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Research on parameters estimation of sea clutter in data preprocessing

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ABSTRACT

In the area of radar image analysis and small target detection in the sea, it is very important to study the characterization of sea clutter. It is modeled as a stochastic process traditionally. Recent research shows that it has chaotic characterization. The sea clutter parameter estimation plays an important role in the radar image processing. To adapt to different sea conditions, both "high sea state data" and "low sea state data" are used in this paper. The paper presents the detailed parameters estimation methods and procedure, which laid the foundation for further image denoising and analysis.

1. Introduction

Sea clutter is the result of radar backscatter from a sea surface which interferes in performance of targets detection seriously in sea clutter. Therefore, it is important to study sea clutter for radar system design, radar image analysis and small targets detection. Traditionally, sea clutter is modeled as a stochastic process. Some successful models, such as Rayleigh, Weibull, and *K*-distribution, have been widely used. The technology of detecting small targets in sea clutter is based on the statistical hypothesis testing theory. It is very difficult to detect a small target with low false alarm probability when sea clutter is very strong.

In recent years, many researchers find that sea clutter is not an entire random signal through the further study. It contains certain factors with a lot of typical characteristics of chaos [1–3]. Sea clutter is considered as chaos for its chaotic characterizations as follows: (1) sea clutter is bounded. (2) The largest Lyapunov exponent of sea clutter is positive. (3) Sea clutter has a finite correlation dimension. (4) Sea clutter is locally predictable; most importantly, the dynamics of sea clutter can be reconstructed by a deterministic model. Compared with classical statistical model, chaotic model [4,5] combines the sea clutter mathematical model and physical property more effectively which can describe the sea clutter in smaller degrees of freedom and provide a new idea to the dynamic system. The performance of the detection would be improved [6,7].

The paper is organized as follows. We start with an introduction of reconstruction of dynamics from a time series [3] in Section 2, which contains the method to estimate the time delay and the embedding dimension. Then correlation dimension and Lyapunov exponent [4] of the time series are discussed. In Section 3, we introduce the database used for the study and results are presented using real-life radar data. Some conclusions are given in Section 4.

2. Chaotic characterization of sea clutter

To apply chaos-based method to radar signals processing, we must demonstrate that sea clutter is chaotic first. We will introduce some concepts of the chaotic invariants of sea clutter, such as the correlation dimension and the maximum Lyapunov exponent. First, we use phase space reconstruction to illustrate the trajectories of the sea clutter. Second, a standard correlation dimension analysis of the data is performed. Third, the method to calculate the maximum Lyapunov exponent is presented.

2.1. Phase-space reconstruction

Information about the dynamics of sea clutter is particularly important in radar signal processing. Phase-space reconstruction is the first step to study the chaotic characterization of sea clutter, which plays an important role in the calculation of chaotic invariants of sea clutter. First we estimate the embedding dimension m and the time delay τ based on Takens' embedding theorem, and then reconstruct the phase space of the data using the parameter m and τ.

Takens' embedding theorem is an existence theorem, which provides the mathematical basis of the dynamic reconstruction problem. It says that if a strange attractor of dimension is in a

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sufficient embedding dimension $m > 2D+1$ (D is correlation dimension), there is a nonlinear function F as follows:

$$y(t+m\tau) = F(x(t),\ x(t+\tau),\ \ldots,\ x(t+(m-1)\tau)) \tag{1}$$

Here we will reconstruct the phase space by a time series $\{x(t);\quad t=1,2,\ldots,N\}$. We assume M is an m-dimensional compact manifold. According to Takens' embedding theory, the map Φ: $M \rightarrow R^m$ defines a corresponding trajectory $\Phi(i)$:

$$\Phi(i) = \{x(i),\ x(i+1),\ \ldots,\ x(i+m-1)\} \tag{2}$$

A chaotic dynamical system is described by the difference equation on M:

$$y(t+1) = \varphi(y(t)) \tag{3}$$

where ϕ is a nonlinear function. Thus we have

$$\Phi(i+1) = \varphi(\Phi(i)) \tag{4}$$

equivalently,

$$\{x(i+1), x(i+2),\ \ldots,\ x(i+m)\} = \varphi\{x(i), x(i+1),\ \ldots,\ x(i+m-1)\} \tag{5}$$

Each point of the left-hand side is determined by the components of the right-hand side. So we define a function F to describe the equation:

$$x(i+m) = F\{x(i),\ x(i+1),\ \ldots,\ x(i+m-1)\} \tag{6}$$

For a time series, we rewrite the equation as follows:

$$x(t+m\tau) = \{x(t),\ x(t+\tau),\ \ldots,\ x(t+(m-1)\tau)\} \tag{7}$$

where τ is the time delay, m is the embedding dimension.

There are two parameters for the phase-space reconstruction: the time delay τ and the embedding dimension m. The size of τ and m is very important to the quality of the phase-space reconstruction. The method of autocorrelation is used to estimate the time delay and GP method [8] is used to estimate the embedding dimension.

2.1.1. Time delay

The estimation of the time delay is important to the performance of the phase-space reconstruction. If τ is too small, the vector of delay is too close to serve as independent coordinates. On the other hand, if τ is too large, the vector of delay is independent and loses the connection with each other. So it is necessary to choose an optimum to compromise these situations between redundancy and irrelevance. In practice, the method of autocorrelation function and mutual information is usually used to estimate the time delay. Because of the simplicity of autocorrelation function and consistency with the dimension estimator, the former method is used here.

For a continuous variable $x(t)$, the autocorrelation function is given as follows:

$$C(\tau) = \lim_{T\rightarrow\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t)x(t+\tau)\,dt \tag{8}$$

For a time series $\{x(t); t=1,\ 2,\ \ldots,\ N\}$, the autocorrelation function is given as follows:

$$R_{xx}(\tau) = \frac{1}{N}\sum_{t=0}^{N-1} x(t)x(t+\tau) \tag{9}$$

A suitable τ is chosen as the first zero-crossing point of the autocorrelation function.

2.1.2. Minimum embedding dimension

Embedding dimension is another important parameter of phase-space reconstruction. The geometry of dynamical system will exist naturally in an uncompacted or unfolded state in a particular dimension known as the embedding dimension. In dimensions below m, the dynamical system is compacted in an unnatural way and its geometry is said to be folded. Takens' embedding theorem showed $m > 2D+1$ is the sufficient condition to the embedding dimension. We should choose an optimal value of m in the phase-space reconstruction. If m is too small, the geometry will become folded. The shape of the reconstructed attractor and the original attractor is completely different. In the contrast, if m is chosen too large, it will increase the complexity of computation and the effect of noise will also be amplified.

2.2. Correlation dimension

Attractor dimension is a very important concept in analysis of nonlinear dynamic system, which can serve as a means of illuminating the complexity of an attractor structure. Correlation dimension is considered to be the most popular method used to perform the estimation of an attractor dimension from practical time series. The correlation dimension with large computing can be used as an effective criterion to justify the presence of chaos. For a system to be chaotic, the correlation dimension must be positive.

For any set of n points in an m-dimensional space, the definition of Grassberger and Procaccia for the correlation dimension is given by

$$D_c = \lim_{r\rightarrow 0}\left\{\frac{\ln(A_r)}{\ln(r)}\right\} \tag{10}$$

$$A_r = \lim_{n\rightarrow\infty}\left\{\frac{s}{n^2}\right\} \tag{11}$$

where s is the total number of pairs of points which have a distance between them that is less than distance r.

On the basis of the definition, Grassberger and Procaccia develop an algorithm to estimate the correlation dimension. This method, which is named GP method, will be introduced as follows:

Given a time series $\{x(t); t=1,2,\ldots,N\}$, we reconstruct a m-dimensional portrait. By the use of Takens' embedding theorem, we can get a group of vectors:

$$X(t) = \{x(t)mx(t+\tau),\ldots,x(t+(m-1)\tau)\tag{12}$$

where τ is the time delay, m is the embedding dimension, $M = N-(m-1)\tau$ is the number of vector points in the reconstruction phase-space.

The correlation integral is defined as:

$$C_n(r) = \frac{1}{M^2}\sum_{i,j=1}^{M}\theta[r-||X(i)-X(j)||] \tag{13}$$

where r is a positive number, θ is the Heaviside function:

$$\theta(x) = \begin{cases} 0, & x \le 0 \\ 1, & x > 0 \end{cases} \tag{14}$$

where $||X(i)-X(j)||$ is the Euclidean norm, which provides a convenient method to calculate the distance between two points.

Correlation integral $C_n(r)$ describes the probability of which the distance between the two points in attractor is less than r. When $r\rightarrow 0$,

$$\lim_{r\rightarrow 0} C_n(r) \propto r^D \tag{15}$$