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Fast selection of the sea clutter preferential distribution with neural networks

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A B S T R A C T

Studies performed on sea clutter readings often include fitting the data searching for the preferential amplitude distribution. In this process, the estimation through the method of moments and the Kolmogorov–Smirnov test are usually used with positive results. However, the procedure cannot be directly applied in the fast selection of the distribution in operational schemes because it consumes a high amount of computational resources. The authors found a new way of estimating the sea clutter preferential distribution by using a neural network that takes histograms of the readings as an input, achieving faster and more precise results than the traditional alternative. The effectiveness of the proposal was verified with computer generated data for the Weibull, Log-Normal and K distributions. Besides, analyses were executed including real radar samples taken with the IPIX radar.

1. Introduction

Nowadays, the radar has evolved from its initial applications in the military field to be widely used in civilian tasks, such as weather forecast, control of air and maritime traffic, and road safety (Melvin, 2014). Yet, the main purpose of the device remains the same: to detect objects within the exploration region and to estimate their position, speed and movement direction, among other features (Meikle, 2008).

When operating in maritime scenarios, in addition to the signal returning from targets, the radar antenna receives undesired contributions from reflections originated at the sea surface. Known as sea clutter, these contributions exhibit a random behavior, which has been deeply studied and reproduced in simulation environments (Oluwale Oyedokun, 2012).

Particularly, the selection of the clutter preferential distribution has been addressed in multiple investigations due to its proven influence in the detection (Sekine et al., 2015; Palama et al., 2015). The Weibull (Ishii et al., 2011; Dong, 2006), Log-Normal (Yim et al., 2007; Sayama and Ishii, 2013) and K (Meng et al., 2013; Tanriverdi, 2012) models are generally accepted as the best ones for representing the fluctuation of sea surface measurements for a wide range of conditions (Machado Fernández and Bueno González, 2012).

In order to estimate which distribution holds a better proximity with a given set of samples, a process based on two steps is usually followed (Gato Martínez et al., 2016; Makhoul et al., 2014; Mandal and Bhattacharya, 2013): (1) the estimation of the shape parameter using the Method of Moments (MoM), and (2) the selection of the best model by applying the Kolmogorov–Smirnov (KS) goodness of fit test. Although its use is extensive, the algorithm cannot be applied in operational environments given its high computational cost, which delays the response of radar systems. Therefore, its application has been limited almost exclusively to conducting a posteriori analysis of the collected information.

For solving the above described problem, the authors aimed at finding a new method for the selection of the sea clutter preferential distribution with an improved performance in terms of speed. The solution, that was finally conceived, managed to significantly accelerate the execution times using Neural Networks (NN) to replace both the MoM estimation and the KS test. Together, the new scheme enhanced the accuracy of results, which indicates it will also contribute to improve radar detection and identification of abnormal features of the sea surface. The technique was validated with computer generated data and radar readings for the Weibull, Log-Normal and K distributions, and it is expected to be extended to other clutter related models such as the Pareto and Compound Gaussian.

The paper proceeds as follows. The next section, under the name of "Materials and Methods", provides the basics of the Weibull, Log-Normal and K distributions, as well as supplementary information on the MoM and the KS test. In addition, the internal variables of the neural network are also described. Later, in "Results and Discussion", the performance of the neural network is compared with that achieved applying the MoM and KS combination, both with computer generated

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data and with samples taken from a database recorded with the IPIX radar. Furthermore, an assessment is made on the importance and application of the presented method. Finally, "Conclusions and Future Research" closes the document, summarizing the main contributions of the paper and offering recommendations on possible research lines.

2. Materials and methods

The current section is divided into three sub-sections. The first one introduces the main definitions related to the Weibull, Log-Normal and K distributions, justifying the choice of these models. The second one describes the traditional alternative for selecting the preferential clutter distribution consisting of two techniques: (1) parametric estimation and (2) decision on the best model. The third and final sub-section presents the characteristics of the neural network used to obtain the new solution.

2.1. Amplitude distributions

The amplitude distributions used in this project were the Weibull (1), the Log-Normal (2), and the K (3). They have all received intensive validation in the radar community and they were categorized as classical distributions for sea clutter modeling in Machado Fernández and Bueno González (2012).

The K distribution is the most widely accepted model for high resolution sea echoes observed at low grazing angles (Ward et al., 2013). The Weibull distribution is a versatile choice that has been used for land (Sayama and Sekine, 2001), weather (Sayama and Ishii, 2013) and ice (Vicen Bueno et al., 2010) clutter; in addition, in Ishii et al. (2011) and Vicen Bueno (2011) it was chosen as the best fitting model for sea clutter data. Finally, the Log-Normal distribution tends to fit measurements in particular situations such as: when the HH polarization is used (Farina et al., 1997), when analyzing the clutter spatial distribution (Dong, 2004), and for cells containing strong mixed target and clutter reflections (Ishii et al., 2011; Sayama and Ishii, 2013).

$$f_W(x|\alpha,\beta) = \frac{\beta x^{\beta-1}}{\alpha^\beta}\exp\left[-\left(\frac{x}{\alpha}\right)^\beta\right] \tag{1}$$

$$f_{LN}(x|\mu,\sigma) = \frac{1}{\sigma x\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{\ln x-\mu}{\sigma}\right)^2\right] \tag{2}$$

$$f_K(x|c,\upsilon) = \frac{4c}{\Gamma(\upsilon)}(cx)^\upsilon K_{\upsilon-1}(2cx) \tag{3}$$

In expression (1), f_W is the Weibull PDF (Probability Density Function), while α and β are the scale and shape parameters respectively. Likewise, in (2) and (3), f_{LN} and f_K are the Log-Normal and K PDFs, being (μ, c) the scale parameters and (σ, υ) the shape parameters. In all cases, the x was used as the independent variable. Moreover, $\Gamma(.)$ is the Gamma function and $K_{\upsilon-1}(.)$ is the Bessel function of the second kind and order $\upsilon-1$ (OConnor, 2011). Complementary formulas such as expressions for computing moments can be found in OConnor (2011) and Cetin (2008).

The shape parameter is the one who plays a decisive role in the detection (Machado Fernández and Bacallao Vidal, 2014). Therefore, the neural network was trained with samples whose shape parameter was altered in the range of possible values, whereas the scale parameter was arranged for forcing the mean to one, similar to what was done in Machado Fernández et al. (2015), Machado Fernández and Bacallao Vidal (2016a) and Machado Fernández (2015). For the Weibull case, it was used: $0,5 < \beta < 6,25$ (Sekine et al., 2015; Sayama and Ishii, 2013; Vicen Bueno, 2011; Dong, 2004; Sayama et al., 2006; Greco et al., 2004), for the Log-Normal model: $0,025 < \sigma < 1,25$ (Sayama and Ishii, 2013; Sayama and Sekine, 2001; Farina et al., 1997; Greco et al., 2004), and for the K distribution: $0,1 < \upsilon < 30$ (Dong, 2006; Sayama et al., 2006; Greco et al., 2004; Antipov, 2001; Nohara and Haykin, 1991). The normalization of the mean simplifies the problem presented to the neural network without disturbing the proportion between the samples. It should be noted that the output of any common CFAR technique remains invariable when fed with normalized samples.

2.2. Method of moments and KS test

When looking to match a statistical distribution with radar readings, the method of moments and the KS test are commonly used (Gato Martínez et al., 2016; Makhoul et al., 2014; Mandal and Bhattacharya, 2013). The first one is responsible for searching the best matching configuration of the parameters for each distribution. Then the second one decides which of the distributions displays a better fit with the readings, making a comparison between the empirical and the theoretical CDFs (Cumulative Distribution Function), being the latter estimated from the MoM calculations.

Expression (4) results from applying the MoM to the Weibull distribution (Nielsen, 2011). The formula needs to be solved by iterative methods because the shape parameter (β) cannot be separated from the Gamma function ($\Gamma(.)$) (OConnor, 2011). Moreover, m_1^2 is the square of the mean and m_2 is the second algebraic moment (intensity).

$$\frac{m_2}{m_1^2} = \frac{\Gamma\left(\frac{2}{\beta}+1\right)}{\Gamma^2\left(\frac{1}{\beta}+1\right)} \tag{4}$$

Once β is obtained, α can be calculated using (5).

$$\alpha = \frac{E[x]}{\Gamma(1+\frac{1}{\beta})} \tag{5}$$

Moreover, the Lognormal parameters can be estimated using (6) and (7) (McLeod, 1998). In this case, the scale parameter (μ) should be estimated first because it is need for the shape parameter (σ).

$$\mu = \frac{1}{N}\sum_{i=1}^{N}\ln x_i \tag{6}$$

$$\sigma = \frac{1}{N-1}\sum_{i=1}^{N}\ln x_i - \mu^2 \tag{7}$$

Lastly, although there are several alternatives, expressions (8) and (9) are usually applied for estimating the K distribution parameters, taking the second (m_2) and fourth (m_4) algebraic moments as input (Yim et al., 2007; Mezache and Sahed, 2010).

$$\upsilon = \frac{1}{\frac{m_4}{2m_2^2}-1} \tag{8}$$

$$c = \sqrt{\frac{\upsilon}{m_2}} \tag{9}$$

The KS goodness of fit test verifies the rejection of the null hypothesis (H_0), which states that the empirical cumulative distribution coincides with the theoretical one denoted $F(x)$. Assuming $S_n(x)$ is the empirical CDF observed in a radar measurement, containing the $x_1, x_2, \ldots, x_n$ samples, the null hypothesis will not be rejected if there are reduced deviations of $S_n(x)$ from $F(x)$. Specifically, the test uses the largest deviation as a measure of the quality of the fit, applying formula (10).

$$D_n = max|F(x) - S_n(x)| \tag{10}$$

After calculating D_n, auxiliary expressions detailed in Marques de Sá (2007) allow verifying the quality of the fit through a variable commonly denoted as p, whose value goes from 0 to 1. As p approaches to one, it is presumed that the fit is more accurate. However, if the variable falls below 0,05 the null hypothesis will be rejected.

When the goodness of fit test is performed on clutter data, it is considered that the model exhibiting the highest p value is the preferential distribution. The CDFs shown in (11), (12) and (13) correspond to the Weibull, Log-Normal and K distributions respectively (Ward et al., 2013; Cetin, 2008), where erf is the error function.

$$F(x|\alpha,\beta) = 1 - \exp\left[-\left(\frac{x}{\alpha}\right)^\beta\right] \tag{11}$$