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DETERMINISTIC CHAOS IN SOUNDS OF ASIAN CICADAS

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We analyze the sound recording of the Southeast Asian cicada *Tosena depicta* with methods of nonlinear time series analysis. First, we reconstruct the phase space from the sound recording and test it against determinism and stationarity. After positively establishing determinism and stationarity in the series, we calculate the maximal Lyapunov exponent. We find that the latter is positive, from which we conclude that the sound recording possesses clear markers of deterministic chaos. We discuss that methods of nonlinear time series analysis can yield instructive insights and foster the understanding of acoustic and vibrational communication among insects, as well as provide vital clues regarding the origin and functionality of their sound production mechanisms. Furthermore, such studies can serve as means to distinguish different insect genera or even species either from each other or under various environmental influences.

Keywords: Cicada; Insect; Sound; Time Series Analysis; Chaos.

1. Introduction

Nonlinear time series analysis[1–3] is a powerful theory that enables the extraction of characteristic quantities, e.g. the number of active degrees of freedom or invariants such as Lyapunov exponents, of a particular system solely by analyzing the time course of one of its variables. In this sense, nonlinear time series analysis offers tools that bridge the gap between experimentally observed irregular behavior and the theory of deterministic dynamical systems.[4–7] Despite the fact that the latter statement is enchanting, it also carries an important warning, namely the fact that if we are to successfully apply methods of nonlinear time series analysis on experimental data, we first have to verify if the data possesses properties typical of deterministic systems. Moreover, we have to verify if the observed irregular behavior

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originated from a stationary system, for it may solely be a consequence of varying system parameters during data acquisition. These are very important issues that have to be addressed before attempting further analyses, especially on real-life recordings, as we will emphasize throughout this work.

Presently, we analyze the sound recording of the Southeast Asian cicada *Tosena depicta*.[8] Cicadas, family *Cicadidae*, are insects belonging to the order *Hemiptera*, suborder *Homoptera*, which live in temperate to tropical climates, and are thus widespread virtually all over the world from Australia, Southeast Asia, Europe to America. For a comprehensive review on various aspects of cicadas, we refer the reader to the seminal work of Williams and Simon[9] and references therein, whilst here we constrain ourselves to the most important facts. Adult cicadas normally grow from one to two inches (in extreme cases, as is e.g. *Pomponia imperatoria*, to six inches), whilst their transparent veined wings span up to six inches across. Cicadas also have characteristic wide apart set small eyes and short antennae protruding on the sides of the head. An interesting fact is that cicadas have an accurately periodical life cycle lasting between two to five years (in extreme cases, as by e.g. *Magicicada*, also to 17 years), which they spent mostly underground as nymphs prior to their remarkably accurate simultaneous molting on nearby plants. Of direct importance for the present work is the fact that male cicadas have sound-producing organs called tymbals, which take the form of membranes located on the sides of the body. Upon vibrating these membranes, male cicadas produce loud stridulatory sounds that are resonantly amplified by their bodies to achieve optimal female attraction. It is the dynamics of this sound production mechanism that we are currently investigating with methods of nonlinear time series analysis.

The present study is, however, not the first to analyze animal sound recordings by methods of linear or nonlinear time series analysis. Wilden *et al.*,[10] for example, introduced the concept of nonlinear dynamics to mammal bioacoustics in order to quantify the complexity of animal vocalizations. Mammalian sounds were also investigated in Refs. 11 to 14. Other examples where nonlinear dynamics was found to play an important role for sound generation include bird songs[15,16] as well as human speech signals.[17–22] However, despite the rather extensive literature existing on this topic, we found no applications of nonlinear time series analysis methods explicitly on insect sounds. The present study thus aims to fill this gap.

We start the analysis by introducing the embedding theorem,[23,24] which enables the reconstruction of the phase space from a single observed variable, thereby laying foundations for further analyses. To determine proper embedding parameter for the phase space reconstruction, we use the mutual information.[25] and false nearest neighbor method.[26] Next, we apply the determinism[27] and stationarity[28] test to verify if the studied data set originates from a deterministic stationary system. Note that deterministic chaos is only one possible source of complex irregular behavior in real-life systems. Other sources, for example, are noise or varying system parameters during data acquisition. By applying the determinism test we are able to determine whether the analyzed irregular behavior is indeed a consequence of deterministic nonlinear dynamics, while the stationarity test enables us to verify if system parameters were constant during data recording. After establishing that the studied sound recording originates from a deterministic stationary system, we calculate the maximal Lyapunov exponent.[29] We find that the latter is positive, from which we conclude that the sound of the studied Southeast Asian cicada *Tosena depicta* possesses properties typical of deterministic chaotic signals. At the end, we summarize the results and outline possible biological implications of our findings.

2. Nonlinear Time Series Analysis

2.1. *Studied sound recording*

We analyze a sound recording of *Tosena depicta* recorded by Gogala and Riede[8] in the Temengor Forest Reserve, Hulu Perak, Malaysia. The audio file was sampled at 22 kHz, thus occupying 1.98×10^5 points at a length of 9 s. An insert of the time series x_i resulting from the audio file is shown in Fig. 1, whereby i is an integer indexing consecutive points in time t. Evidently, the data for the study are of high quality and of sufficient length for relevant analyses. In particular, we note that only $5\% - 10\,\%$ of the whole time series are sufficient to get accurate results whilst keeping the required computational resources reasonably low. A visual inspection of the time series presented in Fig. 1 reveals that the signal is characterized by at least two predominant frequencies, namely the one between consecutive bursts of activity roughly equalling 0.13 kHz, and the one between consecutive spikes in each bursting phase equalling 4.0 kHz. Due to the fact that the studied recording

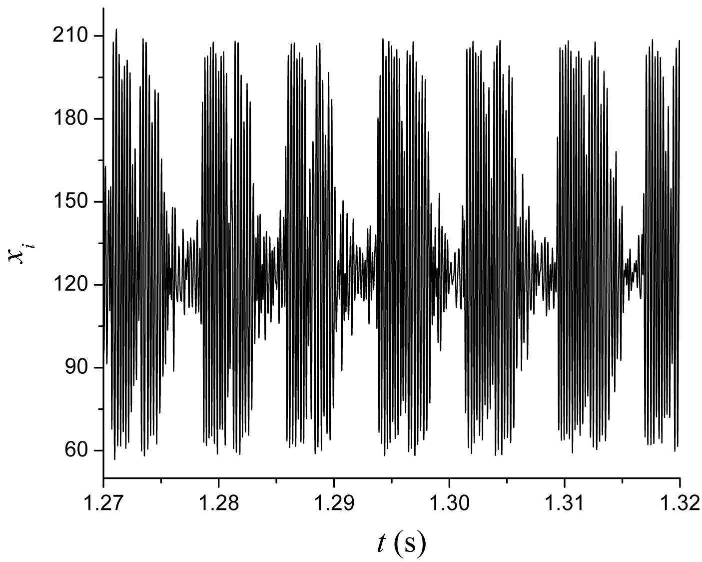

Fig. 1. An insert of the studied sound recording of *Tosena depicta*.

comprises at least two different frequencies, accompanied by its overall irregular appearance, suggests that the sound may originate from a nonlinear or even chaotic deterministic system. In the following, we will apply powerful methods of nonlinear time series analysis to confirm this conjecture in a more rigorous manner.

2.2. *Phase space reconstruction*

Following the succession of tasks we have outlined in the "Introduction" section we start the time series analysis by applying the embedding theorem,[23,24] which states that for a large enough embedding dimension m the delay vectors

$$\mathbf{p}(i) = (x_i, x_{i+\tau}, x_{i+2\tau}, \ldots, x_{i+(m-1)\tau}) \tag{2.1}$$

yield a phase space that has exactly the same properties as the one formed by the original variables of the system. In Eq. (2.1) variables x_i, $x_{i+\tau}$, $x_{i+2\tau}, \ldots, x_{i+(m-1)\tau}$ denote values of the sound recording at times $t = i\mathrm{d}t$, $t = (i+\tau)\mathrm{d}t$, $t = (i+2\tau)\mathrm{d}t, \ldots, t = (i+(m-1)\tau)\mathrm{d}t$, respectively, whereby τ is the so-called embedding delay and $\mathrm{d}t$ is the sampling time of data points equalling 4.545×10^{-5}s.

Although the implementation of Eq. (2.1) is straightforward, we first have to determine proper values for embedding parameters τ and m. For this purpose, the mutual information[25] and false nearest neighbor method[26] can be used, respectively. Since the mutual information between x_i and $x_{i+\tau}$ quantifies the amount of information we have about the state $x_{i+\tau}$ presuming we know x_i,[30] Fraser and Swinney[25] proposed to use the first minimum of the mutual information as the optimal embedding delay. The algorithm for calculating the mutual information can be summarized as follows. Given a time series of the form $\{x_0, x_1, , x_2, \ldots, x_i, \ldots, x_n\}$, one first has to find the minimum ($x_{\min}$) and the maximum ($x_{\max}$) of the sequence. The absolute value of their difference $|x_{\max} - x_{\min}|$ then has to be partitioned into j equally sized intervals, where j is a large enough integer number. Finally, one calculates the expression

$$I(\tau) = -\sum_{h=1}^{j}\sum_{k=1}^{j} P_{h,k}(\tau) \ln \frac{P_{h,k}(\tau)}{P_h P_k}, \tag{2.2}$$

where P_h and P_k denote the probabilities that the variable assumes a value inside the h^{th} and k^{th} bin, respectively, and $P_{h,k}(\tau)$ is the joint probability that x_i is in bin h and $x_{i+\tau}$ is in bin k. For the studied sound recording presented in Fig. 1, the first minimum of $I(\tau)$ is obtained already at $\tau = 1$. We will use this τ in all future calculations.

We now turn to establishing a proper embedding dimension m for the examined sound recording by applying the false nearest neighbor method introduced by Kennel *et al.*[26] The method relies on the assumption that the phase space of a deterministic system folds and unfolds smoothly with no sudden irregularities appearing in its structure. By exploiting this assumption we must come to the conclusion that points that are close in the reconstructed embedding space have to stay sufficiently close also during forward iteration. If a phase space point has a close neighbor that does not fulfil this criterion it is marked as having a false nearest neighbor. As soon as m is chosen sufficiently large, the fraction of points that have a false nearest neighbor ϕ converges to zero. In order to calculate ϕ the following algorithm is used. Given a point $\mathbf{p}(i)$ in the $m-$dimensional embedding space, one first has to find a neighbor $\mathbf{p}(j)$, so that $\|\mathbf{p}(i) - \mathbf{p}(j)\| < \varepsilon$, where $\| \cdots \|$ is the square norm and ε is a small constant usually not larger than 1/10of the standard data deviation. We then calculate the normalized distance R_i between the $m + 1^{st.}$ embedding coordinate of points $\mathbf{p}(i)$ and $\mathbf{p}(j)$ according to the equation:

$$R_i = \frac{|x_{i+m\tau} - x_{j+m\tau}|}{\|\mathbf{p}(i) - \mathbf{p}(j)\|}. \tag{2.3}$$

If R_i is larger than a given threshold R_{tr}, then $\mathbf{p}(i)$ is marked as having a false nearest neighbor. Equation (2.3) has to be applied for the whole time series and for various $m = 1, 2, \ldots$ until the fraction of points ϕ for which $R_i > R_{tr}$ is negligible. According to Kennel *et al.*,[26] $R_{tr} = 10$ has proven to be a good choice for most data sets. The results obtained with the false nearest neighbor method are presented in Fig. 2. It can be well observed that ϕ drops convincingly to zero ($< 1\%$) for $m = 8$. Hence, the underlying system that produced the studied sound recording has eight active degrees of freedom. In other words, it would be justified to mathematically model the cicada's sound production apparatus with no more than eight first order ordinary differential equations.

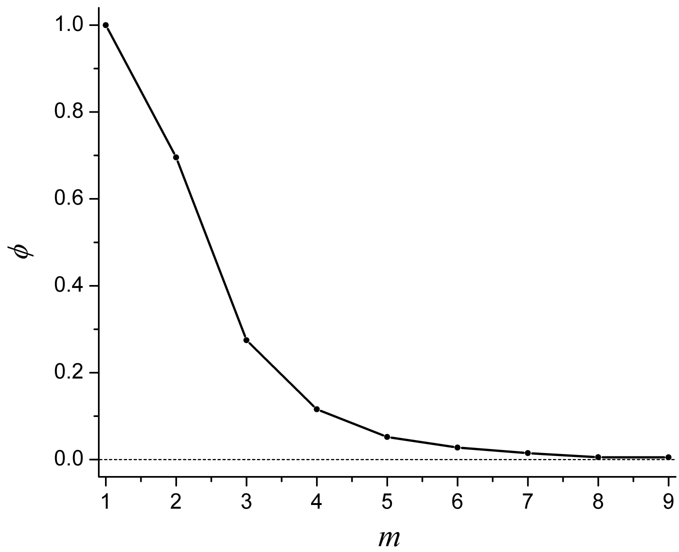

Fig. 2. Determination of the minimal required embedding dimension. The fraction of false nearest neighbors ϕ drops convincingly to zero at $m = 8$.

By now we have acquired all the data that are necessary to successfully reconstruct the phase space of the system from a single observed variable. However, prior to investigating crucial dynamical properties of the attractor, we first have to verify if the studied signal originates from a deterministic stationary system. As already emphasized in the "Introduction", determinism and stationarity are crucial properties that guarantee a relevant analysis and are the best protection against spurious results and false claims. Thus, in order to justify further analyses, we have to verify if the studied sound recording possesses properties typical of deterministic stationary signals.

2.3. *Determinism test*

We apply a simple yet effective determinism test, originally proposed by Kaplan and Glass,[27] that measures average directional vectors in a coarse-grained embedding space. The idea is that neighboring trajectories in a small portion of the embedding space should all point in the same direction, thus assuring uniqueness of solutions in the phase space, which is the hallmark of determinism. To perform the test, the embedding space has to be coarse-grained into equally sized boxes. The average directional vector pertaining to a particular box is obtained as follows. Each pass p of the trajectory through the k^{th} box generates a unit vector $\mathbf{e}_p$, whose direction is determined by the phase space point where the trajectory first enters the box and the phase space point where the trajectory leaves the box. In fact, this is the average direction of the trajectory through the box during a particular pass. The average directional vector $\mathbf{V}_k$ of the k^{th} box is then simply

$$\mathbf{V}_k = \frac{1}{n}\sum_{p=1}^{n} \mathbf{e}_p, \tag{2.4}$$

where n is the number of all passes through the k^{th} box. Completing this task for all occupied boxes gives us a directional approximation for the vector field of the system. If the time series originates from a deterministic system, and the coarse-grained partitioning is fine enough, the obtained directional vector field should consist solely of vectors that have unit length (remember that each $\mathbf{e}_p$ is also a unit vector). Hence, if the system is deterministic, the average length of all directional vectors κ will be 1, while for a completely random system $\kappa \approx 0$. The determinism factor pertaining to the eight-dimensional embedding space presented in Fig. 3 that was coarse-grained into a $16 \times 16 \times \cdots \times 16$ grid is $\kappa = 0.99$, which clearly confirms the deterministic nature of the studied sound recording.

2.4. *Stationarity test*

It remains of interest to verify if the studied sound recording originated from a stationary process. To this purpose, we apply the stationarity test proposed by Schreiber.[28] In general, stationarity violations manifest so that various non-overlapping segments of the time series have different dynamical properties. Since

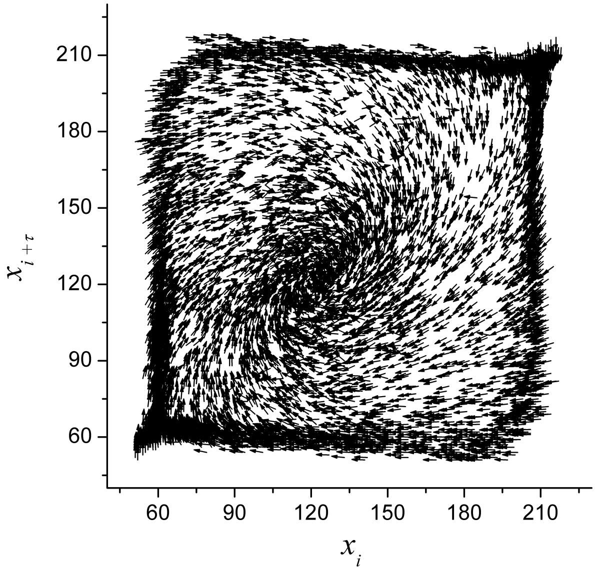

Fig. 3. Determinism test. The approximated directional vector field for the embedding space reconstructed with $\tau = 1$ and $m = 8$. The pertaining determinism factor is $\kappa = 0.99$.

linear statistics, such as the mean or standard data deviation,[2] usually do not possess enough discrimination power when analyzing irregular signals, nonlinear statistics have to be applied. One of the most effective has proven to be the cross-prediction error statistic. The idea is to split the time series into several short non-overlapping segments and then use a particular data segment to make predictions in another data segment. By calculating the average prediction error (δ_{gk}) when considering points in segment g to make predictions in segment k, we obtain a very sensitive statistic capable of detecting minute changes in dynamics, and thus a very powerful probe for stationarity. If for any combination of g and k δ_{gk} is significantly above average, this is a clear indicator that the examined data set originated from a non-stationary process. The accurate description of the whole algorithm can be found in Kantz and Schreiber[2] from page 42 onwards, while here we concentrate on the results that are presented in Fig. 4 and were obtained by diving 10,000 data points into 40 non-overlapping segments of 250 points, thus yielding 40^2 combinations to evaluate δ_{gk} . The average value of all δ_{gk} is 0.75, while the minimum and maximum values are 0.60 and 0.89, respectively. Since all cross-prediction errors differ maximally by a factor of $2/3$, we can clearly refute non-stationarity in the studied sound recording. Noteworthy, this implies that during the recording time the environmental influences on the cicada did not change and thus its singing was stationary both from the listeners as well as from the dynamical point of view. This is of course not surprising since not much can happen in a few seconds time. However, it is important to bear in mind that longer recordings of

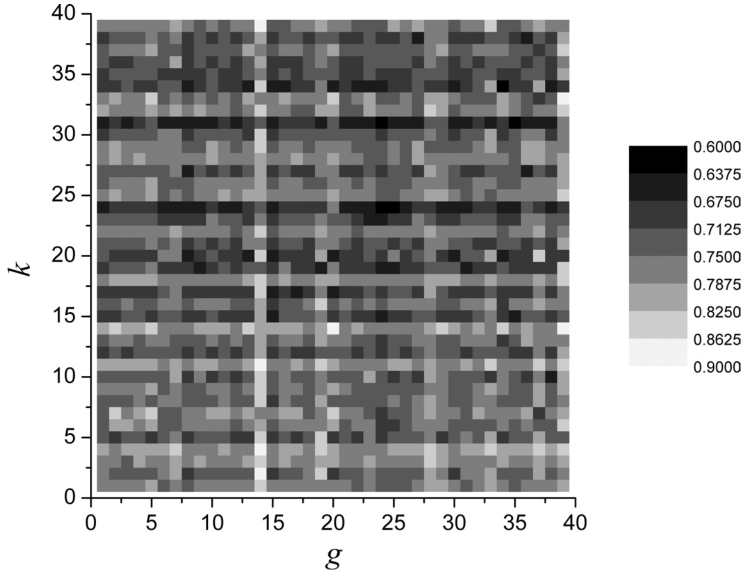

Fig. 4. Stationarity test. The whole time series was partitioned into 40 non-overlapping segments each occupying 250 data points. The color map displays average cross-prediction errors δ_{gk} in dependence on different segment combinations.

real-life activities almost always yield non-stationary data sets since subjects under study often cannot be isolated from environmental effects, or even more likely, it is explicitly not of interest to do so.

2.5. *Maximal Lyapunov exponent*

Finally, it is of interest to determine the maximal Lyapunov exponent pertaining to the studied sound recording. Importantly, since we have already positively established determinism and stationarity in the time series, the following can be considered truly a relevant analysis based on which healthy conclusions regarding the nature of the cicada's sounds can be drawn. In general, Lyapunov exponents determine the rate of divergence or convergence of initially nearby trajectories in phase space.[6] An m-dimensional system has m different Lyapunov exponents Λ_i, where $i = 1, 2, \ldots, m$. Most importantly, already a single positive Lyapunov exponent suffices to positively establish chaos in the studied system. Usually, this Lyapunov exponent is referred to as the largest or maximal and is thus appropriately denoted as $\Lambda_{\max}$. $\Lambda_{\max}$ uniquely determines whether the time series under study originated from a chaotic system or not. If $\Lambda_{\max} > 0$, two initially nearby trajectories of the attractor diverge exponentially fast as time progresses, constituting the extreme sensitivity to changes in initial conditions, which is the hallmark of chaos. Presently, we use the algorithm developed by Wolf *et al.*,[29] which implements the theory in a very simple and direct fashion, whilst virtually identical results as will

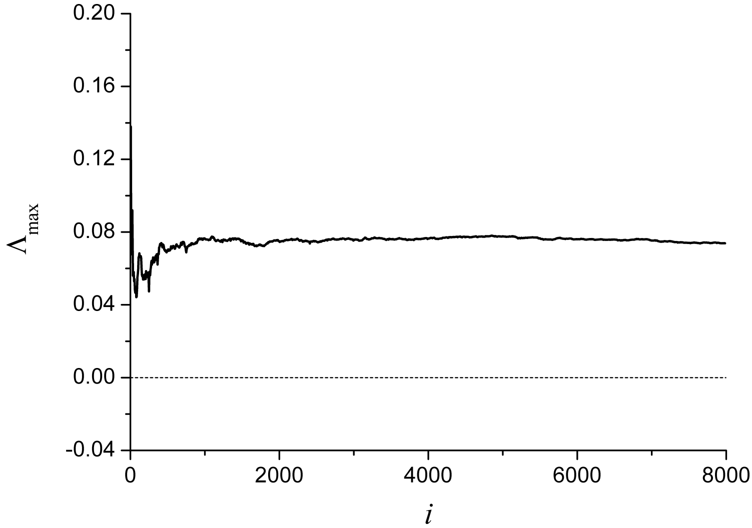

Fig. 5. Determination of the maximal Lyapunov exponent. The value converges extremely well to $\Lambda_{max} = 0.073 \pm 0.002$ in dimensionless units, thus, combined with the results obtained from the determinism and stationarity tests, indicating deterministic chaos in the studied sound recording of *Tosena depicta*.

be reported below can be obtained also with other methods[31,32] for determining Λ_{max} from recorded data sets. The first step of the algorithm consists of finding a near neighbor of the initial point $\mathbf{p}(0)$. Let L_0 denote the Euclidian distance between them. Next, we have to iterate both points forward for a fixed evolution time t_{evolv}, which should be of the same order of magnitude as the embedding delay τ (in our case $t_{evolv} = 5$), and denote the final distance between the evolved points as L_{evolv} . After each t_{evolv} a replacement step is attempted in which we look for a new point in the embedding space whose distance to the evolved initial point is as small as possible, under the constraint that the angular separation between the evolved and replacement element is small. This procedure is repeated until the initial point $\mathbf{p}(0)$ reaches the end of the trajectory in the phase space. Finally, Λ_{max} is calculated according to the equation

$$\Lambda_{max} = \frac{1}{Rt_{evolv}} \sum_{i=1}^{R} \ln \frac{L_{evolv}^{(i)}}{L_0^{(i)}}, \tag{2.5}$$

where R is the total number of replacement steps. By using Eq. (2.5), we calculate Λ_{max} for the attractor presented in Fig 3. As evidenced in Fig. 5, the maximal Lyapunov exponent converges extremely well to $\Lambda_{max} = 0.073$. This is firm evidence that the studied sound recording from *Tosena depicta* living in Southeast Asia originated from a deterministic chaotic system.

Finally, we note that special care should be exercised when determining non-linear dynamical quantities from observed systems due to limited data length, especially if the data originates from a high-dimensional system, as is presently the case ($m = 8$). While for some nonlinear dynamical quantities, such as for example the correlation dimension obtained via the Grassberger-Procaccia algorithm,[2] there exist precise formulae that determine the minimal amount of data points required to obtain a reliable result,[33–35] this is not the case for the estimation of the maximal Lyapunov exponent. Nevertheless, we emphasize that a high degree of reliability can be assured by requiring that the root-mean-square of the maximal Lyapunov exponent fluctuations during convergence must be much smaller than the value we declare as the final result. Since even a few seconds long high quality sound recordings (sampled at 22 kHz or higher) comprise $< 10^5$ data points such reliability-related restrictions are normally easily fulfilled, if only determinism and stationarity in the examined data set are positively established.

3. Discussion

We systematically analyze the sound recording of the Southeast Asian cicada *Tosena depicta* with methods of nonlinear time series analysis. In particular, we outline a careful approach, encompassing a determinism[27,36,37] and stationarity test,[28] which largely eliminates the occurrence of spurious results, and thus guarantees a relevant analysis of the observed system. We find that the studied sound recording originates from a deterministic stationary system and is characterized by a positive maximal Lyapunov exponent.[29,31,32] Thus, we conclude that the sound production mechanism of the studied cicada species possesses properties that are characteristic for deterministic chaotic systems.

We argue that the above-performed analysis is a viable approach for obtaining vital insights into mechanisms of insect sound generation. In particular, it can been seen as the necessary prelude to mathematical modeling, since it provides important information regarding the dynamical properties of the underlying system, such are for example the number of active degrees of freedom given by the dimensionality of the phase space or Lyapunov exponents. In this sense, the nonlinear time series analysis provides the basic framework for such studies clearly indicating the dimensionality as well as complexity of the appropriate mathematical model. Furthermore, as already advocated by Wilden *et al.*,[10] for mammalian communication, such analyses can lay foundations for a more broad classification of acoustic and vibrational communication also among insects, which surpasses the rather limited dichotomous separation of signals on harmonic and atonal sounds[38] that is often employed by biologists. Finally, we argue that if used carefully, methods of nonlinear time series analysis can also serve as means to distinguish different insect genera or even species either from each other or under various environmental influences, whereby the fact that one can intimately and rather accurately characterize a particular sound only by a single Lyapunov exponent opens the possibility of automatization.

At the end, we would like to note that since this work is intended to inspire physicists, mathematicians and biologists alike, we also developed a set of user-friendly programs[39–42] for each implemented method in this paper, so that interested readers can easily apply the theory on their own recordings. An even more comprehensive set of programs is available also through the TISEAN project.[43,44] We recommend greatly to exploit the benefits offered by these sources.

References

1. Abarbanel HDI, *Analysis of Observed Chaotic Data*, Springer, New York, 1996.
2. Kantz H, Schreiber T, *Nonlinear Time Series Analysis*, Cambridge University Press, Cambridge, 1997.
3. Sprott JC, *Chaos and Time-Series Analysis*, Oxford University Press, Oxford, 2003.
4. Schuster HG, *Deterministic Chaos*, VCH, Weinheim, 1989.
5. Ott E, *Chaos in Dynamical Systems*, Cambridge University Press, Cambridge, 1993.
6. Strogatz SH, *Nonlinear Dynamics and Chaos*, Addison-Wesley, Massachusetts, 1994.
7. Kaplan DT, Glass L, *Understanding Nonlinear Dynamics*, Springer, New York, 1995.
8. Gogala M, Riede K, Time sharing of song activity by cicadas in Temengor Forest Reserve, Hulu Perak, Malaysia, *Malays Nat J* **51**:297–305, 1995.
9. Williams KS, Simon C, The ecology, behavior and evolution of periodical cicadas, *Ann Rev Entomol* **40**:269–295, 1995.
10. Wilden I, Herzel H, Peters G, Tembrock G, Subharmonics, biphonation, and deterministic chaos in mammal vocalization, *Bioacoustics* **9**:171–196, 1998.
11. Fitch WT, Neubauer J, Herzel H, Calls out of chaos: the adaptive significance of nonlinear phenomena in mammalian vocal communication, *Anim Behav* **63**:407–418, 2002.
12. Riede T, Herzel H, Mehwald D, Seidner W, Trumler E, Tembrock G, Böhme G, Nonlinear phenomena and their anatomical basis in the natural howling of a female dog-wolf breed, *J Acoust Soc Am* **108**:1435–1442, 2000.
13. Riede T, Herzel H, Hammerschmidt K, Brunnberg L, Tembrock G, The harmonic-to-noise-ratio applied to dog barks, *J Acoust Soc Am* **110**:2191–2197, 2001.
14. Riede T, Mitchell BR, Tokuda I, Owren MJ, Characterizing noise in nonhuman vocalizations: acoustic analysis and human perception of barks by coyotes and dogs, *J Acoust Soc Am* **118**:514–522, 2005.
15. Fee MS, Shraiman B, Pesaran B, Mitra PP, The role of nonlinear dynamics of the syrinx in the vocalizations of a songbird, *Nature* **395**:67–71, 1998.
16. Fletcher NH, A class of chaotic bird calls? *J Acoust Soc Am* **108**:821–826, 2000.
17. Mende W, Herzel H, Wermke H, Bifurcations and chaos in newborn infant cries, *Phys Lett A* **145**:418–424.
18. Titze IR, Baken RJ, Herzel H, Evidence of chaos in vocal fold vibration, in Titze IR (ed.), *Vocal Fold Physiology*, Singular, San Diego, p. 143, 1993.
19. Herzel H, Berry D, Titze IR, Saleh S, Analysis of vocal disorders with methods from nonlinear dynamics, *J Speech Hear Res* **37**:1008–1019, 1994.
20. Narayanan SN, Alwan AA, A nonlinear dynamical systems analysis of fricative consonants, *J Acoust Soc Am* **97**:2511–2524, 1995.
21. Kumar A, Mullick SK, Nonlinear dynamical analysis of speech, *J Acoust Soc Am* **100**:615–629, 1996.
22. Behrman A, Global and local dimensions of vocal dynamics, *J Acoust Soc Am* **105**:432–443, 1999.
23. Takens F, Detecting strange attractors in turbulence, in Rand DA, Young LS (eds.), *Lecture Notes in Mathematics*, Vol. 898, Springer-Verlag, Berlin, p. 366, 1981.

24. Sauer T, Yorke JA, Casdagli M, Embedology, *J Stat Phys* **65**:579–616, 1991.
25. Fraser AM, Swinney HL, Independent coordinates for strange attractors from mutual information, *Phys Rev A* **33**:1134–1140, 1986.
26. Kennel MB, Brown R, Abarbanel HDI, Determining embedding dimension for phase space reconstruction using a geometrical construction, *Phys Rev A* **45**:3403–3411, 1992.
27. Kaplan DT, Glass L, Direct test for determinism in a time series, *Phys Rev Lett* **68**:427–430, 1992.
28. Schreiber T, Detecting and analyzing nonstationarity in a time series with nonlinear cross-predictions, *Phys Rev Lett* **78**:843–846, 1997.
29. Wolf A, Swift JB, Swinney HL, Vastano JA, Determining Lyapunov exponents from a time series, *Physica D* **16**:285–317, 1985.
30. Shaw R, Strange attractors, chaotic behavior, and information flow, *Z Naturforsch* **36a**:80–112, 1981.
31. Rosenstein MT, Collins JJ, De Luca CJ, A practical method for calculating largest Lyapunov exponents from small data sets, *Physica D* **65**:117–134, 1993.
32. Kantz H, A Robust method to estimate the maximal Lyapunov exponent of a time series, *Phys Lett A* **185**:77–87, 1994.
33. Theiler J, Spurious dimension from correlation algorithms applied to limited time-series data, *Phys Rev A* **34**:2427–2432, 1986.
34. Smith LA, Intrinsic limits on dimension calculations, *Phys Lett A* **133**:283–288, 1988.
35. Ruelle D, Deterministic chaos: the science and the fiction, *Proc R Soc Lond A* **427**:241–251, 1990.
36. Wayland R, Bromley D, Pickett D, Passamante A, Recognizing determinism in a time series, *Phys Rev Lett* **70**:580–582, 1993.
37. Salvino LW, Cawley R, Smoothness implies determinism: a method to detect it in time series, *Phys Rev Lett* **73**:1091–1094, 1994.
38. Hauser MD, The evolution of nonhuman primate vocalizations: effects of phylogeny, body weight, and social context, *Am Nat* **142**:528–542, 1993.
39. Kodba S, Perc M, Marhl M, Detecting chaos from a time series, *Eur J Phys* **26**:205–215, 2005.
40. Perc M, The dynamics of human gait, *Eur J Phys* **26**:525–534, 2005.
41. Perc M, Nonlinear time series analysis of the human electrocardiogram, *Eur J Phys* **26**:757–768, 2005.
42. All results presented in this paper can be easily reproduced with the set of programs that can be downloaded from: http://fizika.tk/
43. Hegger R, Kantz H, Practical implementation of nonlinear time series methods: the TISEAN package, *Chaos* **9**:413–440, 1999.
44. The official web page of the TISEAN project is: www.mpipks-dresden.mpg.de/∼tisean