (Fig. 2).

The paper is organized as follows:

- Section III describes the proposed cognitive optimization method.
- Section IV gives an example of implementation.
- Section V concludes the paper.

III. Cognitive Optimization of an Operational Task

A. *First Phase: Perception of the Environment*

The received signal is recorded during an antenna scan using a given waveform. The instrumental domain (Distance - Azimuth) is subdivided into small patches. In each patch, a statistical model describing the mixture of clutter and noise (environmental model) is fitted to the samples to estimate the parameters of the statistical model. Then, knowing the power budget of the radar, for a given target fluctuation model (e.g. Swerling 1, 2, etc.), the RCS of the Minimum Detectable Target (MDT) is calculated (for required P_D and P_{FA}). Fig. 2 illustrates the result of this processing. Details are given in [6].

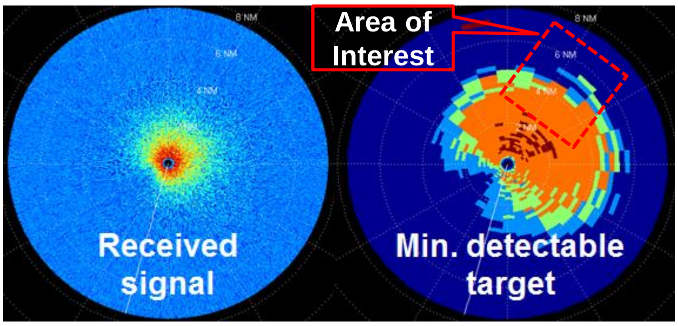

Fig. 2. Raw radar signal (left), map of Minimum Detectable Target (right). The colour indicate the value of MDT: dark blue: very small targets are detectable; orange: only strongest targets are detectable.

B. *Second Phase: Reasoning*

1) *Inference Phase*

The objective of optimization that is described here is to be able to detect any target having a RCS above the threshold σ_T within the area of interest Ω (Fig. 2):

$$\sigma_D(\mathbf{M}) \le \sigma_T\,, \quad \forall \mathbf{M} \in \Omega\,, \tag{1}$$

where σ_D is the RCS of the MDT. If the condition (1) is met with the current waveform, the problem is completed. Otherwise, the environment model described in paragraph 2) is used to infer the sensitivity gain corresponding to the variation of the following means of action (cf. Fig. 3):

- The waveform and dedicated processing among all available waveforms.
- The altitude of the platform and/or its horizontal position with respect to the area of interest Ω.

The most convenient means of action is to play on the waveform and the associated processing since this does not involve any constraint on the flight path of the platform, hence the interest of software-defined radars. The possibility of action on the position of the platform is a specificity of airborne radar which can be moved quickly. However, playing on the position of the platform induces operational constraints that can be more or less acceptable but which must necessarily be taken into account in the optimization process. Nevertheless, the problem may have no solution. For example, the available waveforms having the required resolution may have an insufficient instrumental domain or the required altitude may be too low to place the entire area Ω before the horizon.

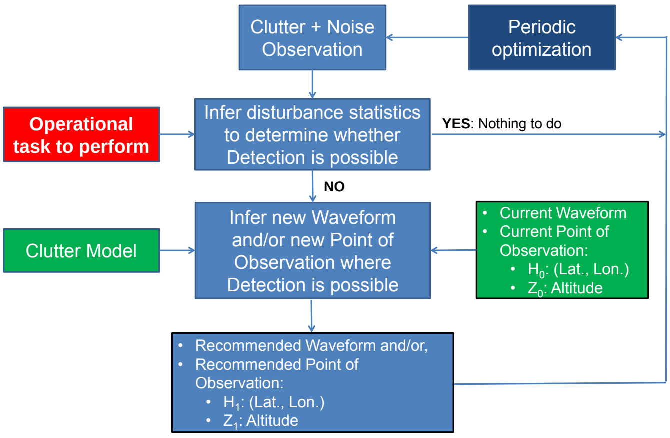

Fig. 3. Optimization loop.

2) *Environment Model*

In the general case, the environment obeys a bimodal statistics since it results from a mixture of clutter and noise:

a) *Sea-clutter Model:*

Clutter is a multiplicative noise. Its intensity distribution can be modelled by a two-parameter Probability Density Function (PDF). At low grazing angles (<10°), a widely used modelling consists of:

- The GIT model (Fig. 4) for average reflectivity σ^0 [7].
- The K-law (Fig. 5) with a shape factor ν for the normalized PDF (first order moment equal to unity) [8].

b) *Noise Model*

The thermal noise is an Additive Gaussian Process. Its power is therefore distributed according to an exponential law. It can be shown that the maximum detection performances of a radar on thermal noise does not depend directly on the waveform but only on the energy emitted towards the target during a processing interval.

C. *Last Phase: Action*

In the case of a manned platform, the recommendations are not necessarily automatically applied: they can be only suggested to the operator as well as the crew, who can take into account other operational constraints in their final choice. In the case of a UAS for which a high data-rate and low-latency connection cannot be guaranteed, the optimization must be carried out automatically. The optimization modalities go beyond the radar framework solely because they necessarily involve the autopilot of the platform.

IV. Implementation of Proposed Method

A. *Model-based Inference*

1) *"Performances and Settings State Equation"*

For a given setting (waveform, processing and platform position) and for each small patch **M** within the area of interest Ω, we define a "state structure" **Y**(**M**) which contains:

- The attainable detection performances: $\sigma_D(\mathbf{M})$;
- The detection conditions: $\mathbf{Q} = (P_D, P_{FA})$;
- The waveform, processing, etc. which are selected: **W**;
- The platform location, and possibly its velocity: **P**;

$$\mathbf{Y}(\mathbf{M}) = [\sigma_D(\mathbf{M}), \mathbf{Q}, \mathbf{W}, \mathbf{P}]. \quad (2)$$

The unknown parameters (wind speed and direction, sea height, etc.) are expressed through a "state equation", $g(.)$ being a function of the unknowns' vector:

$$g(\mathbf{X}) = f[\mathbf{Y}(\mathbf{M})], \quad \mathbf{X} = \text{unknowns vector}. \quad (3)$$

2) Inference

Let us assume that the learning has been done using the settings #1 and that we want to predict the achievable performance with setting #2. We eliminate the unknown parameters by writing (4):

$$f[\sigma_D(\mathbf{M})_2, \mathbf{Q}_2, \mathbf{W}_2, \mathbf{P}_2] = f[\sigma_D(\mathbf{M})_1, \mathbf{Q}_1, \mathbf{W}_1, \mathbf{P}_1]. \quad (4)$$

The attainable performances $\sigma_D(\mathbf{M})_2$ are then obtained using an appropriate resolution method.

B. Example of Implementation

In the general case we should consider a mixture of thermal noise and clutter. **However, for the sake of simplicity, we will consider in the following explanations that sea-clutter is the main disturbance** (i.e. we neglect the thermal noise).

1) Implementation of Clutter Model

a) Threshold as Function of P_{FA}:

According to the sea-clutter modelling proposed in paragraph III.B.2), we can write a couple of formulas:

- **The mean reflectivity** σ^0 depends only on sea-state and observation geometry according to the model in [7]:

$$\mathrm{dB}(\sigma^0) = \alpha(\psi) + \beta(\phi, \psi) + \gamma(V_W, h_a), \quad (5)$$

where $\mathrm{dB}(.) = 10\log(.)$, ψ is the grazing angle, V_W the wind speed, h_a the average height of waves (sea-state) and ϕ the wind aspect angle. By neglecting the curvature of the Earth, $\sin(\psi) = Z / R$ where Z is the altitude of the platform. The effect of the altitude change is visible on Fig. 4.

- **The mean clutter RCS** μ in a resolution cell is the product of the reflectivity (5) by its geometric surface:

$$\begin{aligned} \mathrm{dB}(\mu) &= \mathrm{dB}(\sigma^0) + \mathrm{dB}(A), \\ \mathrm{dB}(\mu) &= \alpha(\psi) + \beta(\phi, \psi) + \gamma(V_W, h_a) + \mathrm{dB}(A), \end{aligned} \quad (6)$$

where $A \approx 0.75\theta_{AZ} R\delta R$ is the surface of a resolution cell, θ_{AZ} is the antenna beam-width, R is the distance and δR is the range resolution of the waveform.

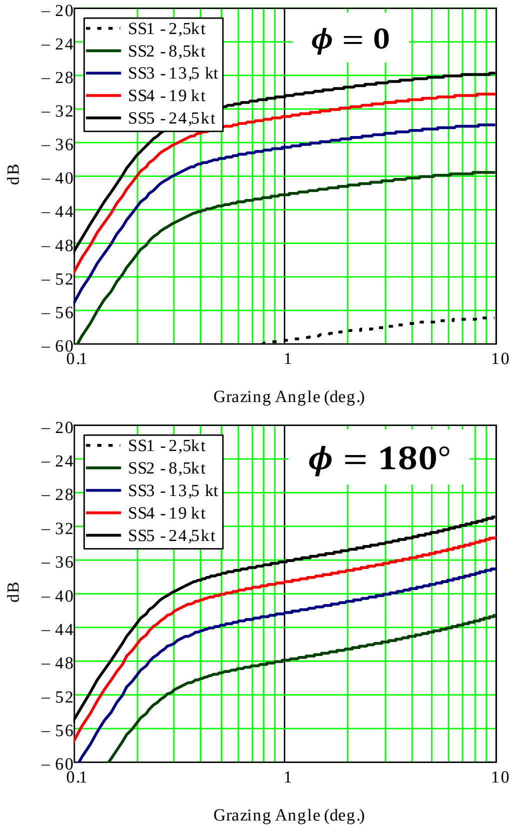

Fig. 4. GIT modelling for two particular aspect angle relative to wind.

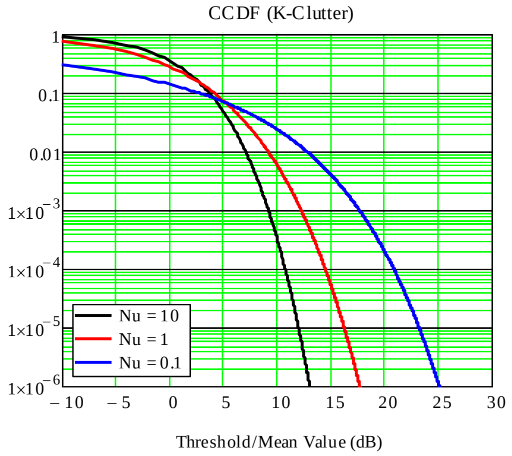

Fig. 5. Complementary Cumulative Density Function in Log scales of normalized K-law for three particular shape factors.

- **The normalized Complementary Cumulative Density Function** (CCDF) of clutter intensity allows calculating the P_{FA} as a function of the normalized threshold [8]:

$$P_{FA} = \frac{2(\nu\lambda_T)^{\frac{\nu}{2}}}{\Gamma(\nu)} K_\nu\left(2\sqrt{\nu\lambda_T}\right). \quad (7)$$

This function is monotonic and the detection threshold λ_T above the local mean intensity μ is got by inverting (7):

$$\mathrm{dB}(\lambda_T) = \Lambda(\nu, P_{FA}). \tag{8}$$

According to [8], the expression of the shape factor is:

$$\log(\nu) = \frac{2}{3}\log(\psi) + \frac{5}{8}\log(A) - \frac{1}{3}\cos(2\varphi) - k\ , \tag{9}$$

where φ is the angle between look direction and swell direction and k a constant depending on the polarization of waves. The shape factor depends only on geometrical and waveform parameters. In Fig. 5, (7) is plotted for three shape factors. Moreover we can make the hypothesis that the wind and the swell have the same direction, therefore: $\varphi \approx \phi$:

$$\mathrm{dB}(\lambda_T) = \Lambda(\nu(\psi, \phi, A), P_{FA}). \tag{10}$$

The detection threshold is equivalent to a threshold RCS:

$$\mathrm{dB}(\sigma_T) = \mathrm{dB}(\mu) + \mathrm{dB}(\lambda_T). \tag{11}$$

b) Taking into account the aimed P_D:

The probability of detection is a monotonic function of both the normalized threshold λ_T and the Signal to Noise Ratio S :

$$\mathrm{dB}(\sigma_{MIN} / \lambda_T) = \mathrm{dB}(S / \lambda_T) = \Delta(\lambda_T, P_D). \tag{12}$$

The function Δ corresponds to the mode of fluctuation of the target RCS, but it depends also on the PDF of the background noise. However, when $\lambda_T >> 1$(which is the case when the clutter is predominant), the function Δ tends to be independent of the PDF of the background noise. Moreover, λ_T may be omitted in (12) for the usual values of required P_D (> 0.5). For instance, on Gaussian noise and for a Swerling 1 target:

$$\begin{aligned} &P_D = \exp\frac{-\lambda_T}{1+S} \Leftrightarrow \\ &\Delta(\lambda_T, P_D) = \mathrm{dB}\left(-\frac{1}{\ln P_D} - \frac{1}{\lambda_T}\right) \approx \mathrm{dB}\left(\frac{1}{-\ln P_D}\right). \end{aligned} \tag{13}$$

c) State Equation

Summarizing (6), (10) and (12), we get:

$$\begin{aligned} \mathrm{dB}(\sigma_{MIN}) = &\underbrace{\alpha(\psi) + \beta(\phi,\psi) + \overbrace{\gamma(V_W, h_a)}^{\text{Unknown}} + \mathrm{dB}(A)}_{\mu} \\ &+ \underbrace{\Lambda(\nu(\psi, \phi, A), P_{FA})}_{\text{Function of } P_{FA}} + \underbrace{\Delta(P_D)}_{\text{Function of } P_D}\ . \end{aligned} \tag{14}$$

So:

$$\begin{aligned} f[\mathbf{Y}] &= \mathrm{dB}(\sigma_{MIN}) - \alpha(\psi) - \beta(\phi,\psi) \\ &\quad - \mathrm{dB}(A) - \Lambda(\nu(\psi, \phi, A), P_{FA}) - \Delta(P_D) \\ g(\mathbf{X}) &= \gamma(V_W, h_a), \qquad \mathbf{X} = (V_W, h_a). \end{aligned} \tag{15}$$

2) Examples of Optimization

a) Optimization through Range-resolution Change

The resolution acts directly on the mean clutter intensity and indirectly on the relative threshold. The optimization consists in solving (16), the unknown being A_2:

$$\begin{aligned} &\mathrm{dB}(A_2) + \Lambda(\nu(\psi, \phi, A_2), P_{FA}) = \\ &\mathrm{dB}(A_1) + \Lambda(\nu(\psi, \phi, A_1), P_{FA}) + \mathrm{dB}\left(\frac{\sigma_{MIN\_2}}{\sigma_{MIN\_1}}\right). \end{aligned} \tag{16}$$

Once (16) is solved, the selected waveform and related processing are the ones whose instrumental domain is compatible with the observation of the area of interest Ω.

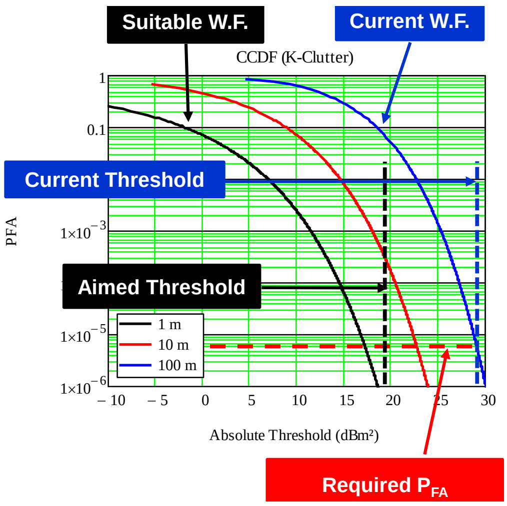

Fig. 6. Method to get a suitable waveform (same P_{FA} in this example).

b) Optimization through Altitude Change

If no available waveform fulfils the objective, another solution is to change the altitude of observation. However, this can be subject to operational restrictions (*e.g.* impossibility to fly under a minimal altitude). The sensitivity gain comes from the decrease of the grazing angle. However, the altitude reduction of the platform may place the area of interest partially beyond the horizon.

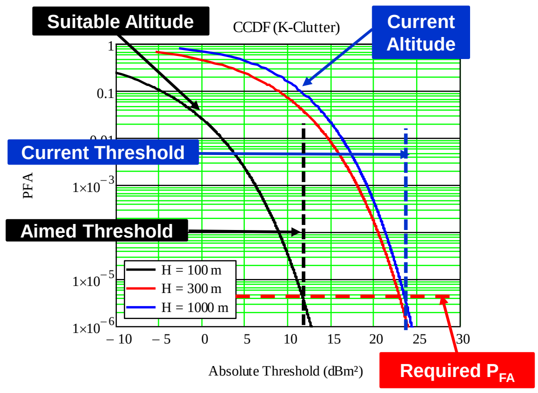

Fig. 7. Method to get a better altitude.

The suitable altitude in obtained in solving (17):

$$\alpha(\psi_2) + \beta(\phi, \psi_2) + \Lambda(\nu(\psi_2, \phi, A), P_{FA}) = \alpha(\psi_1) + \beta(\phi, \psi_1) + \Lambda(\nu(\psi_1, \phi, A), P_{FA}) + \mathrm{dB}\left(\frac{\sigma_{MIN\_2}}{\sigma_{MIN\_1}}\right). \tag{17}$$

V. Conclusion and Perspectives

Some applications of cognitive management of radar have been described in this paper, focusing on the specificities of the Airborne Maritime Surveillance. A model-based approach is proposed to overcome the lack of knowledge of environmental parameters (e.g. wind-speed, height of sea-waves, wind direction). Thank to this model-based approach, it is possible to infer the best waveforms among the available ones or the best altitude of the platform. However, the problem may have no solution despite optimization. This cognitive management will be an enabler for future autonomous systems where the sensors and the platform will have to optimize themselves to accomplish a task. The next step in this study is to extend the method to the general case of “sea-clutter + noise” and study fast algorithms for solving inferences.

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