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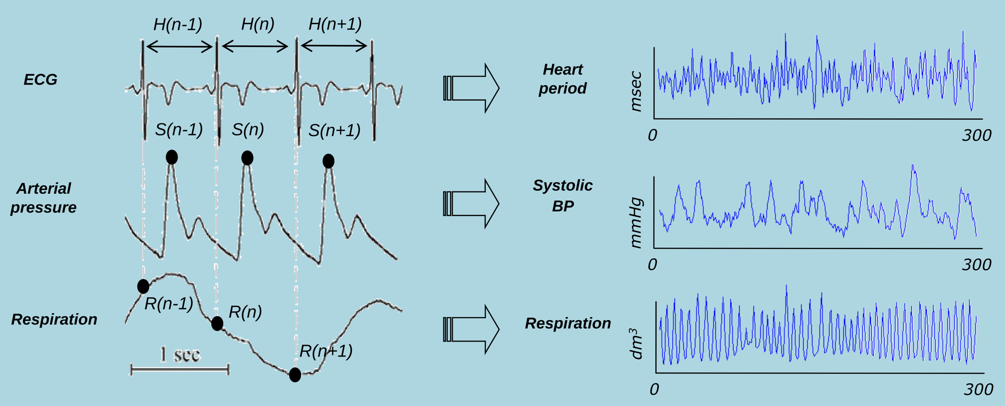
Assessing Transfer Entropy in cardiovascular and respiratory time series: A VARFI approach

A.P. Rocha[1], H. Pinto[1] , C. Amado[1], M.E Silva[2], R. Pernice[3], M. Javorka[4], L. Faes[3]

[1]Faculdade de Ciências, Universidade do Porto, Porto, Portugal & CMUP
[2]Faculdade de Economia, Universidade do Porto, Porto, Portugal & CIDMA
[3]Department of Engineering, University of Palermo, Palermo, Italy
[4]Department of Physiology, Comenius University in Bratislava, Jessenius Faculty of Medicine, Slovakia

INTRODUCTION

Cardiovascular and respiratory time series exhibit a variability produced by different physiological coupled control mechanisms and operate across multiple time scales that result in the coexistence of short-term dynamics and long-range correlations [1].
In this work we apply a Vector Autoregressive Fractionally Integrated (VARFI) framework to estimate the **Transfer Entropy (TE)**, in the cardiovascular and respiratory systems. This allows to quantify the information flow and assess directed interactions accounting for the simultaneous presence of short-term and long-range dynamics.



Simulation Study

We investigated the theorical proprieties of the Transfer Entropy measures incorporating long range correlations in a benchmark trivariate VAR model [2]:

$$R_n = 2\rho_r \cdot \cos 2\pi f_r \cdot R_{n-1} - \rho_r^2 \cdot R_{n-2} + U_{r,n}$$
$$S_n = 2\rho_s \cdot \cos 2\pi f_s \cdot S_{n-1} - \rho_s^2 \cdot S_{n-2} + a \cdot H_{n-2} + e \cdot H_{n-1} + U_{s,n}$$
$$H_n = 2\rho_h \cdot \cos 2\pi f_h \cdot H_{n-1} - \rho_h^2 \cdot H_{n-2} + b \cdot S_{n-1} + c \cdot R_{n-1} + U_{h,n}$$

We set the parameters to reproduce oscillations and interactions commonly observed in cardiovascular and cardiorespiratory variability [2]. Specifically, to mimic the self-sustained dynamics typical of respiratory activity (process R, $\rho_r = 0.9, f_r = 0.25$) and the slower oscillatory activity commonly observed in the so-called low-frequency (LF) band in the variability of systolic arterial pressure (process $S, \rho_S = 0.8$, $f_s = 0.1$) and heart rate (process H, $\rho_h = 0.8$, $f_h = 0.1$). The remaining parameters were set as $a = 0.1, b = 0.4, c = 1, e = c$, [2].

Experimental Data

The H, S and R time series were measured in a group of 62 healthy subjects (19.5 ± 3.3 years old, 37 females) monitored in the resting **supine position (SU)** and in the **upright position (UP)** reached through passive head-up tilt [1].

CONCLUSIONS

Both simulations and real data analysis revealed that the proposed method highlights the dependence of the information transfer on the balance between short-term and long-range correlations in coupled dynamical systems.

REFERENCES

[1] Martins, A., Pernice, R., Amado, C., Rocha, A. P., Silva, M. E., Javorka, M., & Faes, L. (2020). Multivariate and multiscale complexity of long-range correlated cardiovascular and respiratory variability series. Entropy, 22(3). https://doi.org/10.3390/e22030315
[2] Faes, L., Porta, A., Nollo, G., & Javorka, M. (2017). Information decomposition in multivariate systems: Definitions, implementation and application to cardiovascular networks. *Entropy*, *19*(1). https://doi.org/10.3390/e19010005
[3] Faes, L., Marinazzo, D., & Stramaglia, S. (2017). Multiscale information decomposition: Exact computation for multivariate Gaussian processes. Entropy, 19(8), 1–18. https://doi.org/10.3390/e19080408
[4] Krohova, J., Faes, L., Czippelova, B., Turianikova, Z., Mazgutova, N., Pernice, R., Busacca, A., Marinazzo, D., Stramaglia, S., & Javorka, M. (2019). Multiscale information decomposition dissects control mechanisms of heart rate variability at rest and during physiological stress. *Entropy*, *21*(5). https://doi.org/10.3390/e21050526
[5] Faes, L., Nollo, G., & Porta, A. (2011). Information-based detection of nonlinear Granger causality in multivariate processes via a nonuniform embedding technique. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, *83*(5), 1–15. https://doi.org/10.1103/PhysRevE.83.051112
[6] Porta, A., Bassani, T., Bari, V., Tobaldini, E., Takahashi, A. C. M., Catai, A. M., & Montano, N. (2012). Model-based assessment of baroreflex and cardiopulmonary couplings during graded head-up tilt. *Computers in Biology and Medicine*, *42*(3), 298–305. https://doi.org/10.1016/j.compbiomed.2011.04.019
[7] Javorka, M., Krohova, J., Czippelova, B., Turianikova, Z., Lazarova, Z., Wiszt, R., Faes, L., Lazarova, Z., Wiszt, R., & Faes, L. (2018). Towards understanding the complexity of cardiovascular oscillations: Insights from information theory. *Computers in Biology and Medicine*, *98*(March), 48–57. https://doi.org/10.1016/j.compbiomed.2018.05.007

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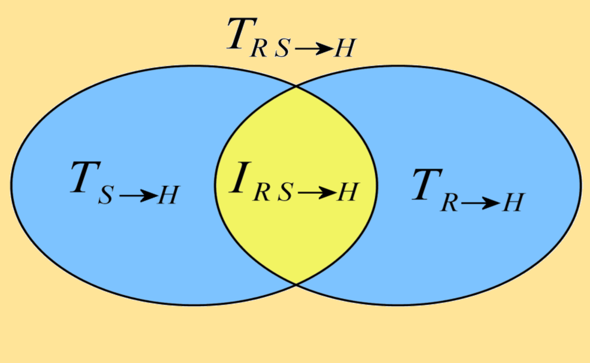
Address for correspondence
Ana Paula Rocha
E-mail address: aprocha@fc,up.pt
Dep. Matemática , Faculdade de Ciências da Universidade do Porto,
Rua do Campo Alegre s/n, 4169-007 Porto

METHODS

Decomposition of the joint TE, in a network of 3 interacting processes R, S, H, considering H as target and S, R as sources.



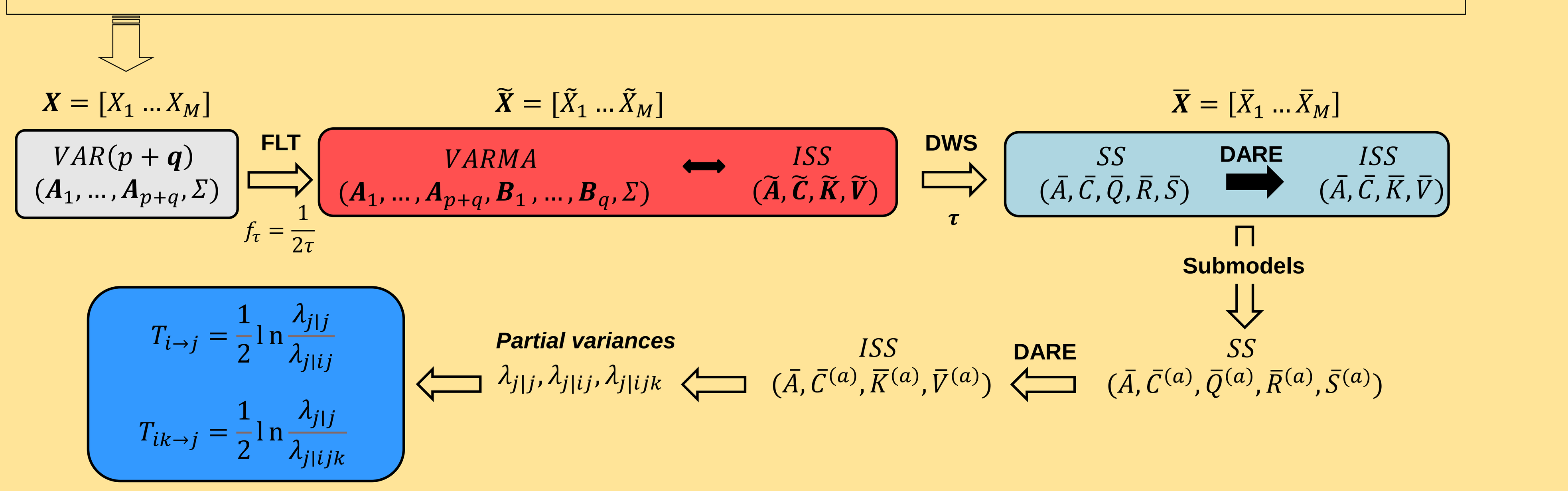
$$T_{RS\to H} = \boxed{T_{R\to H} + T_{S\to H}} + \boxed{I_{RS\to H}}$$

Joint TE **Individual TE** **Interaction TE**

- $I_{R,S\to H} > 0$ - **Synergy**
- $I_{R,S\to H} < 0$ - **Redundancy**.

Exact expressions of the information transfer are obtained using **state space models for coupled Gaussian processes** observed at multiple temporal scales [3]. Recently this framework was extended to VARFI processes [1].

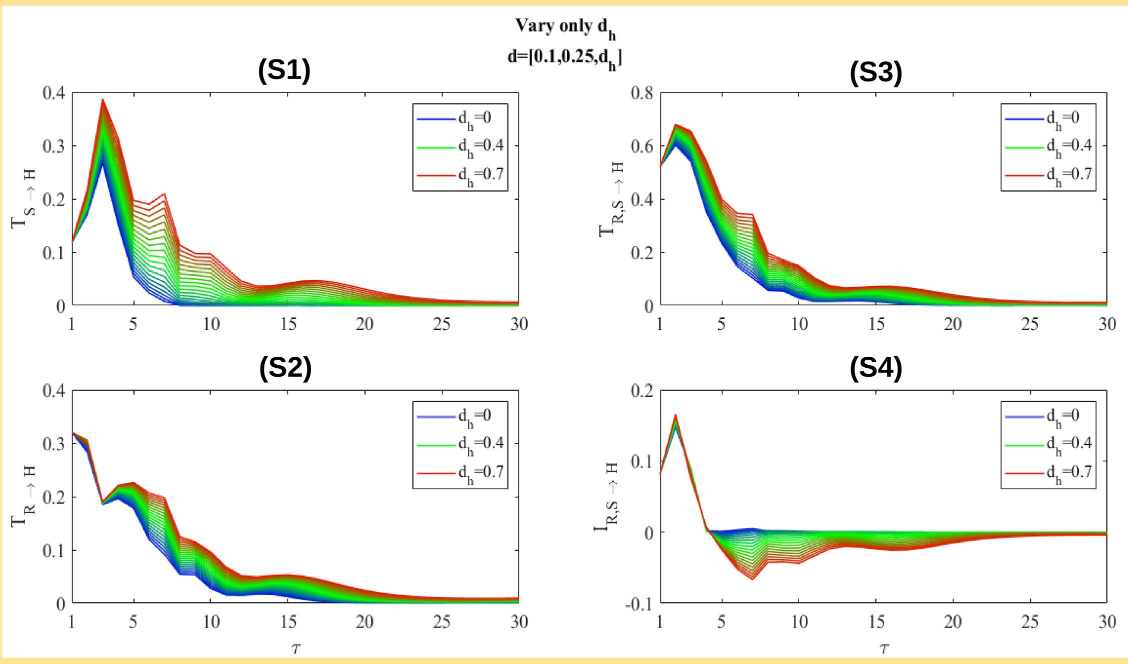
$$\mathrm{VARFI}(p, \boldsymbol{d}) \quad A(L) = \mathbf{I}_\mathrm{M} - \textstyle\sum_{i=1}^{p} A_i L^i;\ (1-L)^{d_i} = \sum_{k=0}^{\infty} G_k^{(i)} L^k \approx \sum_{k=0}^{q=50} G_k L^k = G(B);\ \ A(L)\,\mathrm{diag}((1-L)^{\boldsymbol{d}})X_n = E_n$$



Multiscale representation obtained through filtering **(FLT)** and downsampling **(DWS)** steps. The downsampled process has an innovations form state space model **(ISS)** representation from which submodels can be formed to compute the **partial variances** needed for the computation of the **Transfer Entropy** [3].

RESULTS

Simulation Study



Illustrative theoretical profiles of the multiscale TE, $T_{S\to H}$, $T_{R\to H}$, $T_{R,S\to H}$ and of the interaction $I_{R,S\to H}$ for a VARFI process and varying **d of the target.**

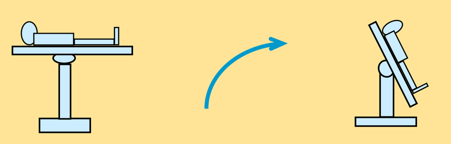
- Generally, the information transfer at long time scales increases with **d of target** (**S1** and **S2**);
- The joint information transfer at long time scales also increases with **d of the target** (**S3**);
- At increasing **d of the target**, ITE decreases (**S4**), suggesting an increased redundancy.

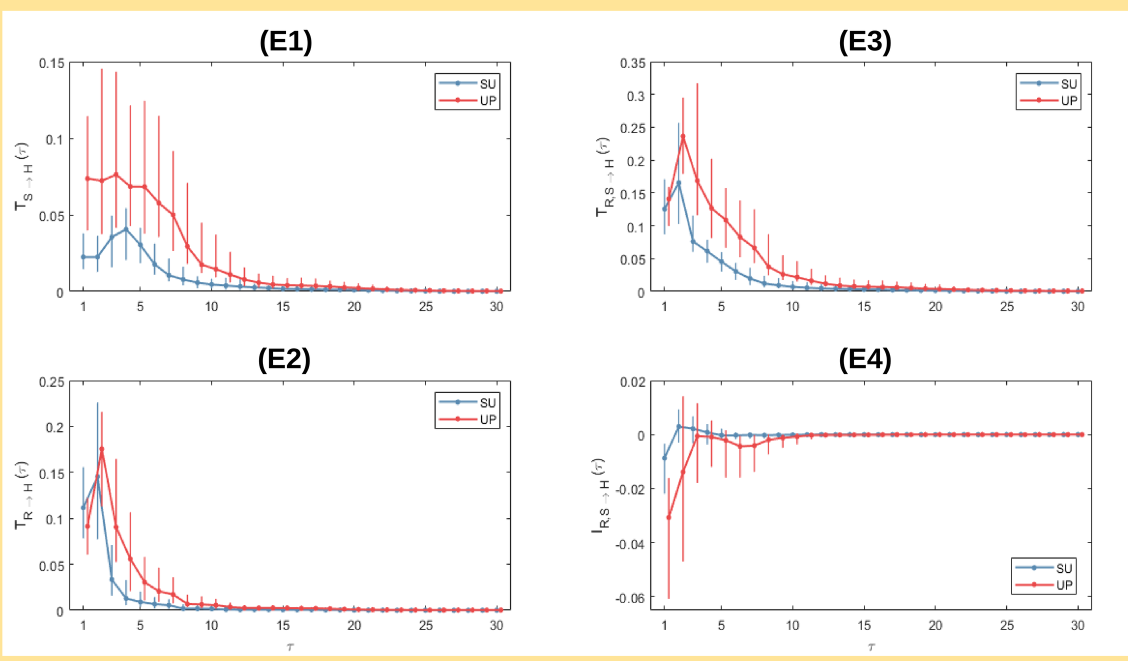
Theoretical profiles of the multiscale TE varying **d of the sources** (*not shown here for brevity*) suggest opposite trends: TE decreasing with d and increase of synergy regarding ITE.

Experimental Data

The **decomposition** of the joint information transfer evidences different types of contributions with **physiological meaning.**

Multiscale TE measures during Supine rest **(SU)** and Head Up Tilt **(UP)**.





Plots represent the distributions (median and interquartile range) of **(E1)** $T_{S\to H}$, **(E2)** $T_{R\to H}$, **(E3)** $T_{R,S\to H}$ and **(E4)** $I_{R,S\to H}$, computed as a function of the time scale τ.

- For SU at $\tau = 1$, $T_{R\to H} > T_{S\to H}$, indicating prevalence of Respiratory Sinus Arrhythmia (RSA) [4];
- The postural stress induced by UP is associated with a markedly higher $T_{S\to H}$ at lower scales up to $\tau \approx 5$ reporting baroreflex activation with UP in agreement with previous works [4-7];
- The postural stress induced by UP is associated with a lower information transfer RESP to RR at $\tau = 1$. This finding agrees with previous works reporting weakening of RSA with UP [4-7];
- At $\tau = 1$ $T_{R\to H}$ in SU is higher than in UP, while at $\tau > 1$ $T_{R\to H}$ in UP is higher than in SU. The multiscale representation highlights that RSA for slow oscillations is enhanced by tilt; this may be an effect of long-range correlations, as suggested by the simulation results in of $T_{R\to H}$ **(S2)** where the information transfer at long time scales increases with d of target.
- The two previous effects determine a higher joint information transfer $T_{R,S\to H}$ during UP for scales up to $\tau \approx 10$.
- The interaction transfer decreases significantly with tilt, denoting stronger redundancy, as expected from previous works [4].