Effects of aging on the redundancy of the cardiovascular control

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Introduction

Aging strongly affects cardiovascular control and the strength of the relations among cardiovascular variables.

Recently, transfer entropy decomposition strategies have allowed the decomposition of the information transferred from a pair of exogenous sources to a target variable into quotes genuinely transferred from each exogenous variable to the destination and a term describing the interactions between the two drivers in contributing to the information carried by the target.

According to these information decomposition strategies redundant or synergic contributions of the two drivers to the information carried by the target can be disentangled.

Aims

To exploit a transfer entropy decomposition strategy for the quantification of redundancy/synergy in cardiovascular control

To track the evolution of the redundancy/synergy in cardiovascular control with age

Modeling dynamical interactions in the full and restricted universes of knowledge (Ωs)

In the full $\Omega = \{y, x_1, x_2\}$ the dynamic of y is described as

$$y_{i|\Omega} = \underbrace{\sum_{k=1}^{p} a_{k|\Omega} \cdot y_{i-k}}_{AR} + \underbrace{\sum_{k=1}^{p} b_{1,k|\Omega} \cdot x_{1,i-k} + \sum_{k=1}^{p} b_{2,k|\Omega} \cdot x_{2,i-k}}_{X_1X_2} + w_{i|\Omega} \qquad ARX_1X_2$$

In the restricted $\Omega = \Omega \backslash x_1 = \{y, x_2\}$ the dynamic of y is described as

$$y_{i|\Omega\backslash x_1} = \underbrace{\sum_{k=1}^{p} a_{k|\Omega\backslash x_1} \cdot y_{i-k}}_{AR} + \underbrace{\sum_{k=1}^{p} b_{2,k|\Omega\backslash x_1} \cdot x_{2,i-k}}_{X_2} + w_{i|\Omega\backslash x_1} \qquad ARX_2$$

In the restricted $\Omega = \Omega \backslash x_2 = \{y, x_1\}$ the dynamic of y is described as

$$y_{i|\Omega\backslash x_2} = \underbrace{\sum_{k=1}^{p} a_{k|\Omega\backslash x_2} \cdot y_{i-k}}_{AR} + \underbrace{\sum_{k=1}^{p} b_{1,k|\Omega\backslash x_2} \cdot x_{1,i-k}}_{X_1} + w_{i|\Omega\backslash x_2} \qquad ARX_1$$

In the restricted $\Omega = \Omega \backslash x_1 x_2 = \{y\}$ the dynamic of y is described as

$$y_{i|\Omega\backslash x_1 x_2} = \underbrace{\sum_{k=1}^{p} a_{k|\Omega\backslash x_1 x_2} \cdot y_{i-k}}_{AR} + w_{i|\Omega\backslash x_1 x_2} \qquad AR$$

One-step-ahead prediction in the full and restricted Ωs

In the full $\Omega = \{y, x_1, x_2\}$ the one-step-ahead prediction is

$$\hat{y}_{i|\Omega} = \underbrace{\sum_{k=1}^{p} \hat{a}_{k|\Omega} \cdot y_{i-k}}_{AR} + \underbrace{\sum_{k=1}^{p} \hat{b}_{1,k|\Omega} \cdot x_{1,i-k} + \sum_{k=1}^{p} \hat{b}_{2,k|\Omega} \cdot x_{2,i-k}}_{X_1X_2} \qquad ARX_1X_2$$

In the restricted $\Omega = \Omega\backslash x_1 = \{y, x_2\}$ the one-step-ahead prediction is

$$\hat{y}_{i|\Omega\backslash x_1} = \underbrace{\sum_{k=1}^{p} \hat{a}_{k|\Omega\backslash x_1} \cdot y_{i-k}}_{AR} + \underbrace{\sum_{k=1}^{p} \hat{b}_{2,k|\Omega\backslash x_1} \cdot x_{2,i-k}}_{X_2} \qquad ARX_2$$

In the restricted $\Omega = \Omega\backslash x_2 = \{y, x_1\}$ the one-step-ahead prediction is

$$\hat{y}_{i|\Omega\backslash x_2} = \underbrace{\sum_{k=1}^{p} \hat{a}_{k|\Omega\backslash x_2} \cdot y_{i-k}}_{AR} + \underbrace{\sum_{k=1}^{p} \hat{b}_{1,k|\Omega\backslash x_2} \cdot x_{1,i-k}}_{X_1} \qquad ARX_1$$

In the restricted $\Omega = \Omega\backslash x_1x_2 = \{y\}$ the one-step-ahead prediction is

$$\hat{y}_{i|\Omega\backslash x_1x_2} = \underbrace{\sum_{k=1}^{p} \hat{a}_{k|\Omega\backslash x_1x_2} \cdot y_{i-k}}_{AR} \qquad AR$$

Mean squared prediction error (MSPE)

Given the one-step-ahead prediction of y, the MSPE of y can be computed as

$$\lambda^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2$$

In the full $\Omega = \{y, x_1, x_2\}$ the MSPE of y is

$$\lambda^2 = \lambda^2|_{\Omega}$$

In the restricted $\Omega = \Omega\backslash x_1 = \{y, x_2\}$ the MSPE of y is

$$\lambda^2 = \lambda^2|_{\Omega\backslash x_1}$$

In the restricted $\Omega = \Omega\backslash x_2 = \{y, x_1\}$ the MSPE of y is

$$\lambda^2 = \lambda^2|_{\Omega\backslash x_2}$$

In the restricted $\Omega = \Omega\backslash x_1 x_2 = \{y\}$ the MSPE of y is

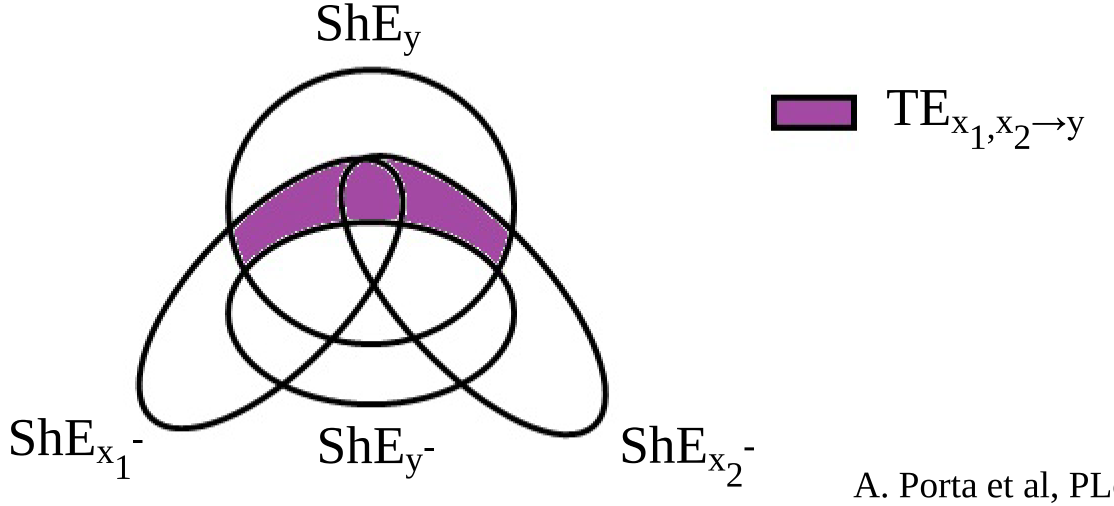
$$\lambda^2 = \lambda^2|_{\Omega\backslash x_1 x_2}$$

Assessing the transfer entropy (TE) from x_1 and x_2 to y

Under the hypothesis of Gaussianity, the TE from x_1 and x_2 to y can be computed as

$$TE_{x_1,x_2 \rightarrow y} = \frac{1}{2} \log \frac{\lambda^2|_{\Omega \backslash x_1 x_2}}{\lambda^2|_{\Omega}}$$

where $\lambda^2|_{\Omega}$ and $\lambda^2|_{\Omega \backslash x_1 x_2}$ are the variances of the prediction error of the ARX_1X_2 and AR models in Ω and $\Omega \backslash x_1 x_2$ respectively



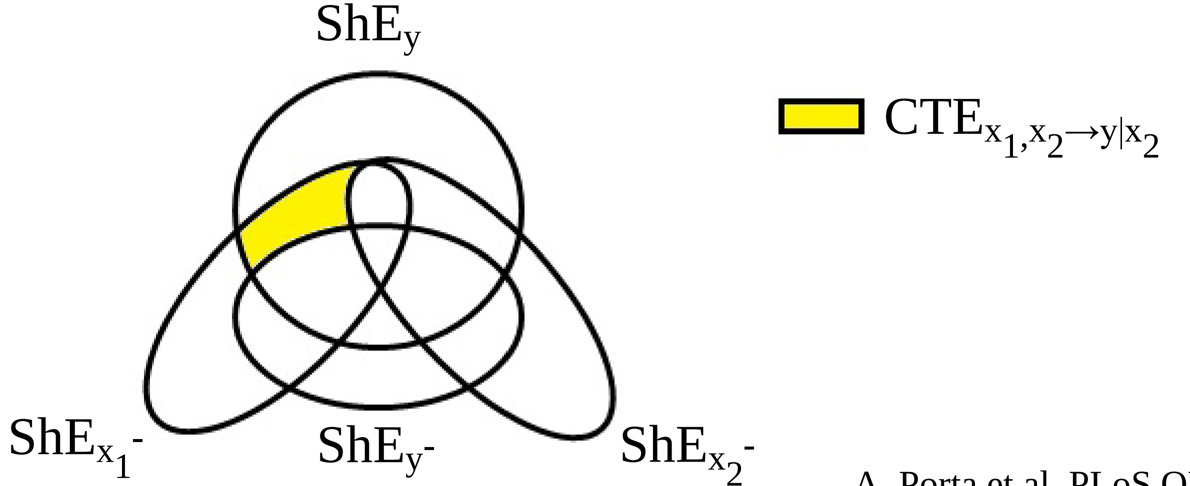
A. Porta et al, PLoS ONE, 10, e0132851, 2015

Assessing the conditional TE (CTE) from x_1 and x_2 to y given x_2

Under the hypothesis of Gaussianity, the CTE from x_1 and x_2 to y given x_2 can be computed as

$$CTE_{x_1,x_2 \to y|x_2} = \frac{1}{2} \log \frac{\lambda^2|_{\Omega \backslash x_1}}{\lambda^2|_{\Omega}}$$

where $\lambda^2|_{\Omega}$ and $\lambda^2|_{\Omega \backslash x_1}$ are the variances of the prediction error of the ARX_1X_2 and ARX_2 models in Ω and $\Omega \backslash x_1$ respectively



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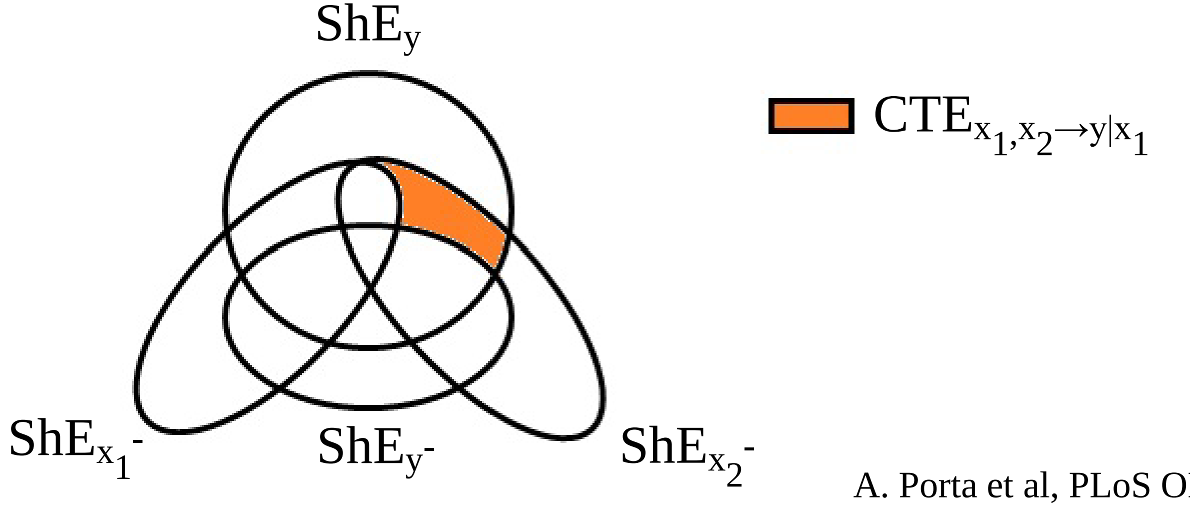
Assessing the conditional TE (CTE) from x_1 and x_2 to y given x_1

Under the hypothesis of Gaussianity, the CTE from x_1 and x_2 to y given x_1 can be computed as

$$\mathrm{CTE}_{x_1,x_2 \to y|x_1} = \frac{1}{2} \log \frac{\lambda^2|_{\Omega \backslash x_2}}{\lambda^2|_{\Omega}}$$

where $\lambda^2|_{\Omega}$ and $\lambda^2|_{\Omega \backslash x_2}$ are the variances of the prediction error of the ARX_1X_2 and ARX_1 models in Ω and $\Omega \backslash x_2$ respectively



A. Porta et al, PLoS ONE, 10, e0132851, 2015

Assessing the interactive TE (ITE) from x_1 and x_2 to y

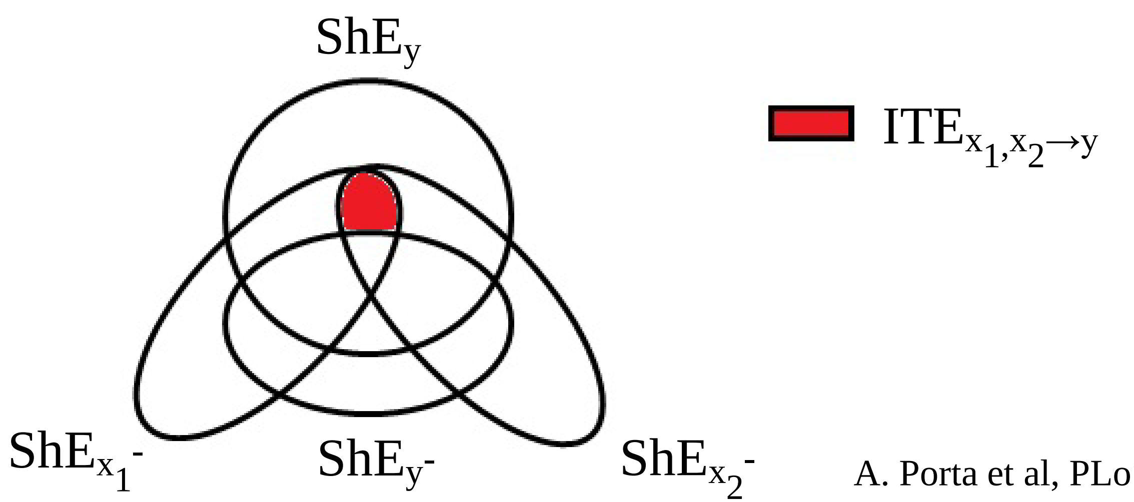
Defined

$$ITE_{x_1,x_2 \to y} = TE_{x_1,x_2 \to y} - (CTE_{x_1,x_2 \to y|x_2} + CTE_{x_1,x_2 \to y|x_1})$$

it can be computed as

$$ITE_{x_1,x_2 \to y} = \frac{1}{2} \log \frac{\lambda^2|_{\Omega \backslash x_1 x_2} \cdot \lambda^2|_{\Omega}}{\lambda^2|_{\Omega \backslash x_1} \cdot \lambda^2|_{\Omega \backslash x_2}}$$

where $\lambda^2|_{\Omega \backslash x_1 x_2}$, $\lambda^2|_{\Omega}$, $\lambda^2|_{\Omega \backslash x_1}$, and $\lambda^2|_{\Omega \backslash x_2}$ are the variances of the prediction error of the AR, ARX_1X_2, ARX_2 and ARX_1 models in $\Omega \backslash x_1 x_2$, Ω, $\Omega \backslash x_1$ and $\Omega \backslash x_2$ respectively



A. Porta et al, PLoS ONE, 10, e0132851, 2015

Experimental protocol

We studied 100 nonsmoking healthy humans (54 males, age from 21 to 70 years)

The population was composed by 20 subjects in each of the following age bins

- from 21 to 30 years (10 males, median age=26 years);
- from 31 to 40 years (11 males, median age=34 years);
- from 41 to 50 years (10 males, median age=45 years);
- from 51 to 60 years (10 males, median age=55 years);
- from 61 to 70 years (13 males, median age=65 years).

We recorded ECG (lead II), noninvasive finger arterial pressure (Finometer PRO) and respiration (thoracic belt) at 400 Hz at rest in supine position (REST) and during active standing (STAND)

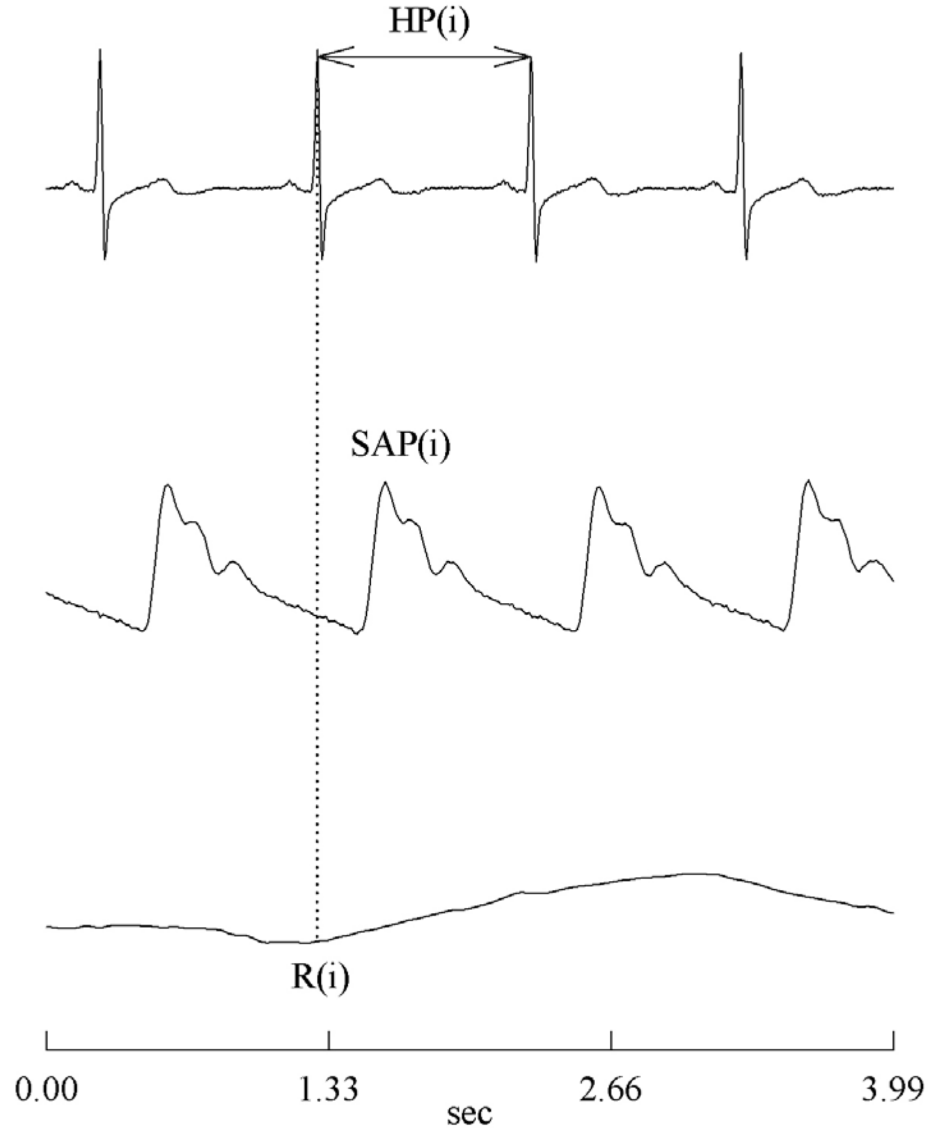
A.M. Catai et al, Entropy, 16, 6686-6704, 2014.

Cardiovascular variables

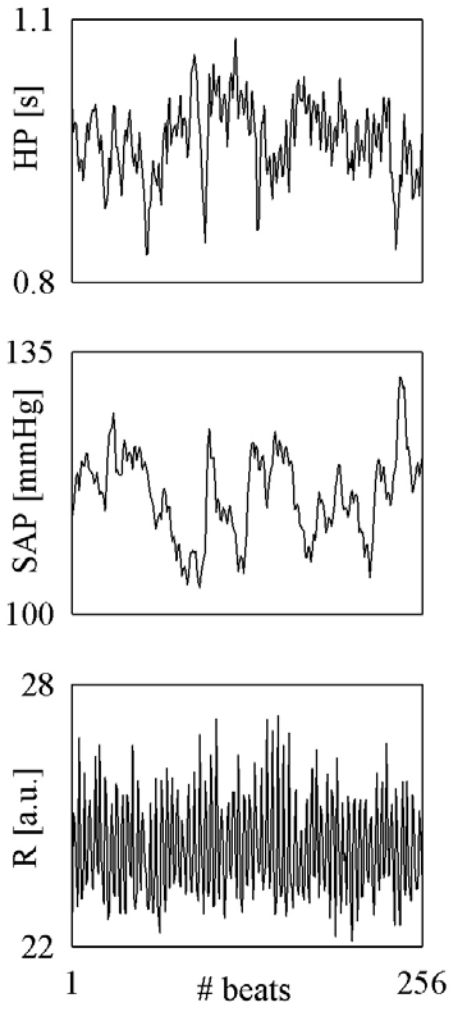
ECG

Arterial pressure

Respiration



Beat-to-beat variability series



HP={HP(i), i=1,…,N}

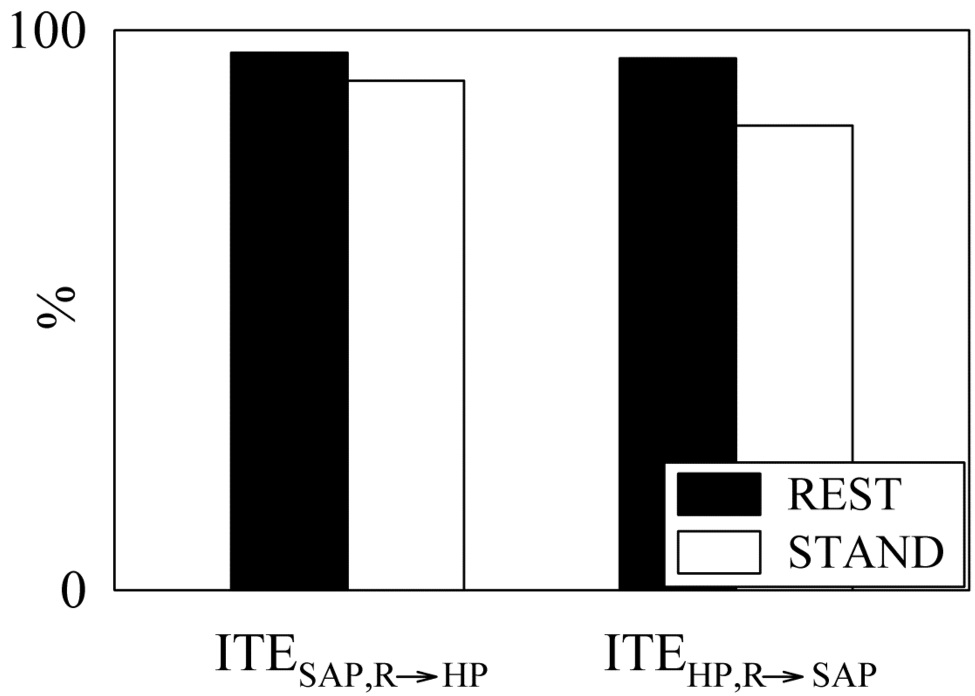
SAP={SAP(i), i=1,…,N}

R={R(i), i=1,…,N}

The full **Ω** = {HP, SAP, R}

1) y = HP, x_1 = SAP and x_2 = R
2) y = SAP, x_1 = HP and x_2 = R

Percentage of subjects featuring redundancy (i.e. ITE>0)



Linear correlation analysis of the terms of the TE decomposition of HP on age at REST and during STAND

TE term	REST			STAND		
	r_P	p	p<0.05	r_P	p	p<0.05
$CTE_{SAP,R \to HP \mid R}$	-0.0476	$6.38 \cdot 10^{-1}$	No	-0.176	$7.94 \cdot 10^{-2}$	No
$CTE_{SAP,R \to HP \mid SAP}$	0.0277	$7.85 \cdot 10^{-1}$	No	-0.0015	$9.98 \cdot 10^{-1}$	No
$ITE_{SAP,R \to HP}$	-0.255	$1.04 \cdot 10^{-2}$	Yes	-0.154	$1.27 \cdot 10^{-1}$	No

TE = transfer entropy; $CTE_{SAP,R \to HP \mid R}$ = conditional TE from SAP and R to HP series given R; $CTE_{SAP,R \to HP \mid SAP}$ = conditional TE from SAP and R to HP given SAP; $ITE_{SAP,R \to HP}$ = interactive transfer entropy from SAP and R to HP series; r_P = Pearson product-moment correlation coefficient; p = probability of the type-I error; Yes/No = the variable is/is not significantly related to age with $p<0.05$.

Linear correlation analysis of the terms of the TE decomposition of SAP on age at REST and during STAND

TE term	REST			STAND		
	r_P	p	p<0.05	r_P	p	p<0.05
$CTE_{HP,R \to SAP \mid R}$	-0.208	$3.77 \cdot 10^{-2}$	Yes	-0.268	$7.09 \cdot 10^{-3}$	Yes
$CTE_{HP,R \to SAP \mid HP}$	-0.241	$1.57 \cdot 10^{-2}$	Yes	-0.223	$2.59 \cdot 10^{-2}$	Yes
$ITE_{HP,R \to SAP}$	-0.107	$2.91 \cdot 10^{-1}$	No	0.127	$2.08 \cdot 10^{-1}$	No

TE = transfer entropy; $CTE_{HP,R \to SAP \mid R}$ = conditional TE from HP and R to SAP series given R; $CTE_{HP,R \to SAP \mid HP}$ = conditional TE from HP and R to SAP given HP; $ITE_{HP,R \to SAP}$ = interactive transfer entropy from HP and R to SAP series; r_P = Pearson product-moment correlation coefficient; p = probability of the type-I error; Yes/No = the variable is/is not significantly related to age with $p<0.05$.

Conclusions

The decrease of the information genuinely transferred from HP to SAP and from R to SAP with age can be taken as an indication of the tendency toward the more important use of cardiac mechanics to control arterial pressure and the augmentation of the arterial stiffness during senescence.

SAP and R contributed redundantly to the cardiac control and the amount of SAP-R redundancy gradually declined with age, thus suggesting that its reduction might contribute to increase the cardiac frailty in old people.

HP and R contributed redundantly to the vascular control and the amount of HP-R redundancy was unrelated to age, thus suggesting that the maintenance of HP-R redundancy with age might contribute to the resilience of the vascular system in healthy senescence.