

Intelligent Radar Detectors

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INTRODUCTION

The **Artificial Neural Networks (ANNs)** are based on the behaviour of the brain. So, they can be considered as **intelligent systems**. In this way, the ANNs are constructed according to a brain, including its main part: the neurons. Moreover, they are connected in order to interact each other to acquire the followed intelligence. And finally, as any brain, it needs having memory, which is achieved in this model with their weights.

So, starting from this point of view of the ANNs, we can affirm that these systems are able to learn difficult tasks. In this article, the task to learn is to distinguish between the presence or not of a reflected signal called **target** in a Radar environment dominated by **clutter**. The **clutter** involves all the signals reflected from other objects in a Radar environment that are not the desired **target**. Moreover, the **noise** is considered in this environment because it always exists in all the communications systems we can work with.

BACKGROUND

The ANNs, as **intelligent systems**, are able to detect known **targets** in adverse Radar conditions. These conditions are related with one of the most difficult **clutter** we can find, the coherent Weibull **clutter**. It is possible because ANNs trained in a supervised way can

approximate the Neyman-Pearson (NP) detector (De la Mata-Moya, 2005, Vicen-Bueno, 2006, Vicen-Bueno, 2007), which is usually used in Radar systems design. This detector maximizes the probability of detection (P_d) maintaining the probability of false alarm (P_{fa}) lower than or equal to a given value (VanTrees, 1997). The detection of **targets** in presence of **clutter** is the main problem in Radar detection systems. Many **clutter** models have been proposed in the literature (Cheikh, 2004), although one of the most used models is the Weibull one (Farina, 1987a, DiFranco, 1980).

The research shown in (Farina, 1987b) set the optimum detector for **target** and **clutter** with arbitrary Probability Density Functions (PDFs). Due to the impossibility to obtain analytical expressions for the optimum detector, only suboptimum solutions were proposed. The Target Sequence Known A Priori (TSKAP) detector is one of them and is taken as reference for the experiments. Also, these solutions convey implementation problems, some of which make them non-realizable.

As mentioned above, one kind of ANNs, the **MultiLayer Perceptron (MLP)**, is able to approximate the NP detector when it is trained in a supervised way to minimize the Mean Square Error (MSE) (Ruck, 1990, Jarabo, 2005). So, **MLPs** have been applied to the detection of known **targets** in different Radar environments (Gandhi, 1997, Andina, 1996).

INTELLIGENT RADAR DETECTORS BASED ON ARTIFICIAL NEURAL NETWORKS

This section starts with a discussion of the models selected for the **target**, **clutter** and **noise** signals. For these models, the optimum and suboptimum detectors are presented. These detectors will be taken as a reference for the experiments. After, it is presented the intelligent detector proposed in this work. This detector is based on **intelligent systems** like the ANNs, and a further analysis of its structure and parameters is made. Finally, several results are obtained for the detectors under study in order to analyze their performances.

Signal Models: Target, Clutter and Noise

The Radar is assumed to collect N pulses in a scan, so input vectors (z) are composed of N complex samples, which are presented to the detector. Under hypothesis H_0 (target absent), z is composed of N samples of **clutter** and **noise**. Under hypothesis H_1 (target present), a known **target** characterized by a fixed amplitude (A) and phase (θ) for each of the N pulses is summed up to the **clutter** and **noise** samples. Also, a Doppler frequency in the target model of $0,5 \cdot \text{PRF}$ is assumed, where PRF is the Pulse Repetition Frequency of the Radar system.

The **noise** is modelled as a coherent white Gaussian complex process of unity power, i.e., a power of $\frac{1}{2}$ for the quadrature and phase components, respectively. The **clutter** is modelled as a coherent correlated sequence with Gaussian AutoCorrelation Function (ACF), whose complex samples have a modulus with a Weibull PDF:

$$p(|w|) = ab^{-a} |w|^{a-1} e^{-\left(\frac{|w|}{b}\right)^a} \quad (1)$$

where $|w|$ is the modulus of the coherent Weibull sequence and a and b are the skewness (shape) and scale parameters of a Weibull distribution, respectively.

The $N \times N$ autocorrelation matrix of the clutter is given by

$$(M_c)_{h,k} = P_c \rho_c^{|h-k|} e^{j\left(2\pi(h-k)\frac{f_c}{\text{PRF}}\right)} \quad (2)$$

where the indexes h and k varies from 1 to N , P_c is the clutter power, ρ_c is the one-lag correlation coefficient and f_c is the Doppler frequency of the clutter.

The relationship between the Weibull distribution parameters and P_c is

$$P_c = \frac{2b^2}{a} \Gamma\left(\frac{2}{a}\right) \quad (3)$$

where $\Gamma(\cdot)$ is the *Gamma function*.

The model used to generate coherent correlated Weibull sequences consists of two blocks in cascade: a correlator filter and a NonLinear MemoryLess Transformation (NLMLT) (Farina, 1987a). To obtain the desired sequence, a coherent white Gaussian sequence is correlated with the filter designed according to (2) and (3). The NLMLT block, according to (1), gives the desired Weibull distribution to the sequence. So, in that way, it is possible to obtained a coherent sequence with the desired correlation and PDF.

Taking into consideration that the complex **noise** samples are of unity variance (power), the following power relationships are considered for the study:

- **Signal to Noise Ratio:** $\text{SNR} = 10\log_{10}(A^2)$
- **Clutter to Noise Ratio:** $\text{CNR} = 10\log_{10}(P_c)$

Neyman-Pearson Detectors: Optimum and Suboptimum Detectors

The problem of optimum Radar detection of **targets** in **clutter** is explored in (Farina, 1987a) when both are time correlated and have arbitrary PDFs. The optimum detector scheme is built around two non-linear estimators of the disturbances in both hypotheses, which minimize the MSE. The study of Gaussian correlated **targets** detection in Gaussian correlated **clutter** plus **noise** is carried out, but for the cases where the hypothesis are non-Gaussian distributed, only suboptimum solutions are studied.

The proposed detectors basically consist of two channels. The upper channel is matched to the conditions that the sequence to be detected is the sum of the **target** plus **clutter** in presence of **noise** (hypothesis H_1). While the lower one is matched to the detection of **clutter** in presence of **noise** (hypothesis H_0).

For the detection problem considered in this paper, the suboptimum detection scheme (TSKAP) shown in figure 1 is taken. Considering that the **CNR** is very

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