

Assessing complexity of the interactions among cardiovascular variables via multivariate linear model-based approach

Alberto Porta

Department of Biomedical Sciences for Health
Galeazzi Orthopedic Institute
University of Milan
Milan, Italy

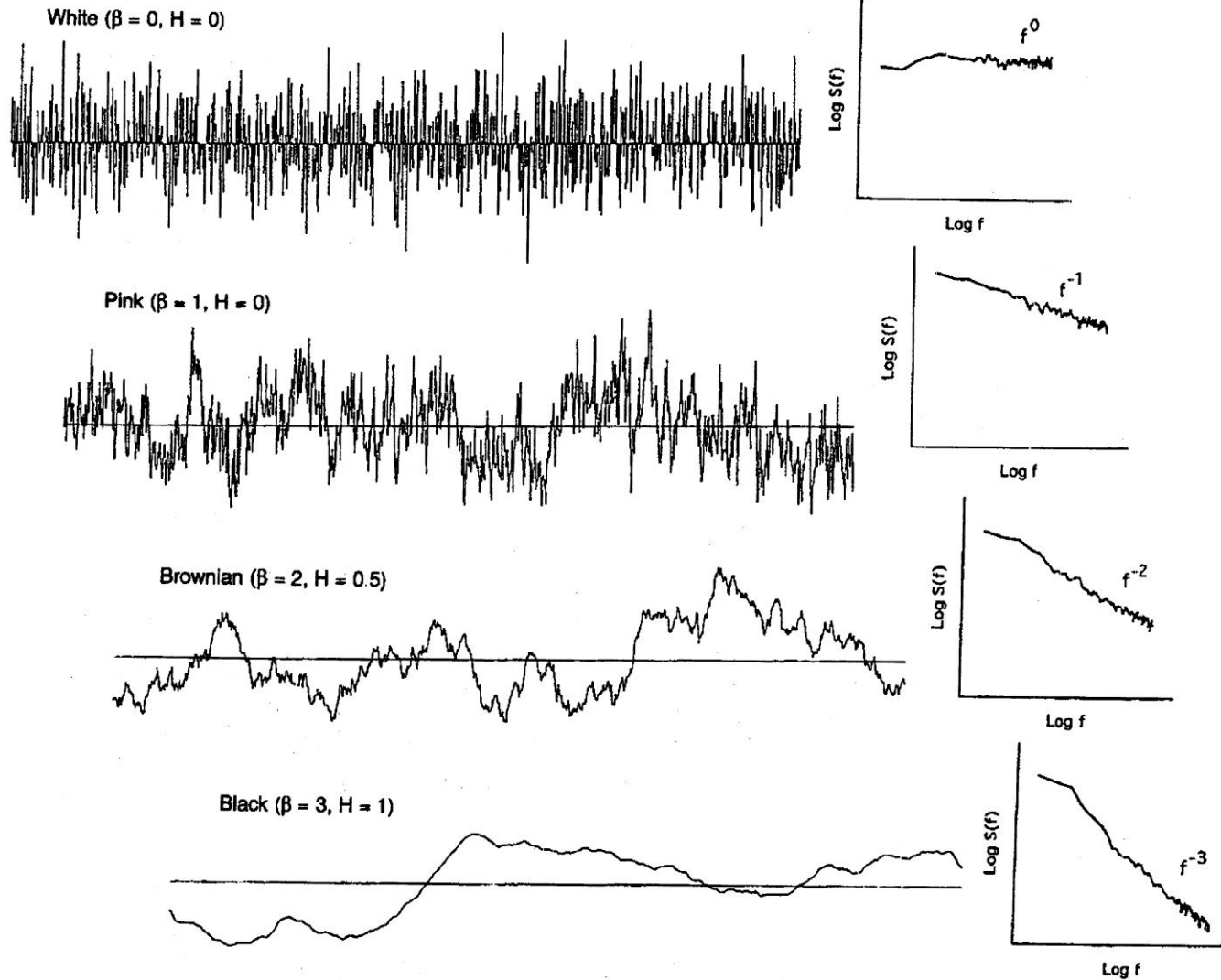
Introduction

Complexity analysis of cardiovascular control provides important physiological and clinical information

The assessment of complexity of cardiovascular control is mainly based on univariate approaches

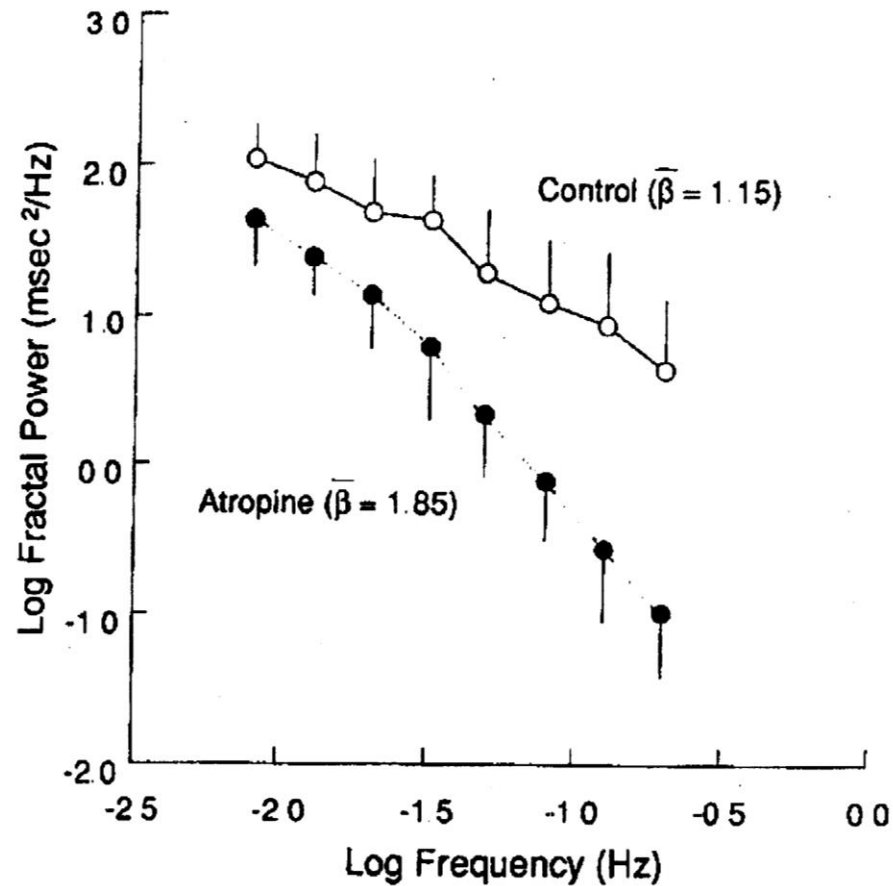
Among these approaches fractal analysis is one of the most commonly utilized

Computer-simulated fractal processes



Complexity decreases with scaling exponent β

Fractal analysis of heart period variability during vagal blockade



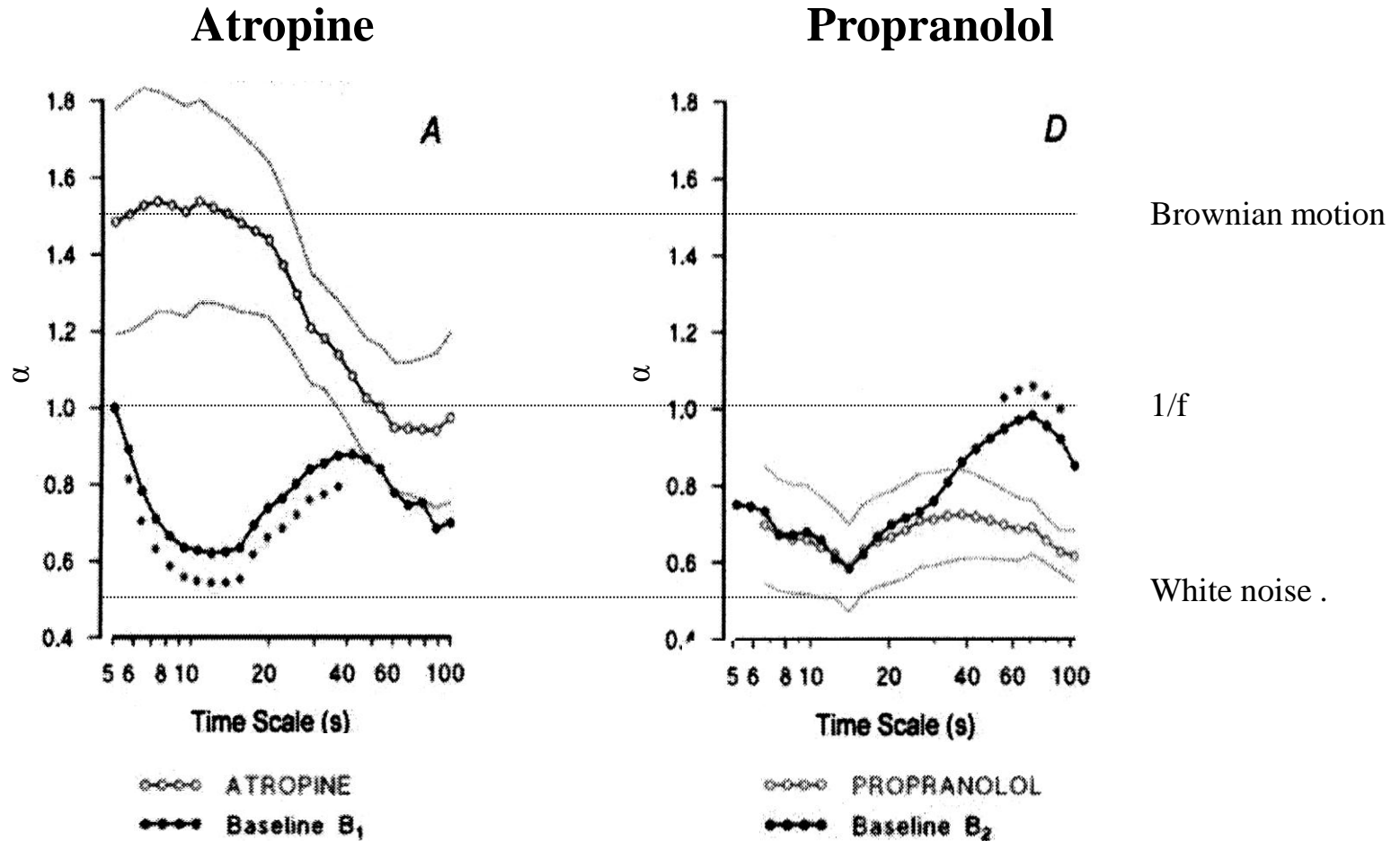
Fractal analysis of heart period variability during β -adrenergic blockade

Table 2. *The effects of propranolol on heart rate variability parameters: study 2*

	Long-Term Data		Short-Term Data	
	Placebo	Propranolol	Placebo	Propranolol
RR, ms	912 \pm 111	1,134 \pm 133*	914 \pm 111	1,128 \pm 138*
SD _{RR} , ms	82 \pm 28	107 \pm 20*	73 \pm 23	96 \pm 19*
%Fractal	83.0 \pm 3.2	85.3 \pm 3.8	69.6 \pm 11.2†	59.4 \pm 13.8†
β	1.15 \pm 0.23	1.03 \pm 0.22	1.17 \pm 0.28	1.02 \pm 0.22
H	0.077 \pm 0.115	0.015 \pm 0.114	0.083 \pm 0.139	0.010 \pm 0.111
%LF	11.9 \pm 3.0	8.9 \pm 1.9	22.5 \pm 10.3†	25.5 \pm 12.3†
%HF	5.2 \pm 2.1	5.9 \pm 2.8	8.0 \pm 3.0	15.0 \pm 3.0*
LF/HF	2.76 \pm 1.57	1.82 \pm 0.81*	3.07 \pm 1.17	1.72 \pm 0.79*

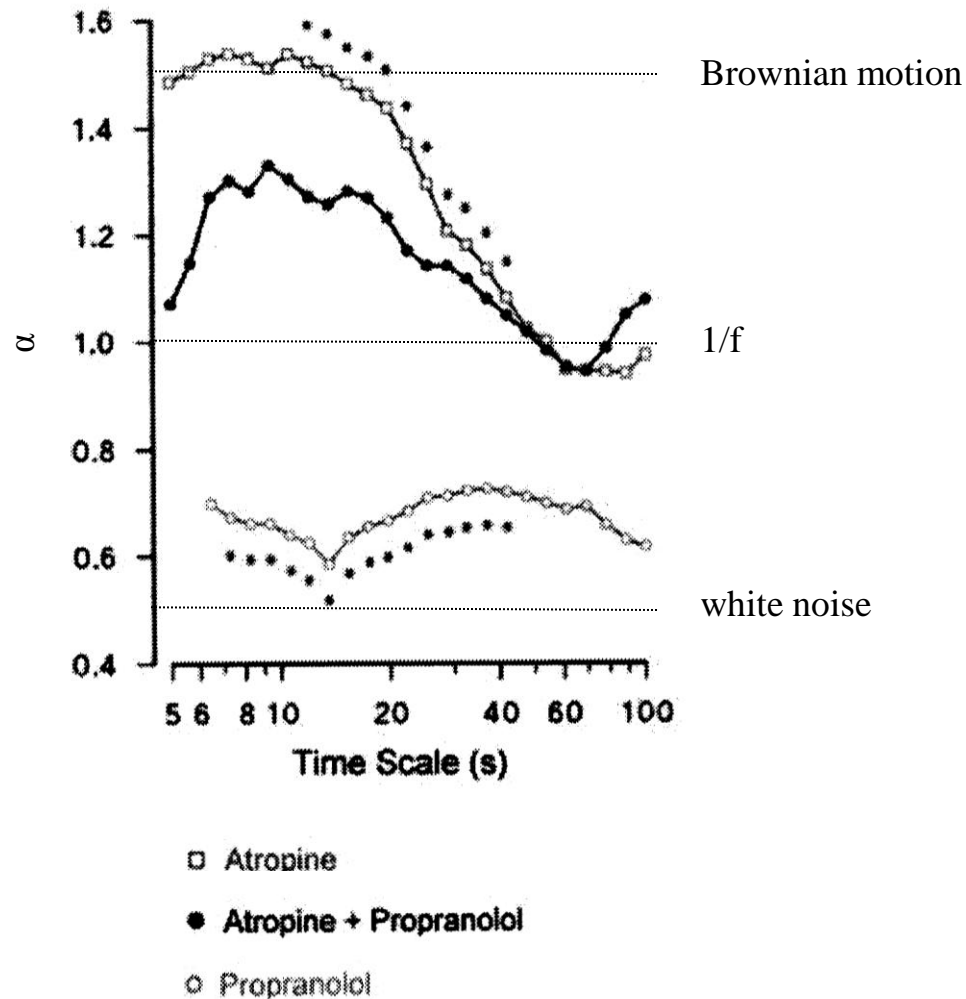
Values are means \pm SD. Short-term data were from the 512-beat study. * P < 0.05 from placebo, and † P < 0.05 from the long-term data.

Overall spectrum of the scaling exponents of heart rate variability via detrended fluctuation analysis

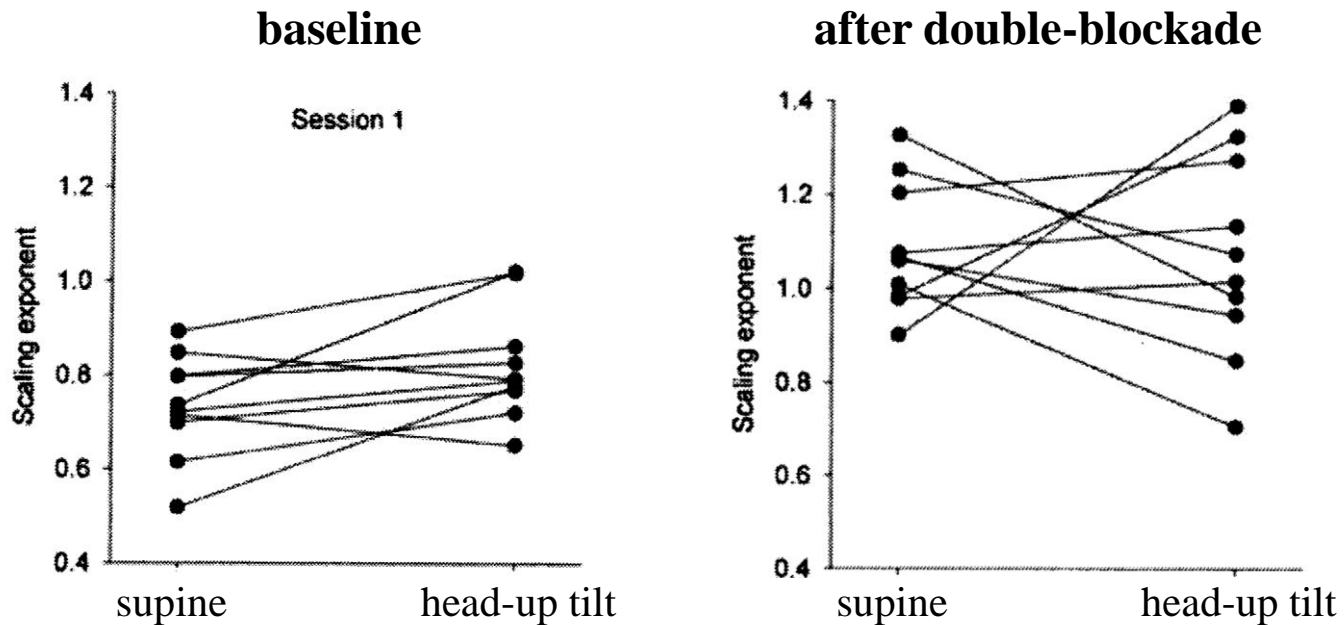


with $\alpha = (\beta+1)/2$

Overall spectrum of the scaling exponents of heart rate variability via detrended fluctuation analysis



Fractal analysis of heart period variability during sympathetic activation



Age-related alterations in fractal scaling of heart period variability

Table 1. *Heart rate and fluctuation measures for subjects*

	Young (<i>n</i> = 10)	Old (<i>n</i> = 10)
Mean heart rate	60.55 ± 8.77	57.22 ± 8.60
Range of heart rate	46–73	41–71
SD heart rate	6.12 ± 1.28	2.82 ± 0.99
Fluctuation measures		
α_s	0.90 ± 0.14	1.12 ± 0.19
α_l	0.99 ± 0.10	0.75 ± 0.17
β	1.14 ± 0.15	1.33 ± 0.29

Values are means ± SD; *n* = no. of subjects.

Drawback of the univariate approaches for the assessment of complexity of the cardiovascular control

Univariate approaches for the evaluation of complexity of cardiovascular control has a major drawback

They cannot take into account the relations among cardiovascular variables and quantify the contribution of specific physiological mechanisms to the overall complexity

Aims

- 1) to propose a multivariate model-based approach to the assessment of complexity of cardiovascular control
- 2) to decompose the complexity of a signal into contributions due to the relations among variables
- 3) to introduce in the assessment of complexity the notion of causality to allow a deeper characterization of the interactions among variables

Outline

- 1) Multivariate model-based approach for the assessment of complexity of the cardiovascular system
- 2) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of open loop interactions
- 3) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of closed loop interactions
- 4) Granger-causality: a method for the quantification of the contribution of specific mechanisms to the overall complexity

Outline

- 1) Multivariate model-based approach for the assessment of complexity of the cardiovascular system
- 2) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of open loop interactions
- 3) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of closed loop interactions
- 4) Granger-causality: a method for the quantification of the contribution of specific mechanisms to the overall complexity

Multivariate AR model

$$y(n) = A(z) \cdot y(n) + w(n)$$

with

$$y(n) = \begin{bmatrix} rr(n) \\ sap(n) \\ r(n) \end{bmatrix} \quad w(n) = \begin{bmatrix} w_{rr}(n) \\ w_{sap}(n) \\ w_r(n) \end{bmatrix} \quad A(z) = \begin{bmatrix} A_{rr-rr}(z) & B_{rr-sap}(z) & B_{rr-r}(z) \\ B_{sap-rr}(z) & A_{sap-sap}(z) & B_{sap-r}(z) \\ B_{r-rr}(z) & B_{r-sap}(z) & A_{r-r}(z) \end{bmatrix}$$

where

w_{rr} , w_{sap} , w_r are WGN with zero mean and variance λ_{rr}^2 , λ_{sap}^2 , λ_r^2

$A_{rr-rr}(z)$, $A_{sap-sap}(z)$, $A_{r-r}(z)$, are causal FIR filters of order p describing the auto-link of a series on itself

$B_{sap-rr}(z)$, $B_{r-rr}(z)$, $B_{r-sap}(z)$ are causal FIR filters of order p describing the cross-link between series (immediate effects are not modeled)

$B_{rr-sap}(z)$, $B_{rr-r}(z)$, $B_{sap-r}(z)$ are causal FIR filters of order $p+1$ describing the cross-link between series (immediate effects are modeled)

The coefficients of $A(z)$ are estimated via least squares approach and the model order p is optimized via Akaike criterion for multivariate processes

Goodness of fit of the multivariate AR model

The one-step-ahead prediction of $y(n)$ is

$$\hat{y}(n/n-1) = \hat{A}(z) \cdot y(n)$$

Defined the prediction error as

$$e(n) = y(n) - \hat{y}(n/n-1)$$

the covariance matrix of the prediction error, Λ^2 , is

$$\Lambda^2 = \frac{1}{N} \sum_{n=1}^N e(n) \cdot e^T(n)$$

where T stands for the transpose operator

$MSPE_{rr}$, $MSPE_{sap}$, and $MSPE_r$ lie on the main diagonal of Λ^2

$MSPE_{rr}$ = complexity of cardiac control

$MSPE_{sap}$ = complexity of vascular control

Experimental protocol

9 healthy males (age: 25-46, 9 men)

We recorded ECG (lead II) and noninvasive finger blood pressure (Finapres 2300) at 500 Hz. Respiratory series was obtained by assessing respiratory-related amplitude changes of the ECG

Experimental sessions were carried out in 3 days

AT: parasympathetic blockade with $40 \mu\text{g}\cdot\text{kg}^{-1}$ i.v. atropine sulfate

PR: β -adrenergic blockade with $200 \mu\text{g}\cdot\text{kg}^{-1}$ i.v. propranolol

AT+PR: β -adrenergic blockade with PR after parasympathetic blockade with AT

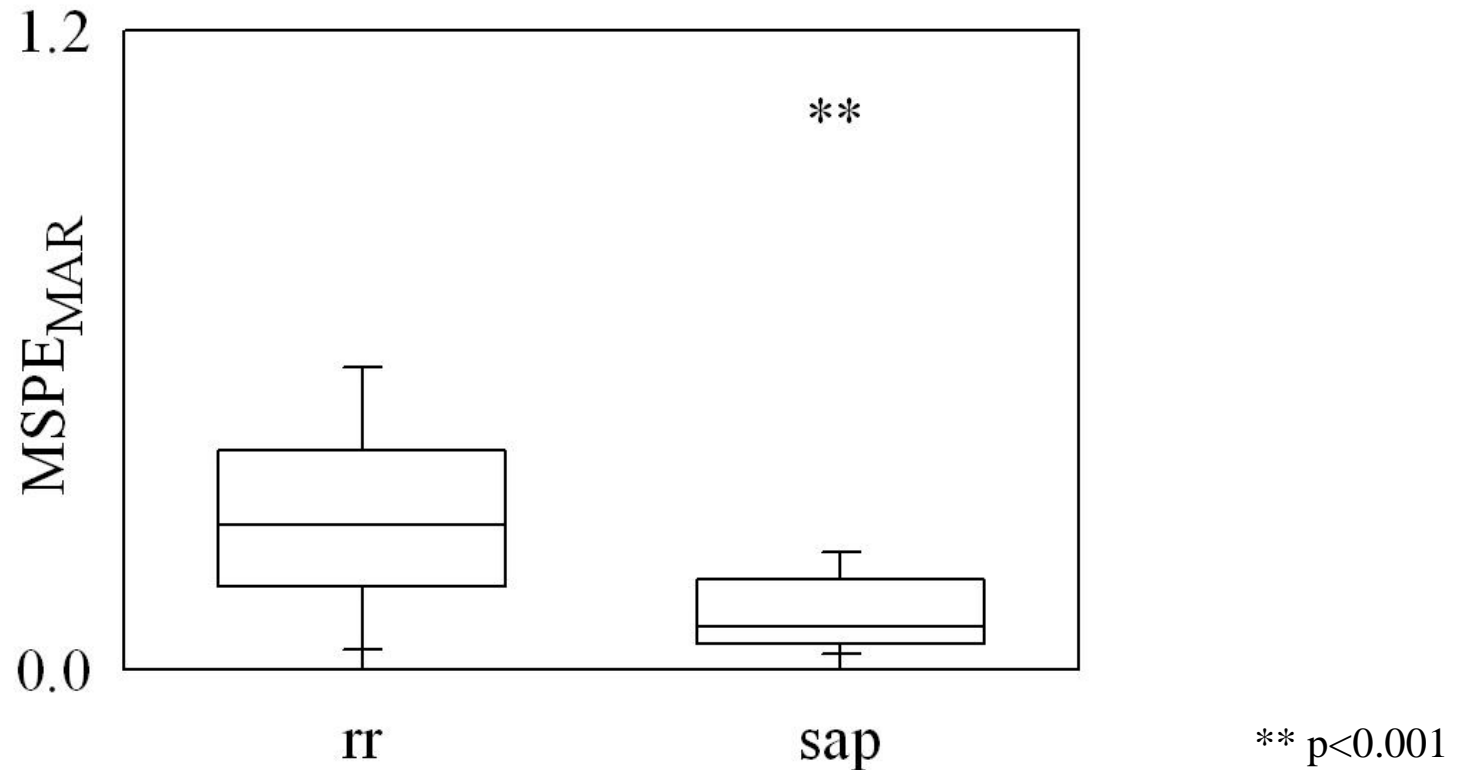
CL: 120 minutes after $6 \mu\text{g}\cdot\text{kg}^{-1}$ per os clonidine hydrochloride to centrally block the sympathetic outflow to heart and vasculature

AT+PR session followed **AT** session

AT, **PR** and **CL** were always preceded by baseline (**B**) recording

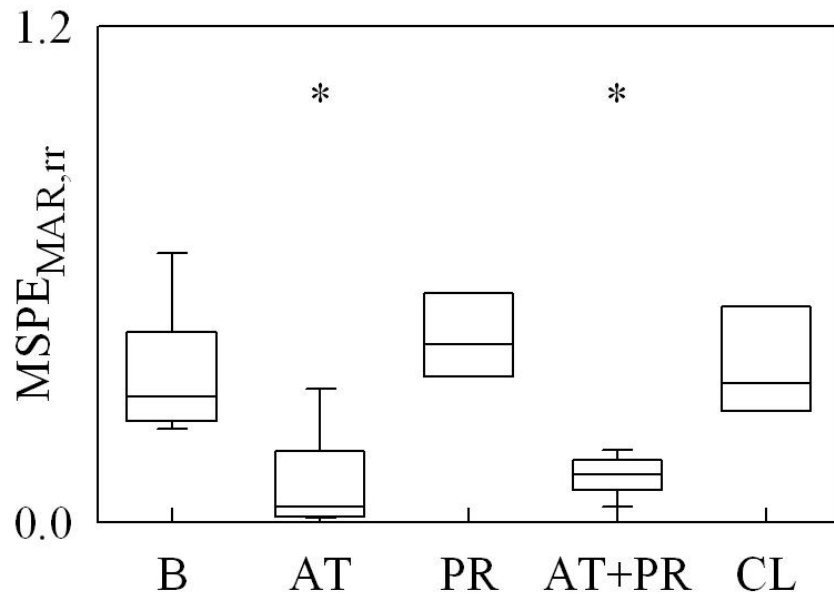
Series of 256 beats were analyzed after linear detrending

MSPE of rr vs MSPE of sap during pharmacological challenges

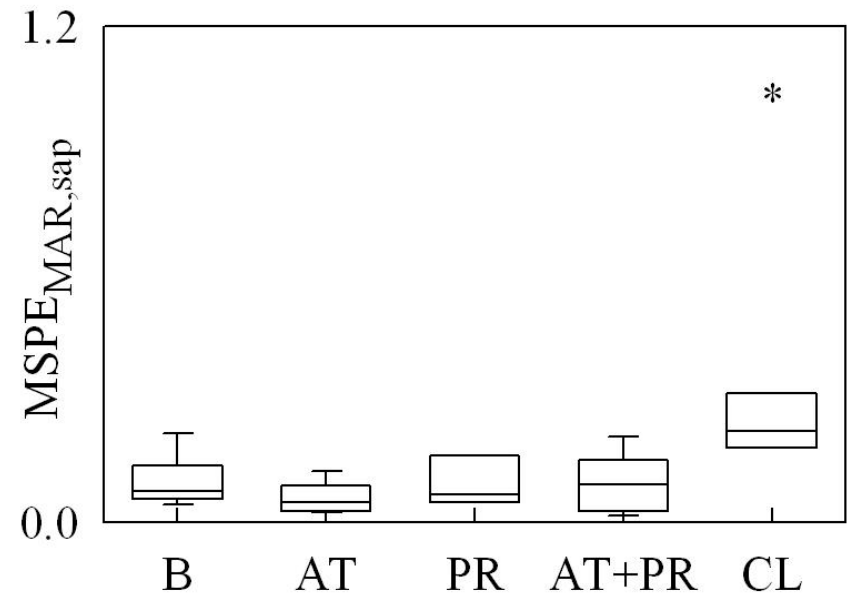


MSPE of rr vs MSPE of sap during pharmacological challenges

MSPE of rr



MSPE of sap



* $p < 0.05$ vs B

Experimental protocol

19 nonsmoking healthy humans (age: 21-48, median=30, 8 men)

We recorded ECG (lead II), noninvasive finger arterial pressure (Finometer MIDI) and respiration (thoracic belt) at 300 Hz during head-up tilt (T)

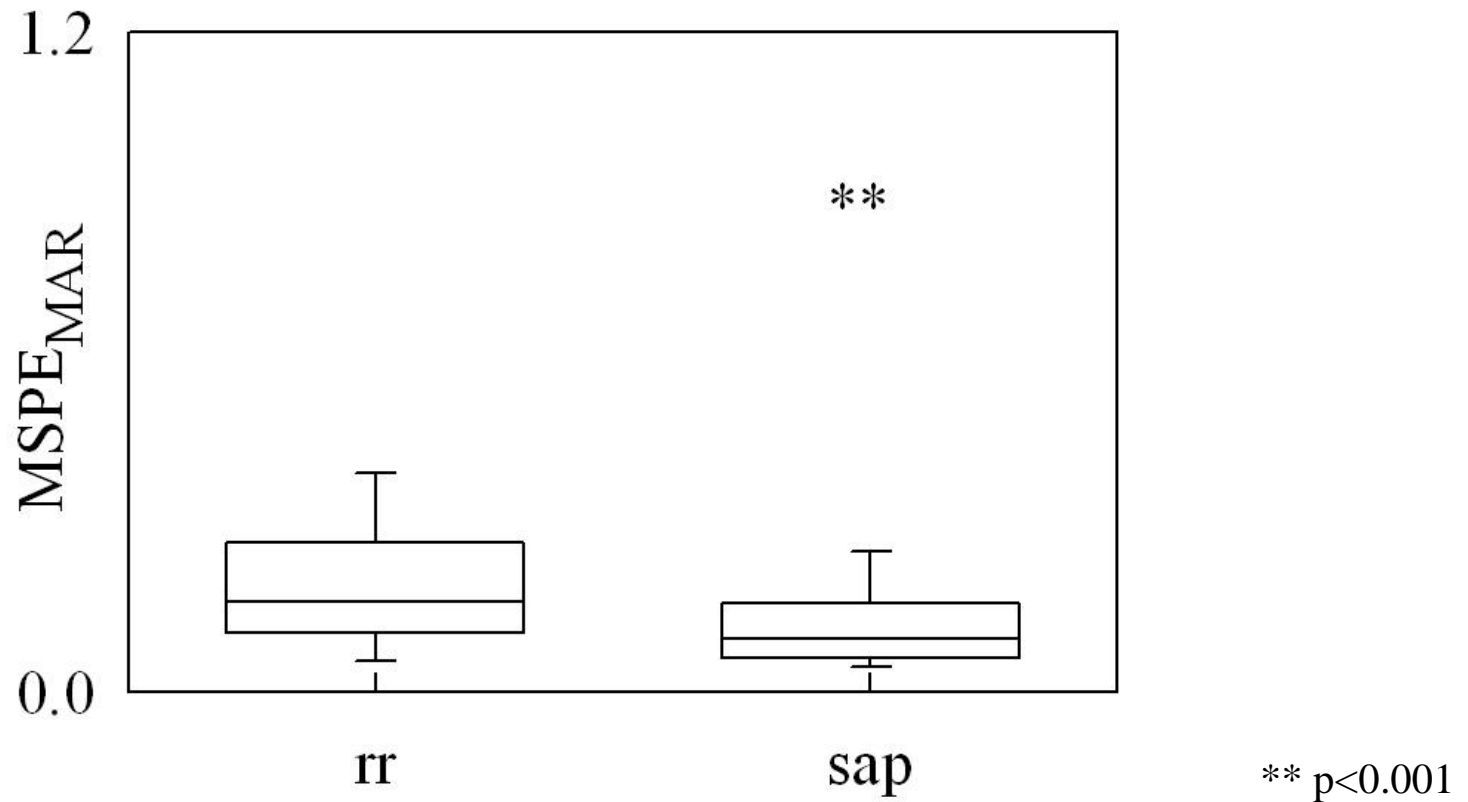


Table angles were randomly chosen within the set { 15,30,45,60,75,90 }

Each T session (10 min) was always preceded by a session (7 min) at rest (R) and followed by a recovery period (3 min)

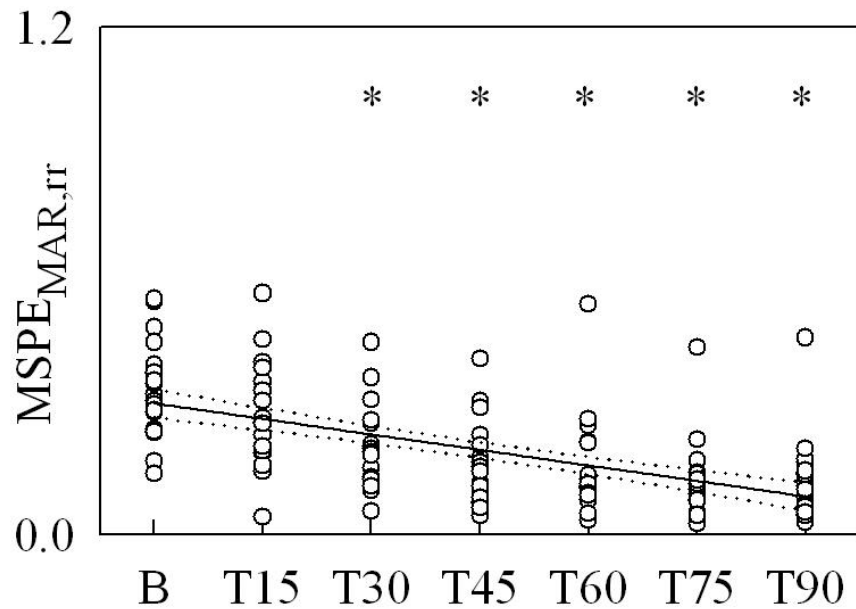
Series of 256 beats were analyzed after linear detrending

MSPE of rr vs MSPE of sap during graded head-up tilt

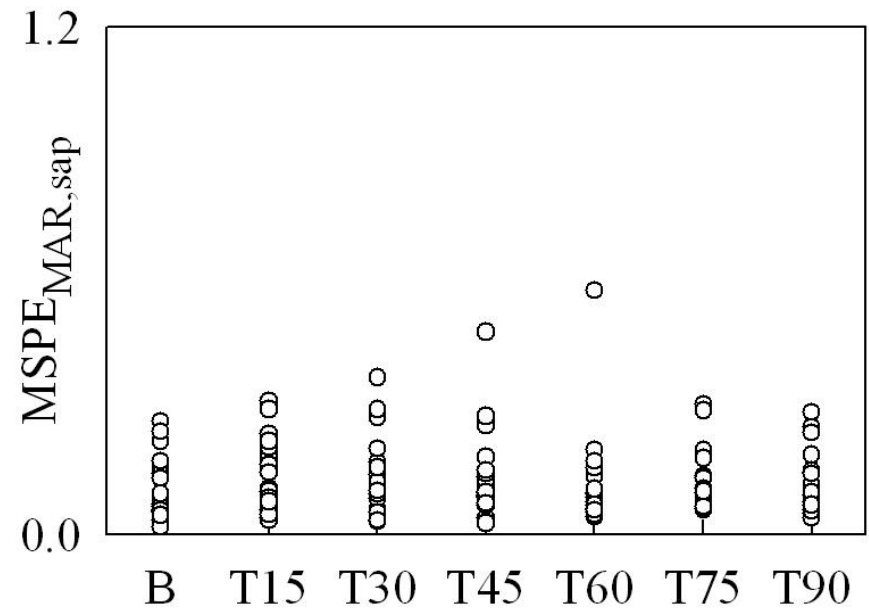


MSPE of rr vs MSPE of sap during graded head-up tilt

MSPE of rr



MSPE of sap



* $p < 0.05$ vs B

Experimental protocol

- 12 Parkinson disease (PD) patients without orthostatic hypotension or symptoms of orthostatic intolerance (age: 55-79, median=65, 8 men, Hoehn and Yhar scale=2-4)
- 12 healthy control (HC) subjects (age: 58-72, median=67, 7 men)

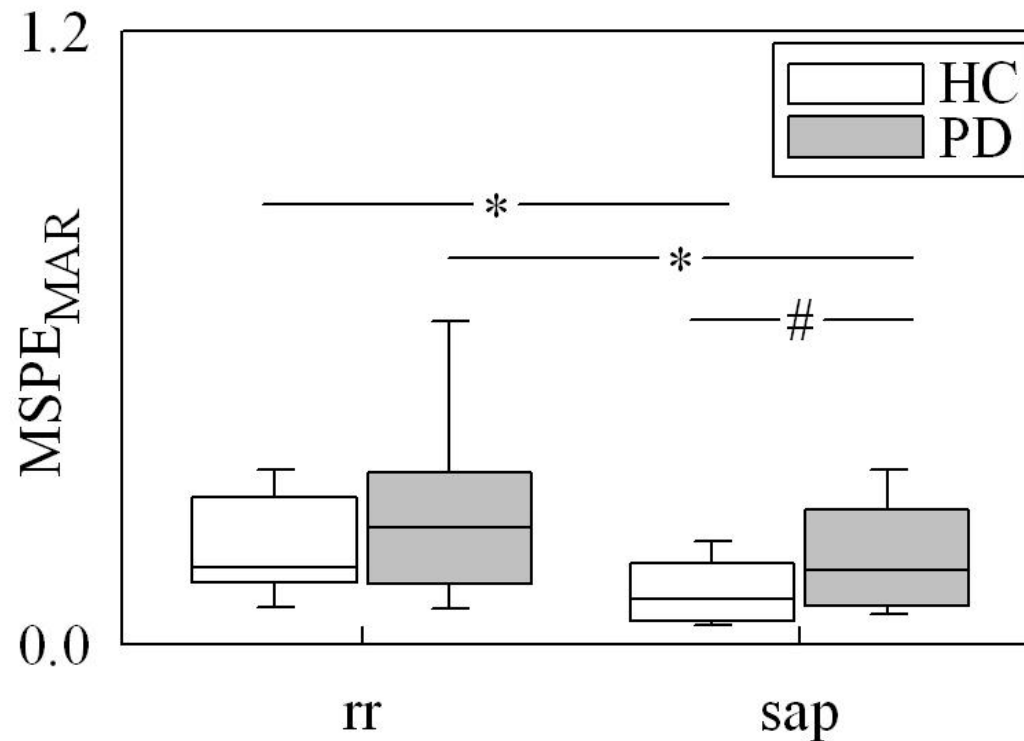
We recorded ECG (lead II), noninvasive finger arterial pressure (Finapress 2300) and respiration (thoracic belt) at 300 Hz during 75° head-up tilt (T75)

Each T75 session (10 min) was always preceded by a baseline (B) session (10 min) at rest in supine position



Series of 256 beats were analyzed after linear detrending

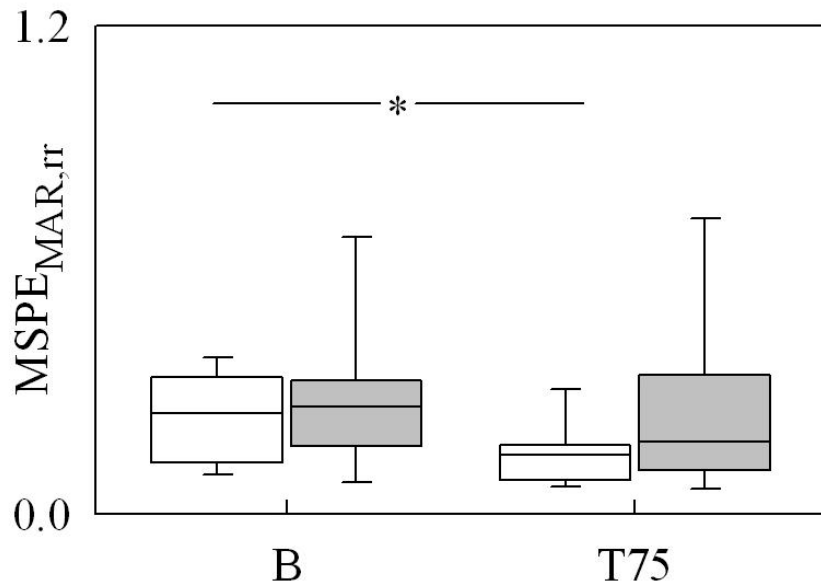
MSPE of rr vs MSPE of sap in Parkinson disease patients



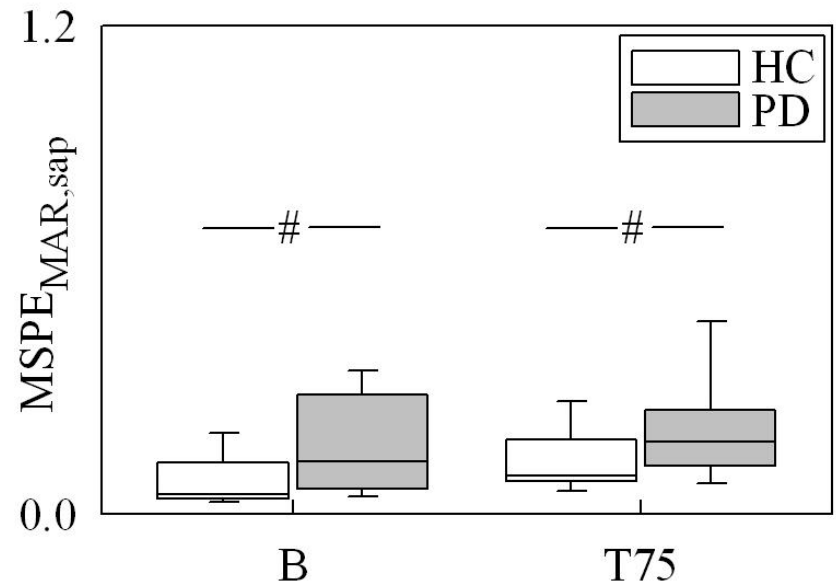
* $p < 0.05$ within population
$p < 0.05$ within series

MSPE of rr vs MSPE of sap in Parkinson disease patients

MSPE of rr



MSPE of sap



* $p < 0.05$ within population

$p < 0.05$ within experimental condition

Conclusions (healthy humans)

Complexity of vascular control is smaller than that of cardiac regulation

Vagal activity keeps high the complexity of the cardiac control

Sympathetic activity keeps low the complexity of vascular control

Complexity analyses of cardiac and vascular controls provide different information

Conclusions (Parkinson disease patients)

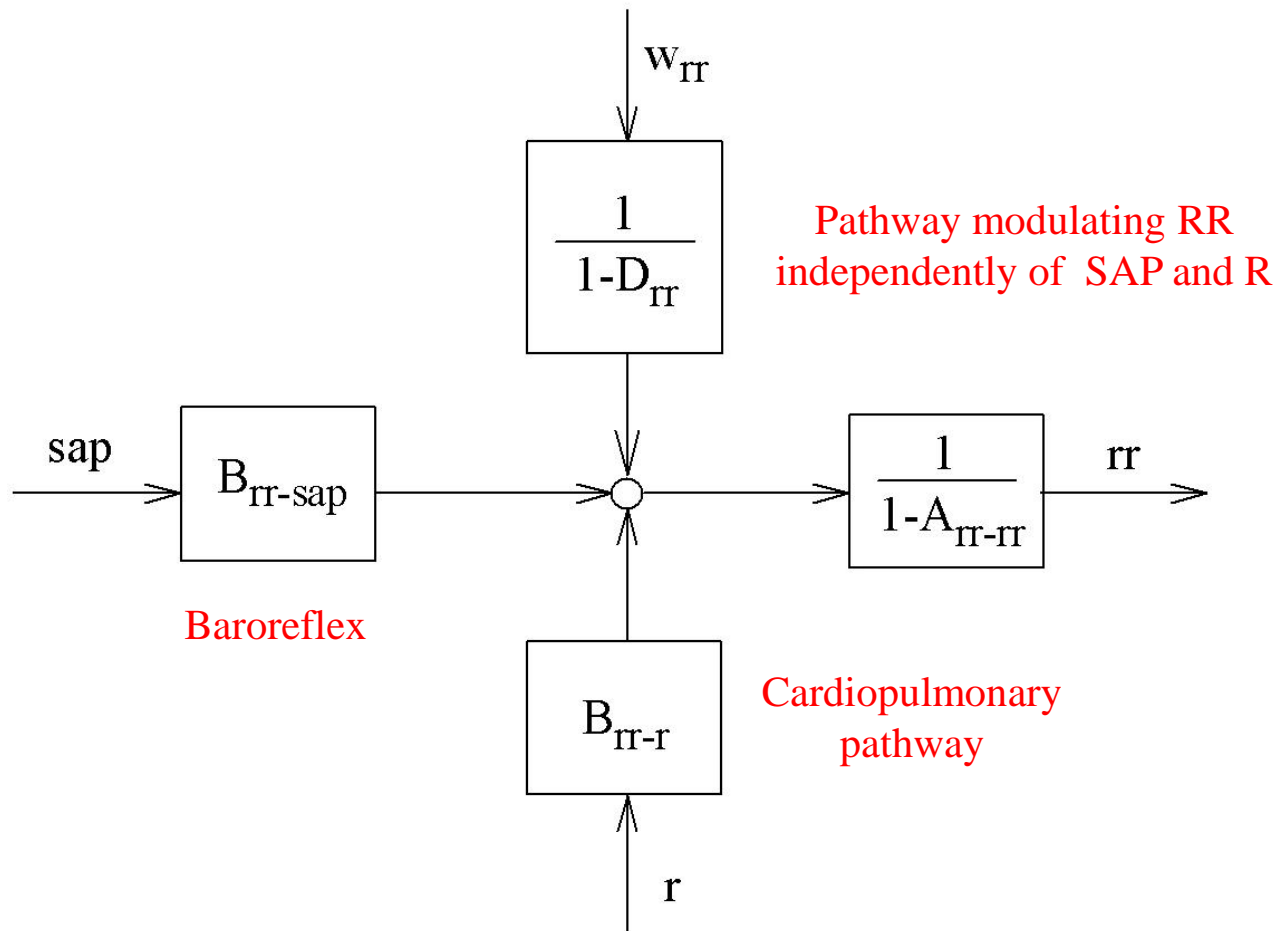
In Parkinson disease patients without orthostatic hypotension or symptoms of orthostatic intolerance the impairment of cardiac control becomes noticeable in response to an orthostatic challenge

In Parkinson disease patients without orthostatic hypotension or symptoms of orthostatic intolerance the impairment of vascular control is noticeable just in baseline condition

Outline

- 1) Multivariate model-based approach for the assessment of complexity of the cardiovascular system
- 2) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of open loop interactions
- 3) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of closed loop interactions
- 4) Granger-causality: a method for the quantification of the contribution of specific mechanisms to the overall complexity

Trivariate open loop model describing heart period variability



Trivariate open loop model describing heart period variability

$AR_{rr}X_{sap}X_rAR_w$ model on rr:

$$rr(i) = A_{rr-rr}(z) \cdot rr(i) + B_{rr-sap}(z) \cdot sap(i) + B_{rr-r}(z) \cdot r(i) + \frac{1}{1-D_{rr}(z)} \cdot w_{rr}(i)$$

AR_{sap} model on sap:

$$sap(i) = A_{sap-sap}(z) \cdot sap(i) + w_{sap}(i)$$

AR_r model on r:

$$r(i) = A_{r-r}(z) \cdot r(i) + w_r(i)$$

where

w_{rr} , w_{sap} , w_r are WGN with zero mean and variance λ_{rr}^2 , λ_{sap}^2 , λ_r^2

$A_{rr-rr}(z)$, $A_{sap-sap}(z)$, $A_{r-r}(z)$, $B_{rr-sap}(z)$, $B_{rr-r}(z)$, $D_{rr}(z)$, are FIR filters of order p in the z-domain

Trivariate open loop model: factorization of heart period variability into partial processes

Under the hypothesis of uncorrelation among w_{rr} , w_{sap} and w_r , the rr series can be factorized as

$$rr(i) = rr(i)|_{w_{sap}} + rr(i)|_{w_r} + rr(i)|_{w_{rr}}$$

where

$$rr(i)|_{w_{sap}} = \frac{B_{rr-sap}}{(1-A_{rr-rr}) \cdot (1-A_{sap-sap})} \cdot w_{sap}(i)$$

baroreflex pathway

$$rr(i)|_{w_r} = \frac{B_{rr-r}}{(1-A_{rr-rr}) \cdot (1-A_{r-r})} \cdot w_r(i)$$

cardiopulmonary pathway

$$rr(i)|_{w_{rr}} = \frac{1}{(1-A_{rr-rr}) \cdot (1-D_{rr})} \cdot w_{rr}(i)$$

Trivariate open loop model: heart period variability decomposition

Under the hypothesis of uncorrelation among w_{rr} , w_{sap} and w_r , the variance of rr series can be factorized as

$$\sigma^2_{rr} = \sigma^2_{rr|w_{sap}} + \sigma^2_{rr|w_r} + \sigma^2_{rr|w_{rr}}$$

where

$\sigma^2_{rr|w_{sap}}$ is the variance of $rr(i)|_{w_{sap}}$

$\sigma^2_{rr|w_r}$ is the variance of $rr(i)|_{w_r}$

$\sigma^2_{rr|w_{rr}}$ is the variance of $rr(i)|_{w_{rr}}$

Assessing the contributions of baroreflex and cardiopulmonary pathways to the complexity of heart period variability

Contribution of baroreflex to RR complexity

$$\chi^2_{\text{rr-sap}} = \frac{\sigma^2_{\text{rr}|w_{\text{sap}}}}{\sigma^2_{\text{rr}}}$$

$$0 \leq \chi^2_{\text{rr-sap}} \leq 1$$

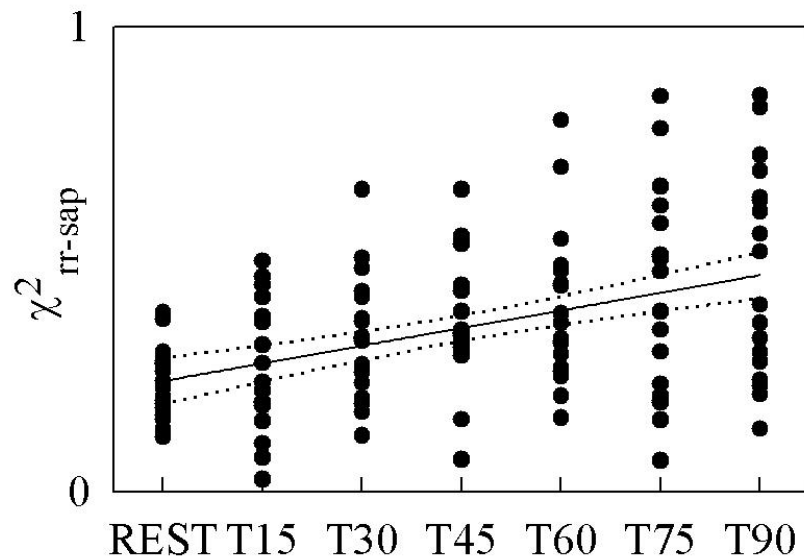
Contribution of cardiopulmonary pathway to RR complexity

$$\chi^2_{\text{rr-r}} = \frac{\sigma^2_{\text{rr}|w_{\text{r}}}}{\sigma^2_{\text{rr}}}$$

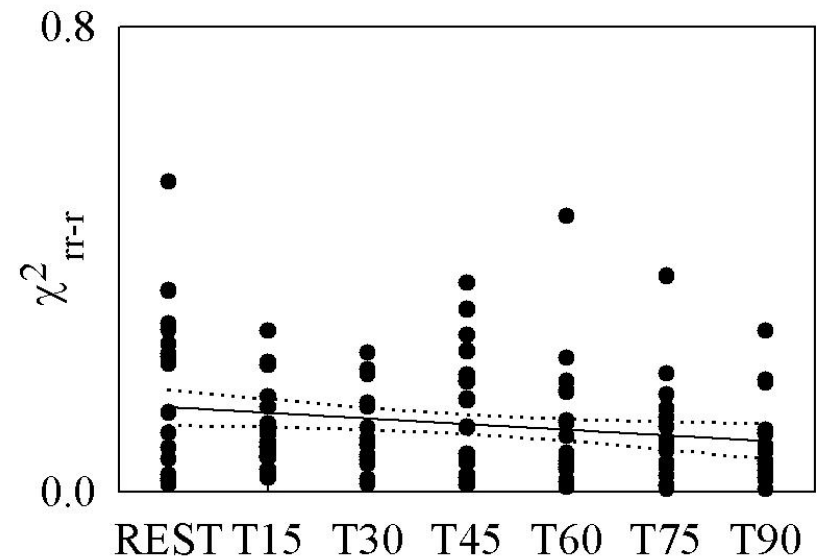
$$0 \leq \chi^2_{\text{rr-r}} \leq 1$$

Baroreflex and cardiopulmonary contributions to the complexity of heart period variability during graded head-up tilt: the open loop trivariate model approach

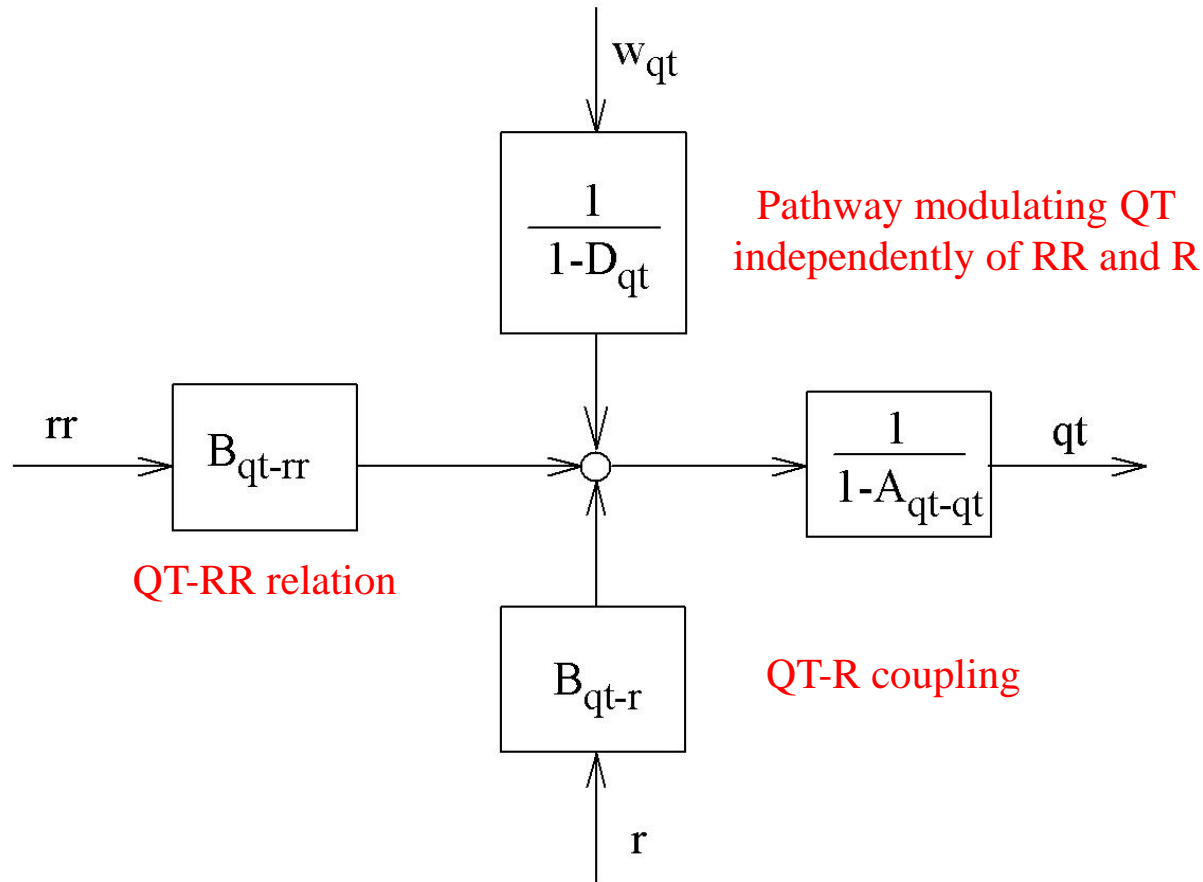
baroreflex contribution



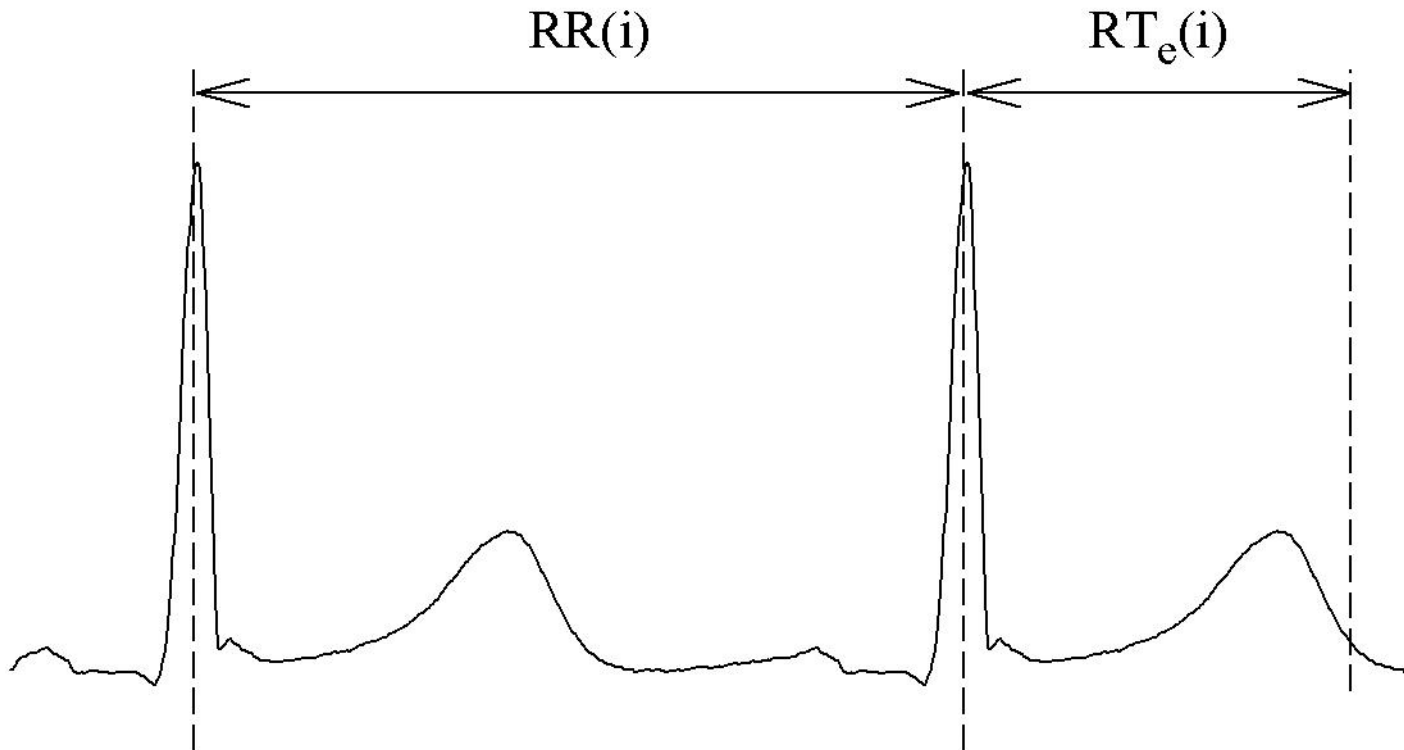
cardiopulmonary contribution



Trivariate open loop model describing QT-RR relation



Approximation of the QT interval and measurement conventions



The i -th RT_e interval follows the i -th RR interval

Experimental protocol

17 healthy young humans (age from 21 to 54, median=28)

We recorded ECG (lead II) and respiration (thoracic belt) at 1 kHz during head-up tilt (T)

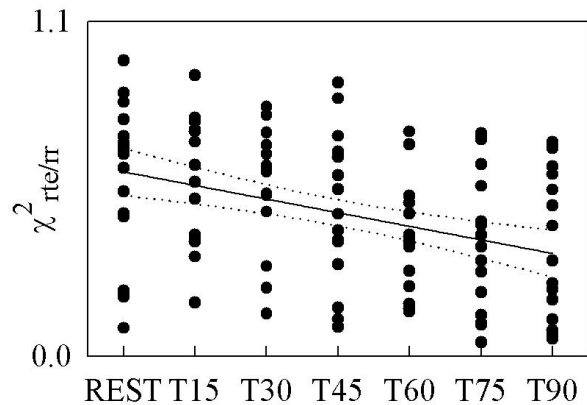


Table angles were randomly chosen within the set { 15,30,45,60,75,90 }

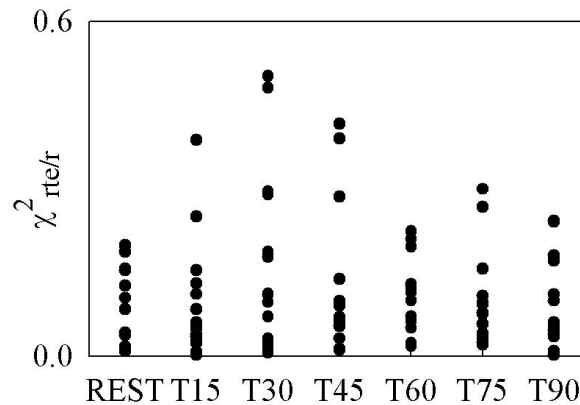
Each T session (10 min) was always preceded by a session (7 min) at rest (R) and followed by a recovery period (3 min)

Contributions to the complexity of RTe variability during graded head-up tilt: the open loop trivariate model approach

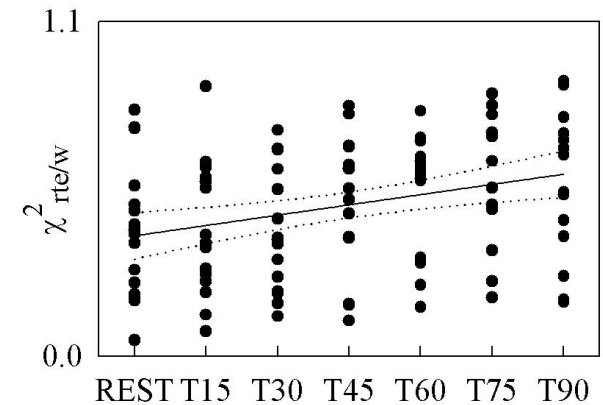
contribution of RR



contribution of R



contribution of influences unrelated to RR and R



Conclusions (open loop model)

The contribution of baroreflex to the complexity of heart period variability gradually increases as a function tilt table angle

The contribution of cardiopulmonary pathway to the complexity of heart period variability gradually decreases as a function of tilt table angle

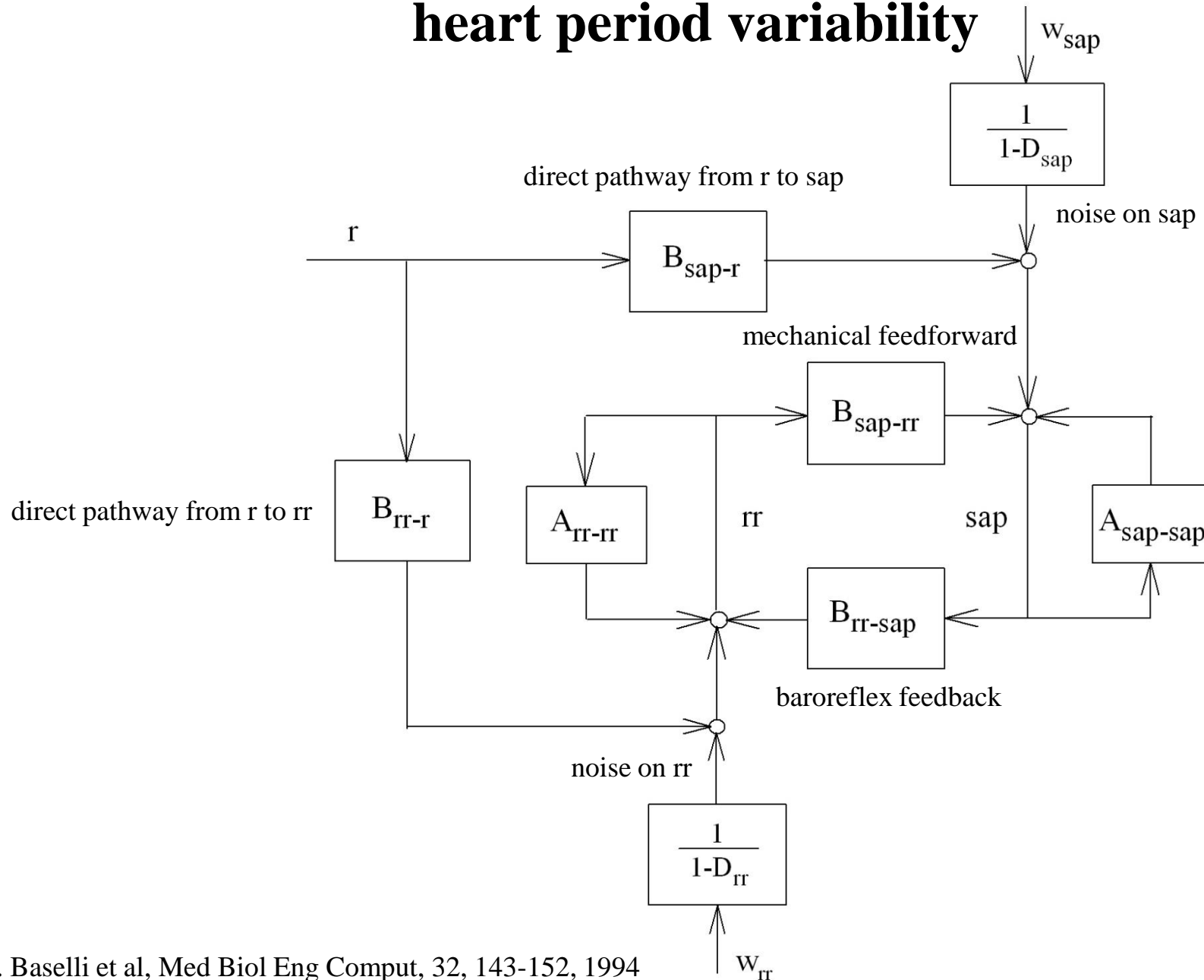
The contribution of the QT-RR relation to the complexity of QT variability gradually decreases as a function of tilt table angle

The contribution of inputs independent of heart period changes and respiration to the complexity of QT variability gradually increases as a function of tilt table angle

Outline

- 1) Multivariate model-based approach for the assessment of complexity of the cardiovascular system
- 2) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of open loop interactions
- 3) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of closed loop interactions
- 4) Granger-causality: a method for the quantification of the contribution of specific mechanisms to the overall complexity

Trivariate closed loop model describing heart period variability



Trivariate closed loop model describing heart period variability

$AR_{rr}X_{sap}X_rAR_w$ model on rr:

$$rr(i) = A_{rr-rr}(z) \cdot rr(i) + B_{rr-sap}(z) \cdot sap(i) + B_{rr-r}(z) \cdot r(i) + \frac{1}{1-D_{rr}(z)} \cdot w_{rr}(i)$$

$AR_{sap}X_{rr}X_rAR_w$ model on sap:

$$sap(i) = A_{sap-sap}(z) \cdot sap(i) + B_{sap-rr}(z) \cdot rr(i) + B_{sap-r}(z) \cdot r(i) + \frac{1}{1-D_{sap}(z)} \cdot w_{sap}(i)$$

AR_r model on r:

$$r(i) = A_{r-r}(z) \cdot r(i) + w_r(i)$$

where

w_{rr} , w_{sap} , w_r are WGN with zero mean and variance λ_{rr}^2 , λ_{sap}^2 , λ_r^2

$A_{rr-rr}(z)$, $A_{sap-sap}(z)$, $A_{r-r}(z)$, $B_{rr-sap}(z)$, $B_{rr-r}(z)$, $B_{sap-rr}(z)$, $B_{sap-r}(z)$, $D_{rr}(z)$, $D_{sap}(z)$

are FIR filter of order p in the z-domain

Trivariate closed loop model: factorization of heart period variability into partial processes

Under the hypothesis of uncorrelation among w_{rr} , w_{sap} and w_r , the rr series can be factorized as

$$rr(i) = rr(i)|_{w_{sap}} + rr(i)|_{w_r} + rr(i)|_{w_{rr}}$$

where

$$rr(i)|_{w_{sap}} = \frac{B_{rr-sap}}{\Delta_{loop} \cdot (1 - D_{sap})} \cdot w_{sap}(i)$$

baroreflex pathway

$$rr(i)|_{w_r} = \frac{B_{rr-sap} \cdot B_{sap-r} + B_{rr-r} \cdot (1 - A_{sap-sap})}{\Delta_{loop} \cdot (1 - A_{r-r})} \cdot w_r(i)$$

cardiopulmonary pathway

$$rr(i)|_{w_{rr}} = \frac{1 - A_{sap-sap}}{\Delta_{loop} \cdot (1 - D_{rr})} \cdot w_{rr}(i)$$

with $\Delta_{loop} = (1 - A_{rr-rr}) \cdot (1 - A_{sap-sap}) - A_{rr-sap} \cdot A_{sap-rr}$

Trivariate closed loop model: heart period variability decomposition

Under the hypothesis of uncorrelation among w_{rr} , w_{sap} and w_r , the variance of rr series can be factorized as

$$\sigma^2_{rr} = \sigma^2_{rr|w_{sap}} + \sigma^2_{rr|w_r} + \sigma^2_{rr|w_{rr}}$$

where

$\sigma^2_{rr|w_{sap}}$ is the variance of $rr(i)|_{w_{sap}}$

$\sigma^2_{rr|w_r}$ is the variance of $rr(i)|_{w_r}$

$\sigma^2_{rr|w_{rr}}$ is the variance of $rr(i)|_{w_{rr}}$

Assessing the contributions of baroreflex and cardiopulmonary pathways to the complexity of heart period variability

Contribution of baroreflex to RR complexity

$$\chi^2_{\text{rr-sap}} = \frac{\sigma^2_{\text{rr}|w_{\text{sap}}}}{\sigma^2_{\text{rr}}}$$

$$0 \leq \chi^2_{\text{rr-sap}} \leq 1$$

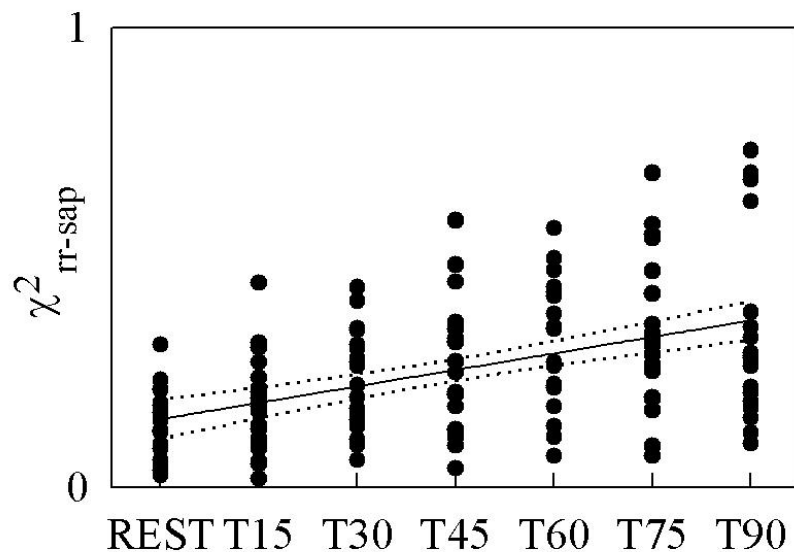
Contribution of cardiopulmonary pathway to RR complexity

$$\chi^2_{\text{rr-r}} = \frac{\sigma^2_{\text{rr}|w_{\text{r}}}}{\sigma^2_{\text{rr}}}$$

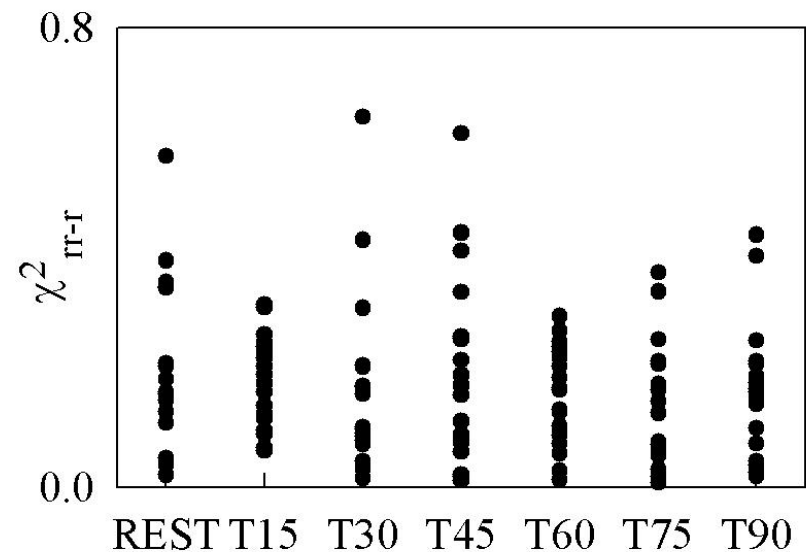
$$0 \leq \chi^2_{\text{rr-r}} \leq 1$$

Baroreflex and cardiopulmonary contributions to the complexity of heart period variability during graded head-up tilt: the closed loop trivariate model approach

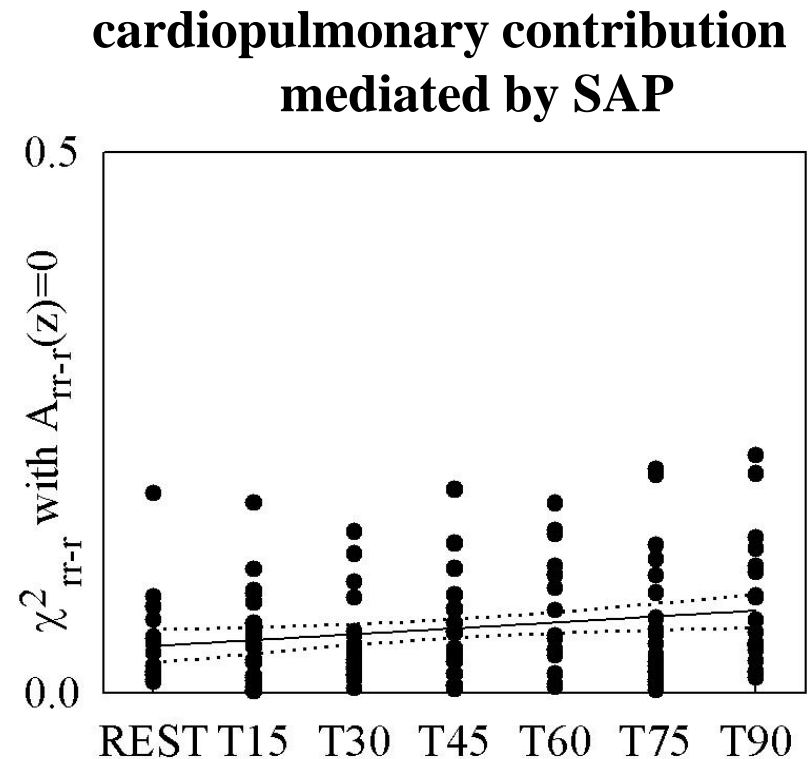
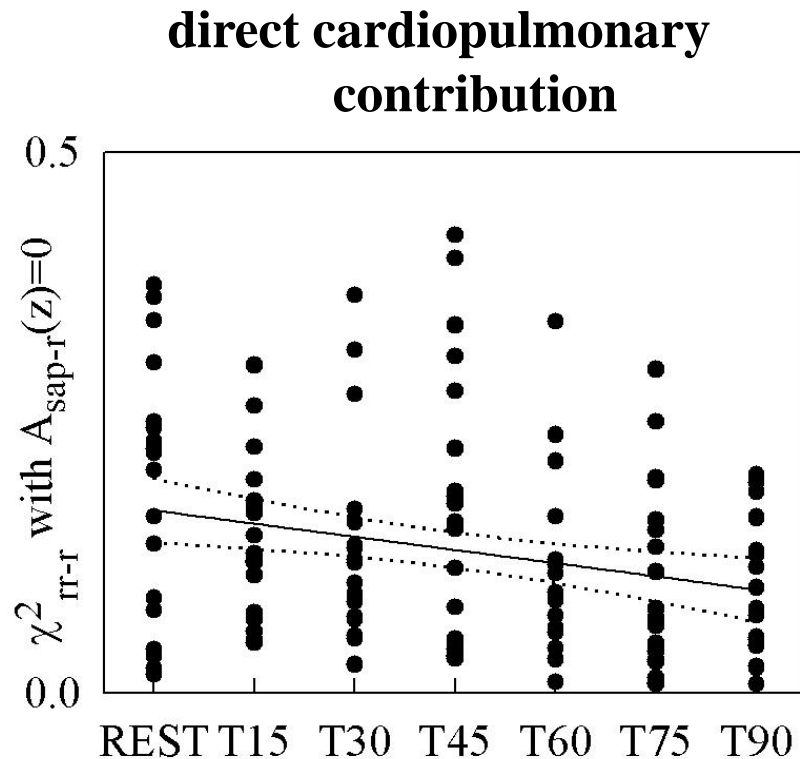
baroreflex contribution



cardiopulmonary contribution



Decomposition of cardiopulmonary contributions to the complexity of heart period variability during graded head-up tilt: the closed loop trivariate model approach



Conclusions (closed loop model)

The contribution of baroreflex to the complexity of heart period variability gradually increases as a function tilt table angle

The contribution of cardiopulmonary pathway to the complexity of heart period variability was unaffected by the orthostatic challenge

The contribution of cardiopulmonary pathway to the complexity of heart period variability can be decomposed into two terms, related to direct link from respiration to heart period and to indirect link mediated by systolic arterial pressure changes

The direct contribution of cardiopulmonary pathway to the complexity of heart period variability decreases, while the indirect one increases with tilt table angles

Outline

- 1) Multivariate model-based approach for the assessment of complexity of the cardiovascular system
- 2) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of open loop interactions
- 3) Multivariate model-based approach for the assessment of the contribution of specific mechanisms to the overall complexity in the case of closed loop interactions
- 4) Granger-causality: a method for the quantification of the contribution of specific mechanisms to the overall complexity

Granger causality: definition

Given $\Omega = \{x_1, \dots, x_i, \dots, x_M\}$ the set formed by M signals
with $x_i = \{x_i(n), n=1, \dots, N\}$

x_j is said to Granger-cause x_i if x_i is better predicted in Ω
than in Ω after excluding x_j (i.e. $\Omega - \{x_j\}$)

Granger causality: modeling

$AR_{xi}X_{\Omega-\{xi\}}$ model in Ω :

$$x_i(n) = A_{xi-xi}(z) \cdot x_i(n) + \sum_{k=1, k \neq i}^M B_{xi-xk}(z) \cdot x_k(n) + w_{xi}(n)$$

$AR_{xi}X_{\Omega-\{xi,xj\}}$ model in $\Omega-\{x_j\}$:

$$x_i(n) = A_{xi-xi}(z) \cdot x_i(n) + \sum_{k=1, k \neq i,j}^M B_{xi-xk}(z) \cdot x_k(n) + w_{xi}(n)$$

Granger causality: assessment of the mean square prediction error

Given the predictors

$$\hat{x}_i(n)|_{\Omega} = \hat{A}_{xi-xi}(z) \cdot x_i(n) + \sum_{k=1, k \neq i}^M \hat{B}_{xi-xk}(z) \cdot x_k(n)$$

$$\hat{x}_i(n)|_{\Omega-\{x_j\}} = \hat{A}_{xi-xi}(z) \cdot x_i(n) + \sum_{k=1, k \neq i,j}^M \hat{B}_{xi-xk}(z) \cdot x_k(n)$$

and defined the predictor errors as

$$e(n)|_{\Omega} = x_i(n) - \hat{x}_i(n)|_{\Omega} \quad \text{and} \quad e(n)|_{\Omega-\{x_j\}} = x_i(n) - \hat{x}_i(n)|_{\Omega-\{x_j\}}$$

the mean square prediction errors (MSPEs) can be assessed as

$$\text{MSPE}_{xi|\Omega} = \frac{1}{N-1} \sum_{i=1}^N e^2(n)|_{\Omega} \quad \text{and} \quad \text{MSPE}_{xi|\Omega-\{x_j\}} = \frac{1}{N-1} \sum_{i=1}^N e^2(n)|_{\Omega-\{x_j\}}$$

Granger causality: predictability improvement

$$F_{x_j \rightarrow x_i | \Omega} = \frac{\text{MSPE}_{x_i | \Omega - \{x_j\}} - \text{MSPE}_{x_i | \Omega}}{\text{MSPE}_{x_i | \Omega}} \cdot \frac{v_{\text{den}}}{v_{\text{num}}}$$

v_{num} = degrees of freedom of the numerator
(i.e. number of coefficients of $B_{x_i - x_j}$)

v_{den} = degrees of freedom of the denominator
(i.e. N – number of coefficients of the model $\text{AR}_{x_i} X |_{\Omega - \{x_i\}}$)

If $F_{x_j \rightarrow x_i | \Omega}$ is larger than the critical value of the F distribution for $p < 0.01$, the null hypothesis of absence of causality from x_j to x_i is rejected and the alternative hypothesis, $x_j \rightarrow x_i$, is accepted

Granger causality: fractional contribution to complexity

$$F_{x_j \rightarrow x_i | \Omega} = \frac{\text{MSPE}_{x_i | \Omega - \{x_j\}} - \text{MSPE}_{x_i | \Omega}}{\text{MSPE}_{x_i | \Omega}} \cdot \frac{v_{\text{den}}}{v_{\text{num}}}$$

$F_{x_j \rightarrow x_i | \Omega}$ represents the fractional contribution of the relation from x_j to x_i to the complexity of x_i in Ω

Experimental protocol

19 nonsmoking healthy humans (age: 21-48, median=30, 8 men)

We recorded ECG (lead II), noninvasive finger arterial pressure (Finometer MIDI) and respiration (thoracic belt) at 300 Hz during head-up tilt (T)



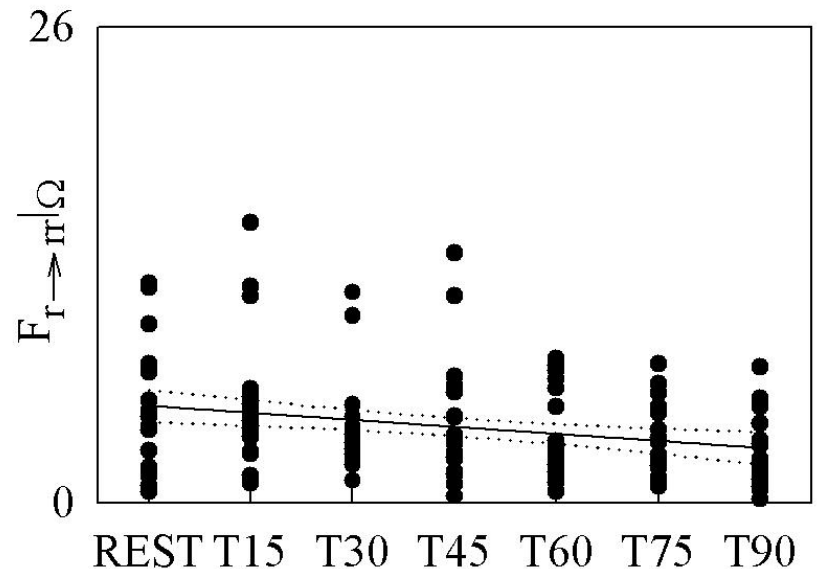
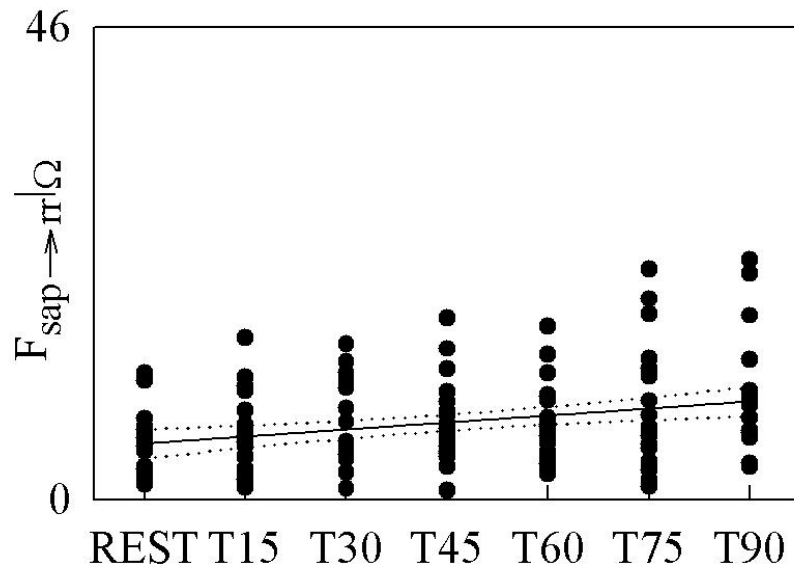
Table angles were randomly chosen within the set { 15,30,45,60,75,90 }

Each T session (10 min) was always preceded by a session (7 min) at rest (R) in supine position.

Series of 256 beats were analyzed after linear detrending

Granger causality: fractional contribution to complexity of heart period variability

Given $\Omega = \{\text{rr}, \text{sap}, \text{r}\}$



A. Porta et al, In: "Methods in brain connectivity inference through multivariate time series analysis", CRC Press, Chapter 15 , in press

Conclusions

Complexity of the cardiovascular control can be assessed through a multivariate model-based approach

This approach is particularly helpful to assess the contributions to complexity of physiological variables given the presence of causal relations with others

Since this approach assesses the interactions between variables in specific time directions (e.g. along baroreflex), it allows the characterization of specific relations among variables