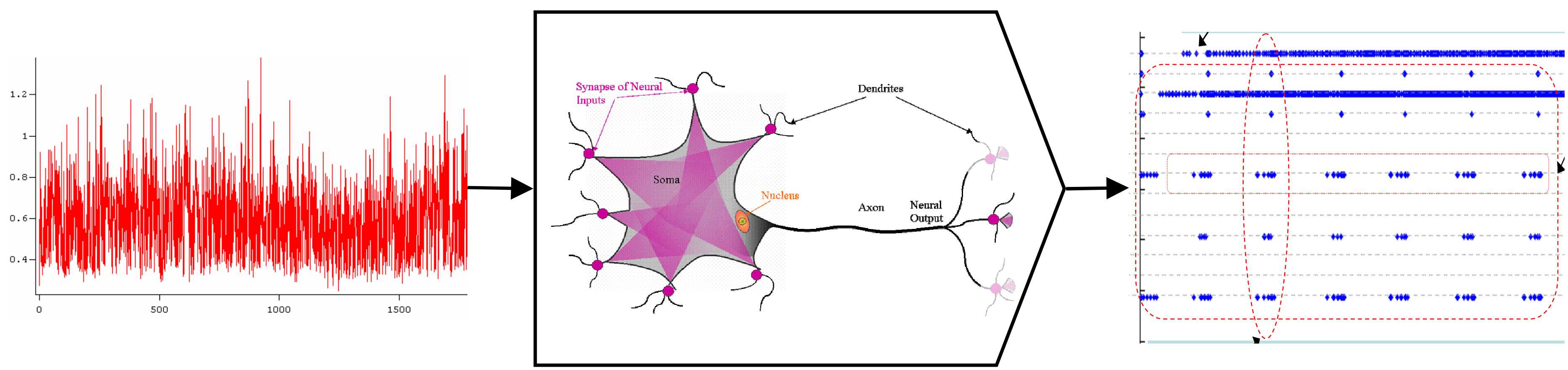
New Neural Architectures
and
New Adaptive Evaluation of Chaotic Time Series



New Neural Architectures

and

New Adaptive Evaluation of Chaotic Time Series

Ivo Bukovsky, Jiri Bila, Madan M. Gupta, & Zeng-Guang Hou

New Neural Architectures
&
New Adaptive Evaluation of Chaotic Time Series

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New Neural Architectures
&
New Adaptive Evaluation of Chaotic Time Series

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Institute of Automation

The Chinese Academy of Sciences

TUTORIAL OUTLINE

1. **Introduction into Evaluation of Complex Time Series by Common Nonlinear Methods**
   - Correlation Dimension, Lyapunov Exponents
   - Recurrence Plot
2. **Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods**
   - Too complex and too nonlinear systems
   - Multi-attractor behavior of chaotic systems
3. **Issues of Evaluation of Real Complex Systems by Existing Nonlinear Methods**
   - Multi-attractor behavior of real complex systems
   - Multi-attractor behavior of heart rate variability
   - Openness of real systems (unknown inputs), Data length

TUTORIAL OUTLINE (cont.)

4. **Evaluation of Complex Time Series using Nonconventional Neural Units**
   - Neural Unit as a Nonlinear Adaptable Forced Oscillator– HRV-HONNU
   - Adaptation Technique for HRV-HONNU
   - **Methodology of Adaptive Evaluation of Complex Time Series – the Adaptation Plot**

5. Applications
   - Adaptive Evaluation of Deterministic Chaotic Systems
   - Adaptive Sample by Sample Evaluation of Real Complex Signals

6. Limitations and Advantages Summary

Principal advantages over common nonlinear methods such as Correlation Dimension, Lyapunov Exponents, or Recurrence Plot are discussed as

ADAPTIVE EVALUATION OF COMPLEX TIME SERIES USING NONCONVENTIONAL NEURAL UNITS

The very idea behind the 'adaptive evaluation' presented here might be stated as follows:

" When we can not evaluate properly mathematically a complex (nonlinear) behaving dynamic system, than we observe and evaluate how another system can learn about the complex behaving one."

" … observe and evaluate how ***another system can learn about the complex behaving one****."*

Some related concepts and examples from:

- *science and technology:*
  - o linear models - control engineering, evaluating error of adaptive models and controllers, linear observers,… (the concept of linear approximation might be considered as somewhat relevant here, but we need go further for real, complex, nonlinear systems)
  - o observing convergence of adapted neural network models
- *nature:*
  - indicating unusual changes of one organism behavior in the environment can indicate the changes of performance of another species or even the global system;
  - indicating unusual weather parameter variations in a single region can indicate changes in dynamics of other region (or a global) weather system;
  - …

ADAPTIVE EVALUATION OF COMPLEX TIME SERIES USING NONCONVENTIONAL NEURAL UNITS

"When we can not evaluate properly mathematically a complex time series, we can observe and evaluate how a nonlinear adaptive model (e.g. a nonconventional neural unit) can learn about the complex dynamics of the time series."

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1. Introduction into Evaluation of Complex Time Series by Nonlinear Methods

- Correlation Dimension

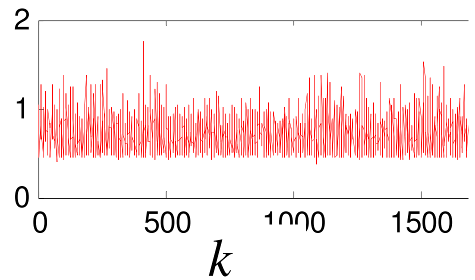
$$CD = \lim_{r \to 0} \frac{\log(C(r))}{\log(r)} \quad \text{where } C(r) = \frac{\text{number of pairs with distance} < r}{\text{number of all pairs}}$$

$C(r)$ …. the correlation function (~the percentage of neighbouring pairs)

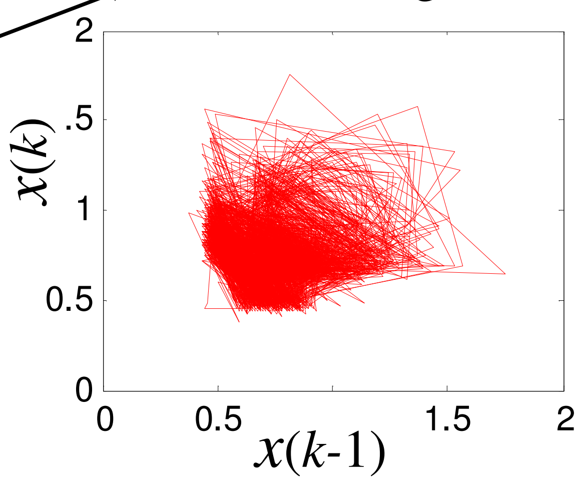
r … distance (radius) in phase space (i.e. in reconstructed phase space = delay coordinate embedding space)

(Grassberger, Procaccia, 1983)

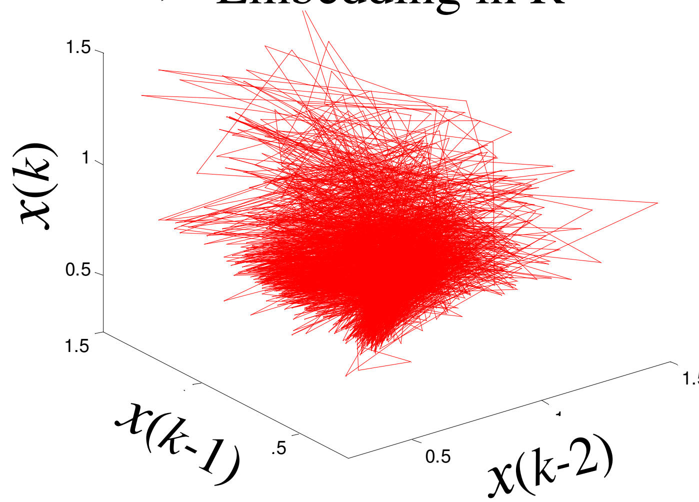
$x(k)$ … time series



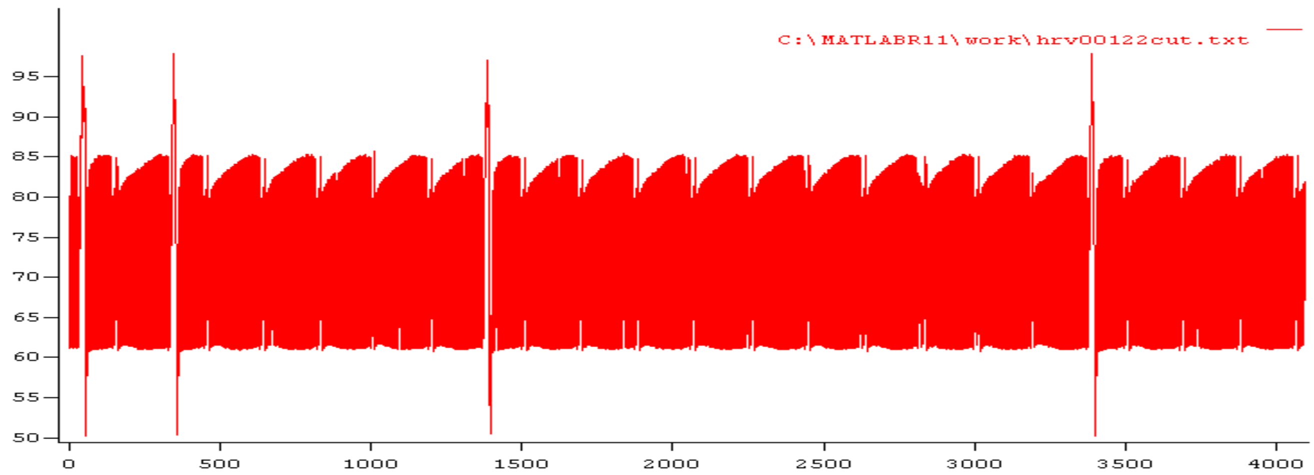
Embedding in R^2



Embedding in R^3

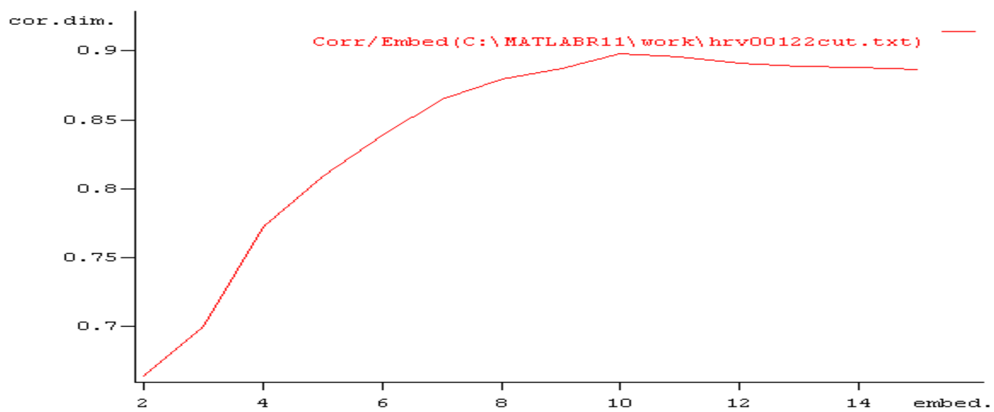


1. Introduction into Evaluation of Complex Time Series by Nonlinear Methods
- Correlation Dimension



Td1=0.1s

Td2=0.2s



$$C(r) = \frac{\text{number of pairs with distance} < r}{\text{number of all pairs}}$$

"Less chaotic time series" ⇔ Correlation Dimension tends to maintain its value with increasing embedding dimension (Dataplore)

1. Introduction into Evaluation of Complex Time Series by Nonlinear Methods
- Lyapunov Exponents

- Largets **Lyapunov exponents (LLE)** can be considered as one of the most generally accepted invariants that reflects the level of chaos of system non-periodic trajectories (orbits) and time series.
- When LLE of time series are found negative (LLE<0), then the time series tends to behave periodic.
- When LLE of time series are evaluated positive (LLE>0), then the orbit is diverging from its previous path and the behavior is usually considered chaotic.
- There are many available resources and to learn about Correlation Dimension and Lyapunov Exponents and many SW to use
  - (starting with Wikipedia, …,programs as Dataplore, downloadable routines for Matlab, …)

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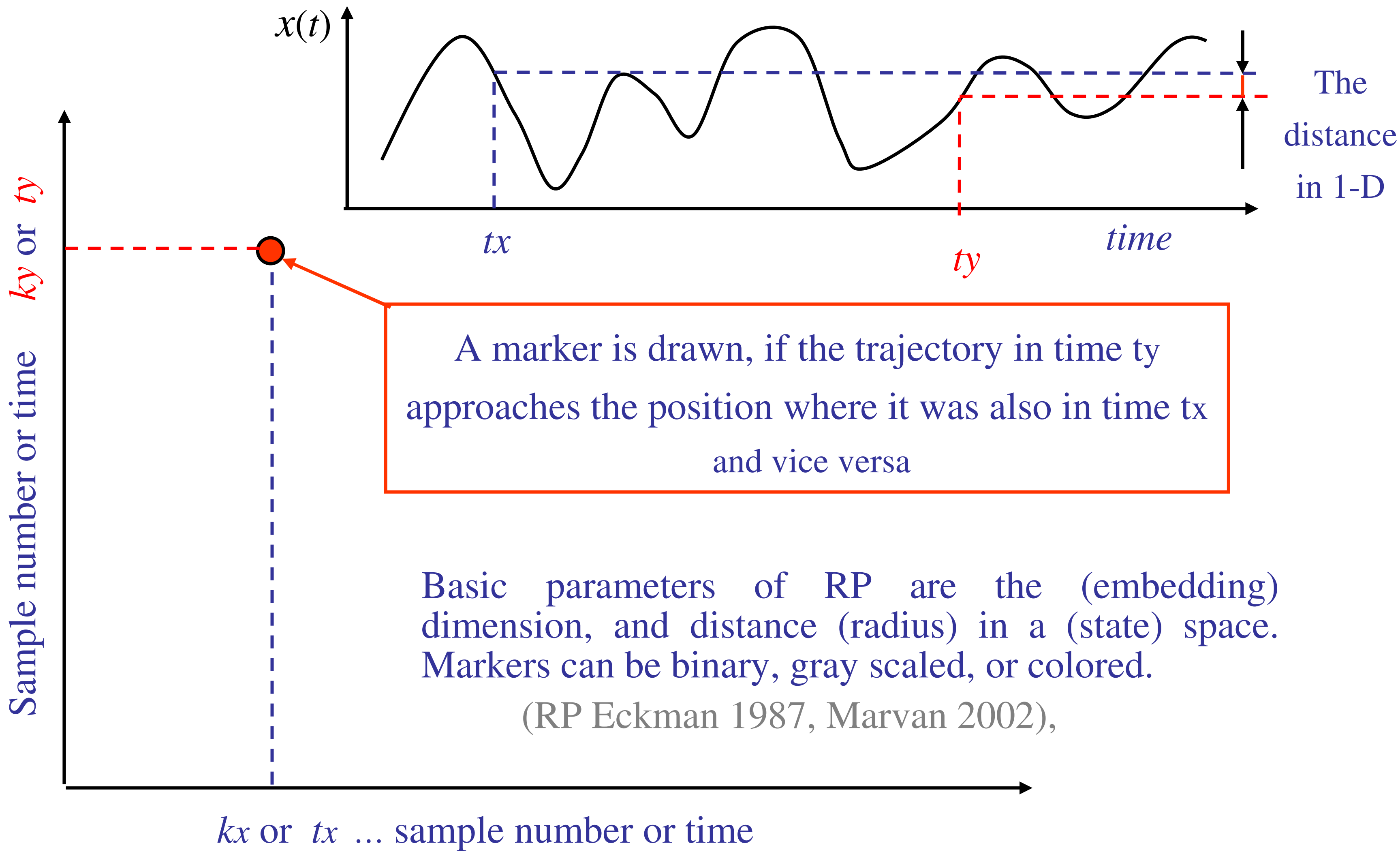
2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods

- Recurrence Plot (RP)

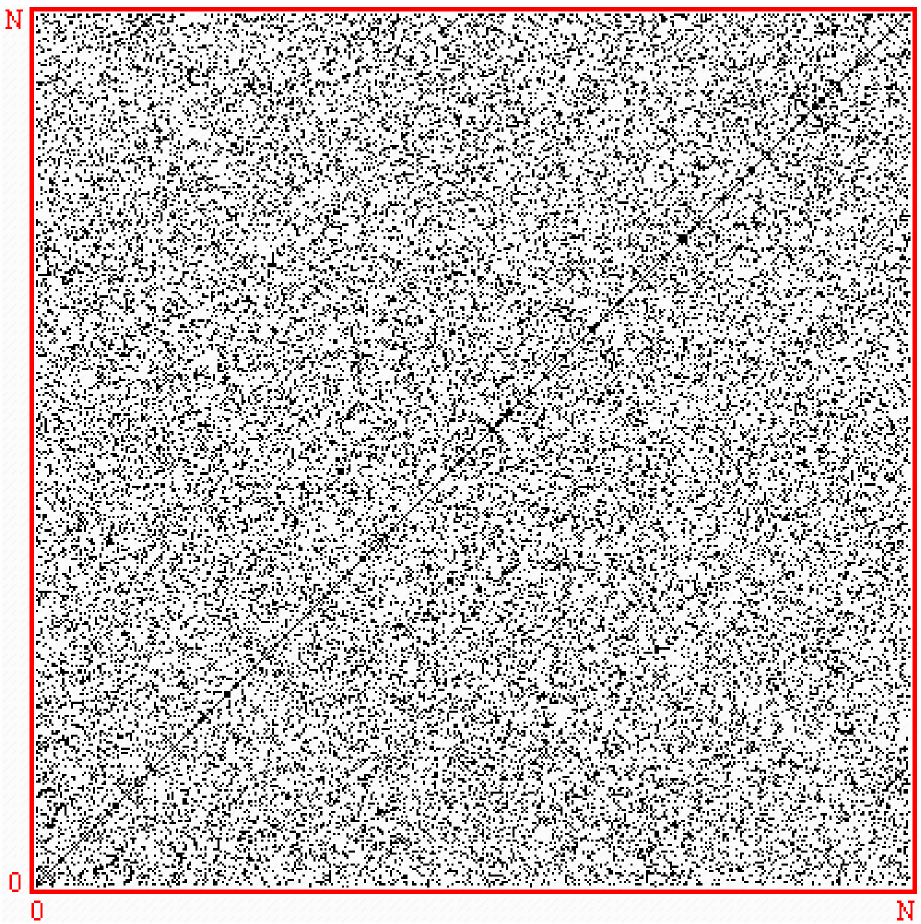


Basic parameters of RP are the (embedding) dimension, and distance (radius) in a (state) space. Markers can be binary, gray scaled, or colored.

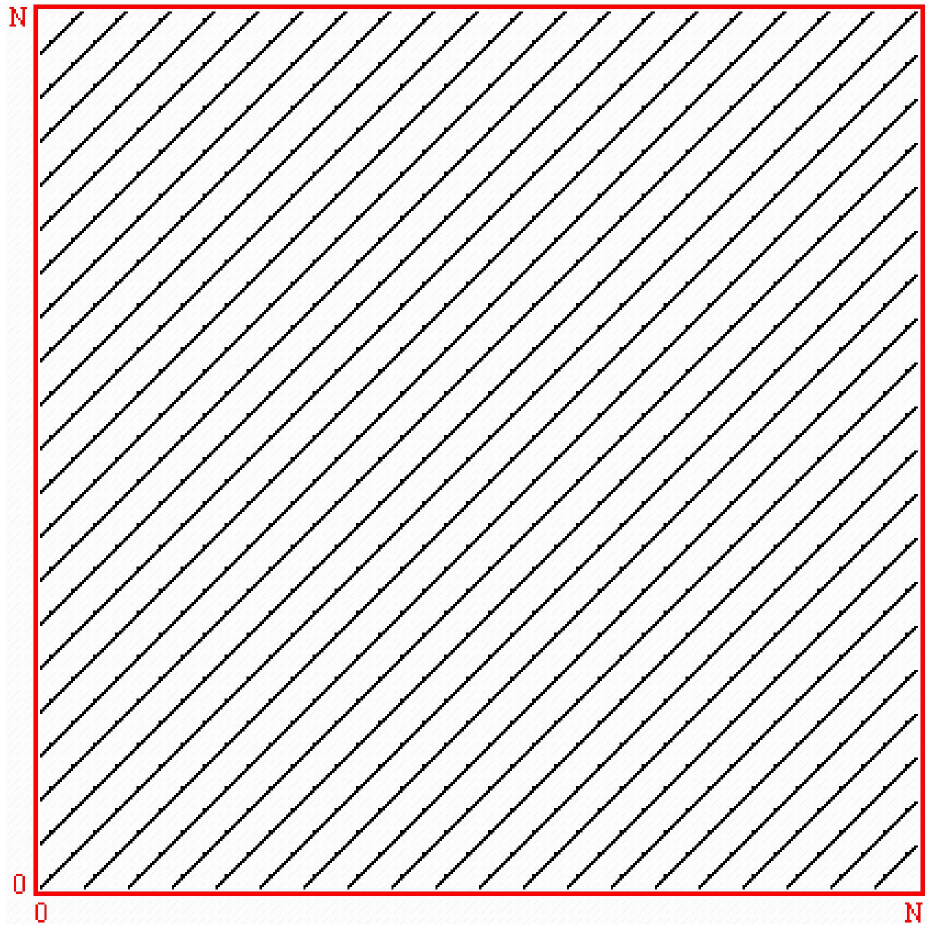
(RP Eckman 1987, Marvan 2002),

2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods

- Recurrence Plot (RP)



Random Signal

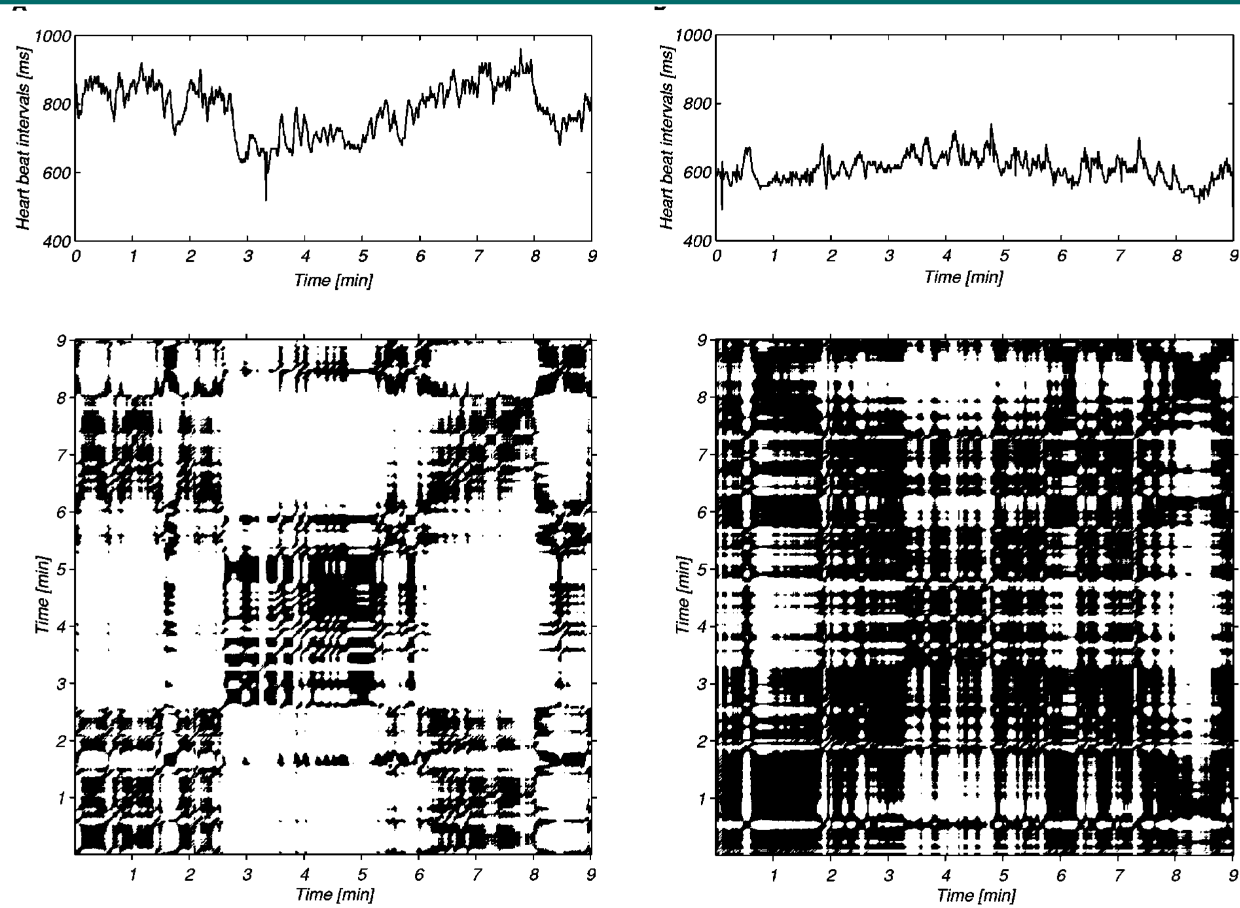


Sinus Signal

2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods

- Recurrence Plot (RP)

"FIG. 4. Recurrence plots of the heart beat interval … embedding of 6 and a radius of 110. The RP before a life-threatening arrhythmia is characterized by big black rectangles, whereas the RP from the control series shows only small rectangles."



[16] Marwan, N., Wessel, N., Meyerfeldt, U., Schirdewan, A., Kurths, J.: "Recurrence-Plot-Based Measures of Complexity and their Application to Heart-Rate-Variability Data", *Physical Review*,

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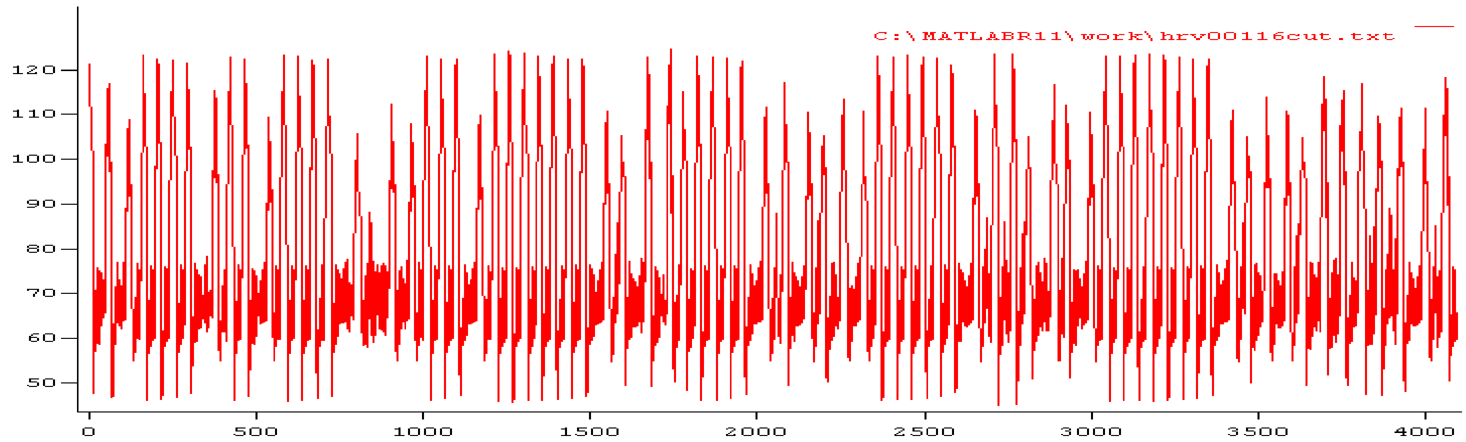
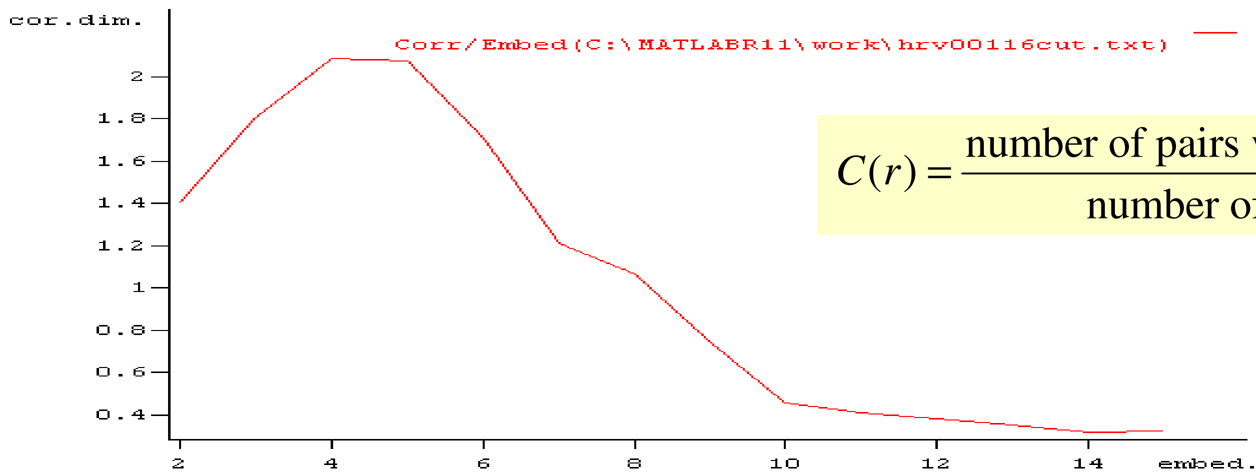


Td1=0.1s

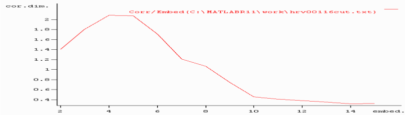
Td2=0.6s

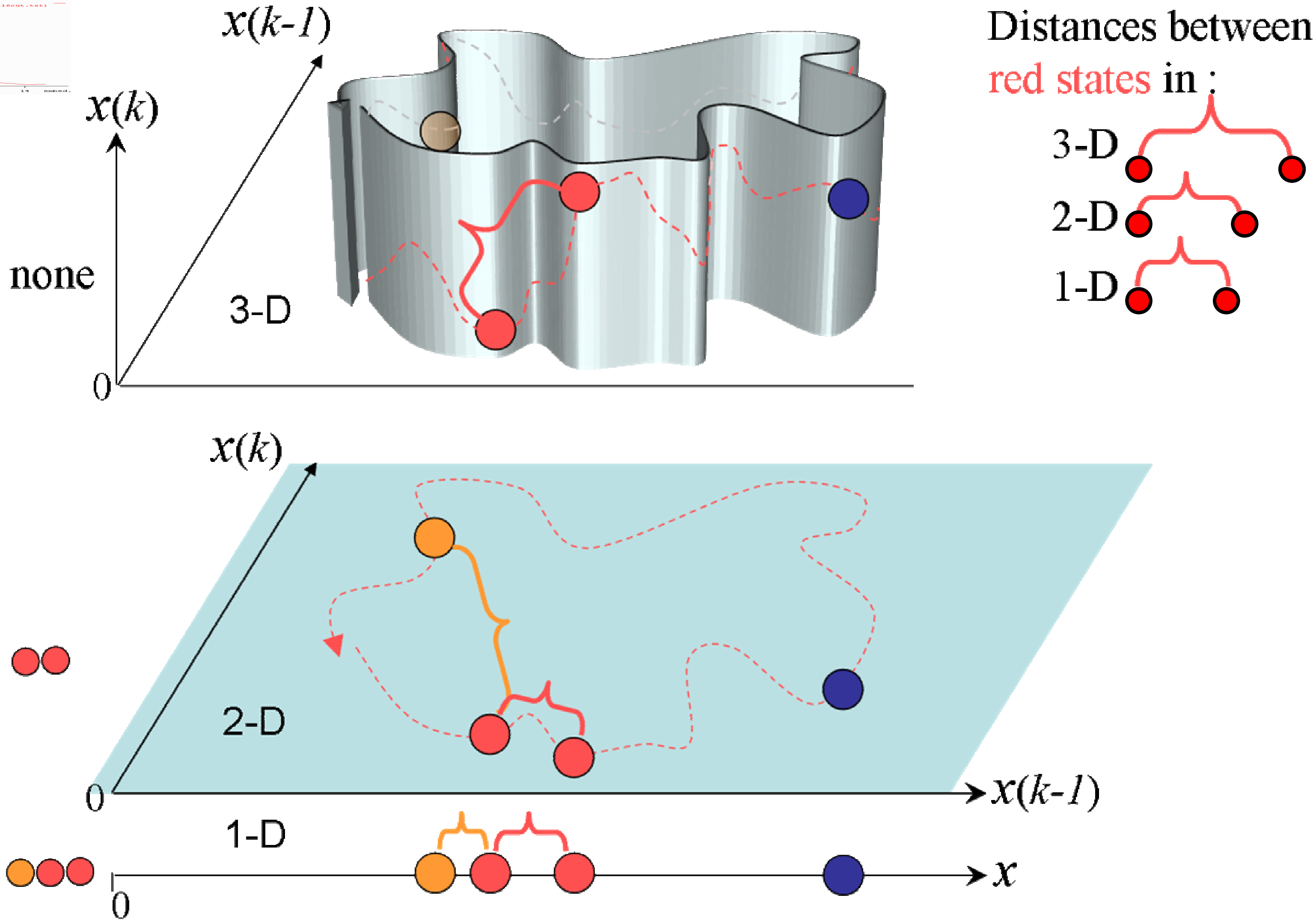


$$C(r) = \frac{\text{number of pairs with distance} < r}{\text{number of all pairs}}$$

"More chaotic time series" ⇔ Correlation Dimension decreases with increasing embedding dimension (Dataplore)

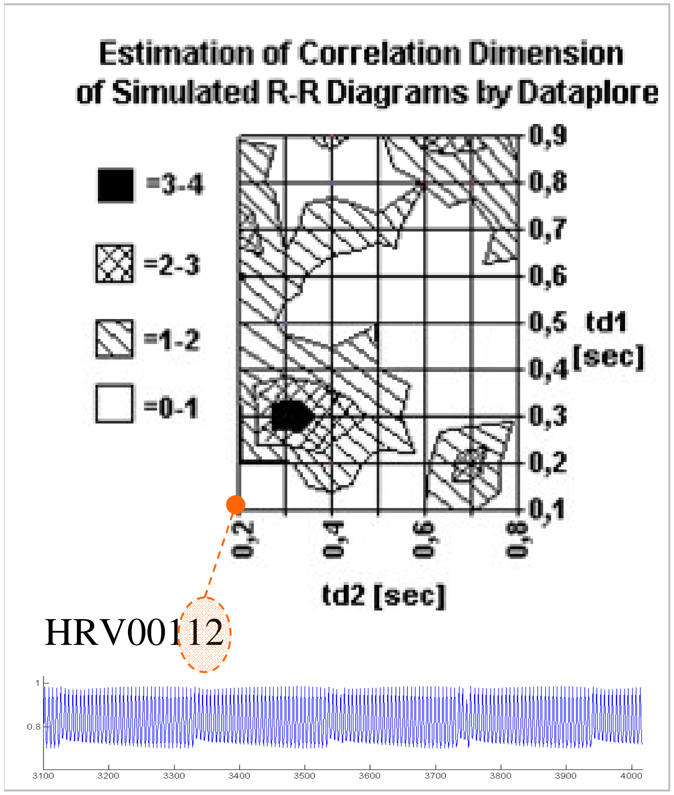
2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods
- Too complex and too nonlinear systems)





2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods
- Too complex and too nonlinear systems

Convergence of Correlation Dimension by Grassberger-Proccacia Method for simulated time-series (by Dataplore)

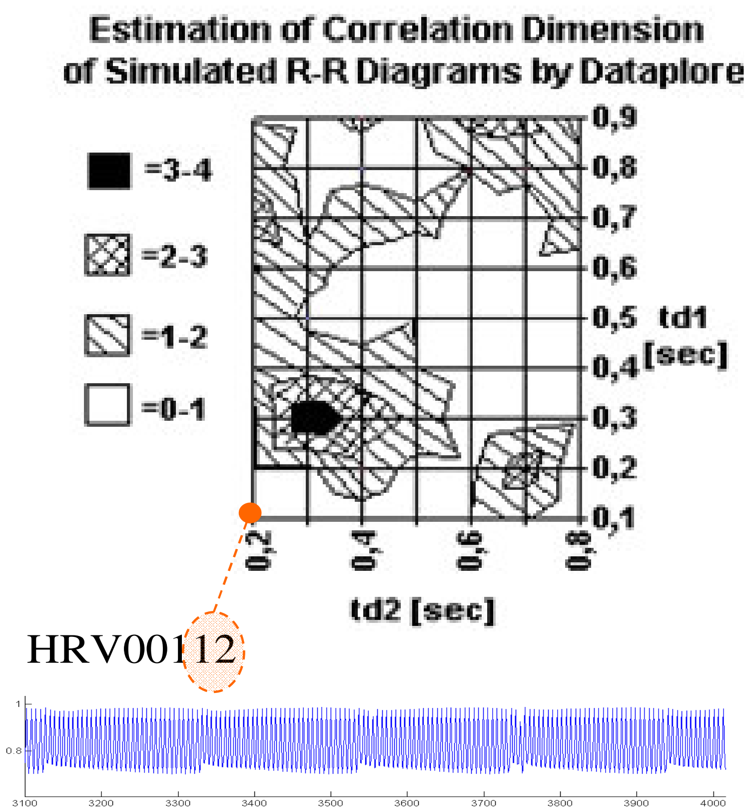


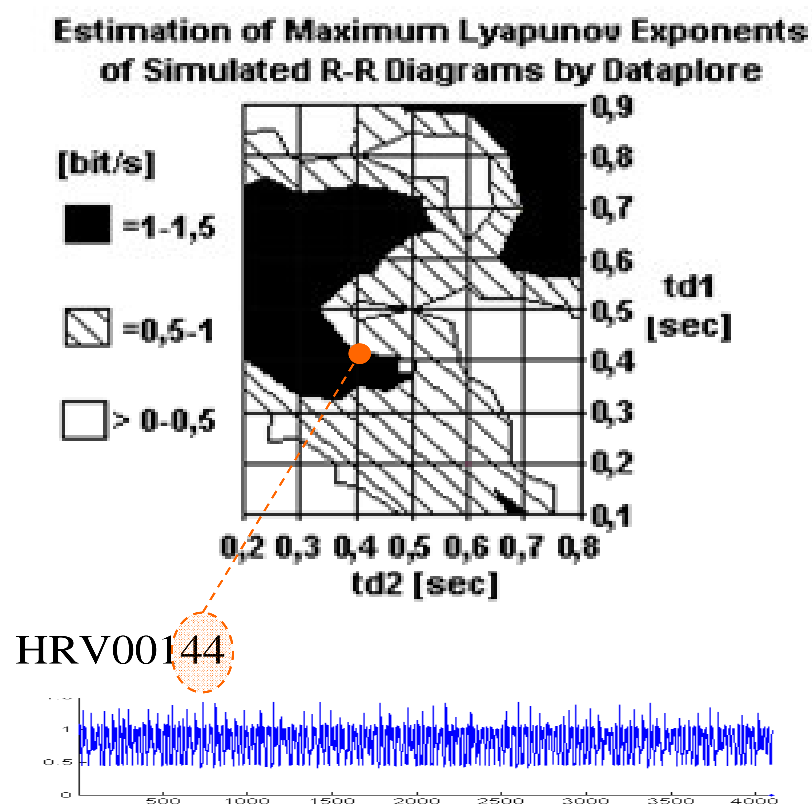
Method Converged		Td2 0.2	0.3	0.4	0.5	0.6	0.7	0.8
Correlation dimension converged		yes	yes					
		yes	yes				yes	
Td1	0.3	yes						yes
	0.4							yes
	0.5							
	0.6							
	0.7	yes						
	0.8							
	0.9	yes	yes					

Each intersection represents a different parameters td1 and td2 of time series generated by the same deterministic system.

- Too complex and too nonlinear systems

of 56 simulated time series evaluated and results visualized bellow





Each intersection represents a different parameters td1 and td2 of time series generated by the same deterministic system.

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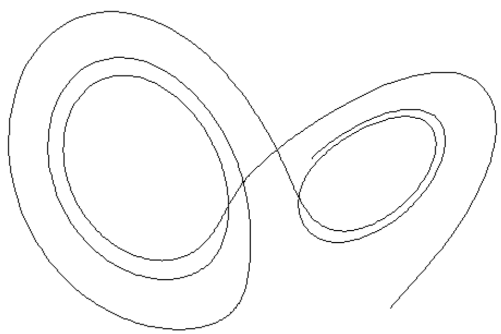
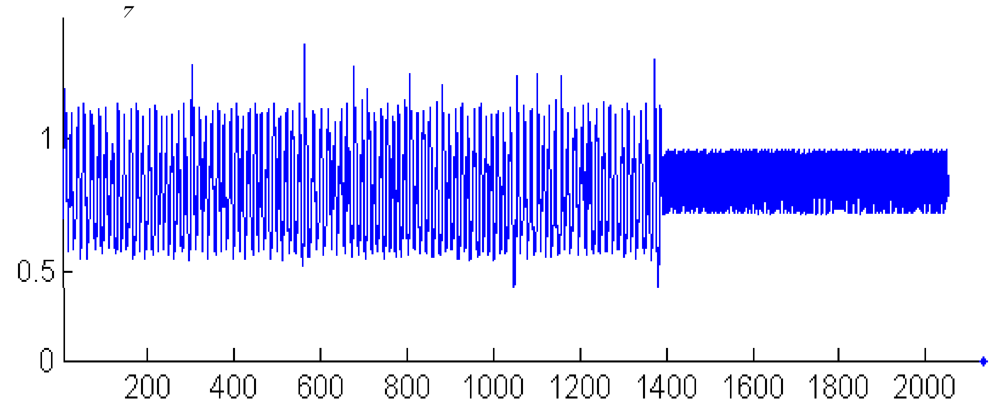
2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods
- Multi-attractor behavior of chaotic systems

Chaotic trajectory of Lorenz system



Simulated time series by deterministic model HRV00136

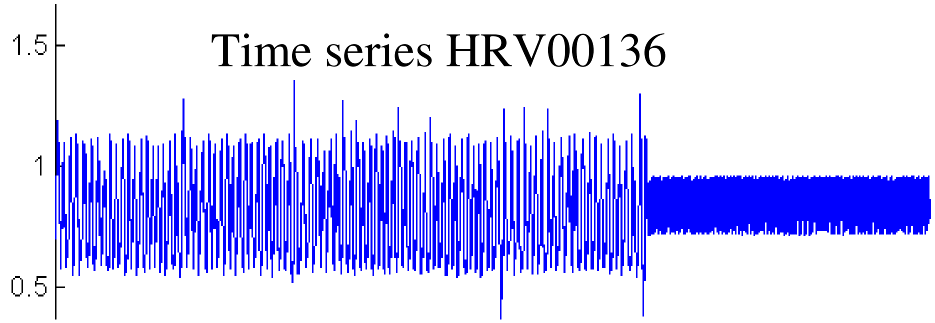


- Attractor – to where the system trajectory is attracted (point, (limit) cycle)
- Chaotic (strange) attractors can be seen as consisting from multiple local ("smaller") attractors (attracting regions)
- Transitions of system trajectory among local attractors of chaotic (nonlinear) deterministic systems happens seemingly freely and relates to high sensitivity of chaotic system.

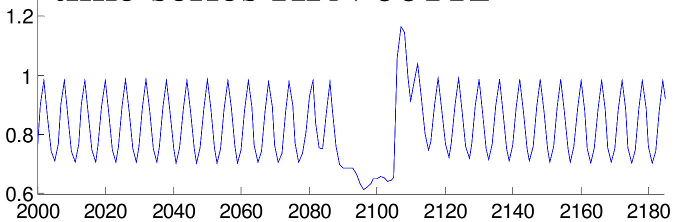
2. Issues of Evaluation of Deterministic Chaotic Systems by Existing Nonlinear Methods

- Multi-attractor behavior of chaotic systems

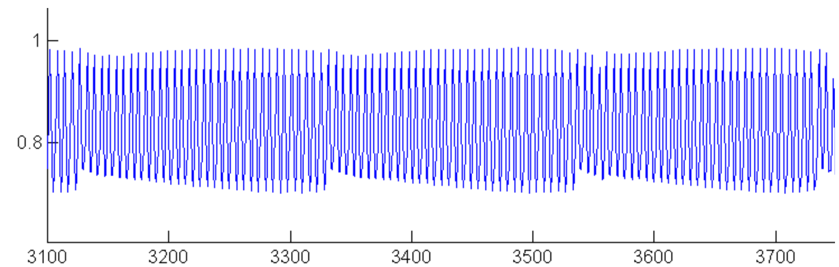
Time series HRV00136



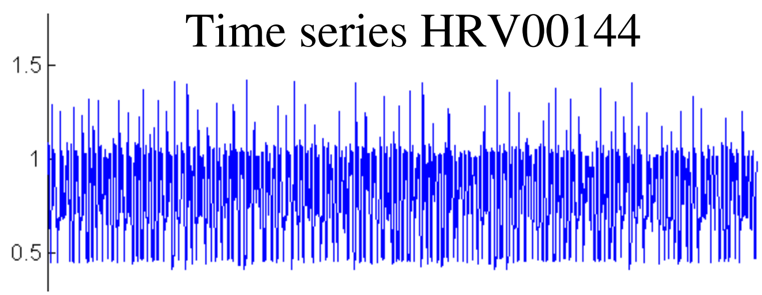
Unusual transition between attractors of time series HRV00112



Time series HRV00112



Time series HRV00144



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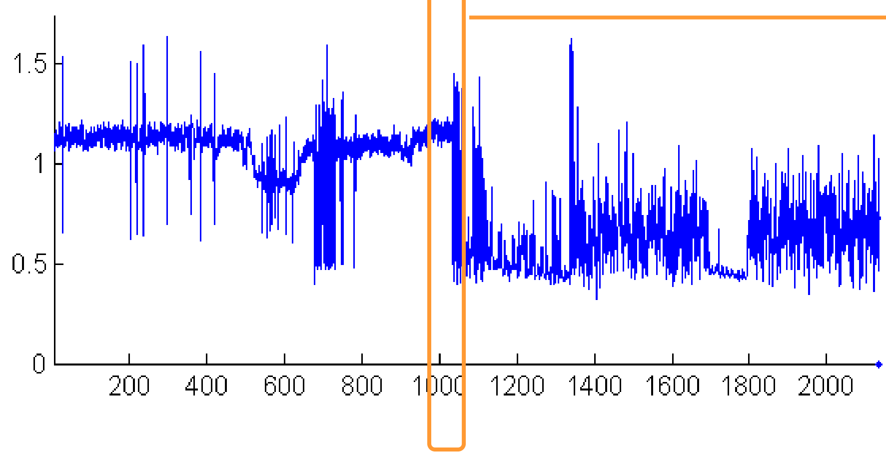
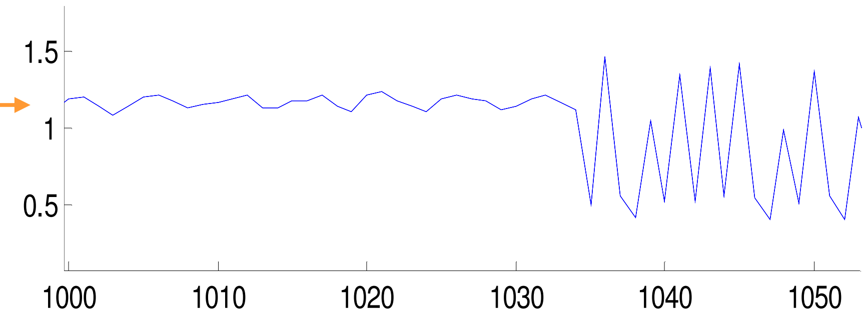
3. Issues of Evaluation of Real Complex Systems by Existing Nonlinear Methods
- Multi-attractor behavior of chaotic systems

- Inter-attractor transitions in real systems interfere with unknown system perturbations (known and unknown inputs) and thus further complicate the system behavior and decrease our chance to understand and analyze the behavior mathematically

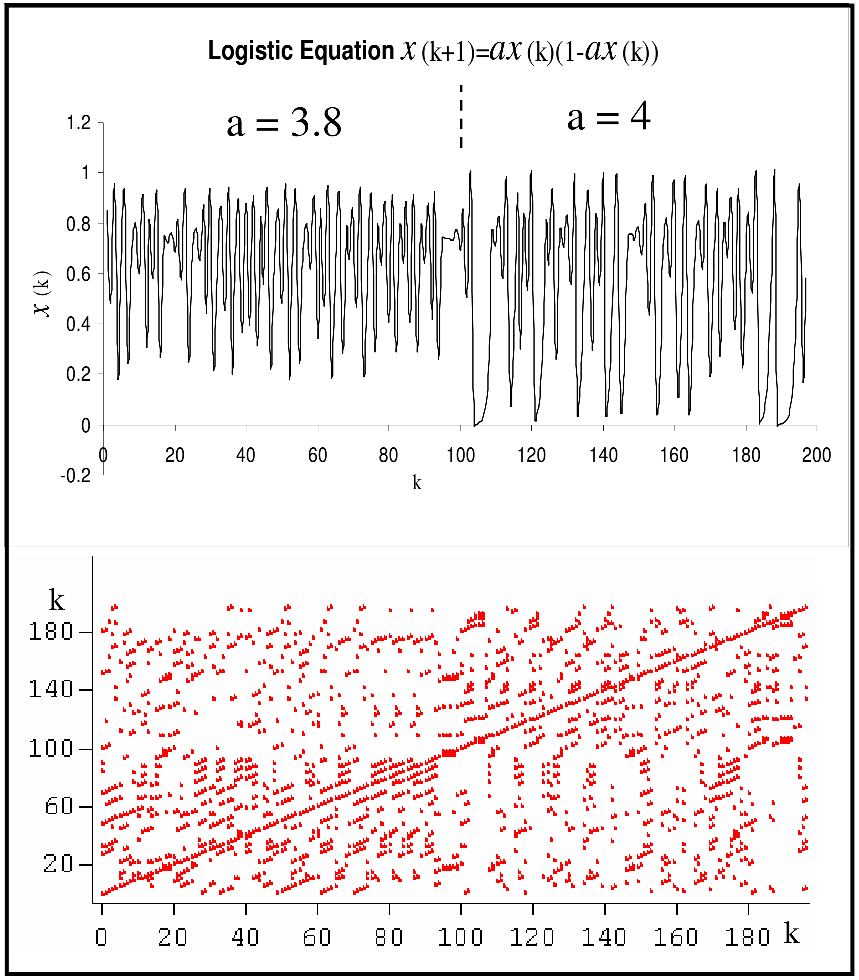
Real heart beat (R-R) of a patient with a cardiac disorder MIT_BIH_202

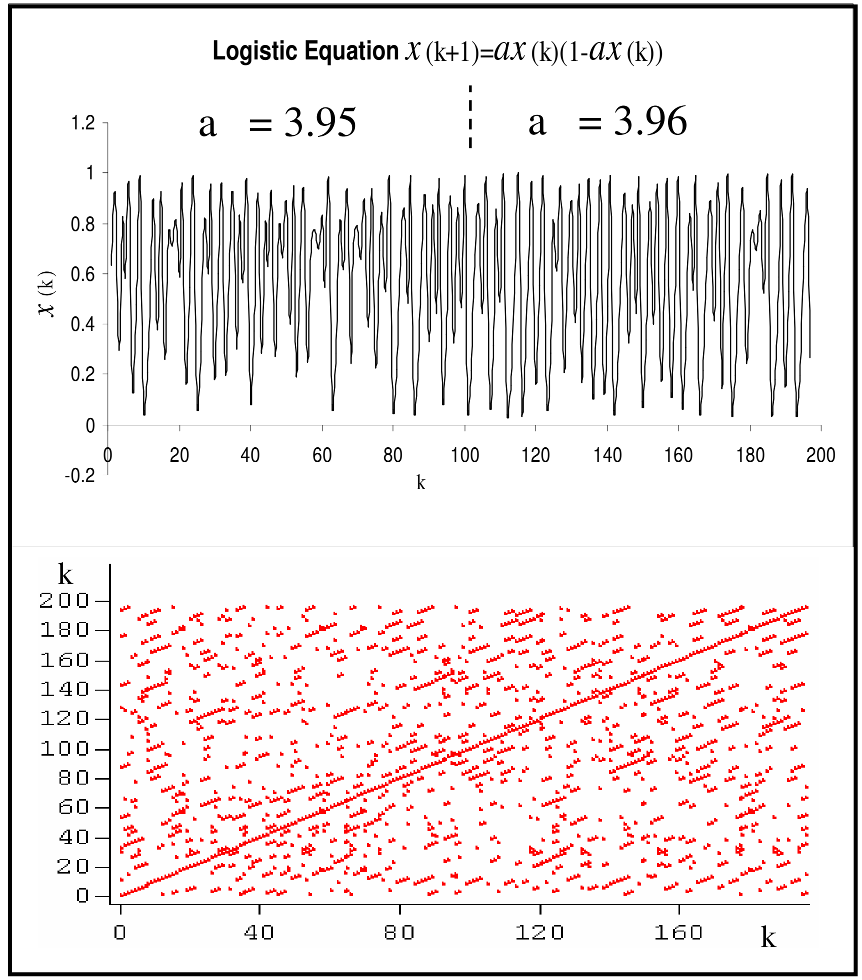




3. Issues of Evaluation of Real Complex Systems by Existing Nonlinear Methods

- Multi-attractor behavior of chaotic systems





3. Issues of Evaluation of Real Complex Systems by Existing Nonlinear Methods
- Multi-attractor behavior of chaotic systems

Correlation dimension (CD) and largest Lypaunov exponents (LLE) suffer from the inaccuracy, are not reliable, or are difficult to interpret if:

– „...the signal is too complicated (too high embedding dimension), not sufficiently self-returning (multi-attractor behavior or perturbations), not long enough, and has inappropriately high noise to signal ratio (Vitkaj, Ph.D. thesis 2001)...“.

The above symptoms are typical for HRV measurements

4. **Evaluation of Complex Time Series using Nonconventional Neural Units**

- **Neural Unit as a Nonlinear Adaptable Forced Oscillator– HRV-HONNU**
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- Methodology of Adaptive Evaluation of Complex Time Series – the Adaptation Plot

5. Applications

- Adaptive Evaluation of Deterministic Chaotic Systems
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6. Limitations and Advantages Summary

4. Evaluation of Complex Time Series using NNU
- Neural Unit as a Nonlinear Adaptable Forced Oscillator (HRV-HONNU)

HRV evaluating methods supported by the use of artificial neural networks suffers from the black (gray) box effect of conventional ANN with nonlinear somatic neural operation (e.g. sigmoid) disables us from analyzing a knowledge hidden in a trained network.

⇩

The need for a new neural architecture which mathematical structure could be analyzed easier.

⇳

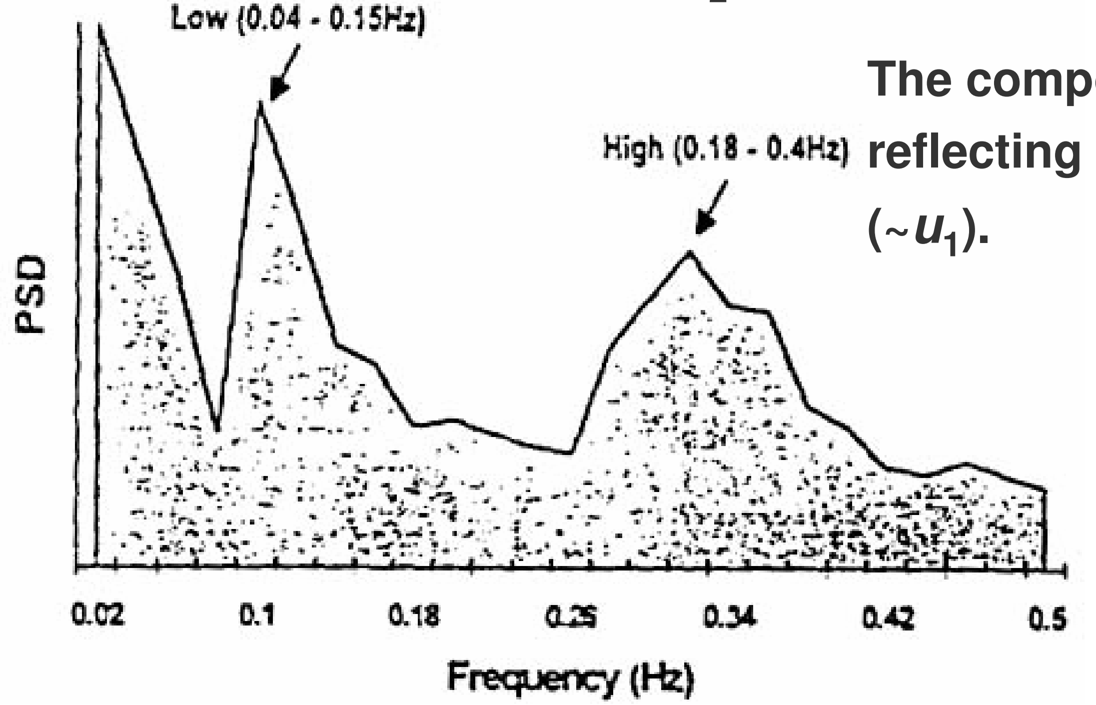
Small number of neural parameters and simple mathematical architectures

4. Evaluation of Complex Time Series using NNU

- Neural Unit as a Nonlinear Adaptable Forced Oscillator (HRV-HONNU)

Power spectral density of heart beat tachogram

The component reflecting tonus of vagus and cardiac sympathetic nerves (~u_2).

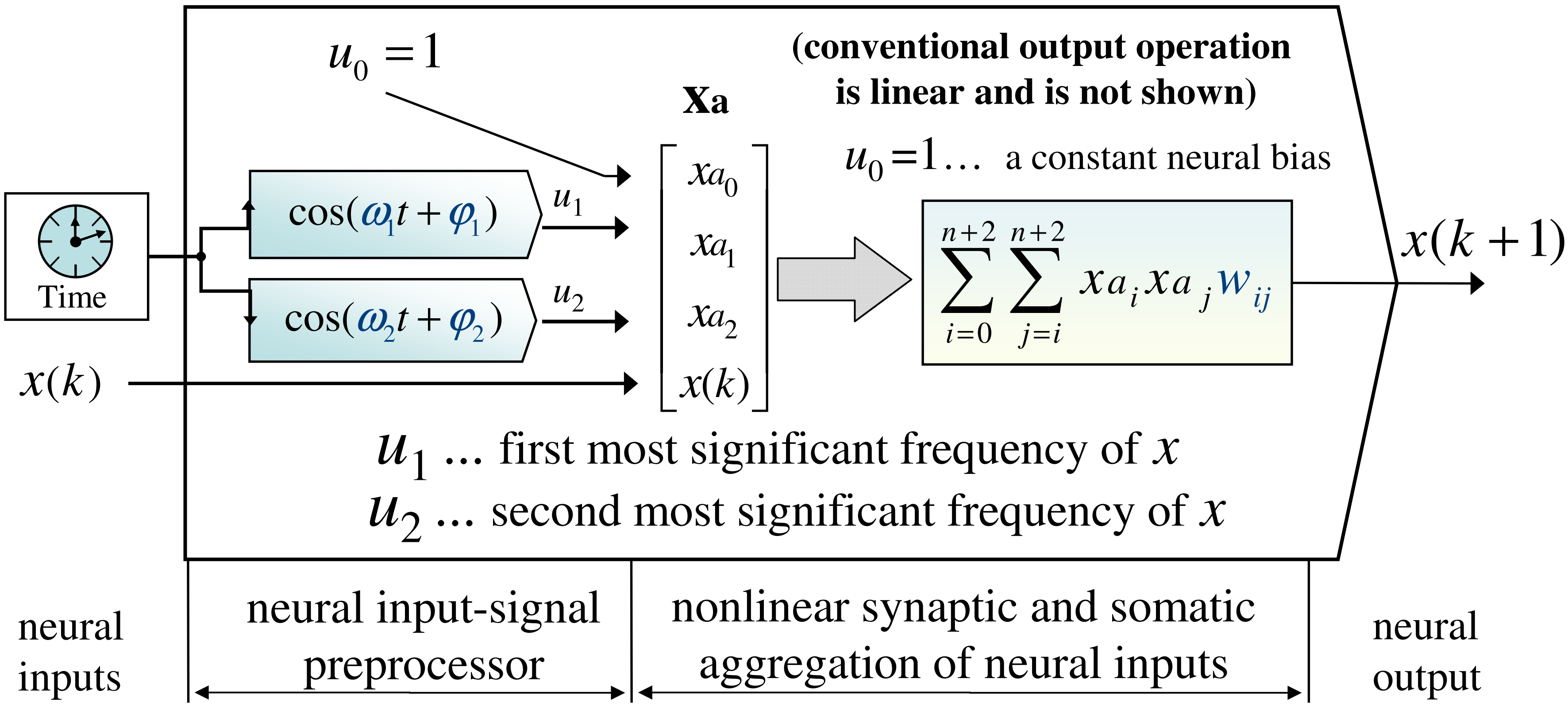


The component reflecting respiration (~u_1).

4. Evaluation of Complex Time Series using NNU

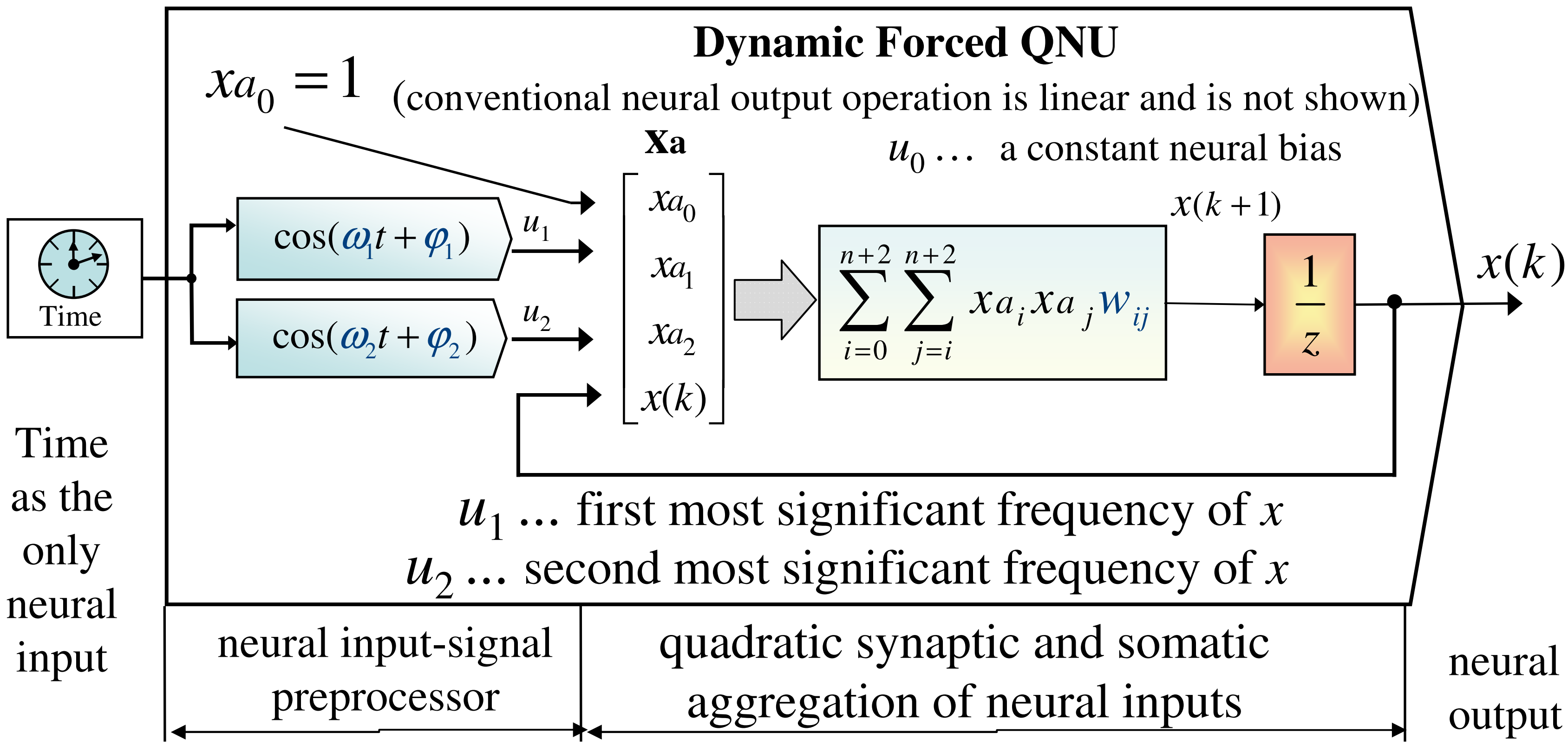
- Neural Unit as a Nonlinear Adaptable Forced Oscillator (HRV-HONNU)

Static Forced QNU



u_1 … a self-tuning influence of breathing rhythm i.e., first most significant frequency component.
u_2 … a self-tunning influence of vagal tonus, i.e., second most significant frequency component.

Dynamic Forced QNU = adaptive forced nonlinear oscillator



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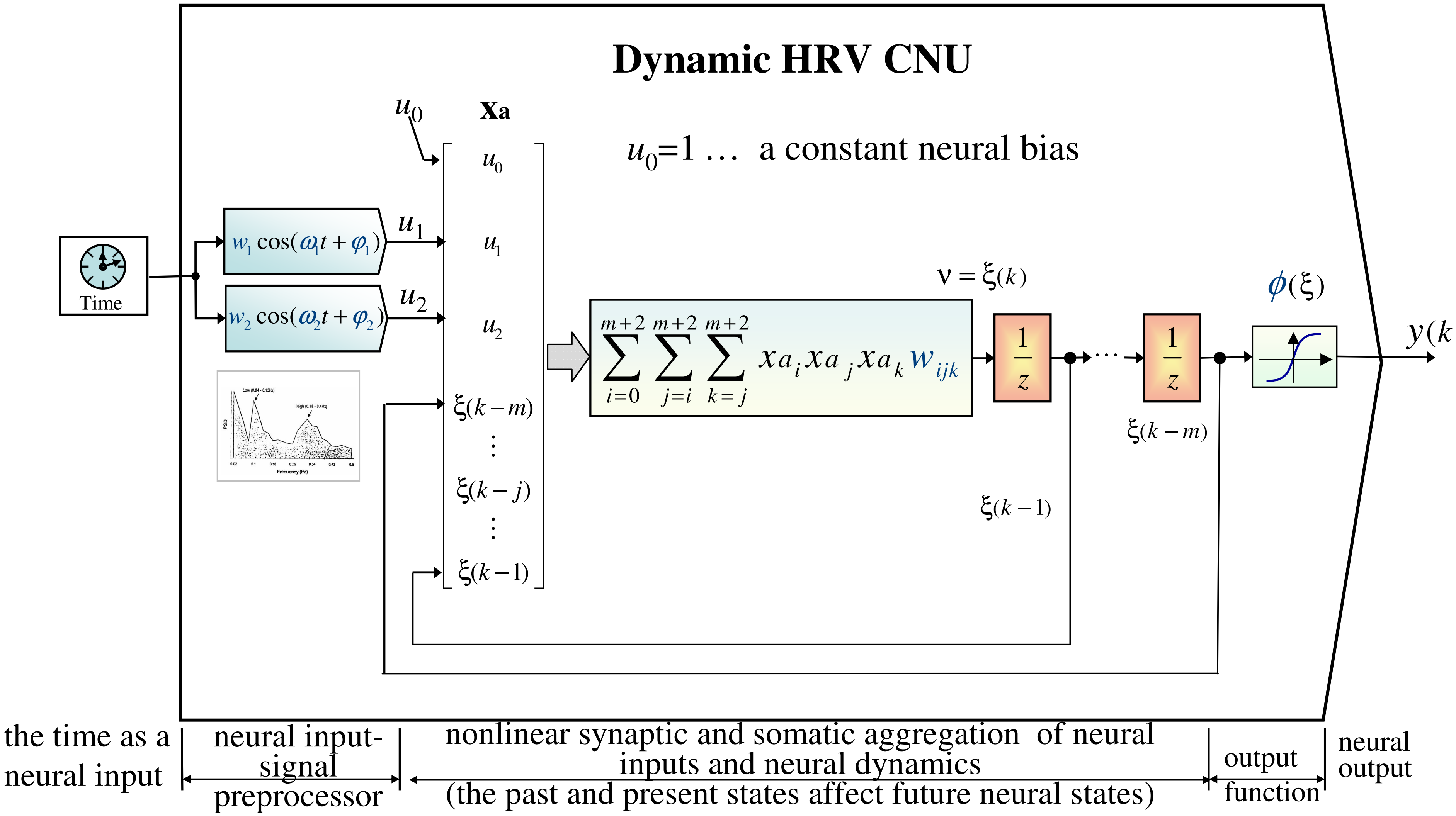

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4. Evaluation of Complex Time Series using NNU
-Adaptation Technique for HRV-HONNU

- Scaling data may be necessary to assure convergence of a dynamic neural unit as well as to improve its convergence
- A significant area (volume) of the basin of attraction of the dynamic systems such as HONNU can be well expected in the vicinity of the origin.
- Eg., for used HONNU and TmD-DNU, at least one equilibrium point is always the origin [0,0,…,0], other equilibria are well expected "not far" from the origin as well. Values of usual R-R inter-beat diagrams oscillated within the range (0 , 1.2)
- Time series, such us R-R (inter-beat) diagrams did not have to be scaled when units are seconds (usually values <0, 1>)

4. Evaluation of Complex Time Series using NNU
-Adaptation Technique for HRV-HONNU

Scale the data if necessary (e.g., to range <0,1>)

↓

Check 2-D or 3-D phase portrait if simple nonlinear mapping is not hidden behind the data.

↓

If not, perform mathematical analysis to estimate the minimum embedding dimension or use some appropriate methods, e.g., the false nearest neighbor method,...

↓

Set random initial neural parameters. Adapt static neural unit in a number of epochs while error and neural parameters still converge over each whole epoch.

↓

If neural parameters of static neural unit do not converge or if error is still high, decrease learning rates or change initial weights, use cubic neural unit instead of quadratic unit, increase embedding dimension.

↓

4. Evaluation of Complex Time Series using NNU
-Adaptation Technique for HRV-HONNU

If error is still too high and convergence poor, estimate number and type of possible system inputs and enhance the neural unit with adaptable input signal preprocessor, e.g., analyze power spectrum of a signal to find significant frequencies and introduce adaptable periodic inputs to increase approximating capability of a unit.

If static neural unit converges, set the learned neural parameters as initial ones and adapt its dynamic version in single run over the whole evaluated signal.

Detect and visualize unusually large increments in of each neural parameter at every sample in order to detect significant changes in system dynamics, inter-attractor transitions, internal or external perturbations, artefacts, noise.

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- Methodology of Adaptive Evaluation of Complex Time Series the **Adaptation Plot**

Determine the reference values (e.g., averages) of increments for each neural parameter of a dynamic neural unit adapted to the evaluated time series:

$$\text{Ref\_}\Delta w_i = \text{ABS}\left(\text{AVERAGE}(\Delta w_i(k))\right) \text{ for } k=1..m\ \ N,$$

where N is the number of samples of the evaluated series.

Detect and visualize variability markers by comparing the neural weight increments to their reference values for every sample during a single epoch adaptation:

for k = 1: N

for i=1:n

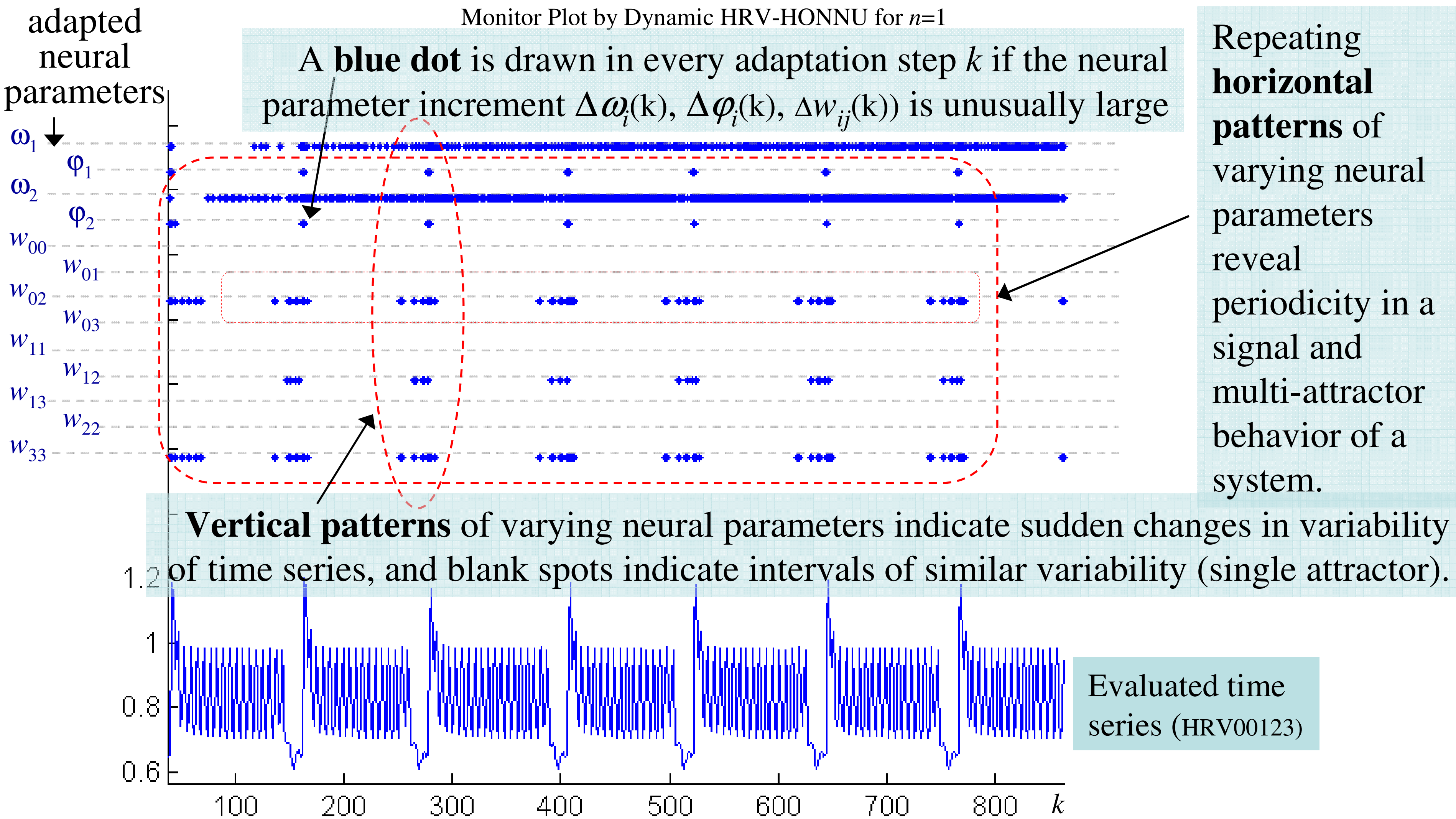
IF $\text{ABS}\left(w_i\,(k+1)\text{-}\ w_i(k\text{-}1)\right) > p\cdot\text{Ref\_}\Delta w_i$ THEN detection is positive, record and draw the marker ;

end if; end for; end for;

where p is the detection sensitivity parameter, w_i represents i^{th} adaptable neural parameter of the neural unit, n is the number of all adaptable neural parameters including the optional signal input preprocessor, N is the length of the series.

4. Evaluation of Complex Time Series using NNU

- Methodology of Adaptive Evaluation of Complex Time Series the **Adaptation Plot**



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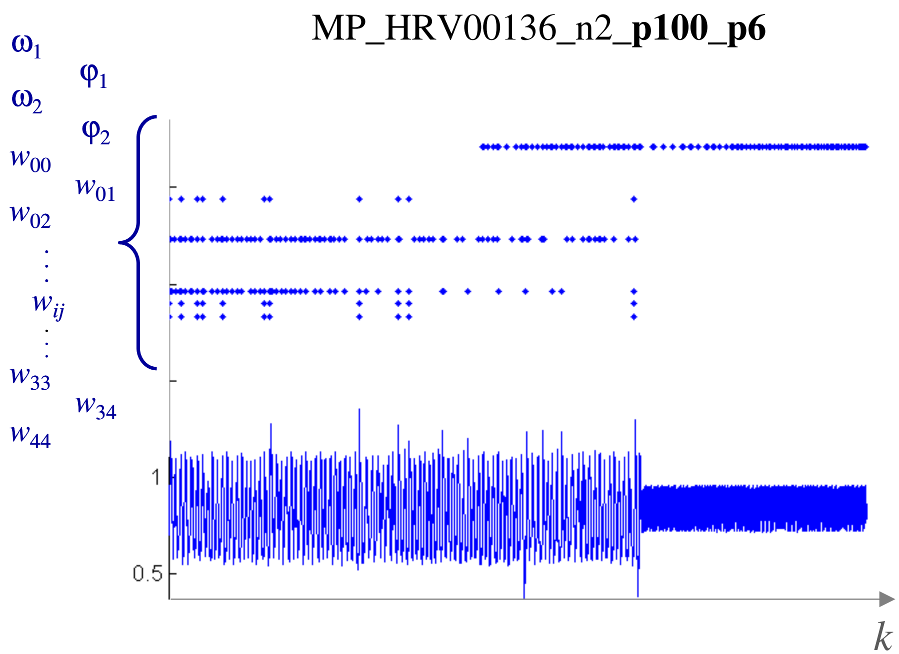
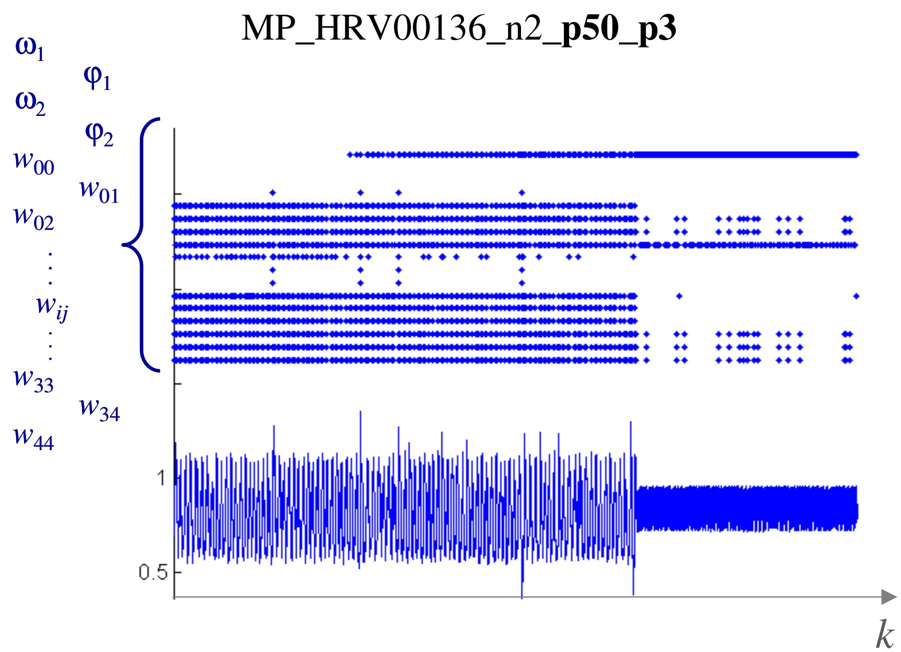
- Methodology of Adaptive Evaluation of Complex Time Series the **Adaptation Plot**





4. Evaluation of Complex Time Series using Nonconventional Neural Units
   - Neural Unit as a Nonlinear Adaptable Forced Oscillator– HRV-HONNU
   - Adaptation Technique for HRV-HONNU
   - Methodology of Adaptive Evaluation of Complex Time Series – the Adaptation Plot

5. Applications
   - **Adaptive Evaluation of Deterministic Chaotic Systems**
   - Adaptive Sample by Sample Evaluation of Real Complex Signals

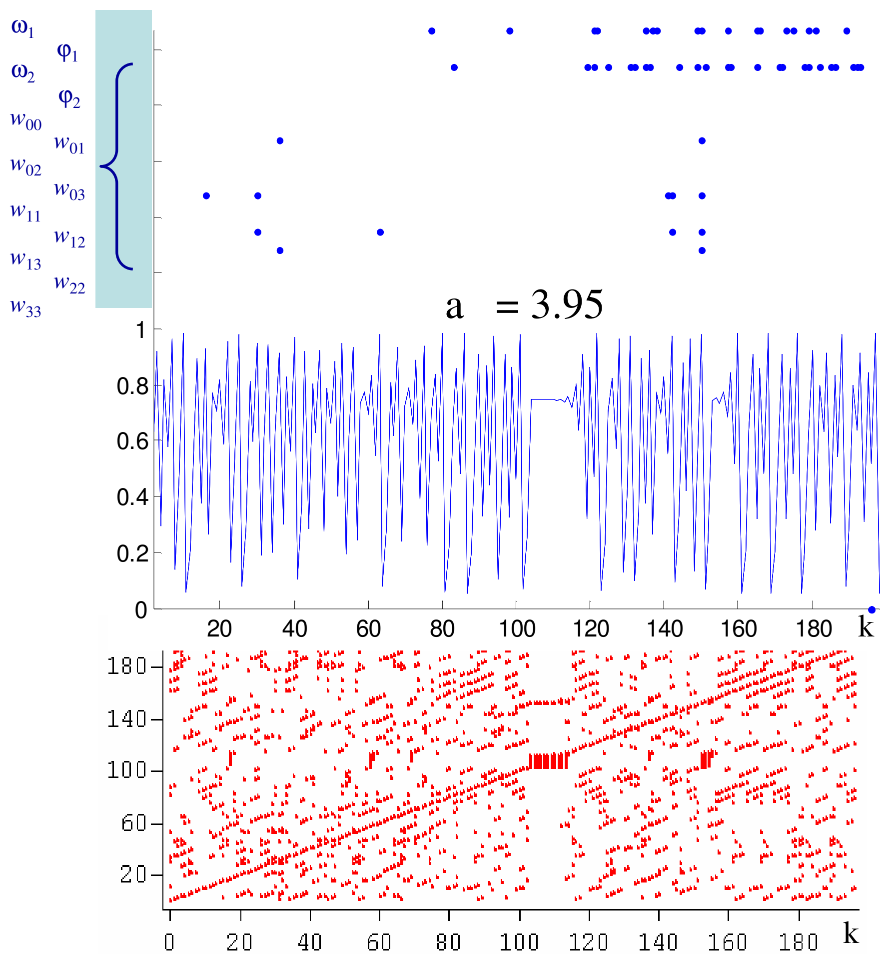
6. Limitations and Advantages Summary

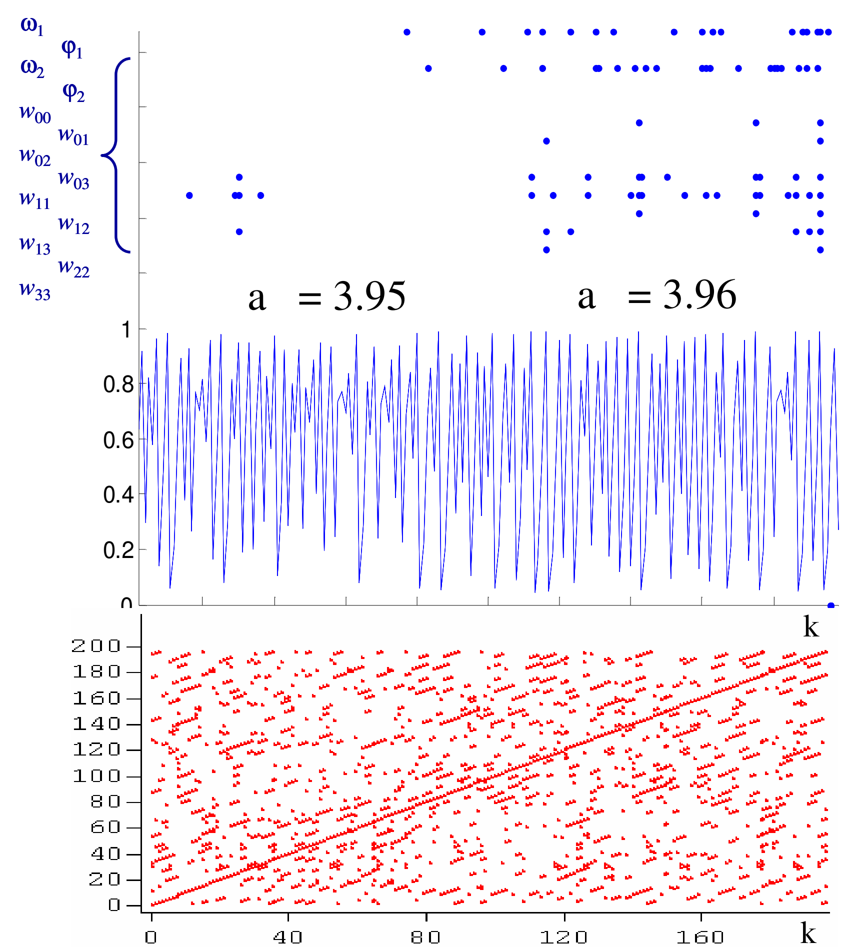
We show results on **two cases** of deterministic time series:

- ***Case 1***: *Time series generated by complex high dimensional dynamic, high nonlinear, deterministic model capable of generating from periodic to highly chaotic time series* (*e.g. simulated HRV time series*).
- ***Case 2***: *Complex time series generated by a relatively simple governing equation running in chaotic mode, e.g. the logistic map:*

$$x(k+1) = a \cdot x(k) \cdot (1 - x(k)) \quad , \qquad a = 3.9 \ldots 4$$

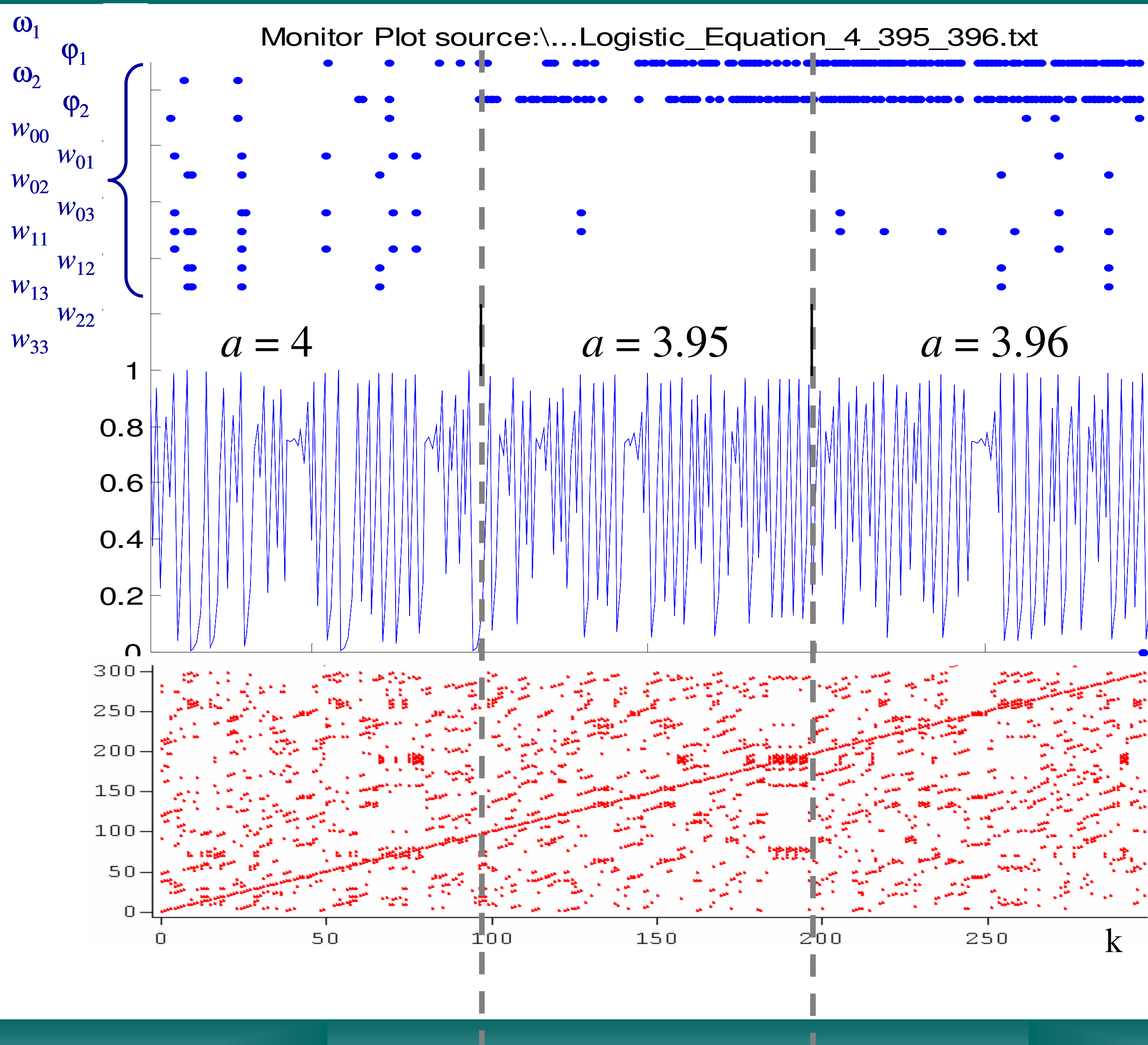
5. Applications
- Adaptive Evaluation of Deterministic Chaotic Systems





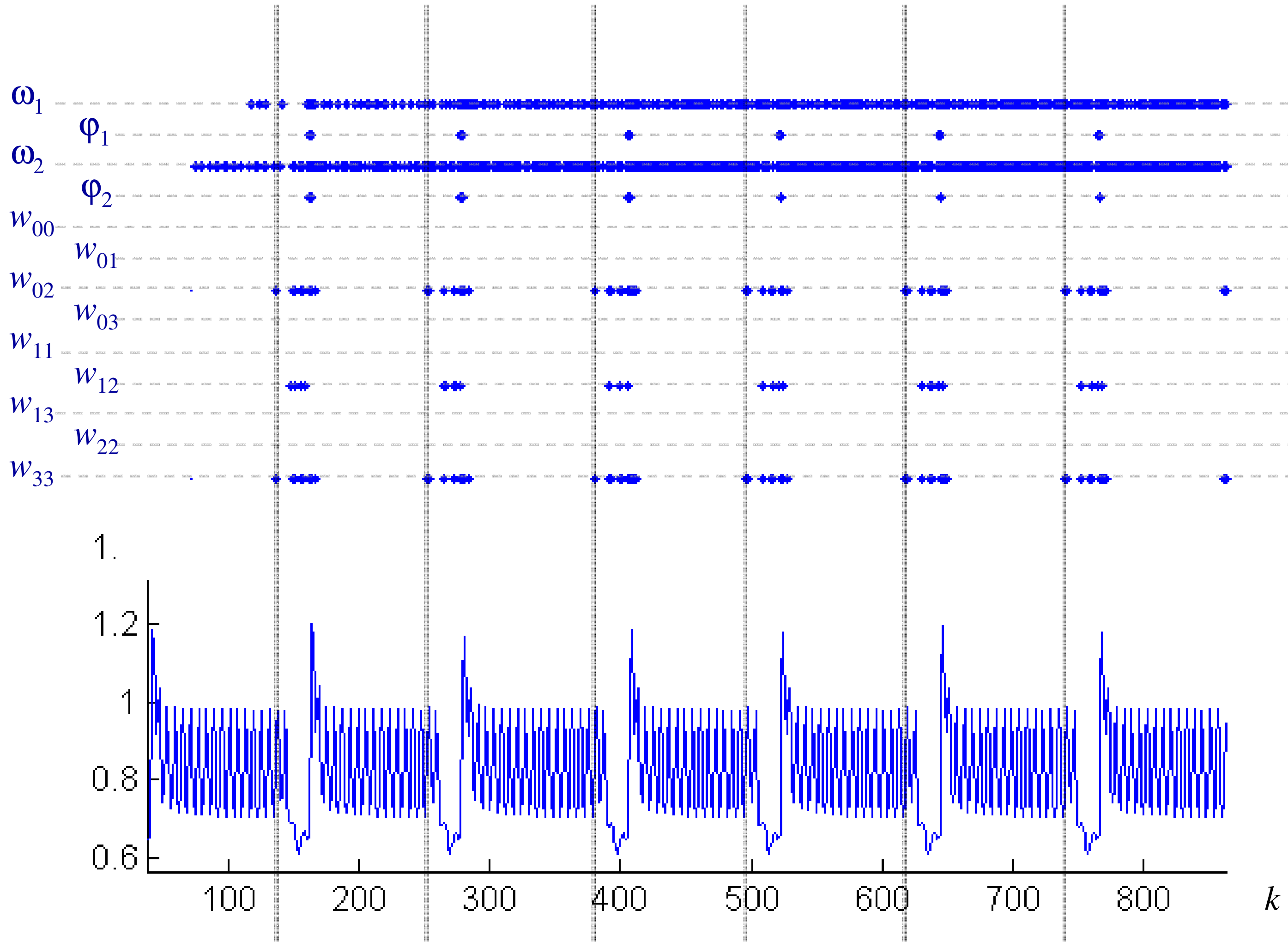
5. Applications

- Adaptive Evaluation of Deterministic Chaotic Systems



5. Applications

- Adaptive Evaluation of Deterministic Chaotic Systems

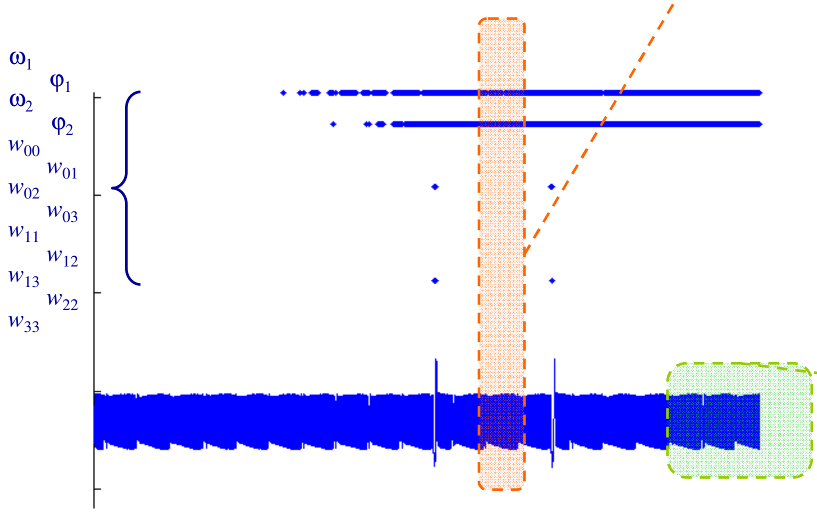


5. Applications

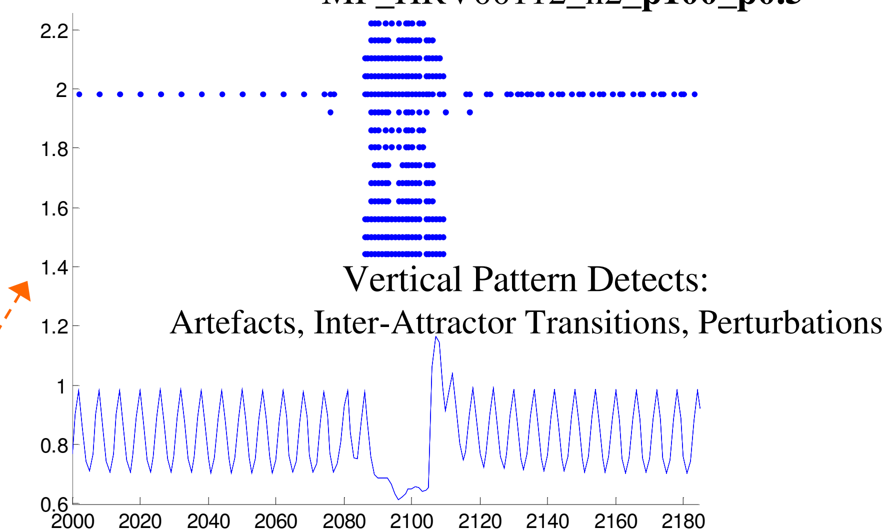
- Adaptive Evaluation of Deterministic Chaotic Systems

Monitoring of artefacts, noise and perturbations in complex signals

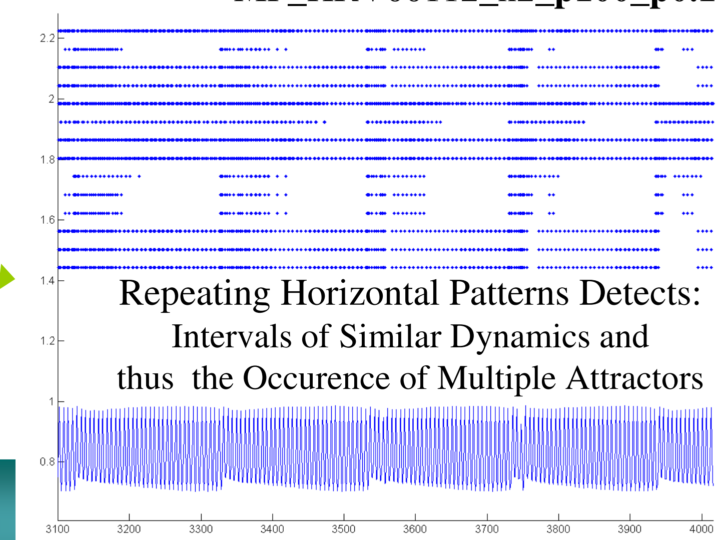
MP_HRV00112_n1_**p50_p7**



MP_HRV00112_n2_**p100_p0.5**

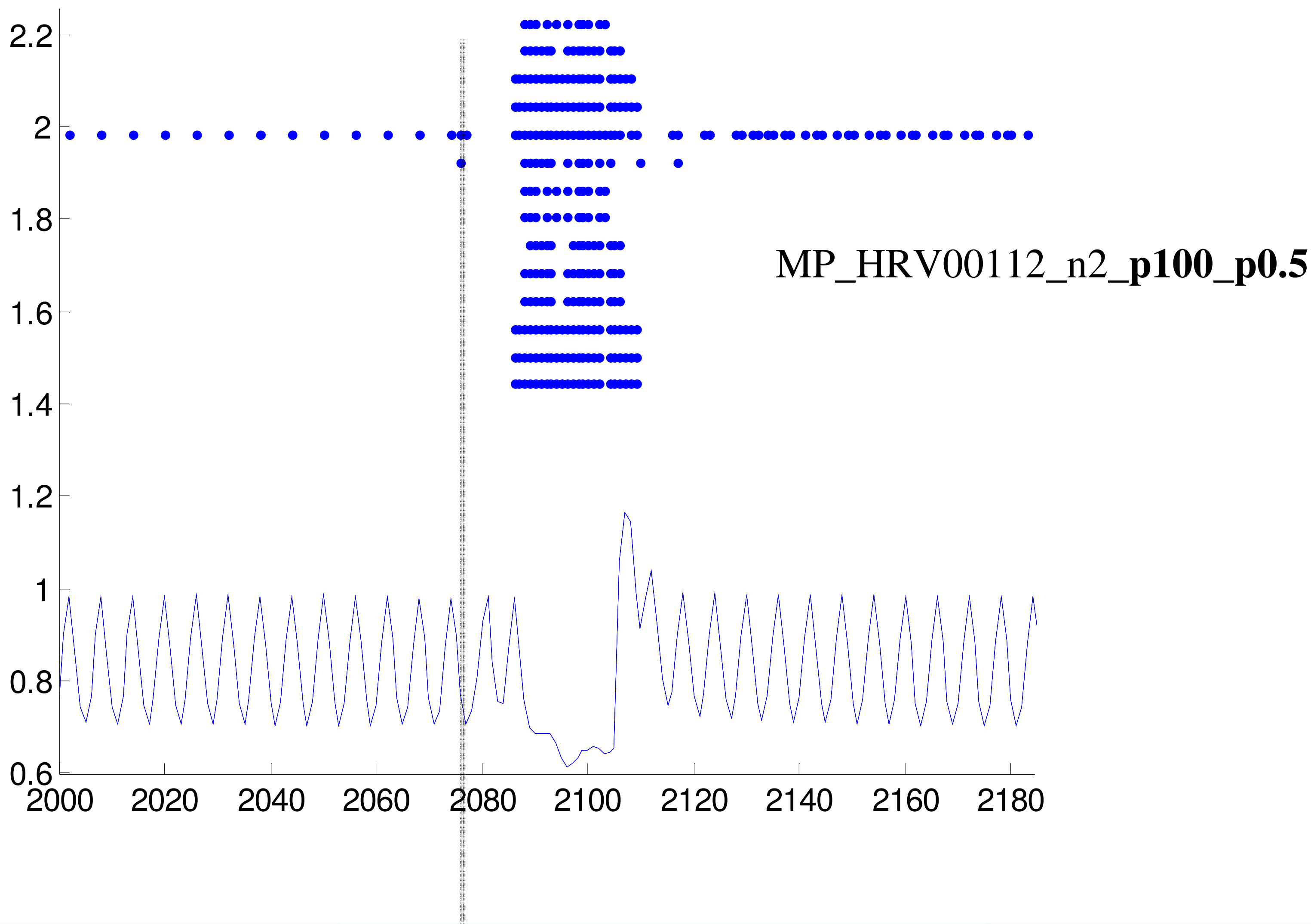


MP_HRV00112_n2_**p100_p0.1**



5. Applications

- Adaptive Evaluation of Deterministic Chaotic Systems



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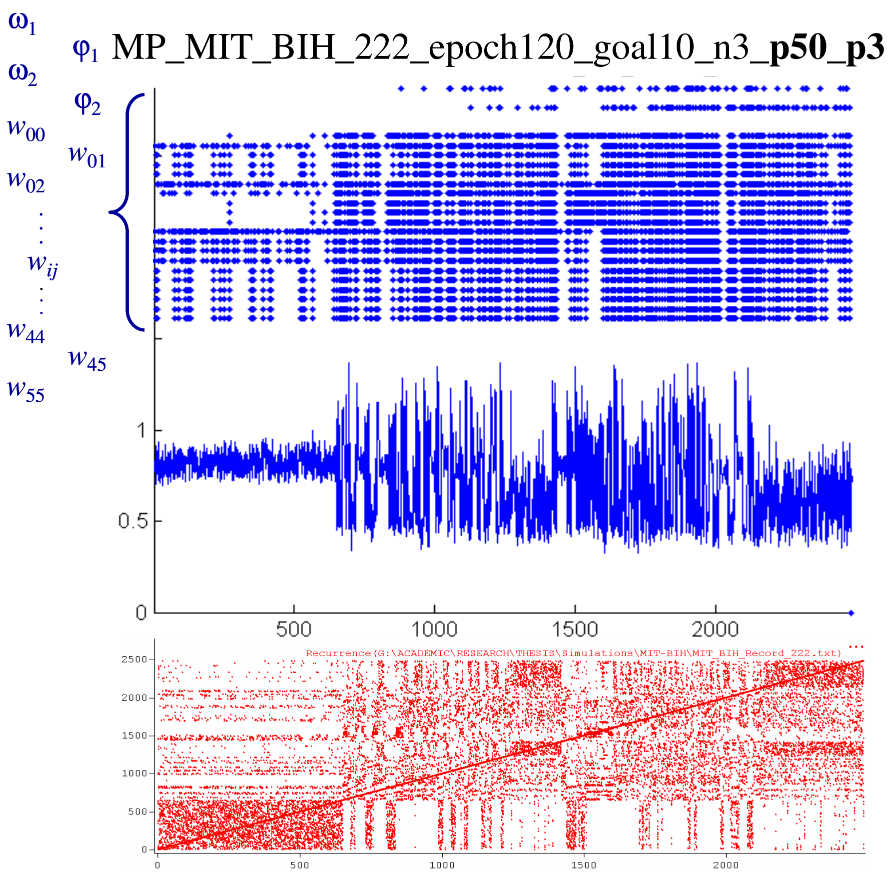
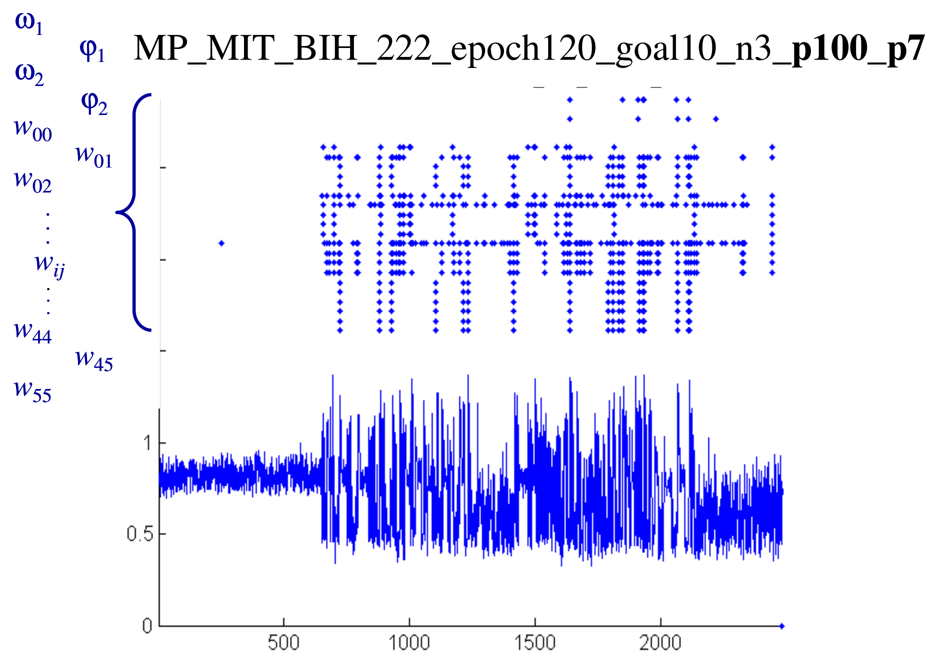
   - **Adaptive Sample by Sample Evaluation of Real Complex Signals**
6. Limitations and Advantages Summary

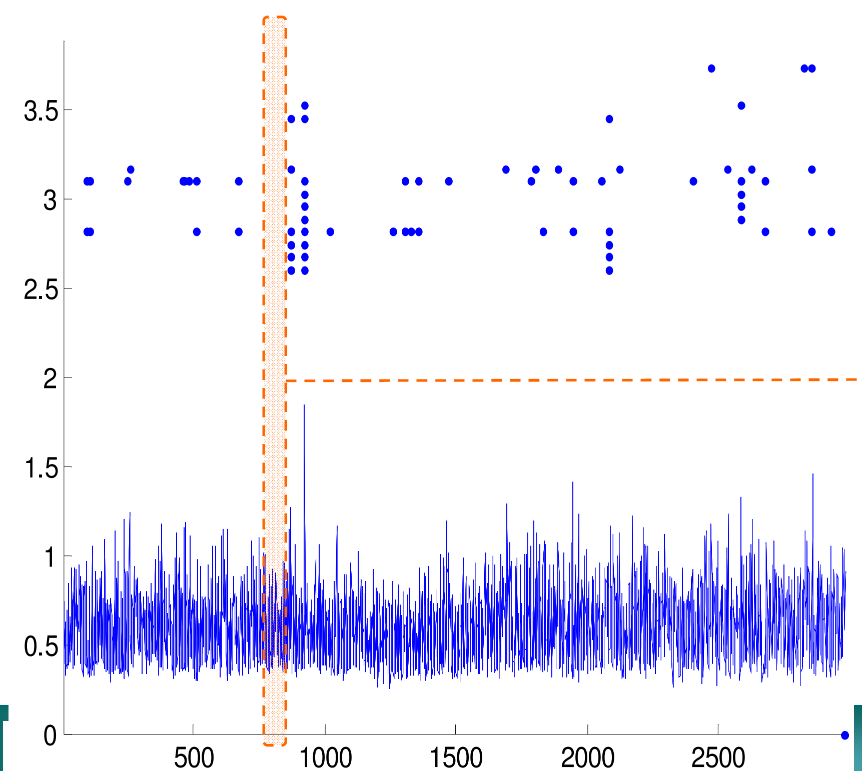
Monitoring of intervals of similar repeating patterns and multi-attractor behavior in heart rate variability.





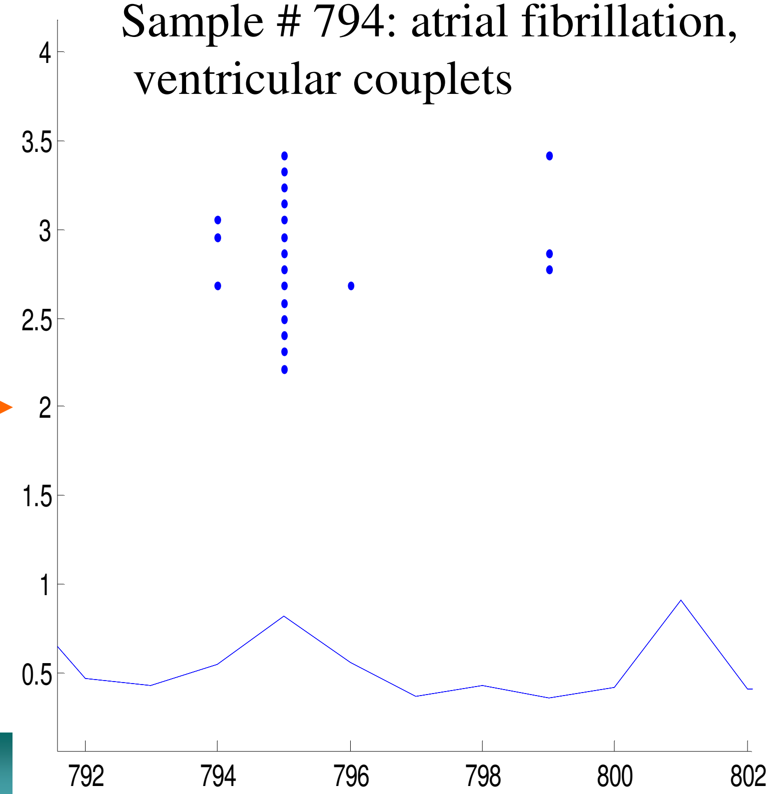
CAPTURING AND EVALUATING DYNAMIC PHENOMENA OF CARDIAC DISORDERS FROM HEART RATE RECORDINGS

MP_MIT_BIH_203_epoch120_goal10_n3_p100_p7

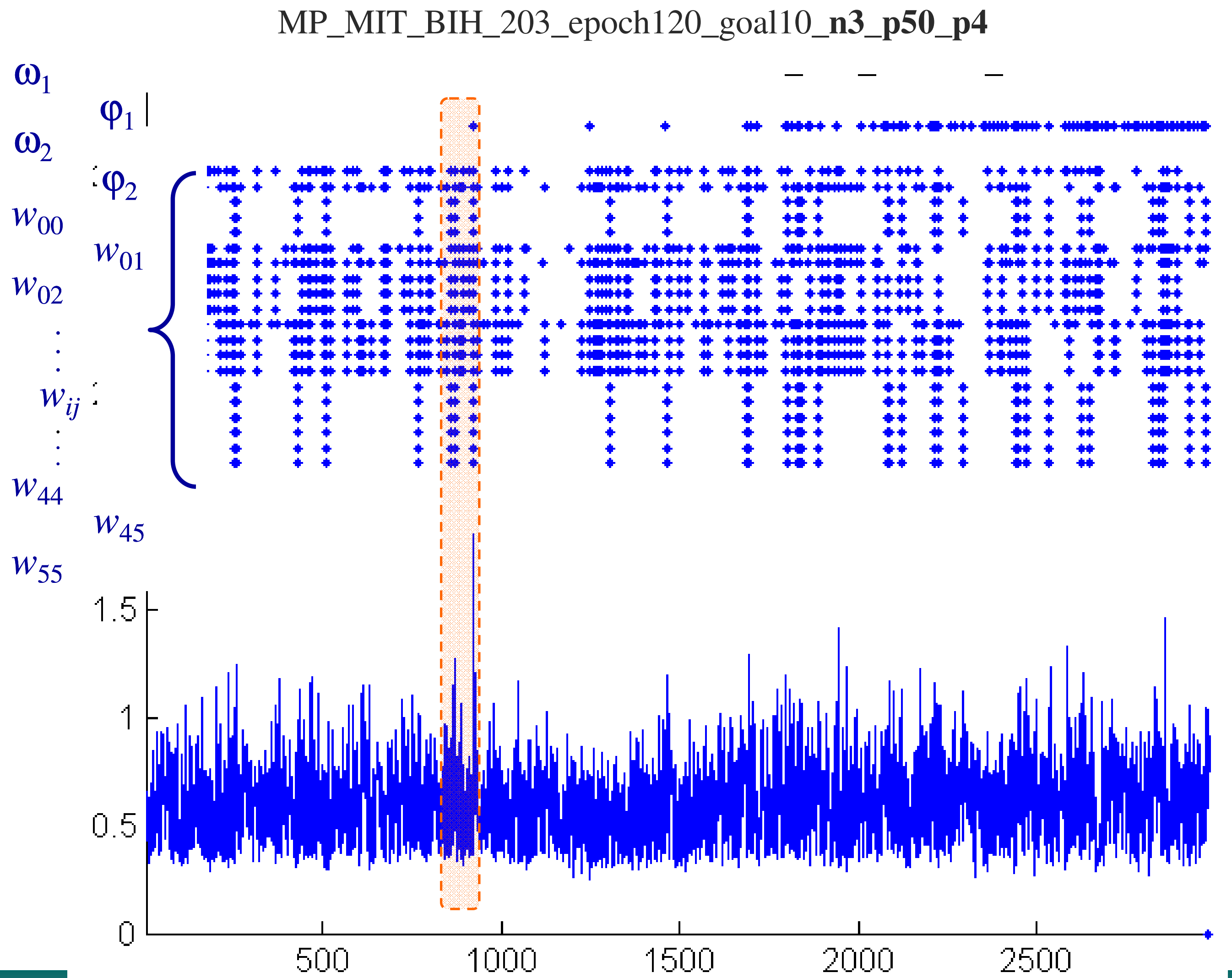


MP_MIT_BIH_203_epoch120_goal10_n2_p50_p3

Sample # 794: atrial fibrillation, ventricular couplets

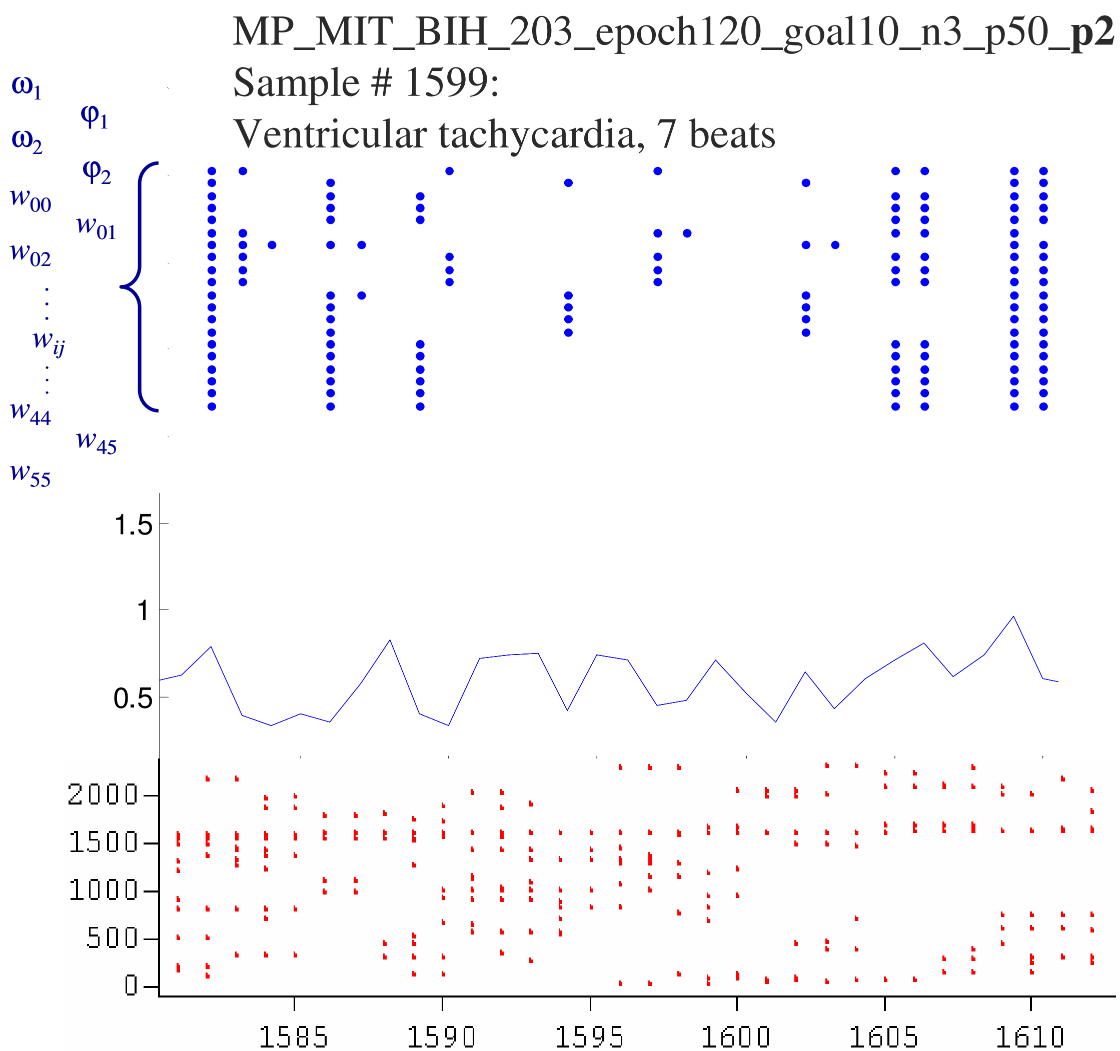


5. Applications
- Adaptive Sample by Sample Evaluation of Real Complex Signals



5. Applications

- Adaptive Sample by Sample Evaluation of Real Complex Signals



6. Limitations and Advantages Summary

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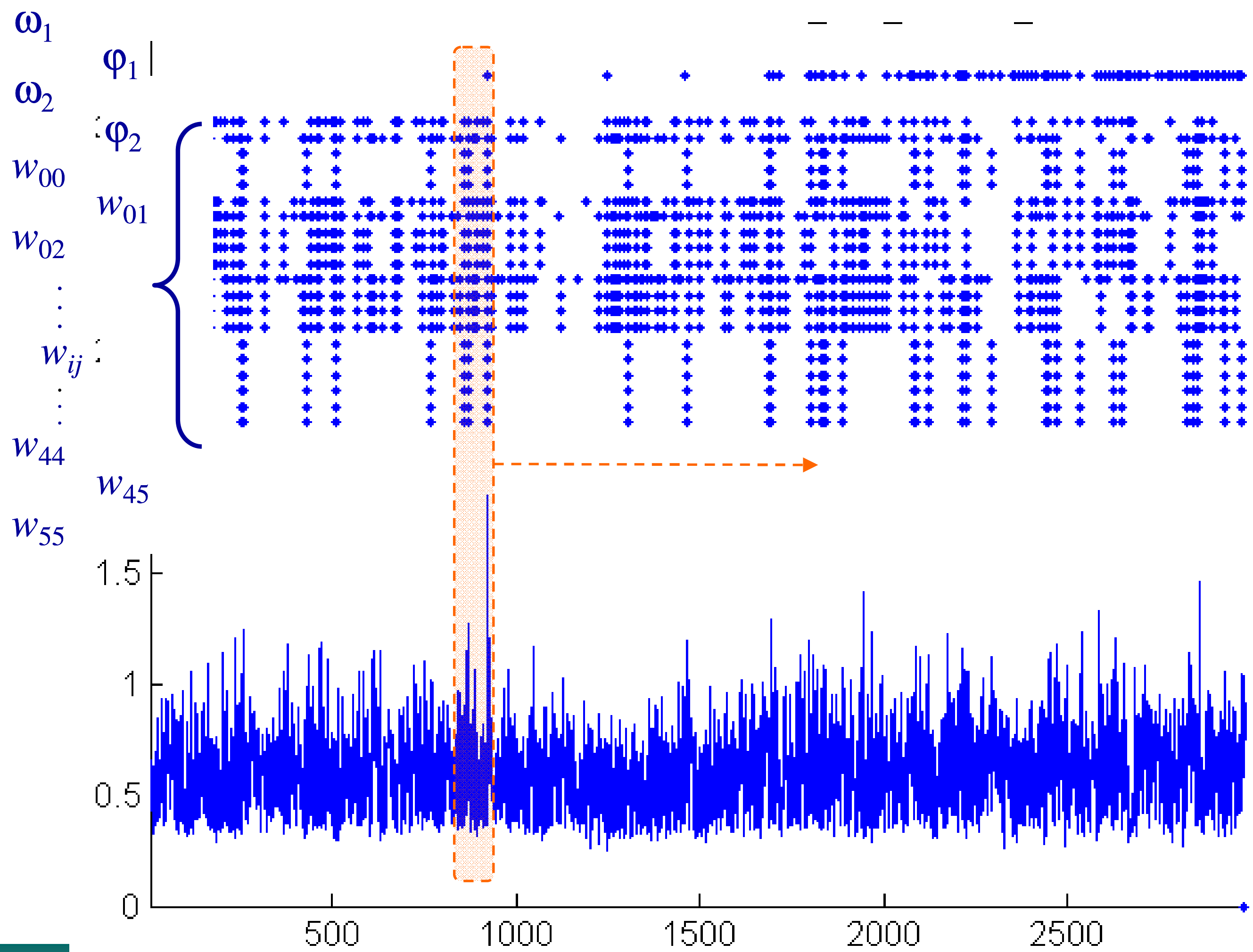
6. Limitations and Advantages Summary

6. Limitations and Advantages Summary

- **New adaptive method for evaluation of complex systems (also applicable to nondeterministic systems)**
- **The proposed method can be used for:**
  - monitoring of sudden, beat-by-beat, changes in complex systems,
  - monitoring of smooth changes in variability,
  - monitoring of intervals of similar variability, repeating patterns, multi-attractor behavior,
  - monitoring of artefacts, noise, perturbations,..
- **The proposed theory, methodologies, and applications can be used by engineers, researchers, and students from various fields and levels of skills.**

Adaptation Plot MIT-BIH 203

MP_MIT_BIH_203_epoch120_goal10_**n3_p50_p4**



5. Applications

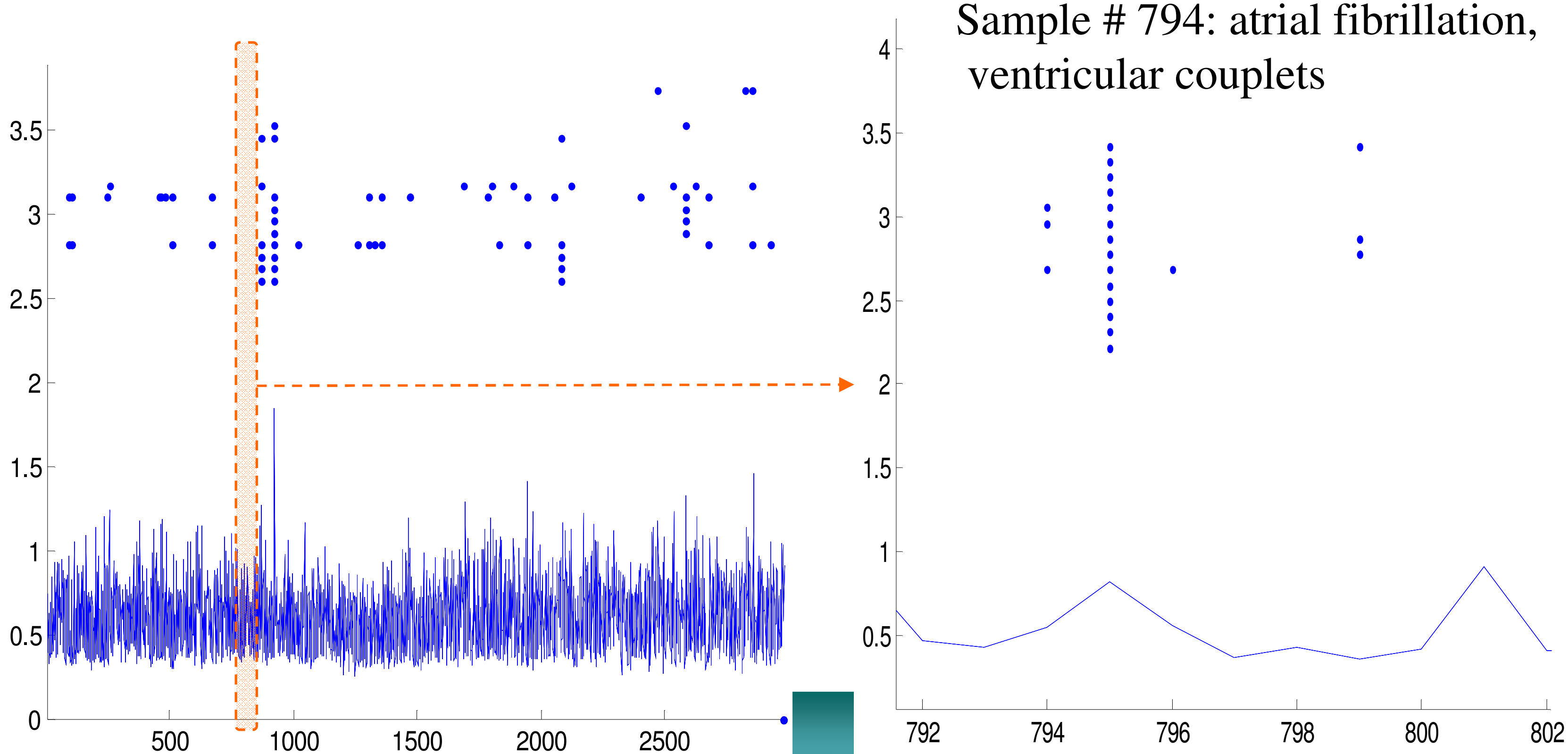
- Adaptive Sample by Sample Evaluation of Real Complex Signals

CAPTURING AND EVALUATING DYNAMIC PHENOMENA OF CARDIAC DISORDERS FROM HEART RATE RECORDINGS

MP_MIT_BIH_203_epoch120_goal10_n3_p100_p7

MP_MIT_BIH_203_epoch120_goal10_n2_p50_p3

Sample # 794: atrial fibrillation, ventricular couplets



Some Challenges for Further Research and Applications

- The **methodology is ready for Beat-by-beat HRV fetal monitoring** is the very important topic of current research. The established theory and methodology enables sensitive monitoring of the variability increase or decrease. Thus, the level of oxygen delivered to the brain of a fetus can be monitored using the adaptive method and visualized in the "adaptation plot".
- Development of **Type-2 HRV-HONNU with the frequency component of the vagal nerve** tonus would be **due to the limit cycle of the dynamic neural unit, rather than** caused **by a periodic input** within the input signal preprocessor (the lower number of neural parameters, more sensitive detection of changes in variability)
- Investigation of **capabilities of HONNU to detect and distinguish between particular types of cardiac arrhythmias** related to the scalability of the detection sensitivity of the proposed method.
- The **investigation of heart beat dynamics** by HRV-HONNU of particular patients **before, during, and after a cardiac surgery**.

THANK YOU

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Google search: ‘Ivo Bukovsky’

Answers

- **The simplification of a model of the blood circulation system (the time series generating model we used)**
  - The model simplifies or neglects physiological mechanisms that are not primarily related to feedback control of heart beat by autonomous nervous system, e.g.
  - E.g., the heart depolarization driven by the **sinoatrial node** is simulated by a saw tooth generator that is reset each ejection.
  - A very important simplification is the concept of **time delays on** ganglial afferent and efferent **neural lines** (Prof. Zitek)
  - Another very important simplification is the concept of **fuzzy blocks** representing **the brain control centers** (symphatic, parasymphatic) (Prof. Bila)
  - The model shows that a physiological nonlinear feedback control by ANS can generate very different signals, from periodic to very chaotic even on deterministic basis