DEEP LEARNING CHAOTICITY ANALYSIS OF BIOLOGICAL TIME SERIES: FROG HEART DYNAMICS

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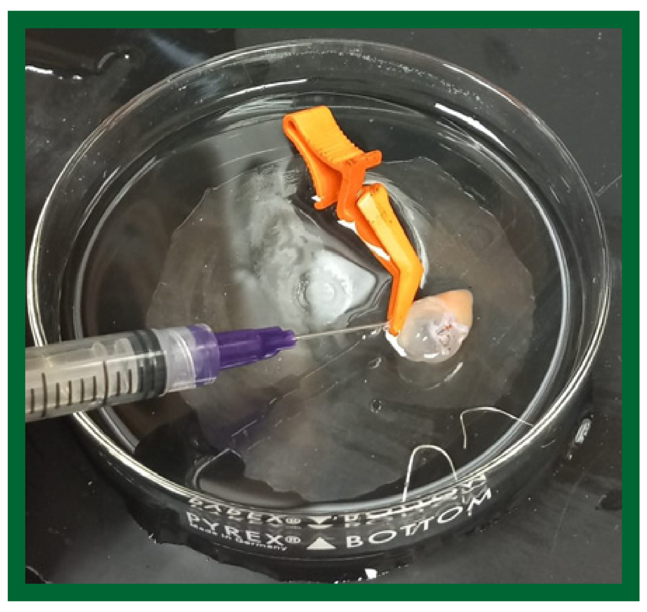
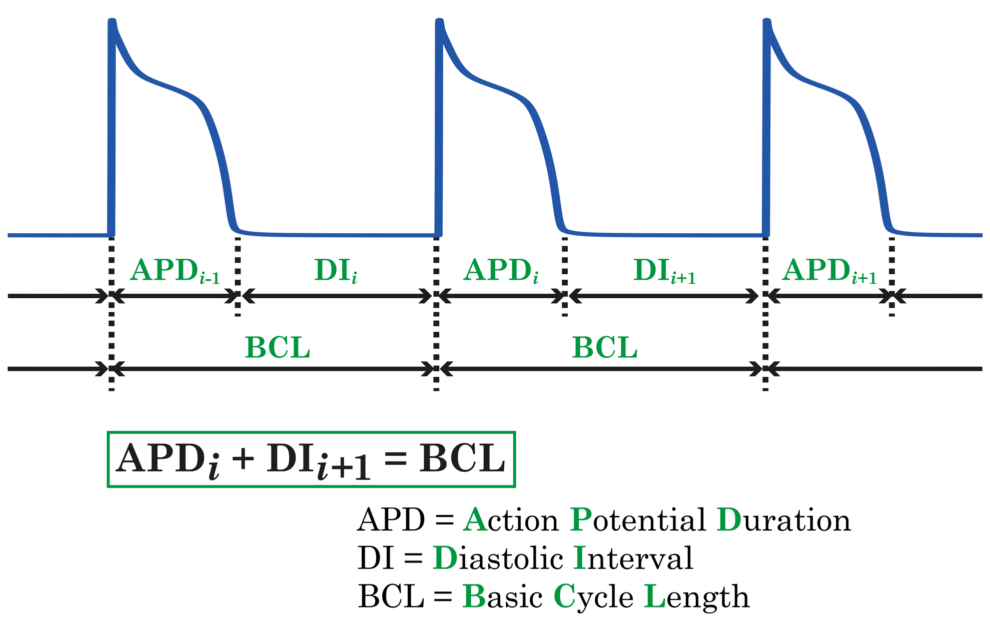
Introduction

Classical techniques as Lyapunov Exponents are often used to perform chaoticity analysis of dynamical systems. However, these techniques sometimes present problems when used on real data as recordings are generally short and noisy. When dealing with large experimental datasets it is necessary to have an automatic algorithm for chaoticity analysis since human intervention on the entire dataset is not feasible. Recently, some authors have used Deep Learning (Artificial Neural Networks) to detect chaos in a dynamical system [1]. **Could Deep Learning (DL) be applied to perform a chaoticity analysis in an experimental dataset?** [2]

Our **experimental dataset** contains 52 time series with different lengths (minimum length 15 and maximum length 205). Such time series correspond to the **Action Potential Duration (APD) of frog heart dynamics for different pacing rates (Basic Cycle Length, BCL)**.





Algorithm for DL Chaoticity Analysis of Biological Time Series

Step 1: Artificial Neural Networks Framework. Train 10 randomly initialized recurrence-like Artificial Neural Networks with time series from the Logistic Map.

Remark. Deep Learning includes all the Artificial Intelligence techniques that use Artificial Neural Networks to learn from data with several levels of abstraction. Recurrence-like Artificial Neural Networks are commonly used for sequential processing since they retain information from past times.

Step 2: DL Chaoticity Analysis of an APD Heart Model. Perform a test analysis in an APD heart model with each Artificial Neural Network trained in *Step 1*.

Step 3: Select one Artificial Neural Network. Establish some criteria on the results of *Step 2* to choose automatically one network of *Step 1*.

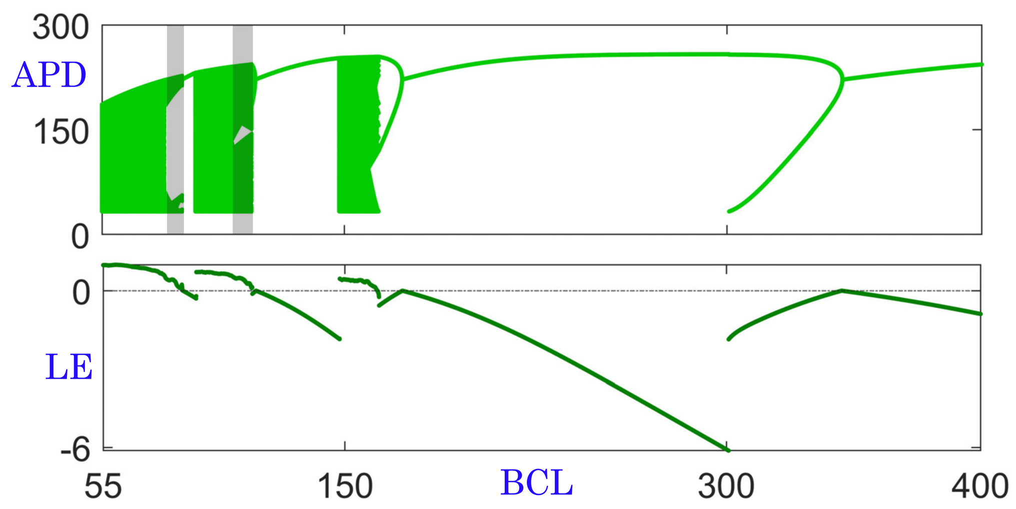
Step 4: DL Chaoticity Analysis of Biological Time Series: Frog Heart Dynamics. Use the network chosen in *Step 3* to perform chaoticity analysis in experimental data.

DL Chaoticity Analysis of an APD Heart Model

APD restitution curve (that describes the dynamics of a single cell) fitted to the kinetics of Beeler-Reuter model [3] gives rise to the discrete equation

$$\begin{aligned}\mathrm{APD}_{i+1} = 258 + 125\exp(-0.068(n\,\mathrm{BCL} - \mathrm{APD}_i - 43.54)) \\ -350\exp(-0.028(n\,\mathrm{BCL} - \mathrm{APD}_i - 43.54)),\end{aligned}$$

where n is the parameter block (lower $n \in \mathbb{N}$ such that $n\,\mathrm{BCL} - \mathrm{APD}_i \geq \mathrm{DI}_{\min}$ with $\mathrm{DI}_{\min}$ the minimum DI set to 43.54ms).



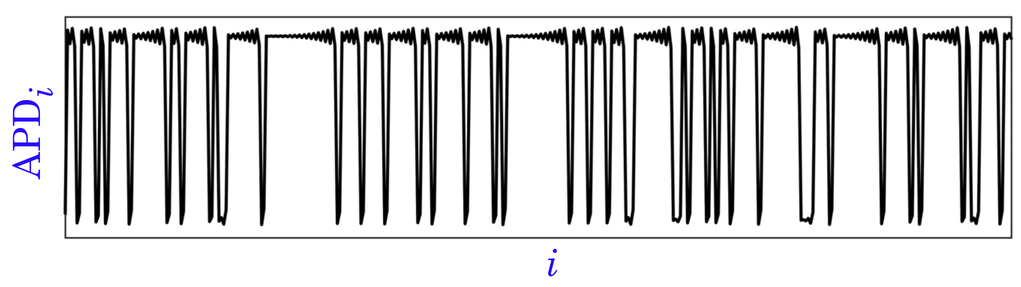
80.292% of the samples have regular behaviour (according to LE value) and the remaining 19.708% are chaotic. 79.803% of regular samples are equilibrium points and the other 20.197% present periodic behaviour.

A DL chaoticity analysis of this APD heart model is performed without noise (no noise), adding Gaussian noise with strength 0.5 ($+0.5\mathcal{N}(0,1)$), and same type of noise with strength 1.0 ($+1.0\mathcal{N}(0,1)$). The following table collects the results for the network chosen in *Step 3*:

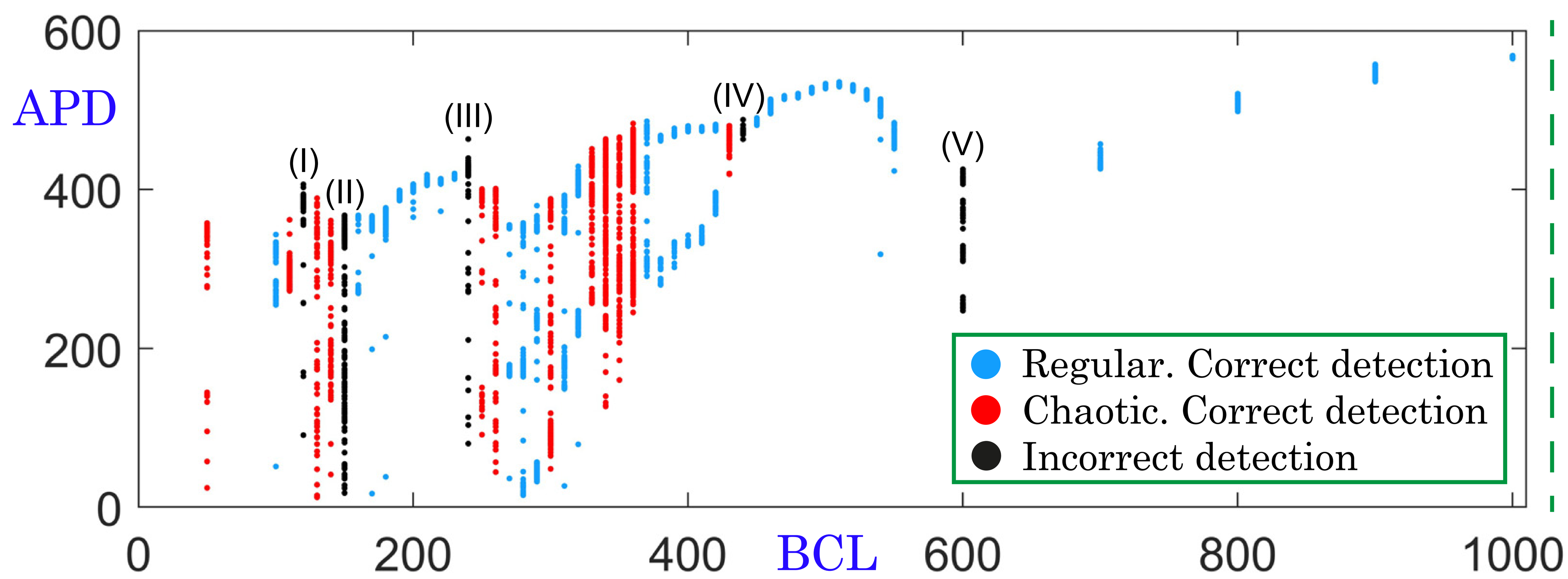
	No noise	$+0.5\mathcal{N}(0,1)$	$+1.0\mathcal{N}(0,1)$
Accuracy	95.092 %	94.825 %	94.750 %
Accuracy Chaotic	76.195 %⋆⋆	75.983 %	75.729 %
Accuracy Regular	99.730 %	99.450 %	99.419 %
Accuracy EPs	100 %	99.649 %	99.649 %
Accuracy POs	98.666 %	98.666 %	98.512 %

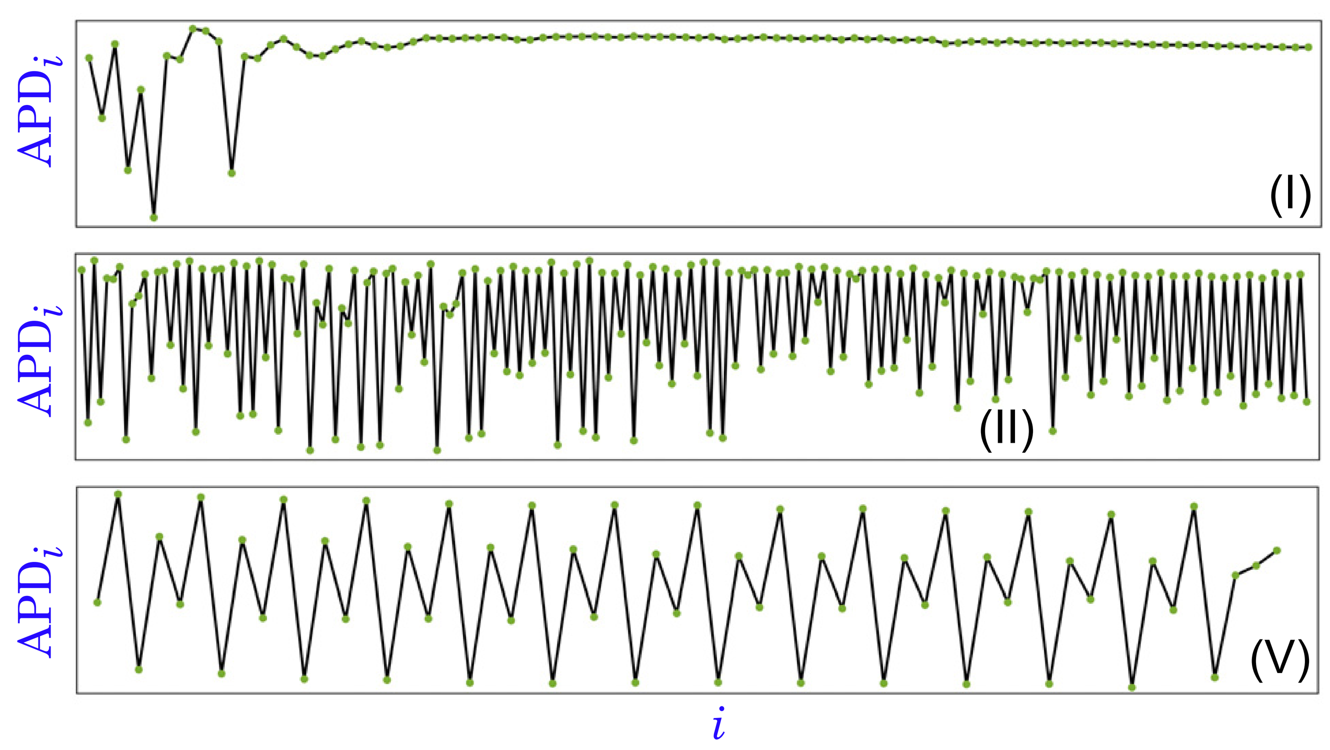
Remark. Accuracy refers to the percentage of samples correctly detected with DL. Accuracy regular (resp. chaotic) corresponds to the percentage of regular (resp. chaotic) samples correctly classified by DL. Accuracy EPs (resp. POs) is the percentage of equilibrium points (resp. periodic orbits) correctly detected as regular with DL.

⋆⋆ Most incorrect DL detections of chaotic samples occur in the grey shaded areas of the bifurcation diagram. This time series is an example of these samples:



DL Chaoticity Analysis of Biological Time Series: Frog Heart Dynamics





	Experimental Results
Accuracy	90.385 % (47 of 52 samples)
Accuracy Chaotic	92.308 % (12 of 13 samples)
Accuracy Regular	89.744 % (35 of 39 samples)

- Samples (I)-(III)-(IV) have been detected as chaotic by the Artificial Neural Network. All these samples have a similar behaviour: short chaotic transient dynamics, asymptotically converging to an equilibrium point (regular). Therefore, the whole time series is chaotic (as DL detected), but dynamically its asymptotic behaviour can be considered as regular (and the samples were labeled under this consideration).
- Sample (II) is detected as regular. The final part of the time series seems to have some periodicity, so it can be considered as regular with a long chaotic transient (in this case the network detection is correct). However, since the behaviour is chaotic most of the time, it was labeled as chaotic.
- Sample (V) is a quasi-periodic orbit detected as chaotic. The score ('probability') for chaotic class given by the Artificial Neural Network is 0.625 (and 0.375 for regular class), so it doubts on the detection.

Conclusions

- Experimental data has some drawbacks as noisy and short recordings. An algorithm based on Deep Learning (Artificial Neural Networks) is proposed to deal with the chaoticity analysis of biological time series.
- A test of the robustness of Artificial Neural Networks when noise is present is carried out in an APD heart model (Beeler-Reuter).
- This analysis allows to select an Artificial Neural Network that can properly perform a chaoticity analysis of biological time series of frog heart dynamics.
- The proposed algorithm does not require human supervision, so it can be considered as an automatic technique for chaoticity analysis of large datasets of biological time series.

References

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