# Multiscale Eigen Analysis on EEG and Heartbeat Dynamics: a Pilot study

V. Catrambone[1*], P. Abry[2], G. Valenza[1], H. Wendt[3], G. Didier[4] and R. Barbieri[5]

***Abstract*— The continuous reciprocal interplay underlying cerebral and cardiovascular interactions has been shown to generate complex and nonlinear dynamics. To this extent, differences in induced cross-temporal dynamics are here investigated via wavelet-based multivariate multiscale analysis. Twelve features were extracted from both EEG and ECG recordings from 24 healthy subjects at rest and during a cold-pressor test. The proposed multivariate analysis using the eigen-structure of the multiscale decomposition was compared with a classical multivariate analysis. Preliminary results show that differences between experimental conditions are enhanced by the application of the proposed multivariate analysis.**

## I. INTRODUCTION

Fractal theory has provided a significant scientific contribution for the study of complex physiological systems, particularly involving nonlinear dynamics in brain and cardiovascular regulation activities [5], [7]. Such dynamics are associated with a variability in time of the Hurst exponent, therefore implying a multifractal (MF) behaviour [5] that has been exploited to discern different pathological conditions [10]. Likewise, MF analysis has been proven effective for the investigation of the brain dynamics [7].

It is known that the Central Nervous System (CNS) and the Autonomic Nervous System (ANS) continuously interact through functional, anatomical, and biochemical links. To this extent, a functional Brain-Heart Interplay (BHI) derives from a multiscale communication and interaction in space and time between the cortical and subcortical areas and sympathetic and parasympathetic dynamics [6].

While the scientific community has been devoting increasing attention to the assessment of functional BHI from both a physiological and analytical viewpoints, a multivariate multiscale characterization of joint brain and heart dynamics has not been performed yet. To overcome this limitation, in this preliminary study we propose a novel application of a multiscale multivariate analysis referred to as *Eigen Wavelet analysis* [1], [2], and compare it with more classical univariate and multivariate analyses. Here we exploit a dataset gathered from healthy subjects undergoing a Cold-Pressor Test (CPT) that elicits a strong sympathovagal response as compared to a resting state.

[1] Research Center E.Piaggio & Dept. of Information Engineering, University of Pisa, Pisa, Italy;

[2] Univ Lyon, ENS de Lyon, Univ Claude Bernard, CNRS, Laboratoire de Physique, Lyon, France;

[3] IRIT, Universit. de Toulouse, CNRS;

[4] Mathematics Department, Tulane University, New Orleans, LA, USA;

[5] Politecnico di Milano, Milan, Italy;

[*] Corresponding author. Email at: vincenzo.catrambone@ing.unipi.it;

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TABLE I

POINT PROCESS-DERIVED METRICS FOR HEARTBEAT DYNAMICS

| Measure | explanation |
|---|---|
| $\sigma^2_{RR}$ | estimated pdf variance of the HRV series |
| $\mu$ | estimated pdf mean value of the HRV series |
| powLF | PSD extracted in the LF-band $[0.040.15)Hz$ |
| powHF | PSD extracted in the HF-band $[0.150.4)Hz$ |
| LH | 2D integral from Bispectrum estimation in the bands (LF,HF) |
| HH | 2D integral from Bispectrum estimation in the bands (HF,HF) |
| pSamEn | estimation of the Sample entropy |

## II. DATASET

Details on the experimental procedure are reported in [3]. Briefly, thirty healthy subject (26.7 yo on average, gender balanced) were asked to submerge their non-dominant hand into iced water after an initial 3-minute resting state. Data from six subjects were discarded because of corrupted recordings. Throughout the experiment, a 128-electrode EEG and ECG signals were continuously recorded with a 500 Hz sampling rate. Heart Rate Variability (HRV) series were derived from ECG following the processing reported in [3] using point-process models for heartbeat dynamics. From these models we derived the linear and nonlinear ANS metrics listed in Table I with a 5min temporal resolution [8], [9]. EEG signals were preprocessed followed the HAPPE pipeline [4] and processed to derive the power within the standard EEG bands $\{\delta = [0.5, 4), \theta = [4, 8), \alpha = [8, 12), \beta = [12, 30), \gamma = [30, 45]\}$Hz through the Welch method ($1s$ time-window, 50% overlap). The median values from the 43 central electrodes located in the bilateral prefrontal and centro-parietal areas were retained for further analysis. EEG series were resampled at a $200Hz$ rate to match ANS dynamics.

## III. MULTIVARIATE MULTISCALE ANALYSIS

**Multivariate wavelet analysis.** Let $\underline{X}(t) = \{X_1(t), \ldots, X_M(t)\}$ denotes the $M = 12$-variate time series constructed from brain-heart measurements sampled at $f_s =$ 200Hz. Let $\psi$ denote a mother wavelet, with $N_\psi$ vanishing moments $N_\psi$ and $\{\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k)\}_{(j,k)\in\mathbb{Z}^2}$ the collection of dilated and translated templates of $\psi$. Let $d_{X_m}(j,k) = \langle 2^{-j}\psi(2^{-j} \cdot -k)|X(\cdot)\rangle$ denote the discrete wavelet transform coefficients of component $X_m$ of $\underline{X}$. The classical multivariate multiscale analysis of $\underline{X}$ consists in forming the $M \times M$ wavelet crosscorrelations functions $S_{m_1,m_2}(j) = \sum_k d_{X_{m_1}}(j,k) d_{X_{m_1}}(j,k)$ that characterize cross temporal dynamics. Further, one can define for each pair of components, $X_{m_1}(t), X_{m_2}(t)$ the wavelet coherence functions $C_{m_1,m_2}(j) = S_{m_1,m_2}(j)/\sqrt{S_{m_1,m_1}(j)S_{m_2,m_2}(j)}$, that consists of scale dependent correlation coefficients and thus permits to assess scale dependencies in cross-temporal dynamics.

**Eigen wavelet analysis.** While classical multivariate analysis would entail analyzing each entry $S_{m_1,m_2}(j)$

| Analysis | # tests | # significant tests |
|---|---|---|
| Univ. | 48 | 12 |
| Multiv. $S$ | 264 | 15 |
| Multiv. $C$ | 264 | 18 |
| Multiv. $\Lambda$ | 48 | 19 |

TABLE II

independently as a function of scales $a = 2^j$ , an original wavelet eigen-analysis approach was recently proposed [1], [2]. Hereby, we consider all components at a given scale $a = 2^j$ by computing the eigenvalues $\Lambda_1(j), \ldots, \Lambda_M(j)$ of matrix $S(j)$ and then associate the behaviour of each $\Lambda_m(j)$ as a function of scales $2^j$ to BHI, thus reversing the classical approach,.

## IV. Experimental Results

**Testing Rest-CPT differences.** Independently from any physiological interpretation, we aim at determining if the information extracted by our novel multivariate multiscale wavelet analysis combined with point-process modeling is able to characterize differences in BHI between rest and CPT.

We focus on the four octaves $7 \leq j \leq 10$ corresponding to time scales ranging from $.853 \leq 2^j \leq 6.826$ seconds or equivalently to frequencies $1.17 \leq f \leq .146$ Hz. For each scale and for each feature, we independently performed the classical Wilcoxon ranksum test for changes in distribution medians across the subjects.

**Univariate, multivariate, and Eigen wavelet analysis.** For the univariate analysis, the diagonal entries $S_{m,m}(j)$ of the matrix $S$ were used for further analyses considering 12 components $\times 4$ scales $= 48$ tests. The classical multivariate analysis uses all upper triangle entries of the matrix $S$, resulting in $M \times (M-1)/2 \times 4 = 264$ tests.

To get rid of changes in amplitude that would not actually correspond to changes in interactions, it is possible to focus on the coherence functions $C_{m_1,m_2}(j)$ for all pairs of components, also yielding to 264 tests.

Finally, the new multivariate eigenwavelet decomposition-based analysis proposed here makes use of the $M = 12$ eigenfunctions $\Lambda_m(j)$, thus producing 12 components $\times 4$ scales $= 48$ independent tests.

The corresponding Wilcoxon ranksum test p-values as functions of all available scales are displayed in Fig 1 for the univariate analysis (left) and eigen-multivariate analysis (right). Due to the limited space, the corresponding plots for the classical multivariate analysis both on matrices $S$ and $C$ as function of scales are not shown here. Significance levels for the test are set to 0.10 and 0.05.

**Results.** As reported in Table II, while univariate analysis is associated with 12 positive tests out of 48, classical multivariate analysis is with 15 positive tests only out of 264 comparisons. On the other hand, the proposed Eigen Wavelet multivariate analysis outperforms the classical multivariate analyses with 19 positive tests out of 48, and it also complements the univariate analysis (that focuses only on the brain or heart features independently) by tracking differences in brain-heart interplay. Significant tests did not show statistical differences following a Benjamini-Hochberg false discovery rate correction for multiple hypothesis testing.

## V. Discussion and Conclusions.

In this preliminary study we investigate functional BHI by using a novel multivariate multiscale Eigen-Wavelet method.

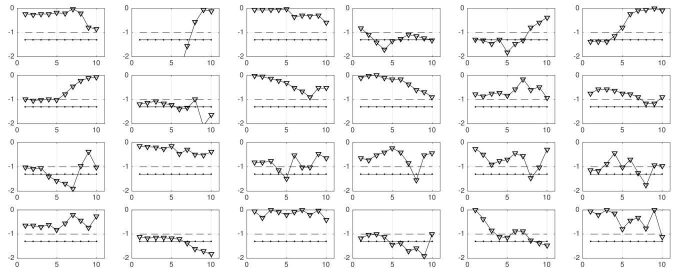

Fig. 1. p-values ($\log_{10}$ as functions of $\log_2$ of scales), for the univariate analysis (left 3 columns) and eigenWavelet-multivariate analysis (right 3 columns). The dashed and solid horizontal lines indicate respectively threshold p-value levels corresponding to 0.10 and 0.05.

We build upon our previous work investigating BHI during CPT [3], in which we found that the functional interplay is enhanced during a strong sympathovagal elicitation. Here we show that the functional interaction between EEG and HRV series exhibits a multiscale behaviour well characterized by a wavelet analysis, and the proposed Eigen-Wavelet method brings a clear statistical improvement with respect to a univariate analysis. Results suggest that CPT induces changes in BHI independently from brain and heartbeat features, as well as from combined brain and heartbeat features, with subtle and fine cross dependencies that a classical multivariate analysis is not able to catch. These results are preliminary and possibly dependent on the small number of subjects and the specific pre-processing techniques employed. For example, a possible bias might be due to the specific pre-processing procedures applied to EEG signals, or to the preliminary selection of EEG and HRV features that were considered for further analyses. Future studies will employ EEG channels from regions already found significant in previous endeavours [3] and a more refined feature selection strategy to better characterize BHI dynamics at different time scales.

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