UNIVERSITÀ DEGLI STUDI DI PALERMO

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An information-theoretic framework to dissect multivariate and multiscale physiological interactions

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Multivariate Interactions:
Information Dynamics

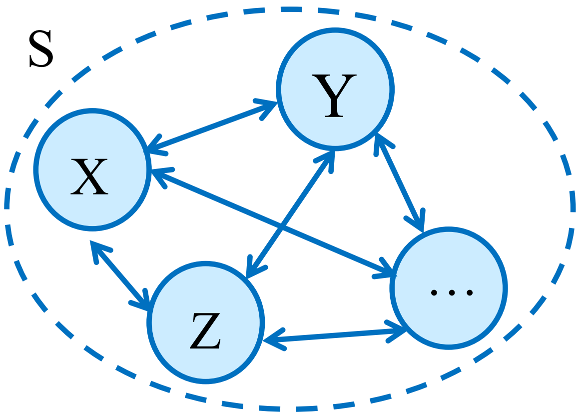
Multiscale Interactions:
State Space Models

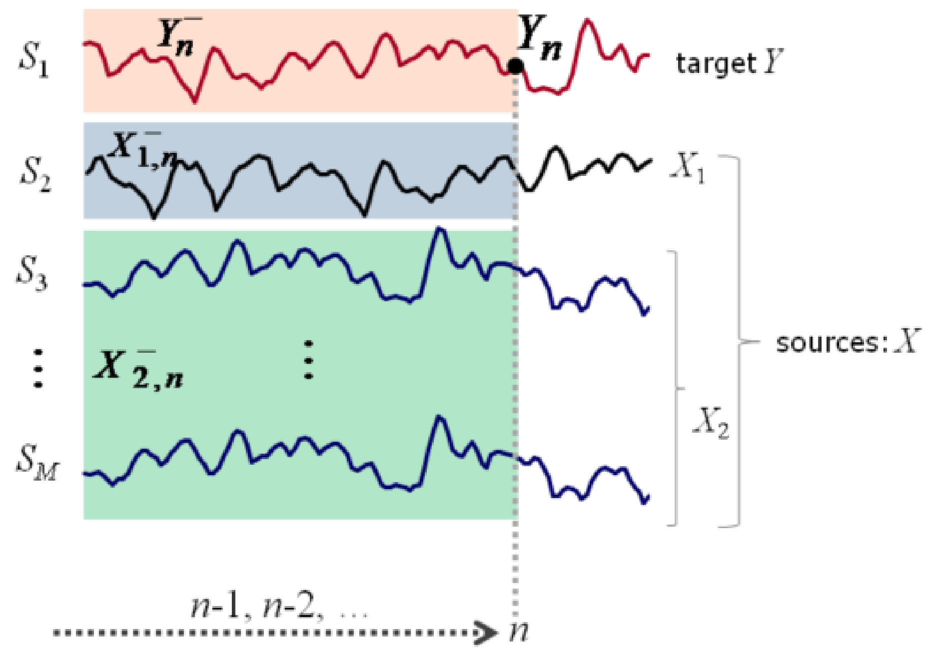
Physiological Interactions:
Brain: epilepsy
Cardiovascular Physiology

INFORMATION DYNAMICS

Physiological Networks ⟷ Networks of Dynamical systems

- Dynamic System $S=\{S_1,\dots,S_M\}$ ➡ • Dynamic Process S





- With reference to a target system Y :

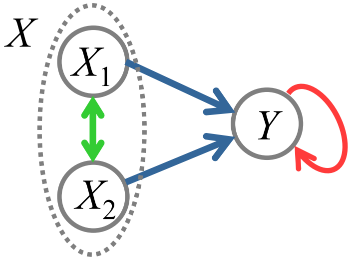
$X=\{X_1,\dots,X_{M-1}\}$ ➡ $S=\{X_1,\dots,X_{M-1}, Y\} = \{X,Y\}$

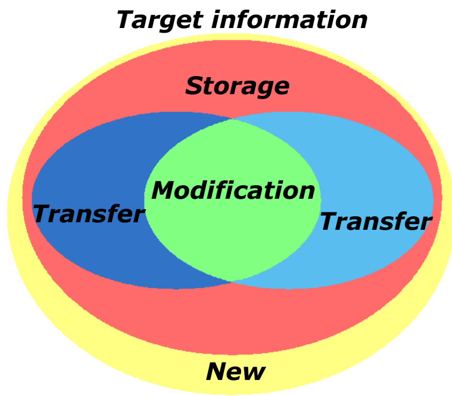
- **Investigation of Statistical dependencies:**
  - ✓ **SELF effects:** $Y_n^- \to Y_n$ ➡ Information storage
  - ✓ **CAUSAL effects:** $X_n^- \to Y_n$ ➡ Information transfer
  - ✓ **INTERACTION effects:** $(X_{1,n}^- \leftrightarrow X_{2,n}^-) \to Y_n$ ➡ Information modification

INFORMATION DECOMPOSITION

- **Decomposition of the "information" contained in the target process**

$S = \{X, Y\} = \{X_1, X_2, Y\}$





$$H_Y = S_Y + T_{X_1 \to Y} + T_{X_2 \to Y} + I_{X_1 X_2 \to Y} + N_Y$$

Information

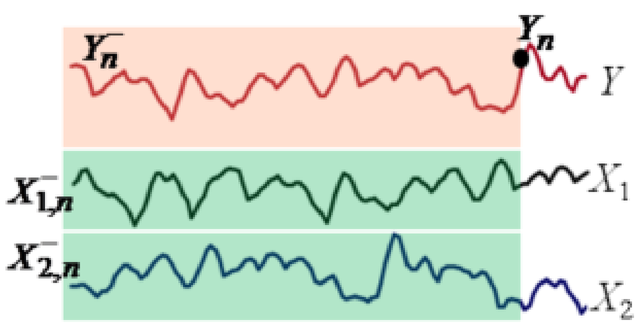
Information Storage *activity*

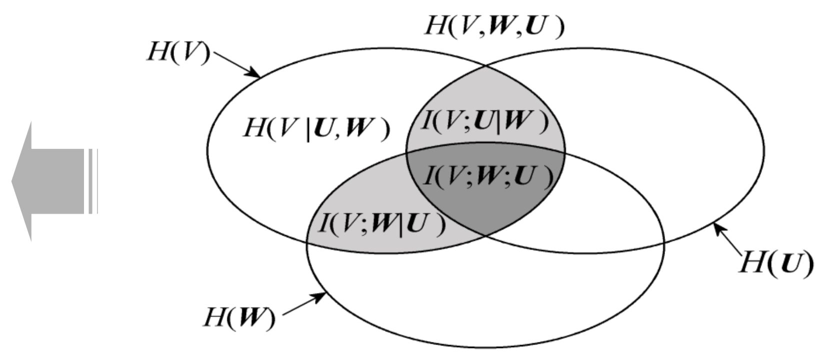
Information Transfer *connectivity*

Information Modification *interaction*

New Information *non-predictable dynamics*

- **Computation: basic information theoretic measures**





ENTROPY:

$$H(V) = -\mathrm{E}[\log p(v)]$$

CONDITIONAL ENTROPY:

$$H(V|U) = H(V,U) - H(U)$$

MUTUAL INFORMATION:

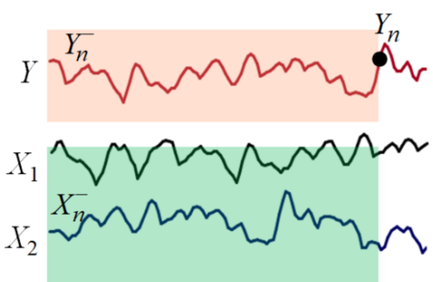
$$I(V;U) = H(V) - H(V|U)$$

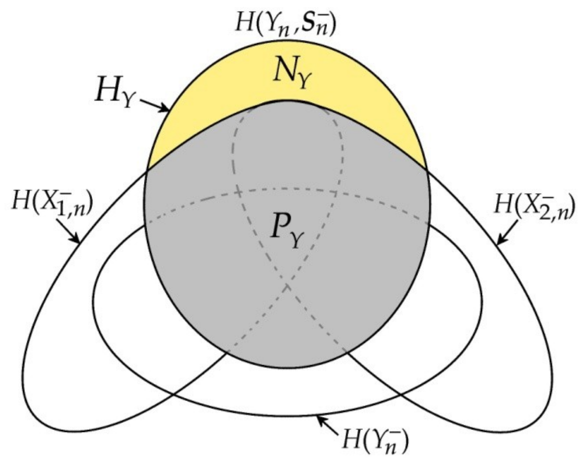
$$I(V;U|W) = H(V|W) - H(V|U,W)$$

INTERACTION INFORMATION:

$$I(V;U;W) = I(V;U) + I(V;W) - I(V;U,W)$$

TARGET INFORMATION DECOMPOSITION





$$H(Y_n) = I(Y_n; \mathbf{X}_n^-, Y_n^-) + H(Y_n \mid \mathbf{X}_n^-, Y_n^-)$$

H_Y	P_Y	N_Y
Information	**Predictive Information**	**New created Information**

- **Present Information** about Y : $H_Y = H(Y_n)$

  Information contained in the present of the process Y

  → ***Uncertainty about the present state of the target***

- **Predictive Information** about Y : $P_Y = I(Y_n; Y_n^-, X_n^-)$

  Information contained in the past of S=(X,Y) that can be used to predict the present of the target Y

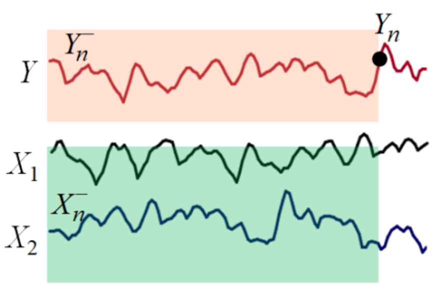
  → ***Predictability of the target given the past network states***

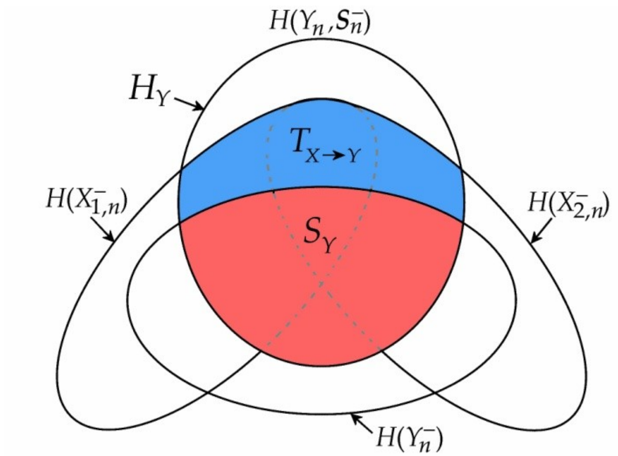
- **New information** about Y : $N_Y = H(Y_n \mid Y_n^-, X_n^-)$

  Information contained in the present of Y that cannot be predicted from the past of S=(X,Y)

  → ***Information generated in the target by the state transition***

PREDICTIVE INFORMATION DECOMPOSITION





$$I(Y_n; \mathbf{X}_n^-, Y_n^-) = I(Y_n; Y_n^-) + I(Y_n; \mathbf{X}_n^- \mid Y_n^-)$$

P_Y	S_Y	$T_{X \to Y}$
Predictive Information	**Information Storage**	**Information Transfer**

- **Predictive Information** about Y : $P_Y = I(Y_n; Y_n^-, X_n^-)$

  Information contained in the past of S=(X,Y) that can be used to predict the present of the target Y

  → ***Predictability of the target given the network past states***

- **Information Storage** in Y : $S_Y = I(Y_n; Y_n^-)$

  Information contained in the past of Y that can be used to predict its present

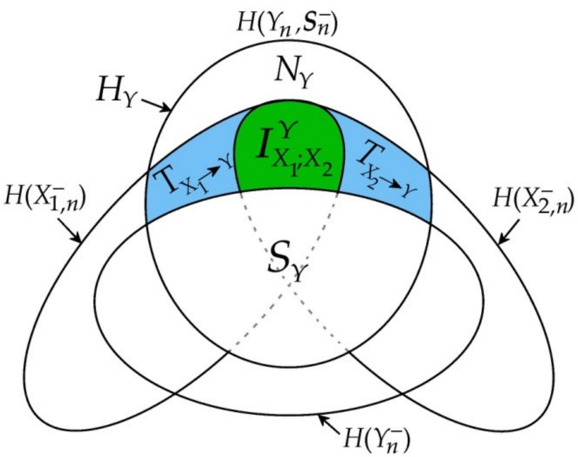
  → ***Predictability of the target from its own past states***

- **Information transfer** from X to Y : $T_{X \to Y} = I(Y_n; X_n^- \mid Y_n^-)$

  Information contained in the past of X that can be used to predict the present of Y above and beyond the information contained in the past of Y

  → ***Causal interactions from all sources to the target***

INFORMATION TRANSFER DECOMPOSITION



$$I(Y_n;\mathbf{X}_n^-\,|\,Y_n^-) = I(Y_n;X_{1,n}^-\,|\,Y_n^-) + I(Y_n;X_{2,n}^-\,|\,Y_n^-) + I(Y_n;X_{1,n}^-;X_{2,n}^-\,|\,Y_n^-)$$

$T_{X\to Y}$ — **Information Transfer**

$T_{X_1\to Y}$, $T_{X_2\to Y}$ — **Individual information transfer**

$I^Y_{X_1;X_2}$ — **Interaction Information Transfer**

- **Joint information transfer**: $T_{X_1,X_2\to Y} = I(Y_n;X_{1,n}^-,X_{2,n}^-\,|\,Y_n^-)$

  Information contained in the past of X_1,X_2 that can be used to predict the present of Y above and beyond the information contained in the past of Y

  → ***Causal interactions from all sources to the target***

- **Individual information transfer**: $T_{X_1\to Y} = I(Y_n;X_{1,n}^-\,|\,Y_n^-)$

  Information contained in the past of X_1 that can be used to predict the present of Y above and beyond the information contained in the past of Y (and of X_2)

  → ***Causal interactions from one source to the target***

- **Interaction information transfer**: $I^Y_{X_1;X_2} = I(Y_n;X_{1,n}^-;X_{2,n}^-\,|\,Y_n^-)$

  Information contained in the past of X_1 and X_2 that can be used to predict the present of Y when X_1 and X_2 are taken individually but not when they are taken together

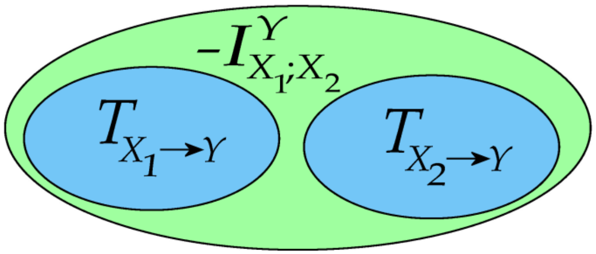
  → ***Redundant or synergistic interactions contributing to transfer***

INFORMATION MODIFICATION: REDUNDANCY AND SYNERGY

- **Interpretation of Information Modification:** $I^{Y}_{X_1;X_2} = T_{X_1,X_2 \to Y} - (T_{X_1 \to Y} + T_{X_2 \to Y})$

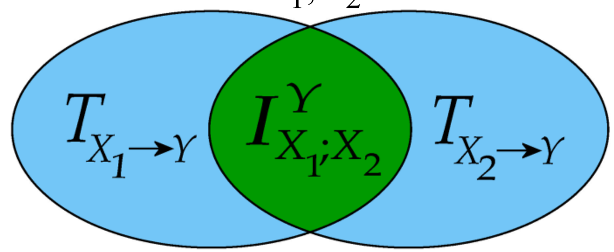
REDUNDANCY:

$T_{X_1,X_2 \to Y} < T_{X_1 \to Y} + T_{X_2 \to Y} \;\Rightarrow\; I^{Y}_{X_1;X_2} < 0$



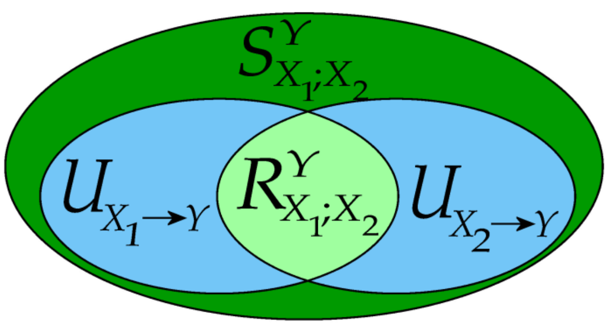
SYNERGY:

$T_{X_1,X_2 \to Y} > T_{X_1 \to Y} + T_{X_2 \to Y} \;\Rightarrow\; I^{Y}_{X_1;X_2} > 0$



Interaction information can be positive or negative

- **PARTIAL INFORMATION DECOMPOSITION (PID)**



[P.L. Williams & R.D. Beer, ArXiv 1004.2515, 2010]

$$T_{X_1,X_2 \to Y} = U_{X_1 \to Y} + U_{X_2 \to Y} + R^{Y}_{X_1;X_2} + S^{Y}_{X_1;X_2}$$

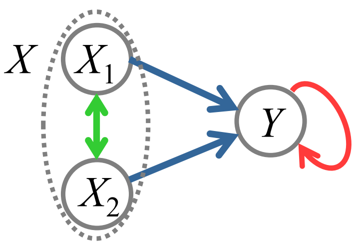
$$T_{X_1 \to Y} = U_{X_1 \to Y} + R^{Y}_{X_1;X_2} \quad , \quad T_{X_2 \to Y} = U_{X_2 \to Y} + R^{Y}_{X_1;X_2}$$

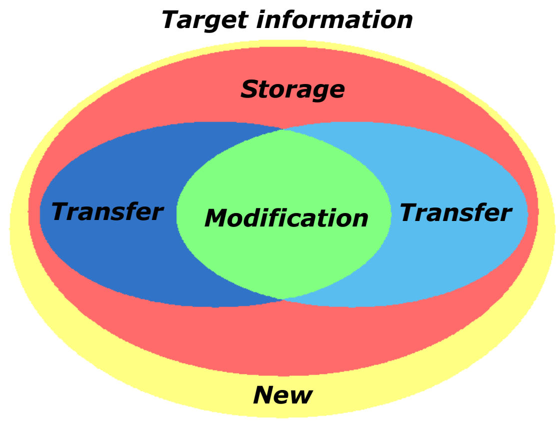
- Minimum mutual information PID: $R^{Y}_{X_1;X_2} = \min\{T_{X_1 \to Y}, T_{X_2 \to Y}\}$
  [A.B. Barrett, Phys. Rev. E 91, 2015]

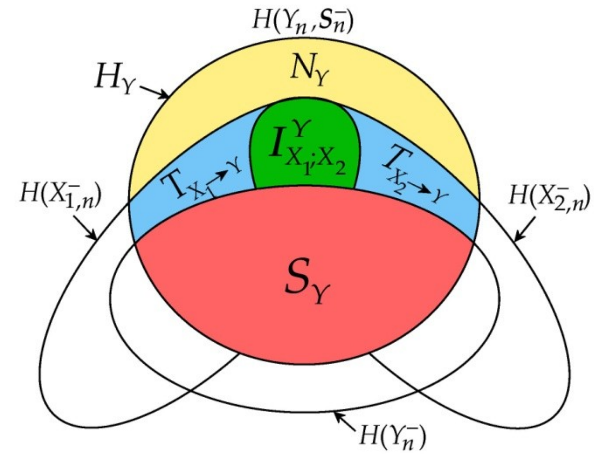
Relation with interaction information:

$$I^{Y}_{X_1;X_2} = S^{Y}_{X_1;X_2} - R^{Y}_{X_1;X_2}$$

THE FRAMEWORK OF INFORMATION DYNAMICS







$$H_Y = N_Y + P_Y = N_Y + S_Y + T_{X\rightarrow Y} = N_Y + S_Y + T_{X_1\rightarrow Y} + T_{X_2\rightarrow Y} + I^Y_{X_1;X_2}$$

Information

Predictive

Information Storage
predictable activity

Individual Transfer
direct causal connectivity

Interaction Transfer

New Information
unpredictable dynamics

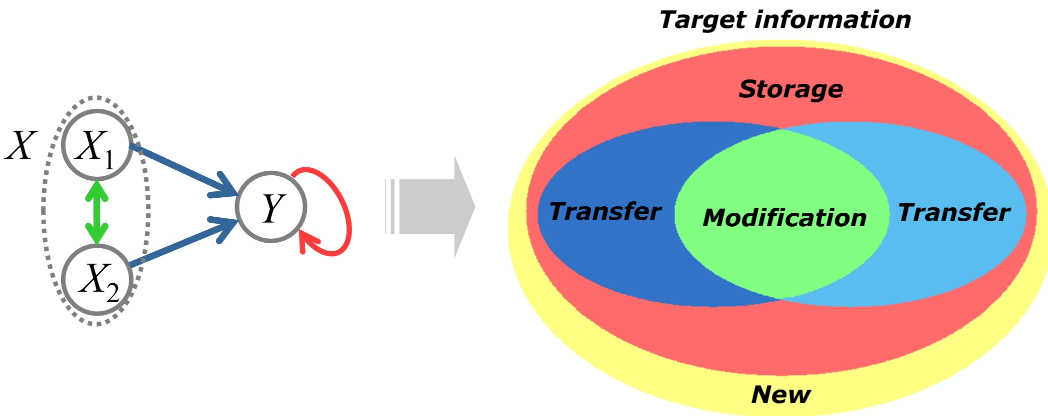
Information Transfer
causal connectivity

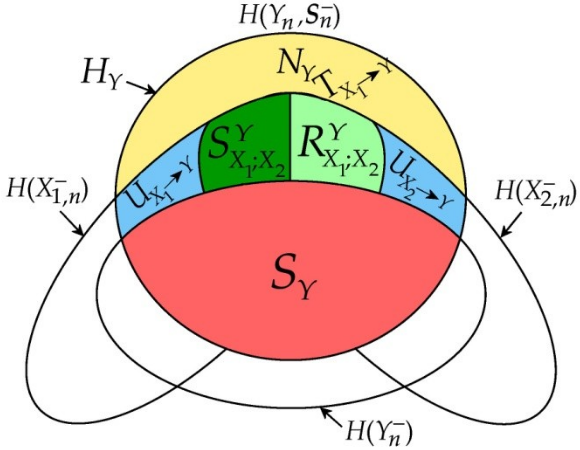
Information Modification
interaction between systems

L Faes, A Porta, G Nollo, *'Information decomposition in bivariate systems: theory and application to cardiorespiratory dynamics'*, ***Entropy, special issue on "Entropy and Cardiac Physics", 2015***, 17:277-303.

L Faes, A Porta, G Nollo, M Javorka, 'Information decomposition in multivariate systems: definitions, implementation and application to cardiovascular networks', ***Entropy, special issue on Multivariate Entropy Measures and their applications***, 2017, 19(1), 5

THE FRAMEWORK OF INFORMATION DYNAMICS





$$H_Y = N_Y + P_Y = N_Y + S_Y + T_{X\to Y} = N_Y + S_Y + U_{X_1\to Y} + U_{X_2\to Y} + R^Y_{X_1;X_2} + S^Y_{X_1;X_2}$$

- H_Y: ***Information***
- N_Y: ***New Information*** — *unpredictable dynamics*
- P_Y: **Predictive**
- S_Y: ***Information Storage*** — *predictable activity*
- $T_{X\to Y}$: ***Information Transfer*** — *causal connectivity*
- $U_{X_1\to Y} + U_{X_2\to Y}$: **Unique Transfer** — *Unique contribution*
- $R^Y_{X_1;X_2}$: **Redundant Transfer**
- $S^Y_{X_1;X_2}$: **Synergistic Transfer**
- $R^Y_{X_1;X_2} + S^Y_{X_1;X_2}$: ***Information Modification*** — *interaction between systems*

L Faes, A Porta, G Nollo, *'Information decomposition in bivariate systems: theory and application to cardiorespiratory dynamics'*, ***Entropy, special issue on "Entropy and Cardiac Physics", 2015***, 17:277-303.

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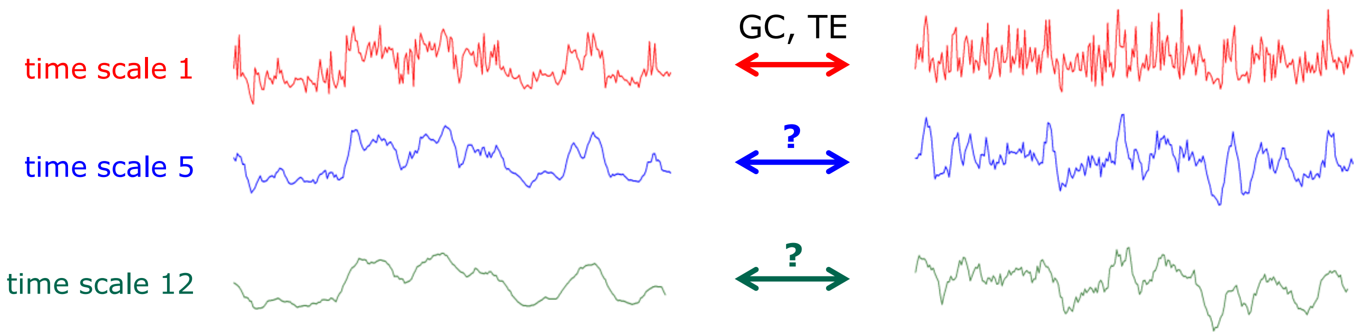
MULTISCALE INFORMATION DYNAMICS

- Many physical processes exhibit dynamics spanning multiple temporal scales
- Multiscale methods to study individual dynamics are well established
  [M Costa et al, Phys. Rev. Lett. 89, 2002]
- Multiscale computation of information transfer is non-trivial



- We propose **a formal extension of information decomposition to multiscale analysis** of jointly stationary multivariate linear processes (VAR)
- Formulations based on VARMA representation and state-space (SS) modeling, leading to **exact computation** of information dynamics from VAR parameters

L Faes, S Stramaglia, G Nollo, D Marinazzo 'Multiscale Granger causality', ***Phys Rev E 96***, 042150, 2017

L Faes, D Marinazzo , S Stramaglia 'Multiscale Information decomposition: exact computation for multivariate gaussian processes', ***Entropy 19***, 408, 2017

MULTISCALE INFORMATION DYNAMICS

MULTISCALE ANALYSIS OF TIME SERIES: CHANGE OF TIME SCALE

- **Traditional procedure for rescaling**

$$Y_n = \{x_n, y_n\} \quad n = 1,\ldots,N$$

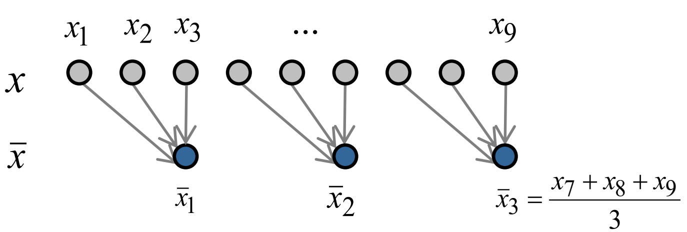
RESCALING (scale factor τ):

$$\bar{Y}_n = \{\bar{x}_n, \bar{y}_n\}, \quad n = 1,\ldots,N/\tau$$

$$\bar{x}_n = \frac{1}{\tau}\sum_{l=0}^{\tau-1} x_{n\tau-l} \quad , \quad \bar{y}_n = \frac{1}{\tau}\sum_{l=0}^{\tau-1} y_{n\tau-l}$$

[M Costa et al, Phys. Rev. Lett. 89, 2002]

Example:
$N = 9, \tau = 3$



- **Rescaling can be seen as a two-step procedure**

$$Y_n = \{x_n, y_n\} \quad n = 1,\ldots,N$$

1) AVERAGING (lowpass filtering)

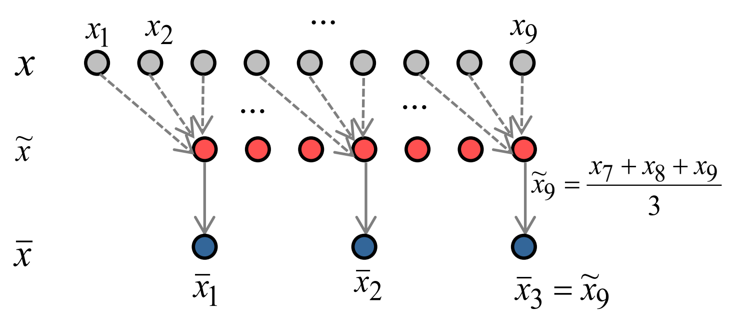
$$\tilde{Y}_n = \frac{1}{\tau}\sum_{l=0}^{\tau-1} Y_{n-l} \quad , \quad n = \tau,\ldots,N$$

2) DOWNSAMPLING

$$\bar{Y}_n = \tilde{Y}_{n\tau} \quad , \quad n = 1,\ldots,N/\tau$$

[J. Valencia et al, IEEE Trans. Biomed Eng. 56, 2009]

Example:
$N = 9, \tau = 3$



MULTISCALE INFORMATION DYNAMICS

MULTISCALE REPRESENTATION OF LINEAR PROCESSES USING STATE SPACE MODELS

Observed time series — *FILTERING* (τ) [1] → **Filtered time series** — *DOWNSAMPLING* (τ) [2] → **Rescaled time series**

$$VAR(\mathbf{A},\mathbf{\Sigma})$$

$$Y_n = \sum_{k=1}^{p} \mathbf{A}_k Y_{n-k} + \mathbf{U}_n$$

$$\mathbf{\Sigma} = \mathrm{cov}(U_n)$$

$$VARMA(\mathbf{A},\mathbf{B},\mathbf{\Sigma}) \leftrightarrow SS(\widetilde{\mathbf{A}},\widetilde{\mathbf{C}},\widetilde{\mathbf{K}},\widetilde{\mathbf{V}}) \quad [1]$$

$$\widetilde{Y}_n = \sum_{k=1}^{p} \mathbf{A}_k Y_{n-k} + \sum_{l=0}^{q} \mathbf{B}_l \mathbf{U}_{n-l}$$

$$\mathbf{B}_l = b_l \mathbf{I} \quad ,l = 0,1,\ldots,q$$

$b_1,\ldots,b_q$ FIR lowpass filter

Cutoff frequency: $f_\tau = \dfrac{1}{2\tau}$

$$\widetilde{Z}_{n+1} = \widetilde{\mathbf{A}}\widetilde{Z}_n + \widetilde{\mathbf{K}}\widetilde{E}_n$$

$$\widetilde{Y}_n = \widetilde{\mathbf{C}}\widetilde{Z}_n + \widetilde{E}_n$$

$$\widetilde{\mathbf{A}} = \begin{bmatrix} \mathbf{A}_1 & \cdots & \mathbf{A}_{p-1} & \mathbf{A}_p & \mathbf{B}_1 & \cdots & \mathbf{B}_{q-1} & \mathbf{B}_q \\ \mathbf{I} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots \\ \mathbf{0} & \cdots & \mathbf{I} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{I} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & & \vdots & \vdots & \vdots & & \vdots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I} & \mathbf{0} \end{bmatrix}$$

$$\widetilde{\mathbf{C}} = [\mathbf{A}_1 \cdots \mathbf{A}_p \mathbf{B}_1 \cdots \mathbf{B}_q]$$

$$\widetilde{\mathbf{K}} = [\mathbf{I}\,\mathbf{0} \cdots \mathbf{0}\,\mathbf{B}_0^{-\mathrm{T}}\,\mathbf{0} \cdots \mathbf{0}]^{\mathrm{T}}$$

$$\widetilde{\mathbf{V}} = \mathrm{cov}(\widetilde{E}_n) = \mathbf{B}_0 \mathbf{\Sigma} \mathbf{B}_0^{\mathrm{T}}$$

$$SS(\overline{\mathbf{A}},\overline{\mathbf{C}},\overline{\mathbf{Q}},\overline{\mathbf{R}},\overline{\mathbf{S}})$$

$$\overline{X}_{n+1} = \overline{\mathbf{A}}\overline{X}_n + \overline{W}_n$$

$$\overline{Y}_n = \overline{\mathbf{C}}\overline{X}_n + \overline{V}_n$$

$$\overline{\mathbf{A}} = \widetilde{\mathbf{A}}^{\tau},\ \overline{\mathbf{C}} = \widetilde{\mathbf{C}},\ \overline{\mathbf{R}} = \widetilde{\mathbf{V}}$$

$$\overline{\mathbf{Q}}_\tau = \widetilde{\mathbf{A}}\overline{\mathbf{Q}}_{\tau-1}\widetilde{\mathbf{A}}^{\mathrm{T}} + \widetilde{\mathbf{K}}\widetilde{\mathbf{V}}\widetilde{\mathbf{K}}^{\mathrm{T}}$$

$$\overline{\mathbf{S}}_\tau = \widetilde{\mathbf{A}}^{\tau-1}\widetilde{\mathbf{K}}\widetilde{\mathbf{V}}$$

[2,3] ↓ *Discrete Algebraic Ricatti Equation (DARE)*

$$ISS(\overline{\mathbf{A}},\overline{\mathbf{C}},\overline{\mathbf{K}},\overline{\mathbf{V}})$$

$$\overline{Z}_{n+1} = \overline{\mathbf{A}}\overline{Z}_n + \overline{\mathbf{K}}\overline{E}_n$$

$$\overline{Y}_n = \overline{\mathbf{C}}\overline{Z}_n + \overline{E}_n$$

[1][Aoki & Havenner, Econ. Rev. 10, 1991] [2][Solo, ArXiv 1501.04663, 2015] [3][Barnett & Seth, Phys. Rev. E 91, 2015]

The State Space model defining the multivariate linear process after rescaling can be obtained from the original VAR parameters and the scale factor τ

MULTISCALE INFORMATION DYNAMICS

EXACT COMPUTATION OF INFORMATION TRANSFER FOR LINEAR PROCESSES BASED ON STATE SPACE MODELS

- **Computation of the partial variance of the target process y_j given a subset of processes Y_a**

$ISS(\overline{\mathbf{A}},\overline{\mathbf{C}},\overline{\mathbf{K}},\overline{\mathbf{V}})$ → SUBMODEL → $SS(\overline{\mathbf{A}},\overline{\mathbf{C}}^{(a)},\overline{\mathbf{Q}}^{(a)},\overline{\mathbf{R}}^{(a)},\overline{\mathbf{S}}^{(a)})$ → *Discrete Algebraic Ricatti Equation (DARE)* → $ISS(\overline{\mathbf{A}},\overline{\mathbf{C}}^{(a)},\overline{\mathbf{K}}\,\overline{\mathbf{V}}\overline{\mathbf{K}}^{\mathrm{T}},\overline{\mathbf{V}}(a,a),\overline{\mathbf{K}}\,\overline{\mathbf{V}}(:,a))$ → $\lambda_{j|a}$

$$\overline{Z}_{n+1}=\overline{\mathbf{A}}\overline{Z}_n+\overline{\mathbf{K}}\overline{E}_n$$
$$\overline{Y}_n=\overline{\mathbf{C}}\overline{Z}_n+\overline{E}_n$$

$$\overline{Z}_{n+1}=\overline{\mathbf{A}}\overline{Z}_n+\overline{\mathbf{K}}^{(a)}\overline{E}_n$$
$$\overline{Y}_n^{(a)}=\overline{\mathbf{C}}^{(a)}\overline{Z}_n+\overline{E}_n^{(a)}$$

- **Submodels containing only the target, the target and one source, and the target and both sources**

  - $a=j$ ⇒ $\lambda_{j|j}$
  - $a=j,i$ / $a=j,k$ ⇒ $\lambda_{j|ji}$, $\lambda_{j|jk}$
  - $a=j,i,k$ ⇒ $\lambda_{j|jik}$

⇒

$$S_j=\frac{1}{2}\ln\frac{\lambda_j}{\lambda_{j|j}}$$

$$T_{i\to j}=\frac{1}{2}\ln\frac{\lambda_{j|j}}{\lambda_{j|ji}}\;,\quad T_{k\to j}=\frac{1}{2}\ln\frac{\lambda_{j|j}}{\lambda_{j|jk}}$$

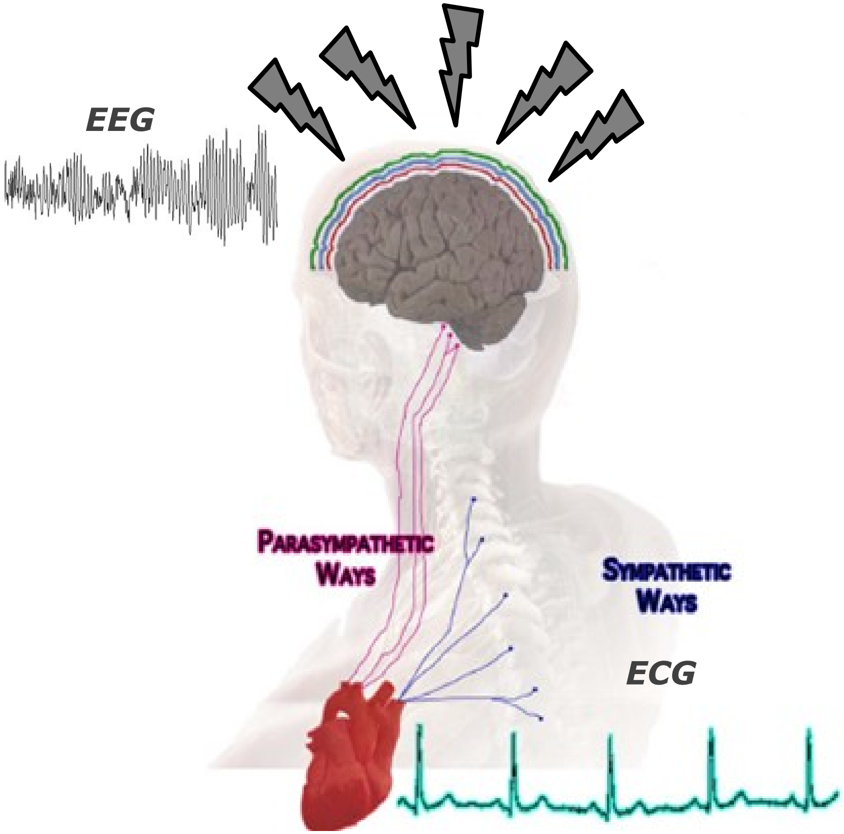
$$T_{ik\to j}=\frac{1}{2}\ln\frac{\lambda_{j|j}}{\lambda_{j|jik}}$$

Information transfer in multivariate linear processes can be computed at any scale τ from the original VAR parameters

APPLICATIONS (1)

STUDY OF BRAIN AND PHYSIOLOGICAL NETWORKS IN EPILEPSY

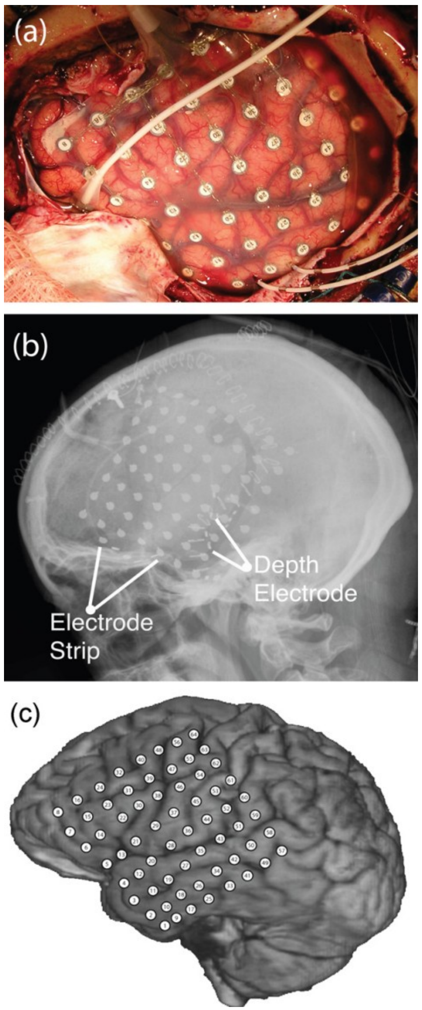
- **The cortical activity changes drastically during an epileptic seizure**
- **The study of brain networks during epilepsy may help in seizure prediction or detection**
- **Seizures influences also the peripheral ANS response**
- **Recent works studied the correlation between the epileptic neural network and the autonomic nervous system**
  [K. Schiecke et al., IEEE Trans. Biomed Eng. 63, 2016]



Application of multiscale partial information decomposition to brain networks and networks of brain-heart interactions during epilepsy

APPLICATIONS (1a)

MULTISCALE INFORMATION TRANSFER IN THE EPILEPTIC BRAIN



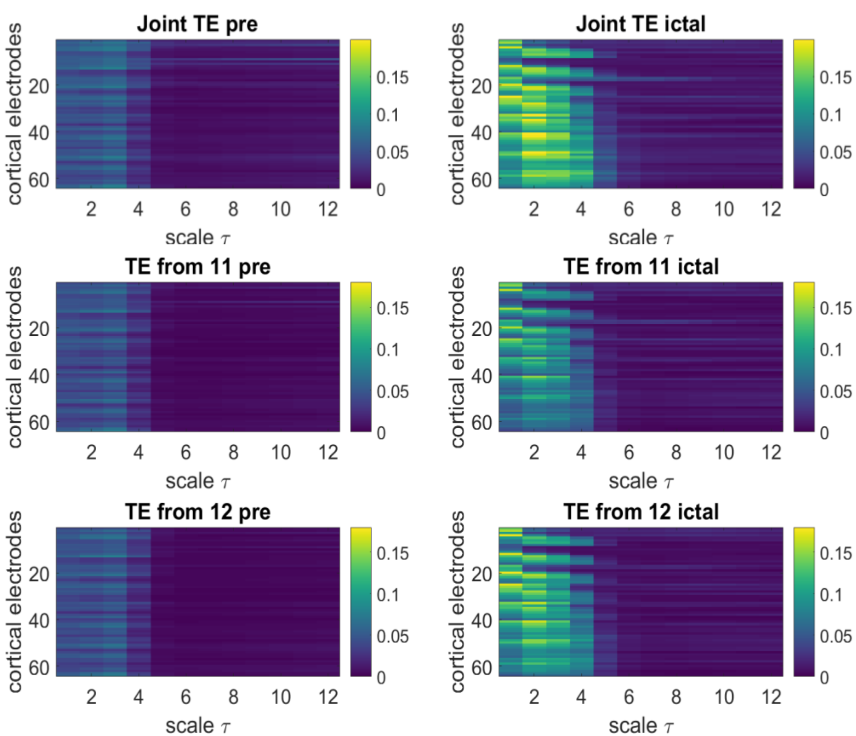
- **Intracranial EEG from a patient with intractable epilepsy (focal seizures, 8 episodes)**
  [MA Kramer et al., Epilepsy Res. 79, 2008]
- **Grid of 8 x 8 cortical electrodes + 2 deep electrodes (left hippocampal region)**
- **10-sec time windows before seizure onset (pre-ictal) and during the seizure (ictal)**
- **Multiscale Partial Information Decomposition:**
  - model order: Bayesian Information Criterion (average p=14)
  - lowpass FIR filter with q=12 coeffs
  - Scale τ=1,...,12 (cutoff freq. f_τ=200 Hz, ..., 16.6 Hz)
  - Computation of PID transfer functions ***from the two deep electrodes to each cortical electrode***

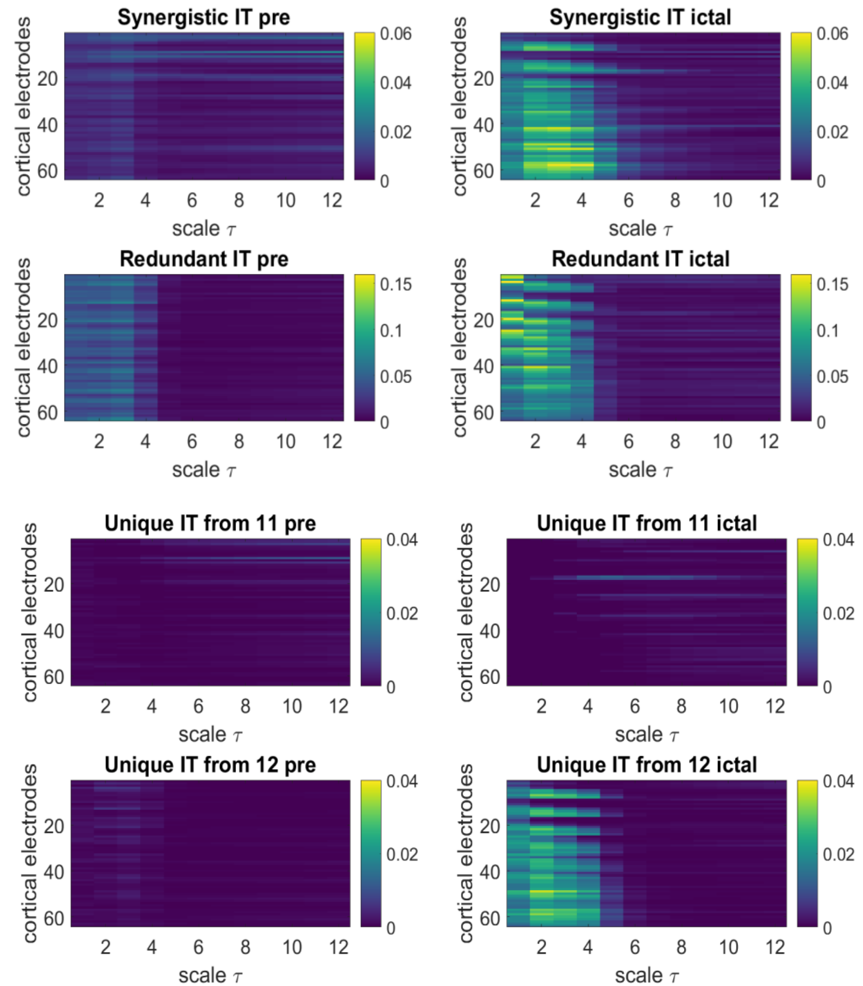
$$T_{ik\to j} = U_{i\to j} + U_{k\to j} + R_{ik\to j} + S_{ik\to j}$$

$$i = \text{deep } 11\ ,\ \ k = \text{deep } 12;\quad j = 1,\ldots,64$$

APPLICATIONS (1a)

MULTISCALE INFORMATION TRANSFER IN THE EPILEPTIC BRAIN





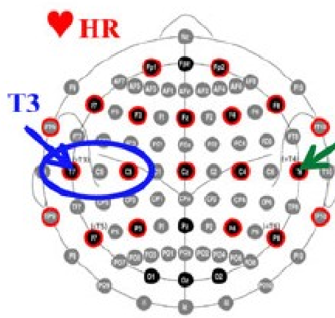
- Increased information transfer during seizure
- Similar patterns of joint TE, TE
- Increased synergistic and redundant TE
- Increased unique TE **only from deep electrode 12** ➡ ***useful for seizure localization***

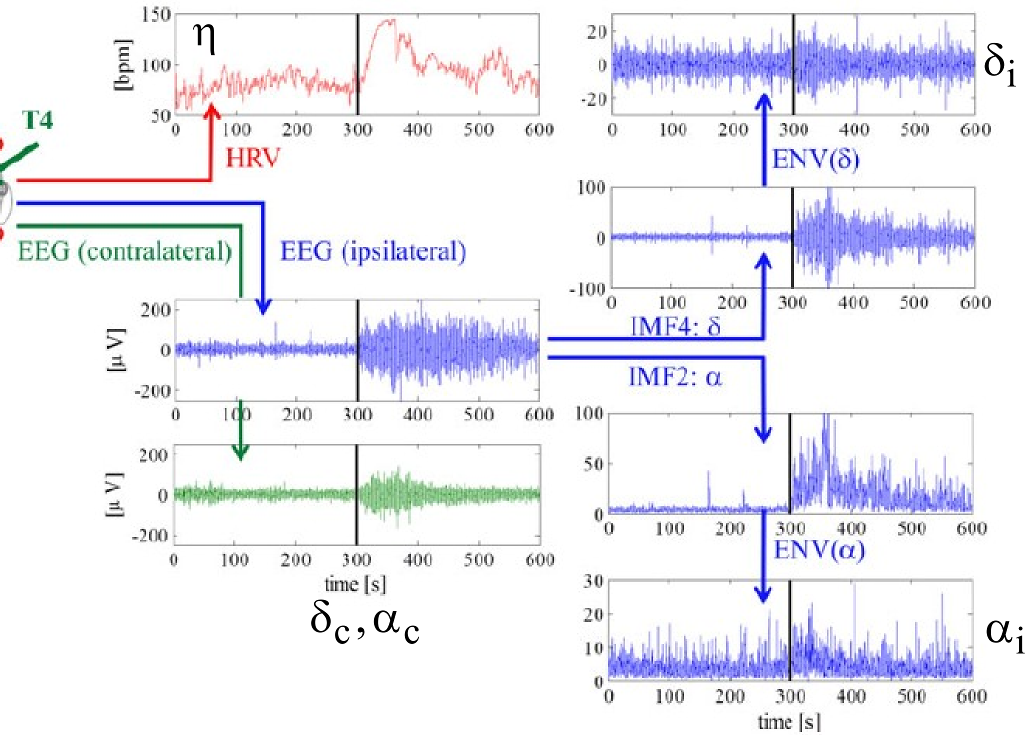
L Faes, D Marinazzo , S Stramaglia 'Multiscale Information decomposition: exact computation for multivariate gaussian processes', ***Entropy* 19**, 408, 2017

APPLICATIONS (1b)

PARTIAL INFORMATION DECOMPOSITION IN EPILEPTIC BRAIN-HEART INTERACTIONS

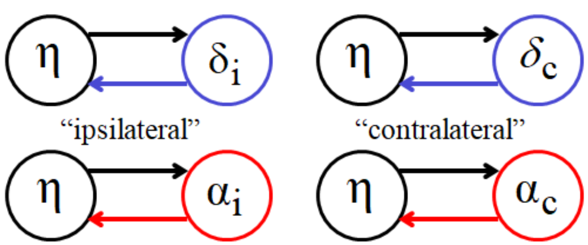
- **PROTOCOL:**
  - ✓ 18 children with **temporal lobe epilepsy**
  - ✓ **Pre-ictal** (5 min)
  - ✓ **Ictal** (~ 1.5 min)
  - ✓ **Post-ictal** (~ 4.5 min)





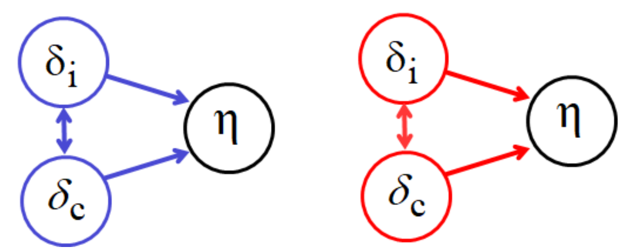
  - ✓ ECG → HRV
  - ✓ EEG:
    - Selection of ipsilateral and contralateral temporal lobe electrodes
    - Extraction of δ and α EEG envelopes

- **Bivariate Information Transfer**



$$T_{\delta\to\eta} = I(\eta_n;\delta_n^- \mid \eta_n^-)\ ,\ T_{\eta\to\delta} = I(\delta_n;\eta_n^- \mid \delta_n^-)$$
$$T_{\alpha\to\eta} = I(\eta_n;\alpha_n^- \mid \eta_n^-)\ ,\ T_{\eta\to\alpha} = I(\alpha_n;\eta_n^- \mid \alpha_n^-)$$

- **Partial Information Decomposition**

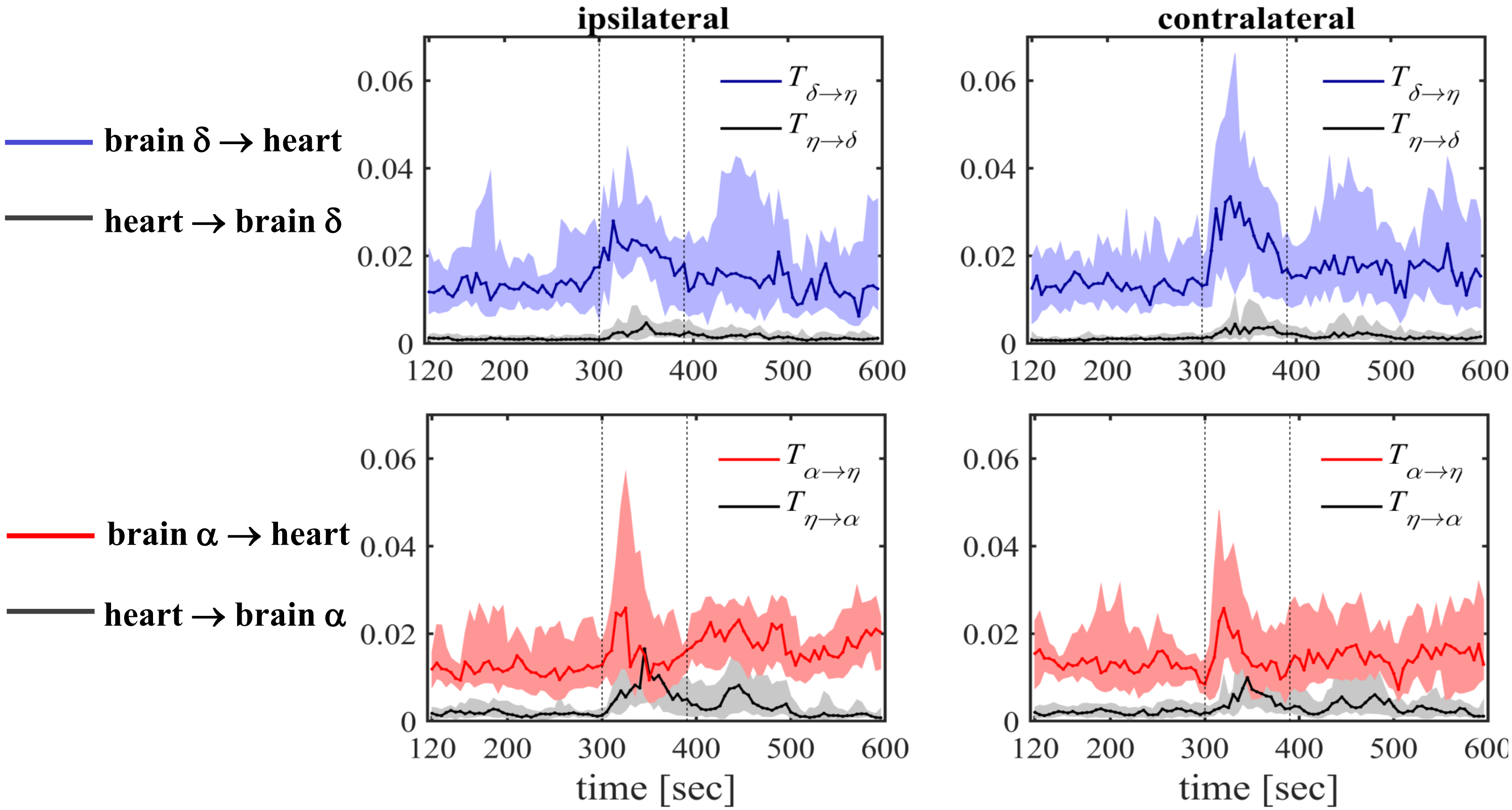


$$T_{\delta_i,\delta_c\to\eta} = U_{\delta_i\to\eta} + U_{\delta_c\to\eta} + R^{\eta}_{\delta_i;\delta_c} + S^{\eta}_{\delta_i;\delta_c}$$
$$T_{\alpha_i,\alpha_c\to\eta} = U_{\alpha_i\to\eta} + U_{\alpha_c\to\eta} + R^{\eta}_{\alpha_i;\alpha_c} + S^{\eta}_{\alpha_i;\alpha_c}$$

APPLICATIONS (1b)

Brain-heart interactions in epilepsy: RESULTS

- **Brain-Heart Information Transfer**



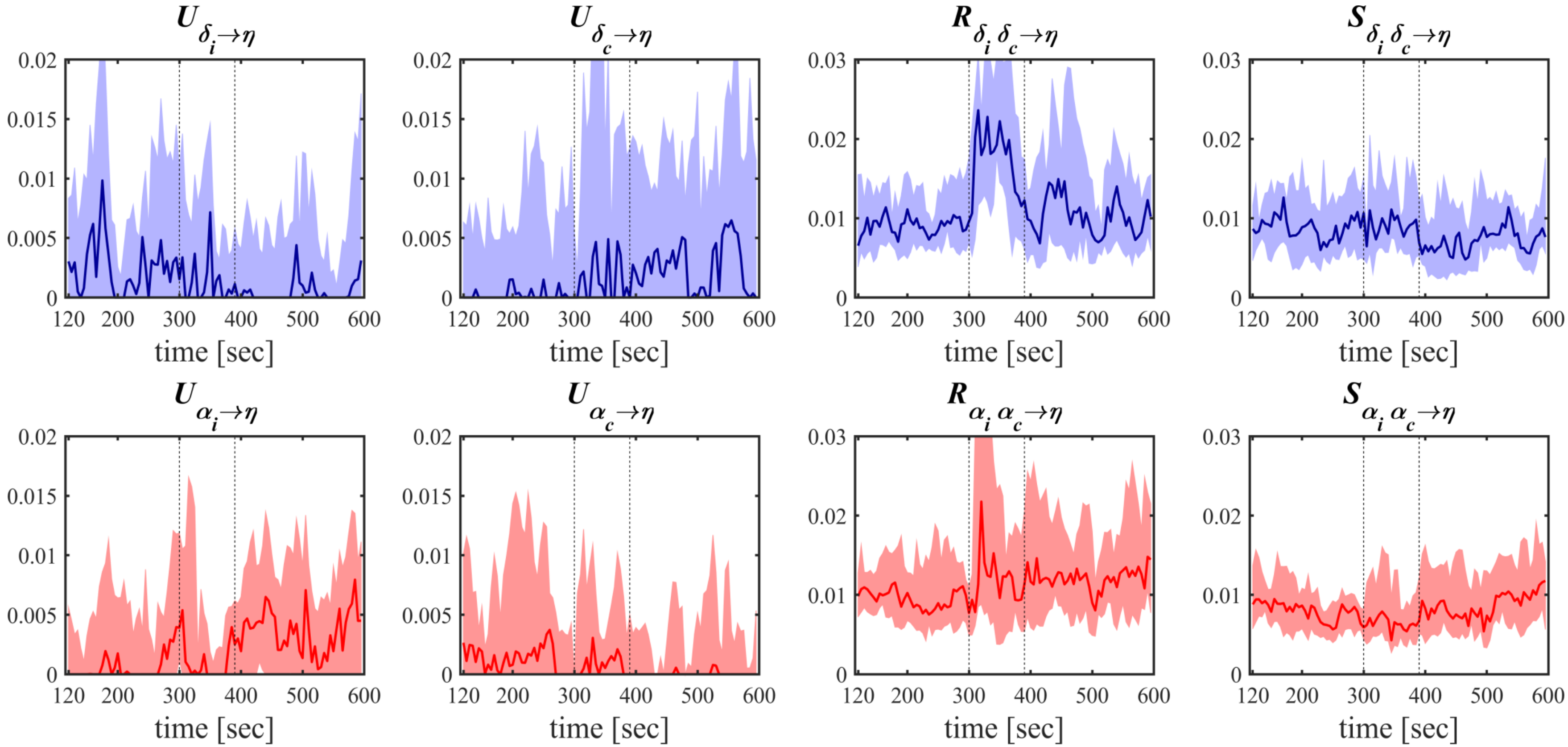
- ***The information transfer is markedly higher along the brain→heart direction***
- ***No evident differences are observed between δ and α waves, pre-ictal and post-ictal phases, or contralateral and ipsilateral sites***

L Faes, R Pernice, M Feucht, K Schiecke, 'Partial Information decomposition of brain-heart interactions in temporal lobe epilepsy in the childhood', **Proc. of the 41th Conf. IEEE-EMBS**, 2019; in press.

APPLICATIONS (1b)

Brain-heart interactions in epilepsy: RESULTS

- **Partial information decomposition of brain→heart information transfer**

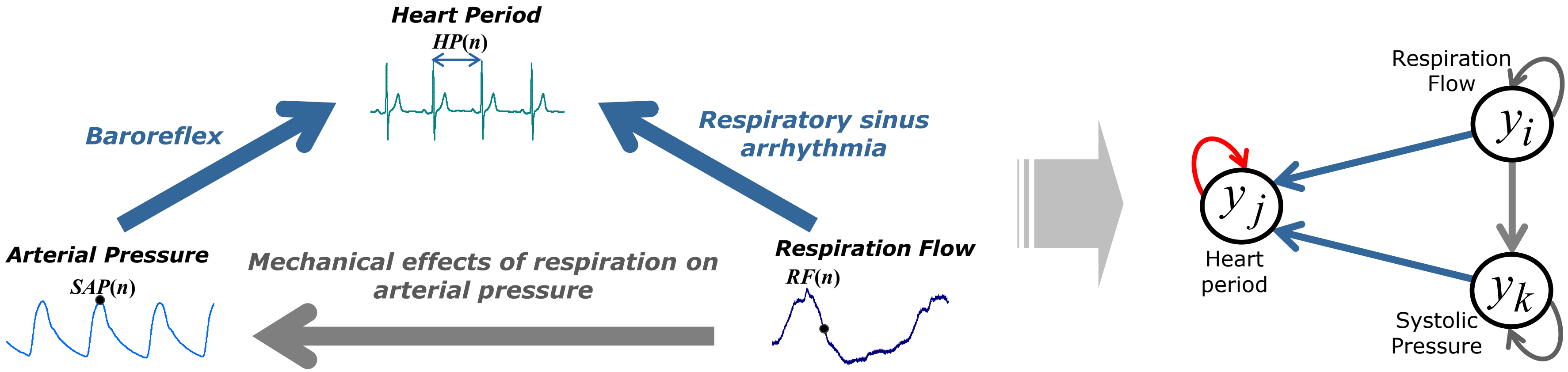


- ***The unique information transfer δ → η is mostly ipsilateral in the pre-ictal phase and contralateral during the seizure and in the post-ictal phase***
- ***These findings document the importance of PID, which removes from the information transfer the redundancy between the EEG activity of the two hemispheres***

L Faes, R Pernice, M Feucht, K Schiecke, 'Partial Information decomposition of brain-heart interactions in temporal lobe epilepsy in the childhood', **Proc. of the 41th Conf. IEEE-EMBS**, 2019; in press.

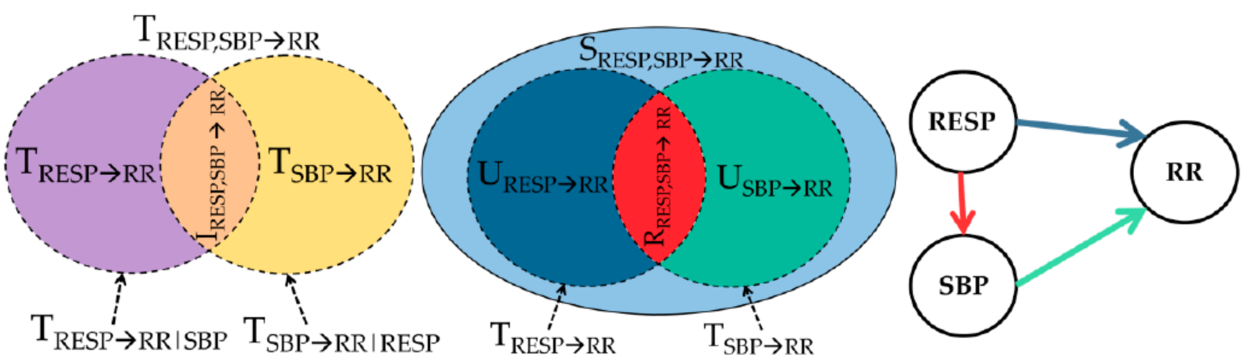
Applications: CARDIOVASCULAR and CARDIORESPIRATORY INTERACTIONS

- **Cardiovascular regulatory physiology**



- **Multiscale Partial Information Decomposition:**

  Sympathetic and parasympathetic systems act at different time scales

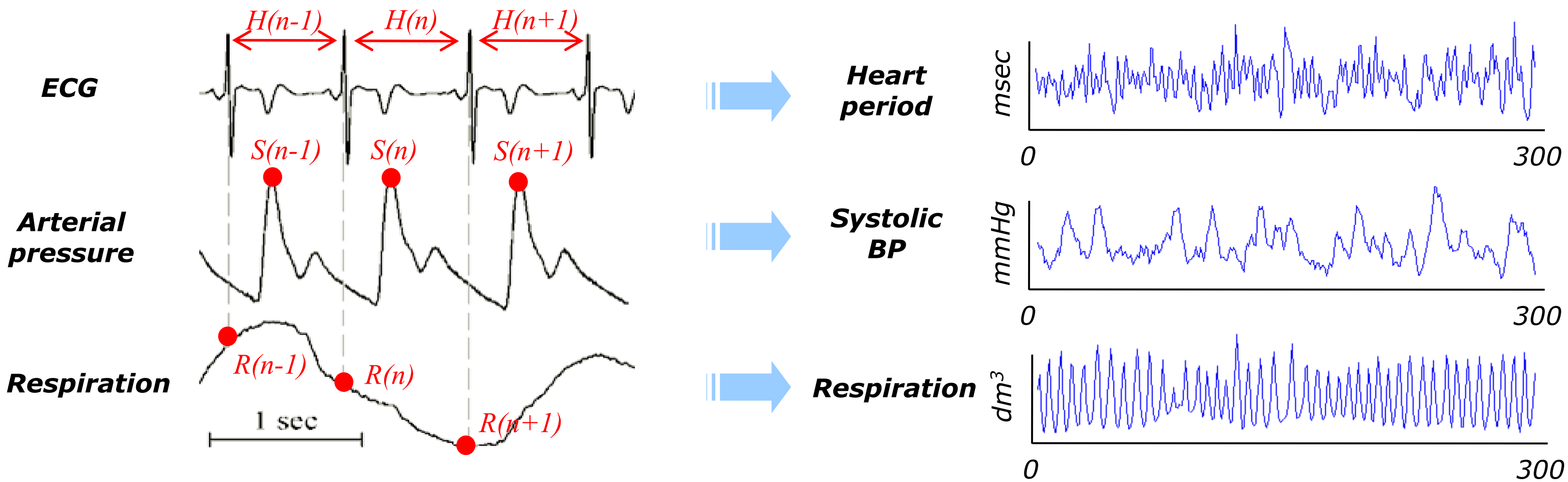


$$T_{SAP,RESP \rightarrow HP} = U_{SAP \rightarrow HP} + U_{RESP \rightarrow HP} + R_{SAP,RESP \rightarrow HP} + S_{SAP,RESP \rightarrow HP}$$

MULTISCALE CARDIOVASCULAR INFORMATION DECOMPOSITION

- ***Protocol: 61 young healthy subjects during head-up tilt and mental stress tasks***

- ***Signals and time series:***



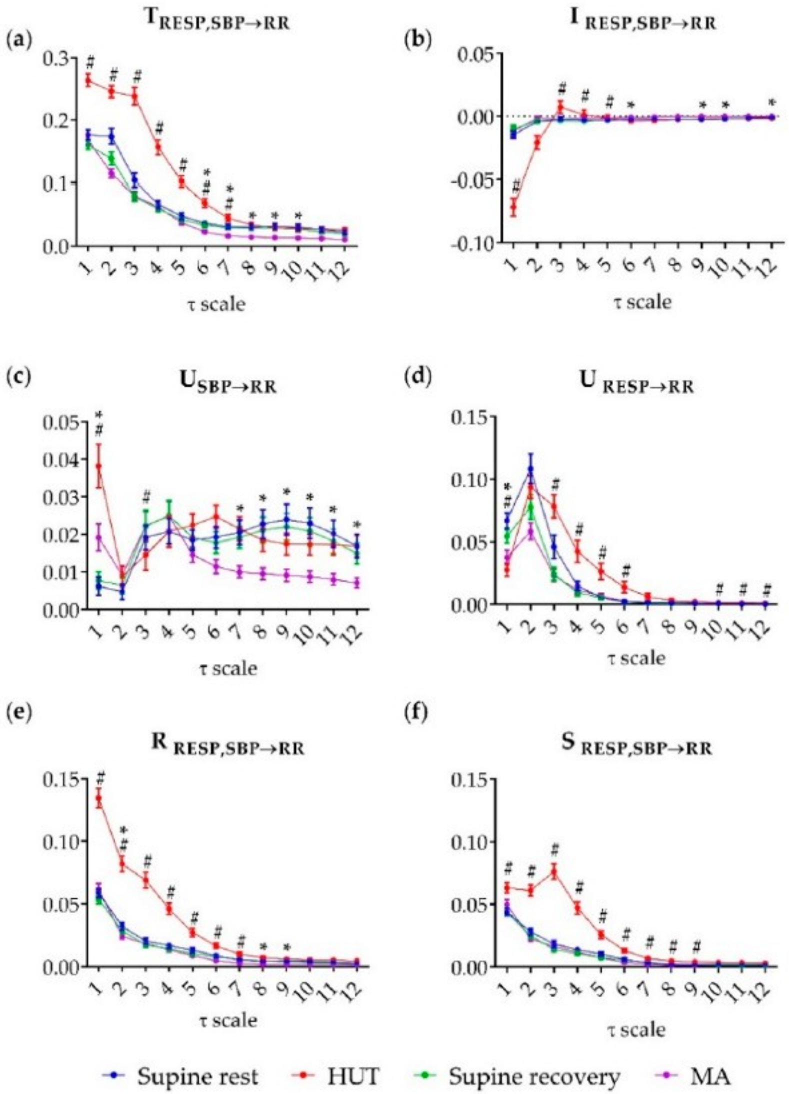
- ***Multiscale information decomposition:***

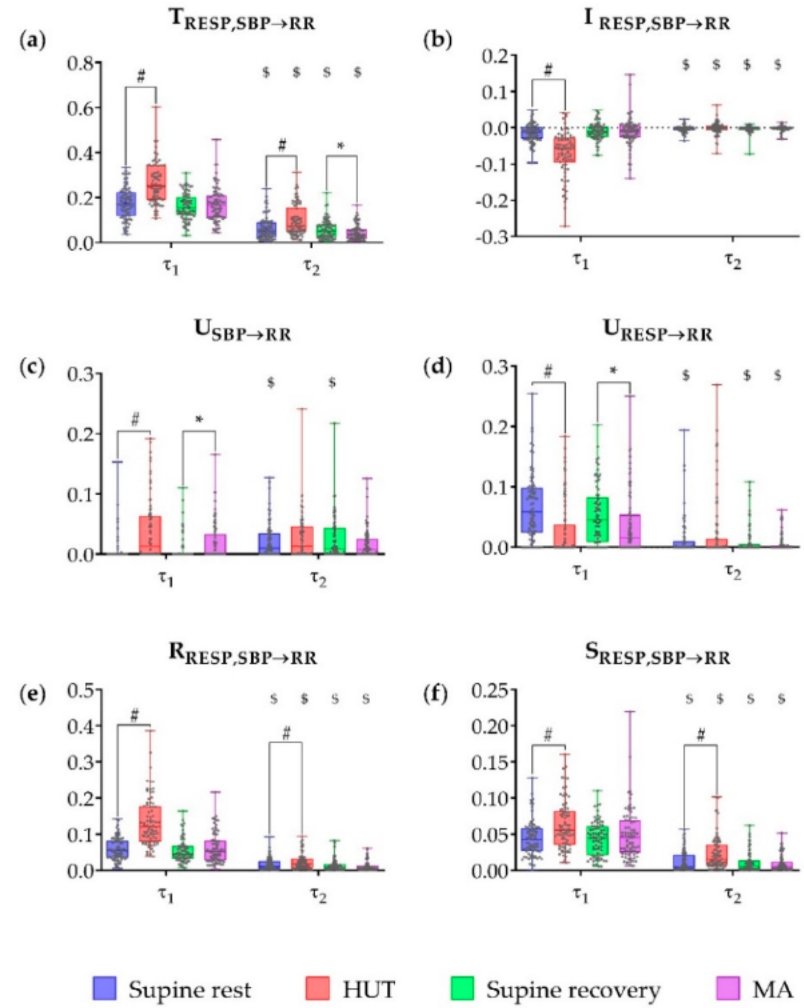
$$T_{\mathrm{SAP,RESP}\rightarrow\mathrm{HP}} = U_{\mathrm{SAP}\rightarrow\mathrm{HP}} + U_{\mathrm{RESP}\rightarrow\mathrm{HP}} + R_{\mathrm{SAP,RESP}\rightarrow\mathrm{HP}} + S_{\mathrm{SAP,RESP}\rightarrow\mathrm{HP}}$$

  - model order: Bayesian Information Criterion (average p=14)
  - lowpass FIR filter with q=12 coeffs
  - Scale τ=1,...,12

APPLICATIONS (2a)

MULTISCALE CARDIOVASCULAR INFORMATION DECOMPOSITION





J Krohova, **L Faes**, B Czippelova, Z Turianikova, N Mazgutova, R Pernice, A Busacca, D Marinazzo, S Stramaglia, M Javorka ‘Multiscale information decomposition dissects control mechanisms of heart rate variability at rest and during physiological Stress’, **Entropy**, 2019; 21:526.

APPLICATIONS (2b)

- **Limits of linear multiscale information dynamics**
  - **The linear representation is restricted to AR processes**
  - **The model cannot account for long range correlations**

- **Linear multiscale analysis based on fractionally integrated AR models**

Observed time series

$ARFI(p,d)$

$$A(L)(1-L)^d X_n = E_n$$

$$A(L) = 1 - \sum_{i=1}^{p} A_i L^i \quad , (1-L)^d = \sum_{k=1}^{\infty} G_k L^k \approx \sum_{k=1}^{r} G_k L^k \equiv G(L)$$

$AR(p+r)$

$$B(L)X_n = E_n$$

$$B(L) = A(L)G(L)$$

$$C_X = \frac{1}{2}\ln 2\pi e \sigma_E^2$$

$$S_X = \frac{1}{2}\ln \sigma_X^2 / \sigma_E^2$$

FILTERING τ [1]

Filtered time series

$ARMA(p+r,q) \rightarrow SS(\tilde{\mathbf{B}}, \tilde{C}, \tilde{K}, \sigma_{\tilde{E}}^2)$

$$\tilde{X}_n = D(L)X_n \qquad \tilde{Z}_{n+1} = \tilde{\mathbf{B}}\tilde{Z}_n + \tilde{\mathbf{K}}\tilde{E}_n$$

$$B(L)\tilde{X}_n = D(L)E_n \qquad \tilde{Y}_n = \tilde{\mathbf{C}}\tilde{Z}_n + \tilde{E}_n$$

FIR lowpass filter $D(L) = \sum_{k=0}^{q} D_k L^k$

Cutoff freq.: $f_\tau = \dfrac{1}{2\tau}$

DOWN SAMPLING τ

Rescaled time series

$SS(\overline{\mathbf{B}}, \overline{C}, \Sigma_{\overline{W}}, \sigma_{\overline{V}}^2, \Sigma_{\overline{V}\overline{W}})$

DARE

$ISS(\overline{\mathbf{B}}, \overline{C}, \overline{K}, \sigma_{\overline{E}}^2)$

$$\overline{X}_{n+1} = \overline{\mathbf{B}}\overline{X}_n + \overline{W}_n \qquad \overline{Z}_{n+1} = \overline{\mathbf{B}}\overline{Z}_n + \overline{\mathbf{K}}\overline{E}_n$$

$$\overline{Y}_n = \overline{\mathbf{C}}\overline{X}_n + \overline{V}_n \rightarrow \overline{Y}_n = \overline{\mathbf{C}}\overline{Z}_n + \overline{E}_n$$

$$C_{\overline{X}} = \frac{1}{2}\ln 2\pi e \sigma_{\overline{E}}^2$$

$$S_{\overline{X}} = \frac{1}{2}\ln \sigma_{\overline{X}}^2 / \sigma_{\overline{E}}^2$$

L Faes, MA Pereira, R Pernice, M Javorka, ME Silva, AP Rocha 'Multiscale information storage of linear long-range correlated stochastic processes', **Physical review E,** 2019, 99:032115

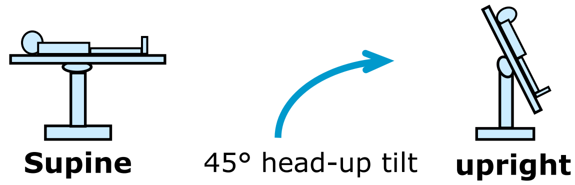
APPLICATIONS (2b)

Multiscale information storage in cardiovascular physiology

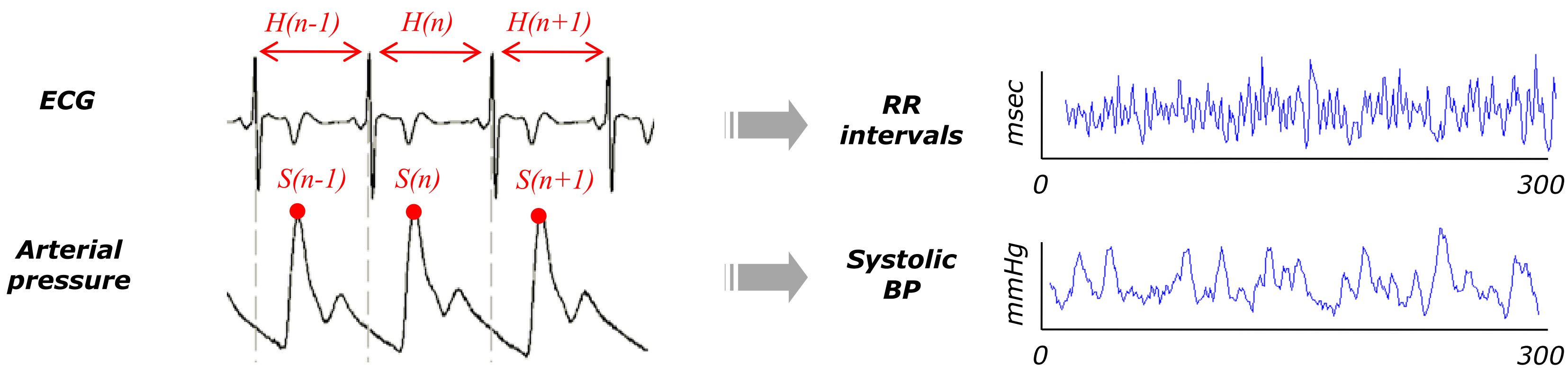
❖ Experimental Protocol

- ❑ ***HEAD-UP TILT***

  61 Healthy subjects
  (37 females, 17.5 ± 2.4 years)



❖ Construction of beat-to-beat variability series



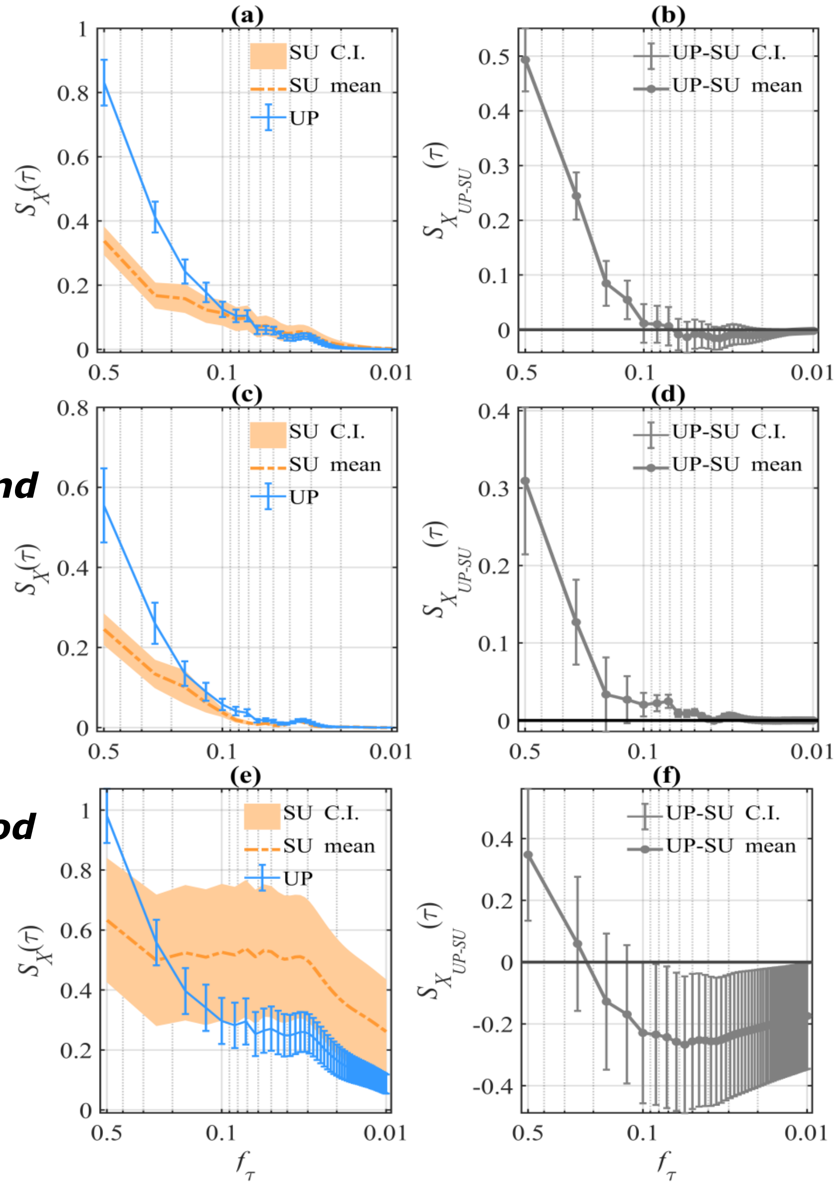
❖ Data analysis
- *Stationary windows of N=300 beats*
- *ARFI identification: computation of d with Whittle semiparametric estimator*
  computation of A(L) with least squares, order p with BIC criterion

L Faes, MA Pereira, R Pernice, M Javorka, ME Silva, AP Rocha 'Multiscale information storage of linear long-range correlated stochastic processes', **Physical review E,** 2019, 99:032115

APPLICATIONS (2b)

Multiscale information storage

Difference upright – supine



- ***AR method***

- from supine to upright:

  ↑ **S_X at short scales**

- ***AR method after detrend***

- from supine to upright:

  ↑ **S_X at short scales**

  Increase of regularity of heart rate variability with tilt

- ***ARFI method***

- from supine to upright:

  ↑ **S_X at short scales**

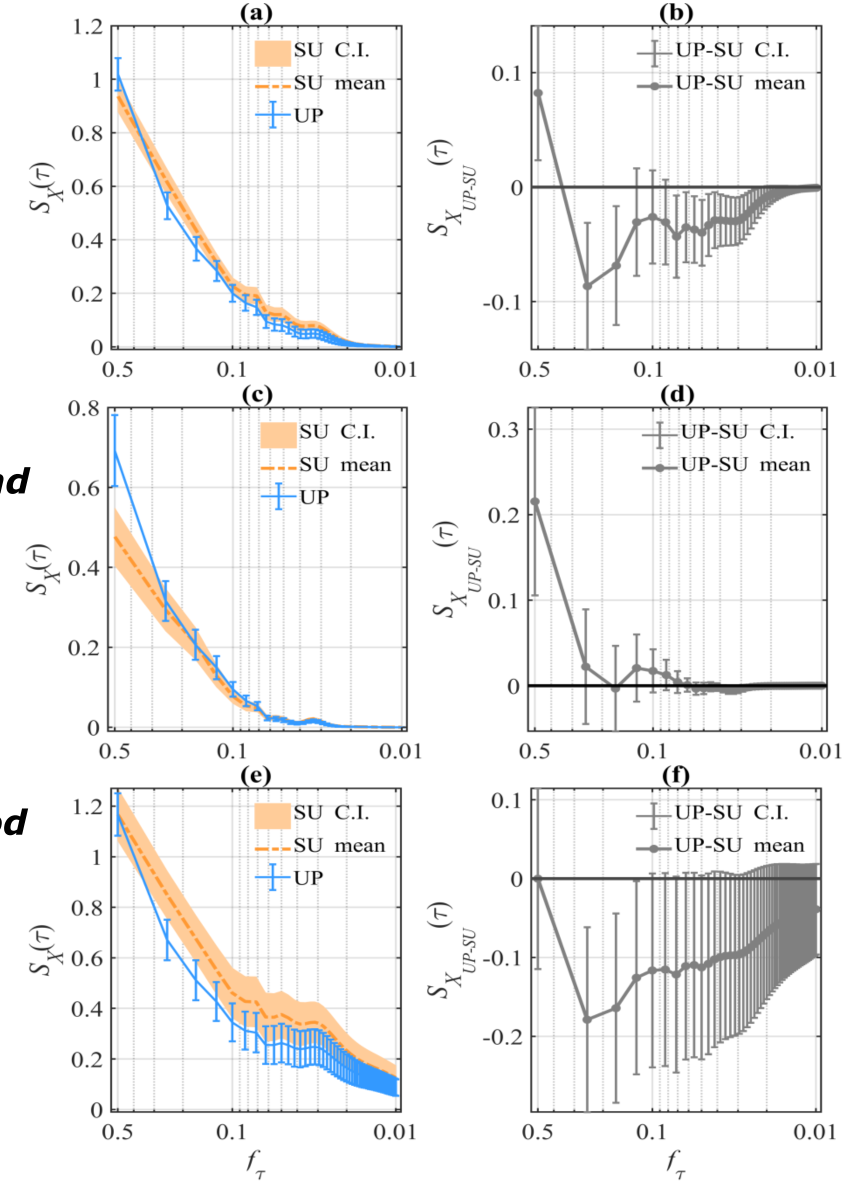
  ↓ **S_X at long scales**

  Higher complexity of heart rate variability with tilt, related to long-range correlations

APPLICATIONS (2b)

Multiscale information storage

Difference upright – supine



- ***AR method***

- from supine to upright:

  ↑ $\boldsymbol{S_X}$ **at scale 1**

  ↓ $\boldsymbol{S_X}$ **at scales >1**

- ***AR method after detrend***

- from supine to upright:

  ↑ $\boldsymbol{S_X}$ **at scale 1**

  ↔ $\boldsymbol{S_X}$ **at scales >1**

  Lower complexity of SAP associated with short term dynamics (respiratory?)

- ***ARFI method***

- from supine to upright:

  ↓ $\boldsymbol{S_X}$ **at scales >1**

  ↔ $\boldsymbol{S_X}$ **at scale 1**

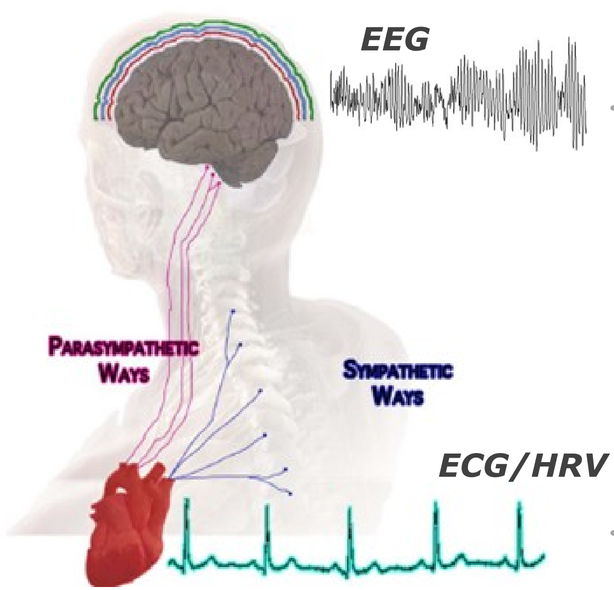
  Higher complexity of SAP associated with slow oscillations (sympathetic?)

CONCLUSION

“An information-theoretic framework to dissect multivariate and multiscale physiological interactions”

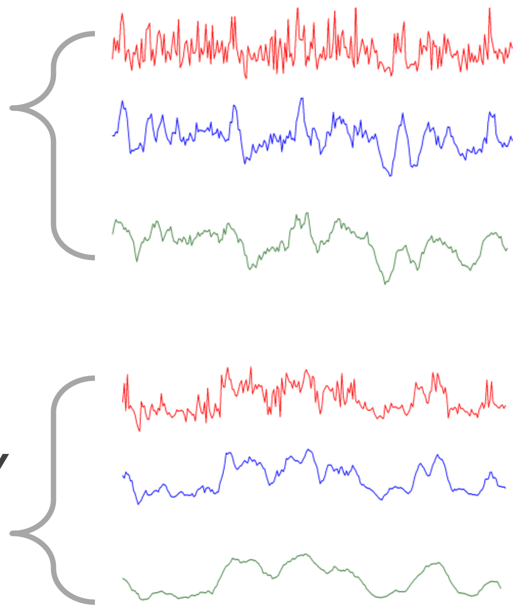
Multivariate analysis

different organ systems



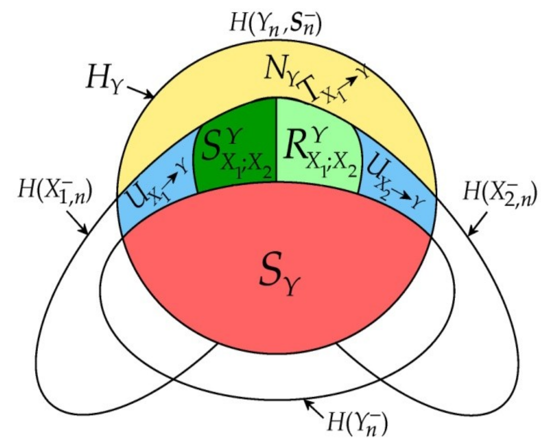
Multiscale analysis

different biological clocks



Information dynamics

Linear regression models



The ability to **handle multivariate and multiscale dynamics** and the **general applicability** should make the proposed tool useful in many contexts within the field of Network Physiology