

# Hardware architecture for adaptive filtering based on energy-CFAR processor for radar target detection

# Santos Lopez-Estrada<sup>1,2a)</sup> and Rene Cumplido<sup>1b)</sup>

 <sup>1</sup> Computer Science Department, National Institute for Astrophysics, Optics and Electronics, P.O. Box 51 and 216, Puebla, 72000, Mexico
 <sup>2</sup> Institute for Research and Technological Development of Mexican Navy, Playa del Este s/n Alvarado Ver. Mexico
 a) santosle@ccc.inaoep.mx
 b) rcumplido@ccc.inaoep.mx

**Abstract:** A hardware architecture that implements an adaptive filter based on energy analysis of radar echoes to improve the detection of the Constant False Alarm Rate (CFAR) algorithm is presented. Signal processing based on energy analysis emphasizes the edge of the echoes improving the performance of the detection process. The energy filter coefficients and CFAR parameters are calculated adaptively by the architecture, reconfiguring the block of coefficient weights according to environment conditions. The architecture accelerates the data processing by a pipeline structure and sliding window for the coefficients convolution with data, resulting in high performance operation. Results of implementing the architecture in a FPGA device are presented and discussed.

**Keywords:** adaptive filtering, target detection, CFAR algorithm, hardware architecture

**Classification:** Science and engineering for electronics

#### References

- A. Farina, F. Gini, and Greco, "High resolution sea clutter data: A statistical analysis of recorded live data," *IEE Proceedings Radar, Sonar and Navigation*, vol. 144, no. 3, pp. 121–130, 1997.
- [2] M. Skolnik, Introduction to radar system, McGraw Hill, New York, 2001.
- [3] G. Richard, *Electronic Intelligence: The analysis of radar signals*, Wiley, 1982.
- [4] K. Laws, "Texture energy measures," DARPA Imaging Understanding Workshop, DARPA, Ed., pp. 47–51, 1979.
- [5] S. Lopez and R. Cumplido, "Decision tree based fpga-architecture for texture sea state classification," 3rd Intenational Conference on Reconfigurable Computing and FPGA's, I. C. S. Press, Ed., pp. 1–7, 2006.
- [6] C. Torres-Huitzil, R. Cumplido, and S. López-Estrada, "Design and implementation of a cfar processor for target detection," *FPL04. Lectures Notes on Computer Science*, vol. 3203, pp. 943–947, 2004.





#### 1 Introduction

The main problem in radar surveillance is to detect the presence of targets in echo signals with added sea clutter. The sea clutter is the term used to describe radar returns caused by reflections in the ocean waves and other atmospheric phenomena. Sea clutter signals can be as strong as the signals returned from the desired target, and can be modeled by means of a probability density function (pdf) such as Weibull or K. Eq. (1) describes the Weibull probability density function, that is an adaptive clutter model, where a is a shape parameter, and b is a scale parameter [1]. The parameters of the pdf distribution that models the sea clutter vary according to the sea state. The sea state can be classified in twelve levels according to the Beaufort/Douglas scale that takes into account wind speed and weaves height. Eq. (2) describes the K pdf, where a is a shape parameter, b is a scale parameter,  $\Gamma(.)$  is a function gamma and K(.) is a Bessel function [1].

$$f(x) = \frac{a}{b} \left(\frac{x}{b}\right)^{a-1} e^{-\left(\frac{x}{b}\right)^a} \tag{1}$$

$$f(x) = \frac{2b}{\Gamma(a)} \left(\frac{bx}{2}\right)^a K(bx)$$
(2)

In radar signal processing, the detection process carries out the separation of the targets and sea clutter, this process is usually performed by an adaptive algorithm named CFAR (Constant False Alarm Rate) [2]. In the literature, multiple variants of this algorithm have been reported, each one designed to detect targets in specific environment conditions. In real applications, these conditions are changing constantly thus it is necessary to adjust the CFAR algorithm and its parameters according to current environment conditions.

Radar returns are composed of target reflections plus sea clutter that can be described as a transient signal in the time domain or as a wide band signal in the frequency domain [3]. Time-frequency and Time-scale analysis are recommended to detect and locate fast transitions in the radar signals such as targets present in clutter. The CFAR algorithm represents only a time scale analysis therefore his performance is poor in presence of changing sea clutter. In this work a complement for the CFAR algorithm is presented, a time frequency analysis of radar returns. This analysis is carried out by an adaptive gradient filter or adaptive textural energy filter that empathize the presence of targets. The filter is implemented in a custom architecture that calculates the filter coefficients according changes in the environment.

## 2 Energy-CFAR filter

The complement for the time-scale analysis is the time frequency analysis that is carried out by the Fast Fourier Transform (FFT), which results in a slow and sometimes deficient signal processing in presence of sea clutter. However, some general statements can be made about the relationship between the frequency components of the FFT and spatial characteristics of radar signals. The frequency is directly related to rate of change and we can associate this property with patterns of intensity variations as a texture in radar signal.







Fig. 1. Proposed Adaptive Energy-CFAR Filter

In this sense the texture energy measures developed by Laws in [4] can be used for enhancing echoes from targets. The energy measure is computed by first applying small convolution kernels to raw radar data X[n], and then performing a windowing operation. The kernel uses a five order window hamming for confining the spectrum in the main lobe of radar signals.

This first evaluation is carried out by a FIR filter implemented in a direct form. A windowing operation generates an energy map. In this process every sample of radar data is replaced with a Texture Energy Measure (TEM). This is carried out by looking in a local neighborhood around each sample and summing together the absolute values of the neighborhood samples. This operation enhances de targets edge increase the performance of target detection of the CFAR algorithm. Eq. (3) describes how to calculate the energy map. Fig. 1 shows a block diagram of proposed adaptive Energy-CFAR filter.

$$Y_{new}[n] = \sum_{i=-7}^{i=7} |Y_{old}[n+i]|$$
(3)

The Energy FIR filter coefficients C[n] are updated dynamically according the environment changes by the square error (MSE) algorithm described by Eq. (4).

$$C_{i}[n+1] = C_{i}[n] + \eta e[n]X[n]$$
(4)

$$e[n] = T[n] - SC[n] \tag{5}$$

Where e[n] represents the error obtained as described by Eq. (5),  $\eta$  is an adjustment parameter that depends on the radar signal power, X[n] is raw radar data, T[n] represents the Energy-CFAR filter output and SC[n]represents the sea clutter according to environment conditions. SC[n] is obtained by the sea clutter model described by Eqs. (1) and (2) using specific shape a and scale b parameters. The selection model is obtained by sea state SS value. These parameters are calculated by a method and architecture described in [5].

#### **3** Energy-CFAR architecture implementation

A block diagram of the processing element (PE) for the FIR filter is shown in Fig. 2(a). This PE can be easily extended to increment the filter order







Fig. 2. Components of the proposed architecture (a) PEFF, (b) PEEM, (c) PEUC, (d) Data dependencies and latency

and takes advantage of the raw radar data dependencies and the shift register characteristics to evaluate the convolution of raw radar data with filter coefficients on the as is shown in the Eq. (6). Fig. 2(d) shows the data dependencies and latency for this PE.

$$Y[i] = C_1 X[i] + C_2 X[i-1] + \dots + C_i X[1]$$
(6)

A block diagram of the PE of the Energy Map module is shown in Fig. 2 (b). This PE takes a neighborhood of 15 samples to evaluate the energy of the central sample according to Eq. (3). In order to increase the number of samples evaluated, this PE can also be easily extended. A block diagram of the PE of the Adaptive Weights Calculator module is shown in the Fig. 2 (c). This PE updates the coefficients and is cloned N-times, where N represents the order of FIR filter; Finally the Sea Clutter generator is implemented Look Up Tables (LUT) that record sea clutter data obtained by the model of the Eqs. (1) and (2). The architecture of the used CFAR module is described in [6].

## 4 Results and discussion

The proposed architecture was validated using two data sets. The first data set is a real range profile (targets plus sea clutter), obtained with an X band





radar (9 GHz) with 30 dB of gain and figure of merit of 3 dB. The data were digitized at 100 MHz and 8 bits. The second data set is a synthetic range profile, the sea clutter is generated with a Weibull and K pdf models, with 256 amplitude levels (8 bits) and thermal noise of 316 mv average. The



Fig. 3. Output of Energy-CFAR, (a) synthetic targets, (b) targets plus Clutter (SS 5), (c) output with typical CFAR algorithm, (d) output with proposed Energy-CFAR architecture, (e) performance of proposed architecture VS typical CFAR variants





synthetic targets were created with 10 to  $50 \text{ m}^2$  of radar cross section (RCS) and amplitude level between 5 and 20 dB.

Fig. 3 shows the outputs obtained after processing the range profile with the proposed architecture. Fig. 3 (a) shows targets with amplitude of 5, 3, 12, 10 and 15 dB and 20, 10, 20, 10 and 12 m<sup>2</sup> of RCS respectively. Fig. 3 (b) shows a range profile composed with targets plus sea clutter (sea state 5) generated with K pdf. In Fig. 3 (c), the output of CFAR algorithm without energy filter is shown. Note that two targets are lost, additionally it presents excessive false detections. Fig. 3 (d) shows the results obtained with the proposed energy-CFAR architecture. The targets are enhanced; this avoids the loss of targets while the clutter is minimized decreasing false detections. In Fig. 3 (e), a comparison of the performance of multiple CFAR variants is shown. The solid line is an ideal CFAR without clutter, the other lines represent the outputs of proposed Energy-CFAR, trimmed mean-CFAR (TM-CFAR), order statistic-CFAR (OS-CFAR) and cell averaging-CFAR (CA-CFAR) [2]. The curves show that processing range profiles with Energy-CFAR yield better performance than the other variants.

For testing and validation, the architecture was implemented in VHDL language and synthesized for a Virtex 2 XC2V1000 Xilinx FPGA using the Xilinxs ISE 9.2 development tool. The maximum operational frequency as reported by the tool is 150 MHz with a maximum throughput delay of 20 ns. The occupied area for the selected FPGA device is just 30%.

# **5** Conclusions

A hardware architecture of an adaptive filter, based on energy analysis for radar targets detection was described. The energy analysis used by proposed Energy-CFAR architecture results better performance that other CFAR variants reported in literature. The processing time obtained by the FPGA-based hardware implementation shows that this module is suitable for being used in modern radar processing systems. The simple design leads to a fast yet small architecture. Finally, the proposed design allows to an easy configuration of the adaptive filtering in order to adjust the system according to changing environment conditions.

