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Artificial intelligence techniques for small boats detection in radar clutter. Real data validation



Artificial Intelligence

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ABSTRACT

Artificial intelligence techniques were applied for detecting small moving targets in maritime clutter environments. Neural detectors are considered to approximate the Neyman–Pearson (NP) in composite hypothesis testing problems. Sub-optimum approaches based on the Constrained Generalized Likelihood Ratio (CGLR) were analysed, and compared to conventional implementations based on Doppler filtering that are designed to filter clutter and improve the Signal-to-Interference Ratio, and Constant False Alarm Rate techniques. The CGLR performance was significantly better at the expense of a high computational cost. As a solution, neural network training sets were designed for approximating the NP detector. The detection of small boats in Gaussian clutter was the defined case study in order to assume the design hypothesis of the conventional solutions and to study their performance under their most favourable conditions. Detection schemes were evaluated using real radar data. Neural solutions based on Second Order Neural Networks provide the best results, being able to approximate the CGLR with a significantly low computational cost compatible with real-time operations.

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1. Introduction

Small moving targets, such as inflatable boats, detection is nowadays quite an important issue in tasks related to sea traffic control, fishery management and ship search and rescue. A traditional security system is based on active radar sensors used for surveillance and monitoring tasks. In Fig. 1, the general structure of a scanning radar is presented. The radar detection problem can be formulated as a binary hypothesis test, where the detector has to decide between target absence (null hypothesis, H_0) and target presence (alternative hypothesis, H_1). The most extended detector criterion in radar applications is the Neyman– Pearson (NP) detector, which maximizes the Probability of Detection, P_D , maintaining the Probability of False Alarm, P_{FA} , lower than or equal to a given value (Neyman and Pearson, 1933; Trees, 1968).

If $\tilde{\mathbf{z}}$ is the observation vector generated at the output of the synchronous detector and $f(\tilde{\mathbf{z}}|H_0)$ and $f(\tilde{\mathbf{z}}|H_1)$ are the detection problem likelihood functions, a possible implementation of the NP detector consists in comparing the Likelihood Ratio (LR), $\Lambda(\tilde{\mathbf{z}})$, to a threshold selected according to P_{FA} requirements, η_{lr} (Trees, 1968), and deciding in favour of H_1 when the LR output is higher than the selected threshold, and in favour of H_0 when the LR output is lower than the selected threshold

(1). This approach requires a complete statistical characterization of the observation vector under both hypotheses, and significant detection losses are expected when the true likelihood functions are different from those assumed in the LR detector design (Aloisio et al., 1994; di Vito and Naldi, 1999). In practice, clutter and target statistics are variable. Although clutter parameters can be estimated from radar measurements, target ones are really difficult to estimate.

$$\Lambda(\widetilde{\mathbf{z}}) = \frac{f(\widetilde{\mathbf{z}}|H_1)}{f(\widetilde{\mathbf{z}}|H_0)} \mathop{\underset{H_0}{\overset{H_1}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{\underset{H_0}{$$

When target parameters are unknown and can be modelled as random variables, the detection problem must be formulated as a composite hypothesis test. The decision rule consisting in comparing the Average Likelihood Ratio (ALR) to a detection threshold fixed according to P_{FA} requirements, is an implementation of the NP detector (Trees, 1968). The ALR can be formulated for the considered case study, characterized by targets whose Doppler shift, Ω_s , is a random variable, in function of the probability density function $f(\Omega_s)$. This is a problem of interest, specially when weak moving targets with low radial speed must be detected in presence of clutter. If the probability density functions of

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Fig. 1. General architecture of a coherent radar receiver. Radar matrix generated after an antenna scan.



Fig. 2. General architecture of a practical coherent radar detector.

the random parameters are unknown, the optimum test expressed in Eq. (2) is formulated assuming that they are uniform in the variation interval (Aref and Nayebi, 1994).

$$\begin{split} \Lambda(\widetilde{\mathbf{z}}) &= \frac{\int f(\widetilde{\mathbf{z}}|H_1, \Omega_s) f(\Omega_s) d\Omega_s}{f(\widetilde{\mathbf{z}}|H_0)} \\ &= \frac{\frac{1}{2\pi} \int_0^{2\pi} f(\widetilde{\mathbf{z}}|H_1, \Omega_s) d\Omega_s}{f(\widetilde{\mathbf{z}}|H_0)} \stackrel{H_1}{\underset{H_0}{\overset{R}{\xrightarrow{}}} \eta_{alr}(P_{FA})} \end{split}$$
(2)

The ALR formulation usually leads to integrals without analytic solution, then suboptimal approaches are proposed: numerical approximations of the ALR, or the Generalized Likelihood Ratio (GLR), which uses the maximum likelihood estimation of the parameters governing the likelihood functions in a LR, as if they were correct (Trees, 1968; Carretero-Moya et al., 2011; Sangston et al., 2012).

Practical radar detectors are based on Doppler Processors, DPs, (cancelers, bank of filters) which exploit the Doppler effect to filter clutter and improve the Signal-to-Interference Ratio, (SIR). The basic scheme of a practical coherent radar is presented in Fig. 2. Again, due to the complex dynamics of the targets, their Doppler shift is usually modelled as a uniform random variable in $[0, 2\pi)$, and, because of that, the basic DP is based on a uniformly distributed filter bank. Assuming that most of the clutter has been rejected, incoherent CFAR techniques are applied to estimate clutter residuals plus thermal noise statistics, and adapt the detection threshold for maintaining the desired P_{FA} (Skolnik, 2008; Curtis, 1999; Mata-Moya et al., 2015). This type of solutions assumes that clutter plus interference can be modelled as Gaussian processes, and filters are designed for maximizing the Moving Target Indicator, MTI, improvement factor (the ratio between the SIR measured at the filter output, and the SIR measured at the filter input) (Skolnik, 2008; Eaves and Reedy, 1987). Nowadays, this approach is still applied in different clutter conditions, and the Gaussian model is the basis of many research works (Shui and Shi, 2012; Xu et al., 2011; Cheikh and Soltani, 2011; Pascal et al., 2008).

In this paper, we prove that the criteria that guide these traditional designs based on anti-clutter filter banks are different from the NP one, giving rise to solutions with significantly lower detection performance.

As an alternative, this paper tackles the design of Neural Network (NN) based detectors for approximating the NP detector in composite hypothesis tests, controlling the computational cost. Learning machines trained in a supervised manner using a suitable error function have been proved to be able to approximate the NP detector (Jarabo-Amores et al., 2009, 2013). Neural networks (Whiteson and Whiteson, 2009; Mata-Moya et al., 2011) and Support Vector Machines (SVM) (Davenport et al., 2010) have been applied to approximate the NP detector. In Mata-Moya et al. (2009) committees of Neural Networks (NNs) were designed for detecting Gaussian targets with unknown correlation coefficient in Additive White Gaussian Noise (AWGN). In the present work, this study was extended, and different types of NNs were designed for detecting small boats in low-state sea clutter. Fluctuating targets with unknown Doppler shift uniformly distributed in $[0, 2\pi)$ were considered for designing the case study. The low SIR expected due to strong clutter returns, together with the wide range of possible target speeds (from 7 knots associated with a small wooden boat to 60 knots associate with a motorboat) are the main challenges to be overcome. As the proposed NN training process is designed to be able of approximating the NP detector, the NN-based solutions results can be extended for any type of radar scenario

Real data acquired by a coherent, pulsed and X-Band radar deployed on Signal Hill by Council for Scientific and Industrial Research (CSIR) (Herselman et al., 2008) were considered. The real amplitude data of clutter returns fit with a Rayleigh distribution associated with the light breeze conditions during the measurements campaign. The considered detectors (constrained-GLR, CGLR, conventional detectors based on DPs and neural solutions) were designed under this assumption and evaluated with simulated data estimating false alarm and detection rates. Finally detection capabilities were presented with the real dataset. NN-based detectors, designed for approximating the NP detector, provided detection performances similar to the CGLR ones, overcoming the conventional schemes, with computational costs that can be compatible with real time operations.

2. Radar system and signals models

Without loss of generality, according to the objectives of proving the suboptimum character of practical implementations and the capability of NN to approximate the ALR, clutter is modelled as a Gaussian process. This is motivated also by the fact that the scheme of Fig. 2 was designed under this assumption, with a basic objective of maximizing the Signal-to-Interference Ratio (SIR) (Skolnik, 2008). This approach is still applied in different clutter conditions being the Gaussian model the basis of many research works (Shui and Shi, 2012; Xu et al., 2011; Cheikh and Soltani, 2011).

In the considered case study, a marine radar was applied for maritime traffic control and surveillance. In marine environments, the Gaussian clutter model fits with real data acquired by low resolution or high resolution with low sea state (Skolnik, 2008). A hypothetical radar similar to the X-band radar deployed on Signal Hill by Council for Scientific and Industrial Research (CSIR) was considered (Herselman et al., 2008). In CSIR website (2014), there is measurement trials available to the international radar research community.

Signal Hill location provided 140° azimuth coverage of which a large sector spanned open sea whilst the remainder looked towards the West Coast coastline from the direction of the open sea. Grazing angles ranging from 10° at the coastline to 0.3° at the radar instrumented range of 37.28NM(Nautical Miles) were obtained. The Pulse Repetition Frequency (PRF) was 2 kHz and the range resolution is 15 m. A collaborative 4.2 m inflatable rubber boat, that can be considered as a point target, was used during some measurements (Fig. 3).

Datasets were recorded with different local wind conditions. The average wind speed varied between 0 knots and 40 knots and the significant wave height ranged between 1 m and 4.5 m. For sea state below or equal to two (related to waves height) or a Beaufort number

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