Chaos Detection in the Firing Activities of Retinal Ganglion Cells in Response to Natural Stimuli

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Abstract

The correlation dimension method and the nonlinear forecasting method are applied to analyze the firing activities recorded by a multi-electrode array (MEA) from the retinal ganglion cells (GCs) of chicken in response to natural stimuli. The results show that neither the correlation dimension method nor the nonlinear forecasting method provides any evidences for chaos in the inter-spike interval (ISI) series derived from retinal GCs. Then the first difference of the ISI (DISI) series is analyzed in the same way and different conclusions are drawn. The correlation dimension method fails again to provide evidences for chaos in the DISI series. The nonlinear forecasting method, however, demonstrates some weak but distinct evidences for chaos in the DISI series, which indicates that the nonlinear forecasting method is more efficient and reliable than the correlation dimension method for chaos detection. On the other hand, the first difference operation of the ISI series makes it comparatively easier for chaos detection in the firing activities of retinal GCs in response to natural stimuli.

1. Introduction

Much of what we know about visual information processing has been obtained from experiments using artificial stimuli, such as spots of light or sinusoidal gratings. However, studies using such simple stimuli alone do not necessarily tell us how a neuron responds to the more complex stimuli encountered in the natural environment [1]. Recent studies using natural stimuli have yielded new insights into the function of the visual system. However, owing to the complex statistical properties of natural stimuli, analyzing the response properties of sensory neurons under natural stimuli is not as straightforward as for the artificial stimuli.

With the great progress being made in nonlinear dynamics, particularly the findings and applications of chaos, there has been much interest in explaining the irregular behavior in neural systems due to their intrinsic strong nonlinearity. Chaos provides a new window to reveal the dynamical properties of neural systems. The most widely used method for chaos detection is the correlation dimension method proposed by Grassberger and Procaccia that use correlation integrals to determine the attractor's correlation dimension [2]. Another way for chaos detection is the nonlinear forecasting method originally developed by Sugihara and co-workers and extended by Sauer [3]-[5]. Since this method is capable of detecting a weak chaos, it has been used to analyze many experimental data. Applying the two methods, Xu and co-workers studied the inter-spike interval (ISI) series derived from a single fiber of the injured sciatic nerves in the anesthetized rat [6]-[7]. Their results showed that there exits weak chaos in the firing activities of sciatic nerves and the nonlinear forecasting method is more efficient and reliable than the correlation dimension method for chaos detection.

In the present study, a multi-channel recording system was used to simultaneously record the firing activities of chicken's retinal ganglion cells (GCs) in response to natural stimuli (movie) and then the correlation dimension method and the nonlinear forecasting method are applied to analyze the ISI series. The results show that neither the correlation dimension method nor the nonlinear forecasting method provides any evidences for chaos in the ISI series. However, the nonlinear forecasting method demonstrates some weak but distinct evidences for chaos in the first difference of the ISI (DISI) series.

2. Methods

2.1. Experiment Procedure

The detailed experimental procedure was fully described previously [8]-[9]. In brief, extracellular recordings were made in isolated chicken retina in

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response to natural stimuli using a multi-electrode array (MEA, Multi Channel Systems MCS GmbH, Germany). The MEA consisted of 60 electrodes (10 μm in diameter) arranged in an 8×8 matrix with 100 μm tip-to-tip distances. A small piece of retina quickly isolated from young born chicken (about 1–3 weeks) was attached with the GC side onto the surface of MEA. Natural stimuli were simulated by a grayscale movie (downloaded from the website of Hateren's lab, http://hlab.phys.rug.nl/vidlib/index.html). The movie was displayed on a computer monitor (796 FD Ⅱ, MAG) and then focused to form a 0.7×0.7 mm image onto the isolated retina via a lens system. Firing activities of GCs were simultaneously recorded by MEA using commercial software MC_Rack (Multi Channel Systems MCS GmbH, Germany) with a sampling rate of 20 kHz and stored for off-line analyses. Recorded spikes from individual neurons were sorted based on the principal component analysis (PCA) [10] as well as the spike-sorting unit in the commercial software (MC_Rack, Multi Channel Systems MCS GmbH, Germany). Then the ISI series are obtained from the spike sequence. The first difference of the ISI (DISI) series:

$$DISI(n) = ISI(n+1) - ISI(n) \tag{1}$$

are also analyzed.

2.2. The Correlation Dimension Method

The concept of the phase space reconstruction is introduced firstly because it has become the foundation to chaotic time series analysis [11]. For an unknown system, let $x_i (i = 1 \cdots n)$ be the measured time series of a state variable. The time delay embedding method is employed to reconstruct the phase space X for an embedding dimension of d and a lag time of τ as follows:

$$X_m = (x_m, x_{m+\tau}, \ldots, x_{m+\tau(d-1)}) \tag{2}$$

where $m = n - \tau(d-1)$ is the number of points on the reconstructed space. Based on the concept of the phase space reconstruction, different chaotic time series methods have been proposed.

Grassberger and Procaccia proposed a simple method to determine the attractor's correlation dimension [2]. In a d-dimensional embedding, the correlation integral is defined as the normalized number of pair of vectors that have Euclidean distance less than l:

$$C(l) = \frac{1}{m^2} \sum_{i \neq j}^{m} \Theta(l - \|X_i - X_j\|) \tag{3}$$

where $C(l)$ is the correlation integral, $\| \ \|$ represents the Euclidean distance and Θ is the Heaviside function. For small values of l, the correlation integral function $C(l)$ behaves according to a power law:

$$C(l) \propto l^{v} \tag{4}$$

The correlation dimension of the attractor can be estimated from the curves of $\ln C(l) \sim \ln l$ and the onset of the plateau known as the scaling region in local slope curves indicates the occurrence of chaos. Although the correlation dimension method has the advantage of simplicity, limitations still exist such as the need of large amount of data. Furthermore, since the correlation dimension method only concerned with the static values of the data, the influence of noise is almost unavoidable.

2.3. The Nonlinear Forecasting Method

Sugihara and May proposed a nonlinear forecasting method to measure the predictability of a dynamical system [3]. Sauer extended this method and defined a normalized prediction error (NPE) to evaluate the accuracy of the prediction [4]-[5]. For each index point X_i in the embedding space X, $\{X_j\}_{j=1,\ldots,k}$ are its k nearest neighbors. With a translation horizon of $H (H \geq 0)$ time steps ahead, the prediction is the average translation given by:

$$\langle v \rangle = \frac{1}{k} \sum_{j=1}^{k} X_{j+H} \tag{5}$$

The difference between the actual and average translation is the prediction error:

$$\varepsilon_{pred} = | X_{i+H} - \langle v \rangle | \tag{6}$$

where X_{i+H} is the translation of the index point. The prediction error for the mean of the time series is:

$$\varepsilon_{mean} = | X_{i+H} - \langle x \rangle | \tag{7}$$

Then the normalized prediction error (NPE) for a translation horizon of H is:

$$NPE(H) = \frac{RMS(\varepsilon_{pred})}{RMS(\varepsilon_{mean})} \tag{8}$$

where RMS indicates root mean square. A value of NPE that less than 1 means that there exist predictability in the time series. For a chaotic system, the long-term behavior is almost unpredictable due to its sensitivity to the initial conditions. The short-term behavior, however, can still be predicted to some extent. Compared with the correlations dimension method, the nonlinear forecasting method analyzes the time series dynamically and works for a relatively short time series. Furthermore, since this method is capable of detecting week determinism, it has become one of the most important tools for analysis of experimental data.

The embedding dimension, d , and the number of nearest neighbors, k , are optimized according to the method described by Schiff and co-workers [5]. Firstly, search for the minimum value of NPE as a function of $d = 1,2,\ldots,d_{\max}$ with $k = 1$. The optimal embedding dimension, d_{opt} , is set to the value of d that corresponds to the minimum NPE. Secondly, search for the minimum value of NPE as a function of $k = 1,2,\ldots,k_{\max}$ with $d = d_{opt}$. Similarly, the optimal number of nearest neighbors, k_{opt} , is set to the value of k that corresponds to the minimum NPE.

In order to assess the predictability of the experimental data, surrogate data is applied to produce statistical controls [12]. Surrogate data refers to datasets that only preserve certain linear statistical properties of the experimental data. In the present study, two types of surrogate data are employed: Fourier shuffled (FS) and amplitude adjusted Fourier transform (AAFT). According to the null hypothesis that the original data is generated by a linearly correlated Gaussian process, the FS surrogate data can be constructed by randomizing the phase of the Fourier transform of the original data and then performing the inverse Fourier transform. The AAFT surrogate data is constructed based on the null hypothesis that the original data is a Gaussian random process that passed through a nonlinear filter. AAFT surrogate data can be generated as follows. Firstly, a Gaussian-distributed time series G_1 that follows the rank order of the original data is generated. The FS surrogate of G_1 results in a new series G_2 . Next, the AAFT data is obtained by rearranging the original data following the rank order of G_2 .

3. Results

The firing activities of totally 29 retinal GCs in response to natural stimuli (a grayscale movie lasted 192 second) were simultaneously recorded. After spike sorting, 29 spike trains were obtained. Fig. 1(a) shows a segment (length=1024) of the ISI series (length=4714) derived from the retina GC with 4175 spikes, which is used to demonstrate the analytical results of the correlation dimension method and the forecasting method. The results of the correlation dimension method are presented in Fig. 1(b) and 1(c). As shown in the Fig. 1(b), the slope of the correlation integrals curves vary greatly, which correspond to the fluctuations of the slope values in the local slope curves (Fig. 1(c)). The stable plateau of the scaling region is difficult to identify, which implies that the correlation dimension method fails to show any evidences for chaos.

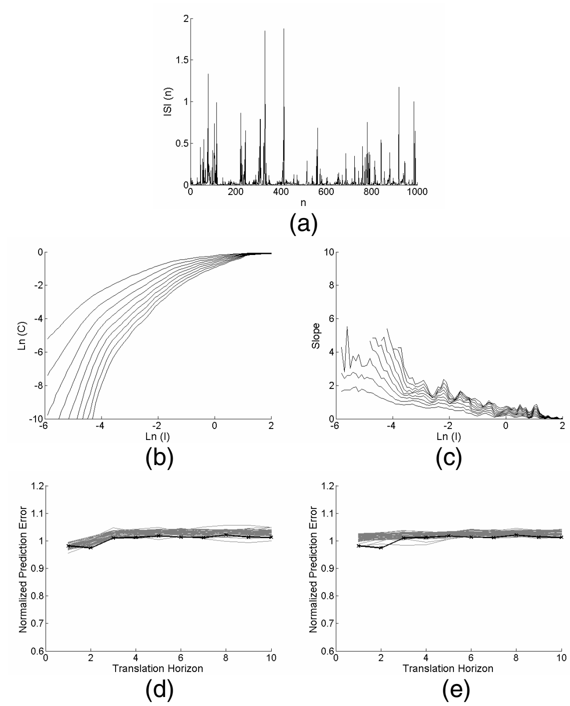

Fig. 1. (a) The ISI series. (b) Results of the correlation dimension method with the form of logarithmic correlation integrals versus logarithmic l. The embedding dimension d is in sequence $2,3,\ldots,10$ from the bottom to the top. (c) Results of the correlation dimension method with the form of local slope versus logarithmic l. The embedding dimension d is in sequence $2,3,\ldots,10$ from the bottom to the top. (d) NPEs of the ISI series (thick line, marked by "×") and 49 sets of FS surrogate data (thin lines) versus H , where H is the number of steps ahead of the index point. (e) NPEs of the ISI series (thick line, marked by "×") and 49 sets of AAFT surrogate data (thin lines) versus H .

Figures 1(d) and 1(e) show the NPEs obtained by predicting the ISI series. As shown in the two figures, the NPEs of the ISI series approximately equal to 1.0

even for $H=1$ and can't be separated from that of the surrogate data generated by both the FS (Fig. 1(d)) and the AAFT (Fig. 1(e)) methods, which indicates that there is no predictability in the ISI series beyond the baseline prediction of the series mean. In other words, no chaos is detected in the ISI series. The ISI series of other 28 GCs are also analyzed in the same way and the similar conclusions are drawn.

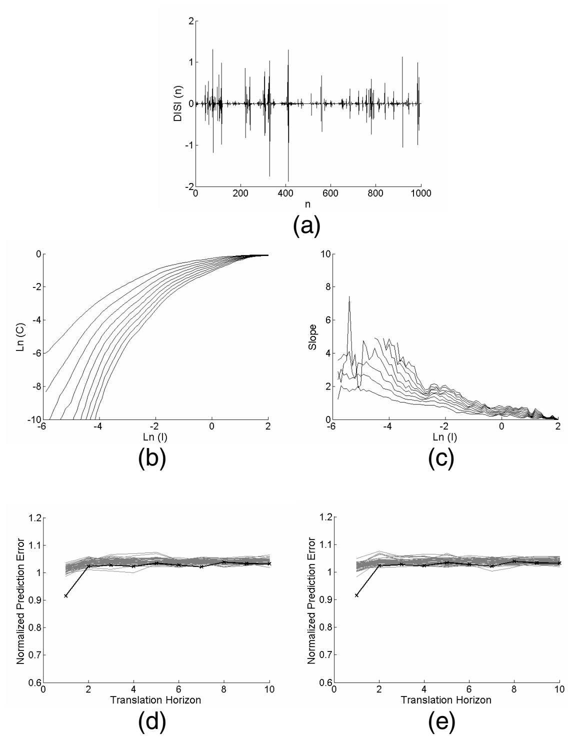

Fig. 2. (a) A segment of the DISI series. (b) Results of the correlation dimension with the form of logarithmic correlation integrals versus logarithmic l. The embedding dimension d is in sequence $2,3,\ldots,10$ from the bottom to the top. (c) Results of the correlation dimension with the form of local slope versus logarithmic l. The embedding dimension d is in sequence $2,3,\ldots,10$ from the bottom to the top. (d) NPEs of the DISI series (thick line) and 49 sets of FS surrogate data (thin lines) versus H, where H is the number of steps ahead of the index point. (e) NPEs of the DISI series (thick line) and 49 sets of AAFT surrogate data (thin lines) versus H.

The DISI series is also investigated. Fig. 2(a) shows a segment (length=1024) of the DISI series (length=4713) derived from the same retina GC. Results of the correlation dimension method on the DISI series are presented in Fig. 2(b) and 2(c). As shown in the two figures, the stable plateau of the scaling region is still difficult to identify, which implies that the correlation dimension method again fails to show any evidences for chaos. Figures 2(d) and 2(e) show the NPEs obtained by predicting the DISI series. As shown in the two figures, only the one-step-ahead $(H=1)$ NPE of the DISI series are less than 1.0 and can be apparently separated from that of the surrogate data generated by both the FS (Fig. 2(d)) and the AAFT (Fig. 2(e)) methods, which indicates that there exists distinct predictability in the DISI series. Furthermore, the one-step-ahead NPE is close to 1.0, which indicates that the degree of predictability is weak. The DISI series of other 28 GCs are also analyzed in the same way and the similar conclusions are drawn.

4. Conclusions

The correlation dimension method and the nonlinear forecasting method are applied to analyze the firing activities of the retinal GCs in response to natural stimuli. According to the analytical results, neither the correlation dimension method nor the nonlinear forecasting method provides any evidences for chaos in the ISI series. The DISI series is also analyzed in the same way. The correlation dimension method fails again to provide any evidences for chaos. The nonlinear forecasting method, however, demonstrates some weak but distinct evidences for chaos.

Two conclusions can be drawn from the analytical results. Firstly, the first difference operation of the ISI series makes it comparatively easier for chaos detection in the firing activities of retinal GCs. There is no doubt that noise derived from measurement and spike sorting procedure plays a negative role during the course of chaos detection, which may be result in the failure when the correlation dimension method and the nonlinear forecasting method are applied to analyze the ISI series. Therefore, it seems that the first difference operation has the ability to reduce noise generated by measurement and spike sorting procedure. However, why does the first difference operation has this ability? Whether this ability is only available when analyzing the data derived from retinal GCs in response to natural stimuli? Answers to these questions need more theoretical analysis and experiments in the future. Secondly, the nonlinear forecasting method is more efficient and reliable than the correlation dimension method for chaos detection. The advantage of the nonlinear forecasting method results partly from the effect of noise reduction through the process of sum and average operation of the nearest neighbor points.

Acknowledgements

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