Methods for Tracking Dynamically Coupled Brain-Body Activities during Natural Movement

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ABSTRACT
A fundamental property of movement is its dynamically changing variability and its adaptive nature. These features seem to be connected to the cognitive control of our actions by the brain. However, it has been a challenge to connect cognitive neuroscience and movement science in developing a framework amenable to study the coupled dynamics of the brain and body during natural movements. Part of the problem has been the lack of proper sensors to probe both activities in tandem. Fortunately, contemporary advances in wireless technology with high sampling resolution have paved the way to address this challenge. In this paper, we make use of wireless wearable sensors and a new statistical platform to study the dynamic interactions of the brain, body and heart during natural walking. To examine the influence of cognitive tasks on deliberate (self-emergent), spontaneous, or inevitable (autonomic) processes, we combine the use of a metronome and specific instructions on paced breathing, while harnessing the heart signal underlying the evoked behaviors. This paper presents a new platform for the individualized behavioral analyses, which incorporates a new set of data types and visualization tools, to quantify the outcome of such experimental paradigm. We discuss our results and suggest that these new methods and paradigm may serve to unify and advance the fields of cognitive neuroscience and neuro-motor control.

1 INTRODUCTION
Recent advances in wireless technology have opened new avenues to translate basic research into applications to performing arts, sports, and clinical fields among others. Amidst this transformative era, we have introduced a new statistical platform for the individualized behavioral analyses (SPIBA) [11] and derived new data types amenable to study the dynamically coupled brain-body activities during performance of natural movements [13]. Using this platform, we are able to examine the fluctuations in amplitude and timing of biophysical rhythms that are continuously output by the nervous systems during natural activities. These rhythms may come from disparate layers of the peripheral and central nervous systems (PNS and CNS) ranging from autonomic to spontaneous to voluntary levels [4].

Owing to their complexity, such as the different frequency ranges and spatio-temporal scales, multiple biophysical signals have been difficult to study in tandem so as to pose new questions on the brain-body closed-loop performance. Indeed, there is a paucity of work that examines the dynamically coupled brain-body activity. Moreover, the extant literature on this topic smooths out the waveforms of interest through averaging under Gaussian, linearity and static (stationary) assumptions. As such, there is gross data loss that prevents us from better understanding the PNS-CNS interactions. In this sense, it may be argued that most science is either about a “disembodied brain” or a “brainless body”, which is often studied by observation using descriptions of unambiguous, overt bodily motions. Such an approach tends to constrain the focus on aspects of goal-directed behavior and leave out the spontaneous/inevitable aspects of the performance, which often occurs largely beneath our conscious awareness [6]. We simply do not know how such spontaneous activity (that we smooth out as “noise” or nuisance) emerges and contributes to the autonomy of our brain exerting over the body in motion.

Other challenges we face when recording brain-body activity may include misalignment of temporal landmarks from different acquisition systems and motor artifacts corrupting cortically-related signals. New wireless technology and collaborative work among scientists and industry have created and maintained an open access platform (e.g., lab streaming layer, LSL) that enables integration of signals from different instruments, while motion-artifact removal from cortical signals are also gaining traction [2]. The present work combines new advances in data acquisition, multilayered data processing, statistical analyses and cognitive neuroscience to introduce a new platform for the personalized study of dynamically coupled brain-body activities during natural movements.
2 EXPERIMENTAL AND COMPUTATIONAL DETAILS

2.1 A Natural Task: Spontaneous/Inevitable vs. Deliberate behavior

Participants were instructed to walk at their own comfortable pace for 12-15 minutes under three different conditions: (1) Under the control condition, participants simply walked around the room as they naturally do; (2) Under the metronome condition, they walked while listening to a metronome beat at 12 times per minute. They were not instructed to do anything about it (hypothesizing spontaneous emergence of responses linked to the metronome); (3) Under the paced breathing condition, the participant was instructed to walk while listening to the metronome beat at the same speed, and to deliberately control their breathing pace. Specifically, each participant was instructed to inhale at the first beat and exhale at the second beat, thus completing six cycles of breath at each minute (Fig.2A). This condition was hypothesized to change the patterns of brain-body coupling and shift heart rhythms in relation to conditions (1) and (2).

2.2 Data Acquisition and Signal Processing

2.2.1 Instrumentation Specs. The participant wore three different types of wireless sensors to harness biorhythms from the CNS and PNS. For the CNS we used electroencephalography (EEG) sensors. For the PNS we used electrocardiogram (ECG) and motion sensors.

The cortical potentials were captured using the Enobio wireless EEG device (Barcelona, Spain) at 500Hz sampling rate with 32 sensors positioned across the scalp. The EEG recording device was positioned on the back of the participant’s head (yellow device in Fig.2B center), which contains an inertial measurement units (IMU) that records head acceleration at 500Hz. Data from this device were recorded by NIC Neuroelectrics (Barcelona, Spain). The acceleration of the participant’s bodily motion was captured using Opal IMUs (APDM Inc., Portland, OR) at 128Hz sampling rate, and were acquired with Motion Studio (APDM Inc., Portland, OR). Participants wore ten opal IMUs with Velcro belts on the wrists, ankles, foot, upper arm on both right and left sides, and on the posterior trunk and anterior chest (Fig.2B). The heart signals were obtained from a wireless Nexus-10 device (Mind Media BV, The Netherlands) and Nexus 10 software Biotrace (Version 2015B) at a sampling rate of 256Hz. Three electrodes were placed on the chest according to the standardized lead II method, and were attached with adhesive tape (Fig.2B).

2.2.2 Lab Stream Layer (LSL) Use. In order to temporally synchronize the signals obtained from the three devices–EEG, ECG sensors, and Opal IMUs, an open source package LSL was used. Among the applications contained in LSL, LabRecorder and Mouse was used so that the EEG data streams would be event-marked by mouse clicks made on the display screen of the computer, from where the softwares interfacing the sensor devices (e.g., Motion Studio, NIC, and Biotrace) were running.

2.2.3 Pre-processing. Acceleration data obtained from the Opal IMUs and ECG heart data were up-sampled to 500Hz using cubic spline interpolation, so that they would later be analyzed at the same sampling rate as the EEG brain potential data.

EEG data was properly band passed to remove 60Hz AC current. Traditional ICA-based methods are used to detect periodic eye-motions (e.g. blinks) and facial (e.g. jaw-related motion) patterns in the waveforms [1]. Here, we incorporated new analyses specifically involving head motions, where the output from an IMU embedded in the head cap was used to detect head jerks (rate of change of acceleration) and their coherence patterns with the rates of change of the EEG-signal were tracked. Specifically, the EEG data were band passed at 16-31Hz (i.e., beta frequency band) and coherence analyses of the two data’s rate of change were examined. Acceleration peaks of head jerks were followed by peaks of change in cortical signals at the beta band frequency after approximately 40ms, implying that these cortical signals reflected head motion artifacts. Hence, when 0.1% highest peaks of head acceleration (i.e., head jerks) occurred, the acceleration signals were compared against the beta band cortical signals via cross correlation, and if the cortical signals lagged the head acceleration peaks, these instances were
excluded. Overall, this resulted in eliminating approximately 0.001% of the entire data.

Subsequently, the cortical data from each channel were referenced by the channel that had the least noise. Specifically, for each channel, the peaks extracted from the fluctuations in the amplitude of the cortical waveform were studied as a Gamma process (see section 2.3.2) and the channel with the lowest scale value (i.e., lowest noise to signal ratio, NSR) was chosen to have the lowest noise and was set as the reference. Indeed, there are many artifacts in the cortical signals that are traditionally removed by hand and visual inspection, and generally cannot be fully eliminated. Given the massive amount of data we continuously track here, hand-visualization analyses were not feasible. In that sense, our introduction of automatic assessment of noise and re-referencing to a channel with the least NSR are our best bet to reduce the impact of such artifacts while implementing it in an automated way. The rationale behind this approach is further explained in the following sections 2.3.1-2.3.3.

2.3 Statistical Platform for Individualized Behavioral Analysis

2.3.1 Waveforms. Raw biophysical data that are continuously registered from physiological sensors (i.e., data derived from physiological rhythms) such as bodily kinematics, electroencephalography (EEG), electrocardiogram (ECG), electromyography (EMG), respiration patterns, etc., give rise to a time series of peaks and valleys. Their fluctuations properly normalized as in (equation 1) produce spike trains (coined “the micro-movements” [8, 10]) that we treat as a random point process (Fig. 3A-B):

\[
\text{NormPeak} = \frac{\text{Peak}}{\text{Peak} + \text{AverageMin}}
\]  

(1)

In a series of micro-movements, the order of the original signal’s amplitude peak values is preserved, but the frame/time values are lost. To recover all the frame values and preserve the sampling resolution of the original signal, we set the non-peak values to 0 and superimpose the micro-movements (i.e., normalized peak amplitude) on the original frames. An example of a spike train in the original frame order is shown in Fig.3C, which is based on the micro-movements signal (Fig.3B) extracted from the raw data signal (Fig.3A). Note, this is done for all sensors’ signals, thus allowing us to integrate them from different levels of the nervous systems, e.g., the CNS (EEG-spikes) and the PNS (motion-spikes).

2.3.2 SPIBA: using a Gamma Process. The spike trains are treated under the assumption of independently identically distributed (I.I.D.) events, representing a continuous random process under the general rubric of a Poisson Random Process, where events in the past may (or may not) accumulate evidence towards prediction of future events (see also [6–11] for various examples to different nervous system’ biorhythms). These spike trains are used as input to a Gamma process to empirically estimate the Gamma parameters (e.g., using maximum likelihood estimation with 95% confidence intervals) [10, 11]. The estimated shape and scale parameters are tracked on the Gamma parameter plane (where the vertical axis represents distribution’s dispersion/scale parameter, and the horizontal axis represents the distribution’s skewness/shape parameter). These estimated parameters are further used to estimate the spike train’s Gamma probability distribution functions (PDF) and its moments, to profile noise-to-signal transitions inherent in the multilayered, dynamically evolving biophysical data.

2.3.3 Statistical Inference. The above-mentioned Gamma parameter plane provides information on the noise to signal ratio (NSR), which is equivalent to the scale parameter value of the estimated Gamma PDF [3]. Thus, higher noise will correspond to a higher value along the vertical axis on the Gamma plane (i.e., scale axis). It is also important to emphasize that when the estimated shape parameter a of the PDF equals a=1, the data follows a memoryless Exponential PDF. This is the most random distribution whereby events in the past do not accumulate information predictive of future events [3]. Larger values across the horizontal axis of the Gamma plane (i.e., shape axis) represents PDFs with more symmetry, with a variety of skewed distributions between the two extremes. These statistical features enable direct inference from the moment by moment fluctuations in the biophysical signals that are continuously output by the nervous systems. As such, they allow interpretations of natural behaviors under different conditions.
In order to analyze the interactions that occur across the brain and body, spike trains of each sensor data (which we will refer to as nodes from hereon) were examined in terms of nodes that comprise a large network, made up of brain-related and the body-related sub-networks. The idea introduced here is to use network connectivity analyses commonly used in brain science [5] and extend it to the study of peripheral networks introduced by our group to study natural movements such as gait and reach [12]. To that end, we will present several examples of the use of this framework to dynamically track the brain-body coupled network. (Note that we can track the individual subnetworks of the brain and the body as well, but due to space constraints, we will focus on the brain-body coupled network in this paper.)

First, all spike train data were separated by 1 minute worth of time series at 500Hz to provide a minute-by-minute profiling of the behavior. Then, for each pair of nodes across the brain and body during each minute, cross coherence was computed yielding the coherence and lead-lag phase values at varying frequencies (Fig.3E).

For each minute, the maximum coherence value was extracted for each pair of nodes, along with the corresponding phase (via cross spectral power density) and frequency values. These can be visually represented in the form of matrices as shown in Fig.3F. In Fig.3F (left), each entry of the coherence matrix contains the max coherence value during a minute time-frame for each pair of nodes represented in the rows and columns. Here, the first 31 items of rows and columns belong to nodes within the brain network, and the next 11 items belong to nodes within the body network. The phase lead-lag matrix in Fig.3F (middle), contains the phase (degrees) value when the maximum coherence value occurs between the corresponding pair of nodes. The frequency matrix in Fig.3F (right) contains the frequency value when the maximum coherence value occurs between the corresponding pair of nodes. In Fig.3G, the three matrices are those corresponding to the positive (lead) values of the phase lead-lag matrix, where the node from row i leads the node from column j. The matrices thus obtained are the adjacency matrices used to build a weighted directed graph representing the full brain-body network, as shown in Fig.3H. Note, we can further decompose the signal into different frequency bands and provide the analyses described below for each frequency band (e.g. the traditionally studied alpha, beta, gamma, theta, mu, gamma bands). However, due to space constraints, this paper will use the full frequency spectrum to illustrate the methods.

One novel element in our approach (besides extending brain connectivity analyses to connectivity analyses of brain-body coupled networks) is the combination of the micro-movements underlying the activity of the node and the SPIBA framework to examine the dynamic evolutions in the node’s stochastic signatures.

**2.4 Visualization Tools**

**2.4.1 PNS-CNS Networks.** Cross coherence analyses on paired nodes yielded an adjacency matrix to represent a weighted-directed graph, which visualizes the network of nodes and their links. In Fig.3H, the ‘PNS Network’ graph shows the 11 nodes from the body and the ‘CNS Network’ graph shows the 31 nodes from the brain, during a single minute. The arrows show the directionality of the paired nodes, and the arrow weights represent the phase level, where thicker arrows would imply longer lead-lag relationship between the two nodes. The edge colors of the node represent the coherence strength specified in the color bar. Based on the coherence strength and connectivity weights, nodes can be spontaneously separated into modules (sub-network). To detect them, we use the modularity metric [5]. Each module maximizes the number of within-group edges and minimizes between-group edges. Generally, there were 2-3 modules within each minute, and the color of each node represents the module in which the node is included. See also Fig.4A.

The ‘Coupled Network’ graph in Fig.3H shows all 42 nodes from the brain and body, with the same specification rules as the ‘PNS Network’ and the ‘CNS Network’ graph. Here, the ‘Coupled Network’ graph shows the interaction mainly between the nodes from the body and nodes from the brain, where the upper left portion of the nodes in a circular shape correspond to those in the brain, and the lower right portion of the nodes in a stick-figure shape correspond to those in the body.

These networks allow us to visualize the dynamic minute-by-minute interactions between each pair of nodes, within the brain, within the body, and between the brain and body. In order to visualize the progression of network connections throughout the recording duration, rather than from a single static minute, minute-by-minute profile of these networks can be exhibited in videos for each CNS (see video here), PNS (see video here), and and Coupled networks (see video here).

**2.4.2 Reciprocally Connected Network.** The network of coherence among paired nodes can also be visualized by looking for self-emerging patterns from sub-network (module) synergies within the coupled network (Fig.4A). During each session of recordings, for each node, we counted how many minutes that node participated in a particular module (Fig.4B-top) and computed the proportion of times across a condition that a given node stayed in each module (Fig.4B-bottom). If a pair of nodes had the same proportion of time staying in each module during the entire session (i.e. node i led node j and node j led node i equal number of times within the module), then the two nodes were considered reciprocally connected. Thus the network graph can be represented with double arrows pointing in both directions for those reciprocally connected nodes (Fig.4C). Essentially, reciprocally connected pairs of nodes exhibited the same pattern of modularity during the recording session, implying synergies between these pairs of nodes.

This visualization allows us to understand the connectivity in regards to self-emerging patterns of coupled brain-body activity dynamically unfolding and changing from session to session.

**2.4.3 Additional tools to summarize coupled PNS-CNS modules as a measure of sub-networks’ togetherness.** The modularity metric was further used to visualize the patterns of brain-body togetherness for each self-emerging module (Fig.5A). Here, we count the number of times the node participated in the same module (Fig.5B). Then, we categorize these nodes by regions (e.g. Parietal region is comprised of nodes in the right/left parietal lobes; Arms region...
Figure 4: Connectivity-Modularity Analyses. (A) Weighted directed graph for the body-brain coupled network, where the pairwise node coherence level is shown in the colors of the marker edge (see color bar). Based on the coherence level, three modules (sub-networks) emerge at minute 15 (shown in the colors of marker-face: yellow, cyan and magenta) across the brain and body. Directed arrows inform the leading node in each pair. (B) Number of minutes (see color bar) each node (x-axis) participated in one of three modules (y-axis) across a 15min session (top), and the proportion of time spent in each module (x-axis) for a single node shown in bar-plot (bottom). (C) Reciprocal connections between brain and body nodes (double arrows). Node color signifies the strength of reciprocal connections (i.e., number of links coming in and out of the node across the session; see color bar). Node size reflects the number of reciprocal connections the node is involved in (larger nodes indicate higher occurrence of reciprocity).

contains the right/left upper-arms and wrists). This regional subdivision is arbitrary (i.e., it can be sub-divided in other ways) and allows us to ask how two known regions relate to each other. For each region, we examine whether those regional nodes participated in a certain module for more than half of the maximum time counts (stars are marked on the peaks if they exceed the 1/2 threshold in Fig 6A). Then we examine one region from the body and another region from the brain in pairs, to see if the two regions exceeded the ½ threshold (i.e., participated together). If both regions do not exceed the threshold, they would be considered ‘disjointed’. This can be represented in a binary matrix shown in Fig 6B for all three modules, where yellow indicates the brain-body region togetherness (1) and blue indicates disjoint-ness (0). Fig 7B is a graphical network representation of Module 1, where the double sided arrow indicates the togetherness between the two regions from the brain and the body.

2.4.4 Summary Statistics Profile. Underlying each node is a stochastic signature of spike trains that was mentioned in sections 2.3.1-2.3.3. Here, we define the spike train of each node and use them as input to a Gamma process, where the Gamma parameters are empirically estimated. One way to visualize the statistics of each node’s spike trains is a four-dimensional graph, as is shown in Fig.10 with the estimated Gamma PDF in the top insets of Fig 10A, 10B and the corresponding estimated Gamma parameters plotted on the Gamma parameter plane in the bottom insets of Fig 10A, 10B. In the 4D graphs, the empirically estimated mean, variance, and skewness of the fitted Gamma PDFs for each node during each condition are plotted on the x, y, and z axes respectively. The size of the marker reflects the level of kurtosis, where larger size indicates

high kurtosis level of the fitted PDF. The colour of the marker is differentiated across conditions. This graph allows us to visualize the statistical features of each node and understand how the stochasticity changes across different conditions for the brain nodes and for the body nodes.
3 RESULTS AND DISCUSSION

3.1 Spontaneously Emerging Modules in the Brain-, the Body- and the Coupled-Networks Differentiate CNS-PNS States

3.1.1 PNS-CNS Networks. For each minute and for each condition, the brain-body coupled network was visualized, and exhibited dynamic interactions between the brain and body throughout the experiment. Generally, the nodes self-grouped into 2-3 modules, and the presence of these modules changed throughout the 12-15 minutes of recording for all conditions. Fig. 8 shows an example of the coupled network at minute 5 for each condition. The progression of the network connections during the entire recording for each condition for a representative participant can be viewed in these videos: control, metronome, and paced breathing conditions.

3.1.2 Reciprocally Connected Network. For each condition, the reciprocal connections of the coupled network were visualized as shown in Fig. 9. For this participant, self-emerging reciprocal connections were fairly sparse when the participant was naturally walking, from a passive/spontaneous task (i.e., metronome condition) to a deliberate task (i.e., paced breathing condition), self-emerging reciprocal connections became denser. It can be construed that for this participant, as the additional task load increased, the interactions between the brain and body became more active. This was a pattern generally found across other participants, whereby differences in reciprocal connections were found from one condition to the next. The extent and strength of such interactions varied across individuals.

3.2 Different Noise-to-Signal Profiles Characterize Gait under Different Mental and Autonomic Demands

The stochastic signatures of each node within the entire network were examined across all conditions. Fig. 10A shows the estimated Gamma moments for each brain node based on its empirically estimated PDF for each condition, which is differentiated by the color of the markers. Fig. 10B shows the estimated Gamma moments of the nodes belonging to the body. The top insets of Fig. 10A, 10B shows the estimated Gamma PDF for each minute for a single representative node from the brain (Pz node for control condition, F4 node for the metronome condition, P7 node for the paced breathing condition) and body (lumbar node for control condition, and right foot node for the metronome and paced breathing condition). The bottom insets of Fig. 10A, 10B shows the estimated scale and shape parameters in log values plotted on a Gamma parameter plane for the corresponding node shown in the insets positioned above.
Table 1: Pairwise Kruskal-Wallis Non-parametric Test of Empirically Estimated Gamma Parameters between Conditions

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Pair</th>
<th>$\chi^2$</th>
<th>df</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shape</td>
<td>Control vs. Metronome</td>
<td>6.28</td>
<td>1</td>
<td>0.01*</td>
</tr>
<tr>
<td></td>
<td>Metronome vs. Breathing</td>
<td>0.67</td>
<td>1</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>Control vs. Breathing</td>
<td>7.41</td>
<td>1</td>
<td>0.01*</td>
</tr>
<tr>
<td>Scale</td>
<td>Control vs. Metronome</td>
<td>5.61</td>
<td>1</td>
<td>0.02*</td>
</tr>
<tr>
<td></td>
<td>Metronome vs. Breathing</td>
<td>1.53</td>
<td>1</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>Control vs. Breathing</td>
<td>3.92</td>
<td>1</td>
<td>0.05*</td>
</tr>
</tbody>
</table>

For nodes from both brain and body, the statistics under the naturally walking condition (control) exhibited systematically increasing levels of skewness and kurtosis compared to conditions of spontaneous metronome and deliberate paced breathing. As such, differences in the estimated Gamma parameters from the naturally walking condition against the other two conditions were found to be statistically significant (Table 1) using the pairwise Kruskal-Wallis test. Note, this test was used solely as a comparison of mean ranks across conditions so as to gain insights on the range of the family of PDFs that the tasks evoked.

3.3 Different ‘togetherness’ patterns across brain and body regions were detected across conditions

The examination of togetherness in brain-body regions produced different patterns for each self-emerging module in the network and for each condition. These can be seen in the patterns of Fig.11, implying change in interactions across different sub-regions of the brain and body and across different conditions. In Fig.12, these patterns were summarized by bar-plots quantifying the overall network of brain regions and body parts recruited by all modules within a condition. Indeed, we can see that the togetherness strength varies across different regions and across different conditions.

3.4 Different IBI (inter-beat interval) patterns in natural, spontaneous and deliberate walking patterns

Given the differences in the brain-body coupled network’s modularity-based and togetherness-based profiles across conditions, and given the differences in the underlying stochastic signatures of the nodes across conditions, we also examined the stochastic properties of the heart’s inter-beat interval (IBI) activity. We examined the variability while walking with spontaneous (i.e., metronome condition) or deliberate load (i.e., paced breathing condition) in relation to natural walking (control condition). The results are shown in Fig.13 for two representative participants, including a case study of a participant with Autism spectrum disorder (ASD), where differences across conditions in the estimated PDFs and the noise level are shown for each person. Among neurotypical participants, we found a consistent pattern of an increase in NSR (scale/dispersion) and decrease in shape/skewness for the deliberate paced breathing condition in relation to the natural walking (control) condition, with the spontaneous metronome condition generally varying between these two. This pattern was inverted for the ASD person. Overall, we can see that different families of PDFs emerged across the conditions that infer profound statistical differences between naturally walking and walking subject to additional task loads.

In the particular case of the patient with ASD, it is noticeable that the range of shapes in the PDFs was closer to the random Exponential limit (left of the x-axis) than to the Gaussian limit (towards the right of x-axis). Further when examining other ASD participants we found that the range of values of their estimated PDF parameters were very narrow across all conditions. This is in marked contrast to controls who exhibited ample cross-talk.
between the deliberate/spontaneous processes of the CNS-PNS interactions and the inevitable heart-processes of the ANS.

4 CONCLUSIONS
In summary, we have presented a new platform and data type to study the coupled dynamical systems, such as the brain/CNS and the body/PNS, during performance of natural movements. The new methods and paradigm may serve to unify and advance the fields of cognitive neuroscience and neuro-motor control. They may also be of use to the community of performing artists as they involve coupled interactions between different networks of the individual.

We illustrate the use of this platform and data types to integrate activities of biophysical signals harnessed from different CNS and PNS locations, as the individual engages in the same biomechanical task of walking under different levels of task load. In this study, we found that simply placing a metronome in the background spontaneously elicited different patterns of entrainment across the brain-body networks, thus dramatically changing the network synergies. Likewise, instructing the person to breathe at a certain pace changed the interactions in the brain-body coupled network (along with the interactions within each CNS/brain and PNS/body network).

We presented new ways to visualize self-emerging patterns that recruited different subnetworks during three different conditions, and quantified various levels of spontaneously arising pairwise-node coupling (self-emerging reciprocal connections) and regional coupling (togetherness detected in selected brain-body regions). We also presented new methods to track the evolution of the stochastic signatures underlying the nodes within these networks, and revealed the NSR ratio dynamically changing across different conditions.

The dynamics of these data are best appreciated in movies that the deliberate/spontaneous processes of the CNS-PNS interactions and the inevitable heart-processes of the ANS.

and leave out the continuous flow of activities generated by the multi-layered nervous systems.

We underscore that biorhythms of the nervous systems can now be examined in an integrated fashion across multiple levels of intentionality, ranging from inevitable/autonomic, to automatic/spontaneous, to deliberate. We hope that this multi-layered approach in understanding the CNS and PNS dynamic interactions will help us advance interdisciplinary research across the computational and movement fields.

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