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Sea surface target detection based on complex ARMA-GARCH processes

Yunjian Zhang [a], Yixiong Zhang [a,*], Zhenmiao Deng [a,1], Xiao-Ping Zhang [b], Hui Liu [a]

[a] School of Information Science and Engineering, Xiamen University, China
[b] Department of Electrical and Computer Engineering, Ryerson University, Canada

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ABSTRACT

In financial applications, it is common practice to fit return series by AutoRegressive Moving-Average (ARMA) models with Generalized AutoRegressive Conditional Heteroscedastic (GARCH) errors. In this paper, we develop a complex-valued ARMA-GARCH model for the sea clutter modeling application. Compared with the AR-GARCH model, the additionally introduced MA terms make the proposed model capable of considering the dependence of conditional variances of adjacent echo measurements as model coefficients, improving the modeling precision by taking advantage of the strong correlations between adjacent measurements. Based on the complex-valued ARMA-GARCH process for sea clutter modeling, we further develop a sea surface target detection algorithm. By analyzing a large number of the practical sea clutter data, we evaluate its performance and show that the proposed sea surface target detector offers a noticeable improvement for the probability of detection, comparing with the state-of-the-art AR-GARCH detector.

1. Introduction

Accurate modeling of sea clutter is of great importance in remote sensing and radar applications, and it benefits optimum detection algorithm design and performance prediction [1–9]. To comprehensively investigate the statistical characteristics of practical clutter under different environmental conditions, a variety of experiments have been carried out, and the databases are available to the international research community, e.g., the McMaster Intelligent PIXel Processing Radar (IPIX) database [10] and the Council for Scientific and Industrial Research (CSIR) database [11]. At times, however, the data necessary for the statistical description of the amplitude and the power of clutter are either not available or scarce for various sea states, grazing angles, polarizations and wind directions. Alternatively, the computer simulation program provides an inexpensive and reliable environment to obtain the synthetic clutter data at various frequency bands [12,13].

For low grazing angles, sea clutter is generally characterized by Weibull [14], K [15], log-normal [16], Pareto [17], and Compound-Gaussian (CG) [18] Probability Density Functions (PDFs), etc. It is noted that the Pareto distribution is also a good model for high grazing angle sea clutter [19]. Traditional statistics-based detection methods, however, cannot obtain the expected results when the model of sea clutter and target does not fit the practical complicated environment [20]. Moreover, these traditional distributions cannot precisely model the possible temporal dependencies in the return series.

The CG process can be expressed as a product model [18]

$$c_t = \sqrt{\tau_t} g_t \tag{1}$$

where the fast-changing component g_t, which accounts for local scattering, is referred to as speckle. The nonnegative real stochastic variable τ_t, which represents the variation of the local power of the clutter due to the tilting of the illuminated area, is referred to as texture. The product model describes the scattering mechanism for observation time intervals on the order of the Coherent Processing Interval (CPI) of the radar system [21]. Therefore, the CG model is widely used to characterize the heavy-tailed clutter distributions in radar applications, especially sea clutter modeling [22]. The texture of the CG process, which controls the variance of the compound process, is commonly assumed to follow certain distribution, e.g., Gamma [23], inverse Gamma [23,24], and inverse Gaussian [25]. However, in practice, it is difficult to determine which texture distribution is optimal.

The introduction of Generalized AutoregRessive Conditional Heteroscedastic (GARCH) processes [26] for sea clutter modeling [27] provides a novel method to model the amplitude of clutter echo as a time series. Here, the term "heteroscedastic" means that the variance is not constant but time-varying. In [28], the authors

* Corresponding author.
E-mail address: zyx@xmu.edu.cn (Y. Zhang).
[1] EURASIP member.

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propose a complex nonlinear ARCH model and the corresponding detector, which achieves higher probability of detection, comparing with the linear GARCH detector. Both linear and nonlinear GARCH-type processes, however, cannot consider the strong correlations between adjacent clutter returns. Therefore, in order to have a quantitative idea, it is necessary to first estimate the data autocorrelation functions by means of the average of their temporal autocorrelation functions [27]. Subsequently, according to the estimated autocorrelation functions, one can predict that samples from two pulses separated a certain interval are not correlated. For instance, if after six pulses, the autocorrelation function is approximately zero, then we extract one sample from six successive samples. This data extraction method is apparently inefficient, since most of the radar resources are wasted. Hence, a family of GARCH-type processes have been investigated for sea clutter modeling and a generalized nonlinear-asymmetric GARCH model, combining with the AutoRegressive (AR) process, is proposed in [29]. Due to the introduction of AR process, the interval of extraction can be moderately reduced.

It is worth noting that the GARCH process is also a product model, as observed in the next section. Therefore, it naturally inherits the advantages of the CG model. The main difference between GARCH and CG processes is that the conditional variances of GARCH processes are time-varying and dependent on historic information. Two primary features of the GARCH process are leptokurticity and volatility clustering (i.e., large changes tend to follow large changes and small changes tend to follow small ones), which are exactly shown in sea clutter measurements. The history information is used to improve the model characterization at current time and future predictions. While the correlations between adjacent clutter measurements are strong, samples from two pulses separated by a time interval become uncorrelated. It means that when using a GARCH process (or a nonlinear GARCH process) for clutter modeling, it is necessary to first analyze the autocorrelation function of clutter to determine the proper time interval. Apparently, this method is inefficient or even not available when the radar dwell time is relatively short, leading to insufficient data length for precise parameter estimation.

Subsequently, Pascual et al. [30] propose a complex Two-Dimensional AutoRegressive GARCH (AR-GARCH-2D) process for sea clutter modeling. By introducing AR terms, the correlations of adjacent measurements are modeled as coefficients of the conditional mean. However, not only the clutter measurements but also their conditional variances are dependent, because the conditional variance is composed of past information including clutter measurements. Therefore, it is natural and reasonable to add Moving Average (MA) terms in conditional mean expression of the model to obtain more precise modeling of practical sea clutter. The new clutter model comes with two advantages: 1) data extraction is no longer necessary and the required radar dwell time can be greatly reduced; 2) the conditional mean of practical clutter is more precisely modeled, resulting in smaller conditional variances, which is closely related to the decision threshold of the detector, as shown in Section 4.3.1.

In this paper, by using practical sea clutter data, we demonstrate that the proposed ARMA-GARCH detector offers a noticeable improvement for the probability of detection, comparing with the AR-GARCH detector. It is worth mentioning that we mainly discuss the 1-D situation to expound the advantages of adding MA terms in the conditional mean expression. In other words, the pulse dimension (slow time dimension) clutter is modeled as a complex ARMA-GARCH process. In fact, the ARMA-GARCH process and the corresponding detection algorithm can be conveniently extended to the 2-D case by incorporating range dimension (fast time dimension) measurements and conditional variances of range dimension in the current conditional variance expression. Meanwhile, however, the required data size for parameter estimation increases. Moreover, the range resolution of the radar data used in this paper is 30 m, which leads to negligible coefficients of the range dimension. As a result, the 2-D and 1-D processes, as well as the corresponding detectors, are essentially the same. This viewpoint is demonstrated by numerical simulations in Section 4. It is inferred that with the improvement of radar resolution, the 2-D detector may achieve better performance.

The rest of this paper is organized as follows. Section 2 briefly introduces the complex 1-D and 2-D ARMA-GARCH processes, as well as the parameter estimation algorithm and model order selection criteria. Based on the 1-D model for the sea clutter, a binary hypothesis test detection algorithm is developed in Section 3. In Section 4, numerical simulations are conducted to validate the advantages of the proposed detector.

2. Novel clutter model based on complex ARMA-GARCH process

2.1. A novel clutter model

In the new clutter model, we model sea clutter measurements as a complex ARMA(p,q)-GARCH(m,n) process c_t, defined by the following

$$\varphi(B)c_t = \psi(B)\varepsilon_t \tag{2}$$

$$\varepsilon_t = \sqrt{h_t}\eta_t \tag{3}$$

$$h_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i |\varepsilon_{t-i}|^2 + \sum_{i=1}^{n} \beta_i h_{t-i}, \tag{4}$$

where $\varphi(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p$ and $\psi(B) = 1 + \psi_1 B + \cdots + \psi_q B^q$ are polynomials of B with no common factors; B is the backward-shift operator, e.g., $B^p y_t = y_{t-p}$; positive integers p, q, m, n are model orders; and η_t is a sequence of i.i.d. circular normal stochastic variables, i.e., $\eta_t \sim \mathcal{CN}(0,1)$; $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ are coefficients of conditional variance h_t, while the restrictions on them guarantee the positivity of h_t. The unconditional variance of the GARCH part is finite if $\sum_{i=1}^{m} \alpha_i + \sum_{i=1}^{n} \beta_i < 1$ [26]. Moreover, suppose that all roots of $\varphi(B) = 0$ and $\psi(B) = 0$ lie outside the unit circle, then c_t is strictly stationary and ergodic [31]. Also note that $\{\varphi_i\}_{i=1}^{p}$ and $\{\psi_i\}_{i=1}^{q}$ are complex coefficients of the model.

The in-phase and quadrature components of the received radar echoes respectively correspond to the real and imaginary part of $c(t)$. From (2)–(4), it is seen that comparing with the AR-GARCH process, not only the past measurements $\{y_{t-i}\}_{i=1}^{p}$ but also the past conditional variances $\{h_{t-i}\}_{i=1}^{q}$ are incorporated in the echo model, resulting in more accurate modeling precision of the current conditional variance, which is essential for the detection performance.

Let $\mathcal{F}_t$ denote the sigma-field generated by the past information, i.e., h_τ, c_τ and ε_τ for $\tau < t$. Then, if we condition c_t to $\mathcal{F}_t$ from (2), we see that c_{t-i}, ε_{t-i}, $i = 1, 2, \ldots$ are given and only ε_t is random; thus

$$c_t|\mathcal{F}_t \sim \mathcal{CN}\left(\sum_{i=1}^{p} \varphi_i c_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i}, h_t\right). \tag{5}$$

Incorporating the range dimension measurements and conditional variances of the range dimension in (4), we obtain conditional variance expression of the 2-D ARMA-GARCH model

$$h_{rt} = \alpha_0 + \sum_{i,j \in \Lambda_1} \alpha_{ij} |\varepsilon_{r-i,t-j}|^2 + \sum_{i,j \in \Lambda_2} \beta_{ij} h_{r-i,t-j}, \tag{6}$$

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