Towards a Real-time Application to Reveal Entrainment Among People

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Abstract—The use of wireless technology and advanced signal processing for personalized healthcare is extremely promising. A relevant application appears to be the field of group dynamics, in which the study of a heart-rate measure, the RR interval time series, can reveal valuable information about individuals, as well as the group as a whole. In this paper, we present the results of computing the wavelet coherence among the RR interval time series of a group of people during a Kundalini yoga meditation session, revealing entrainment among them during specific activities and additional important information, such as patterns of heart rate variability that are common to all members of the group. We propose a novel method to study the connections among people in real time, underlying the bounds in the accuracy as a function of the delay introduced.

I. INTRODUCTION AND RELATED WORK

The concept of entrainment among people is a key aspect in studying the dynamics of a group. The study of interactions among two or more people connected by some form of social relationship [1] is relevant to many fields, including group work, entertainment [2], and team sports [3]. The coordination of players for certain disciplines in athletics, such as team sports, can dramatically influence the well-being of a single player and the results of the group as a whole. The study of group dynamics is also relevant in the fields of psychology, sociology, communication studies, and medicine. Relevant examples can be found in [4]. In all these disciplines that study group dynamics, there is still the need to quantify the effects of group behavior and how these effects can change the individual performance, or improve the balance of the group.

Wireless technology can be an important enabler for this task, because it provides the capability of sensing and storing many physiological signals, such as blood pressure, temperature, heart rate, movement, and body composition, see e.g., [5] and references therein. The devices used to sense and store this physiological data are tiny, unobtrusive, and relatively inexpensive sensors that can be worn on a daily basis, thus generating a large volume of data. Once this huge amount of data is available, there arises the challenge to process it and extract relevant information. Towards this goal, in [6] we proposed an approach to measure the entrainment in a group of people using physiological signals. More specifically, we collected heart-rate data from a group of practitioners performing Kundalini Yoga meditation [7]. The data obtained is in the form of RR interval time series which is defined as the time interval between successive R peaks of the QRS complex from a typical electrocardiogram (ECG). In Fig. 1 we show four seconds of an ECG recorded through our wireless sensor. The ECG shows 4 consecutive RR intervals, labeled as \(RR(1), \ldots, RR(4)\). We also highlighted in the figure the Q, R and S points of the QRS complex.

The heart-rate variability (HRV) is the measure of the variation in the beat-to-beat RR intervals [8], which reveals valuable information about the well-being of an individual. HRV is regulated by the opposite influence of the sympathetic and the parasympathetic branches of the autonomic nervous system. It is generally analyzed in the frequency domain, that is divided into three major bands, see [9]: the very low frequency (VLF, in the range 0.003-0.04 Hz), the low frequency (LF, in the range 0.04-0.15 Hz), and the high frequency (HF, in the range 0.15-0.4 Hz). The HF band is usually influenced by the respiratory sinus arrhythmia, due to breathing, while the LF is influenced by the Mayer waves of blood pressure. It is not clear what is producing the oscillations at VLF; it may be related to long-term fluctuations in the thermoregulatory system or regulation of blood pressure and water balance. Although many signal processing techniques have been proposed to study these kind of nonstationary signals, a natural choice to study them in the frequency domain, adopted in this paper, is the use of wavelet analysis, as proposed in [10].

Exploiting wavelet coherence analysis, in [6] we proposed a method to reveal entrainment among people as a form of coherence of the spectral components of the instantaneous heart-rate signal of the individuals in the group. The drawback of the approach in [6] is the fact that it requires the whole dataset to calculate such coherence, revealing the entrainment only a posteriori, after the meditation session is concluded and the data has been fully processed. In this paper, the main goal is to improve this approach, making it possible to reveal entrainment in real time, or after a short delay. This is a key aspect, since in many applications it is important to have
immediate feedback on the presence or absence of coherence among individuals. For example, during a meditation session, an individual can track if s/he is connected with the rest of the group, and therefore if s/he is performing the activity in the best way. Or, alternately, the instructor can track all the practitioners, to help each of them to get in sync with the group.

The main contributions of this paper are:

- The analysis of the effects due to an incomplete dataset on the calculation of the coherence; this is the basis for calculating coherence in real time.
- A method to compute the coherence locally, introducing a small approximation but allowing the calculation of the coherence considering only a small interval in time, not the entire original signal.
- The performance analysis of the accuracy in the calculation of the coherence, as a function of the parameters introduced to calculate the coherence locally.

The rest of the paper is organized as follows: in Sec. II we introduce the experimental scenario, then in Sec. III we briefly summarize the mathematical tools adopted in this paper to calculate the coherence, and in Sec. IV we propose the method to calculate the coherence in real time. In Sec. V we show the accuracy of this method and Sec. VI concludes the paper.

II. EXPERIMENTAL SCENARIO

In this section we briefly describe the experimental scenario in which we collected the data used in this paper. The scenario of interest, detailed also in [6], is a Kundalini yoga meditation session, where a group of practitioners guided by a professional instructor performs Kundalini yoga. This type of yoga is a meditation technique [7] that includes different activities. Some activities consist of small body movements, some include hyperventilation, i.e., the practitioners are requested to breathe at a faster rate than necessary, while other activities involve chanting which helps all the practitioners coordinate their breathing patterns with the group. The activities performed in the yoga sessions and the devices used to collect the RR interval data from each person involved are presented. We conducted the experiment over ten yoga sessions, obtaining similar results from each. We present the analysis of only one of them here, but it would remain valid for the other sessions.

A. Yoga session: activities

We consider five practitioners performing Kundalini yoga meditation techniques as described in [7], for a period of approximately 70–90 minutes per session. The entire meditation session is divided into activities of varying time intervals which, for convenience, are labeled here as A1, ..., A4, A7, and A8. There is a dedicated period between activities which allows a practitioner to relax and provides the instructor some time to explain the next technique and answer any doubts. Activities A1 and A7 involve rhythmic chanting, the former with a breathing period of about 11 seconds, and the latter with a breathing period of about 4 seconds. Activities A2 and A3 comprise of specific body movements that are not synchronized among the members of the group. Activity A4 involves individual meditation without synchronized breathing. A detailed description of these activities can be found in [6].

A very interesting breathing pattern can be found in activity A8. In this activity, all practitioners chant together the words Aad Sach Jugad Sach for a duration of 22 minutes. This chant consists of four phases with approximately 5 minutes of coordinated breathing. In the first phase, the practitioners breathe at the rate of one breath per chant. Then they progressively increase the speed of chanting and breathe at the rate of one breath per 2 chants, one breath per 3 chants, and finally one breath per 4 chants.

B. Physiological signals monitor devices

Each practitioner wears a POLAR Team2 Pro system heart rate monitor device during the whole duration of the Kundalini yoga session. The signal is recorded in the form of RR intervals which is collected off-line using the POLAR Team2 software on a central server. The collected data is publicly available online on the website of our HealthWare research group [11] which is a novel effort to build a repository of such physiological signals and analyze them from daily activities.

C. Preprocessing of RR intervals

The RR interval time series is not equally sampled, since we can have a new sample only when the device detects a new heart pulse. Therefore it is necessary to preprocess the RR signal. The preprocessing consists of two steps: the first is the removal of the artifacts that are introduced by the sensor, and the second is the resampling of the RR signal at a frequency of 4 Hz. These two methods are detailed in [6].

III. MATHEMATICAL PRELIMINARIES

In this section we summarize the mathematical techniques that are the basis of the real-time framework developed in this article.

A. The Continuous Wavelet Transform: CWT

We assume an equally sampled time series \( x \), whose elements are \( x(k) \), with \( k = 1, \ldots, K \), and the time difference between samples is \( \Delta t \). The elements of the Continuous Wavelet Transform (CWT) for \( x \) are defined as [12]:

\[
W_x(k,s) = \sum_{i=1}^{K} x(i) \Psi_\sigma(i-k),
\]

where \( \Psi_\sigma(\cdot) \) is the scaled, translated, and normalized version of the discrete basis function, which in our case is a Morlet wavelet [13], and \( ^* \) is the complex conjugate. The scaling factor \( \sigma \) is calculated as:

\[
\sigma = (\Delta t)/s,
\]

where \( s \) is the wavelet scale, which is a discrete variable proportional to the period. The Morlet wavelet, represented in Fig. 2, is obtained by the modulation of a sinusoid by a Gaussian. Its normalized version is defined as:

\[
\Psi_\sigma(k) = (\sigma)^{1/2} \pi^{-1/4} e^{j\omega_0 k} e^{-k^2/2}.
\]

The CWT gives us a valid tool to analyze the time evolution of the spectral components of our time series.
B. The Cross Wavelet Transform: XWT

In order to compare the spectral components’ time evolution of the two time series of interest, we calculate the Cross Wavelet Transform (XWT) that gives us information about the distribution of the cross power between the two signals in the frequency domain and how this distribution evolves over time. The XWT between the time series $x$ and $y$, named $W_{xy}$, is defined, element by element, as:

$$W_{xy}^{(k,s)} = W_x^{(k,s)} \left( W_y^{(k,s)} \right)^*.$$ (4)

C. Pairwise Wavelet Coherence

In order to quantify the degree of coherence at a specific time and frequency between a pair of time series, namely $x$ and $y$, we adopt the wavelet coherence. This function is defined as [14], [15]:

$$C_{x,y}^{(k,s)} = \left| \mathcal{S} \left( W_{xy}^{(k,s)} \right) \right|^2 \frac{\mathcal{S} \left( W_x^{(k,s)} \right)^2 \mathcal{S} \left( W_y^{(k,s)} \right)^2}{\mathcal{S} \left( W_{xy}^{(k,s)} \right)^2},$$ (5)

where $\mathcal{S}(\cdot)$ is a smoothing function in time, $k$, and in scale, $s$. The smoothing function in scale is a rectangular function, i.e.,

$$g(s) = C \text{ rect}(0.6s),$$ (6)

where $C$ is a constant, $\text{rect}(b) = 1$ for $|b| \leq 0.5$, $\text{rect}(b) = 0$ otherwise, and the smoothing function in time is a Gaussian, whose standard deviation is a function of $s$, i.e.,

$$h_{\sigma}(k) = e^{-\frac{(k\sigma)^2}{2}}.$$ (7)

IV. REAL-TIME COHERENCE ANALYSIS

In this section we propose how to actually modify the techniques presented in Sec. III in order to calculate in real time, with a given finite delay, the coherence among a group of signals. We start with an example that clarifies the main problems encountered when calculating the coherence in real time. In Fig. 3 we show the coherence plot between two subjects during a Kundalini yoga meditation session. We calculated this coherence at three different time instants, approximately dividing the yoga lesson into thirds: Fig. 3(a) (after the first third of the yoga lesson), Fig. 3(b) (at approximately two thirds), and Fig. 3(c) (at the end of the lesson). The black continuous line in the three figures represents the limit under which boundary effects cannot be ignored [12], since they can significantly modify the coherence plot. We can see in the figure that the values above, but close to, that threshold are also slightly altered.

In performing this calculation using the procedure detailed in Sec. III, two major problems arise:

1) border effects: when we calculate the instantaneous coherence, border effects play a major role, especially at low frequencies;

2) high computation complexity: according to the procedures in Sec. III, all the components of the signal are involved in the coherence calculation, thus introducing complexity that can be hard to manage in a real-time application.

In this section, to address the border effects problem,
we analyze the accuracy limits as a function of the delay introduced in the coherence calculation. First, we address the complexity problem, proposing an approximation to calculate the coherence locally, in order to reduce the computation complexity.

The first step is to recognize which samples are needed to calculate a point in the coherence plot with coordinates \(k_0\) and \(s_0\), say \(C_{x,y}^{(k_0,s_0)}\). From Eq. (5), we see that we need all the points of the CWTs \(W_x^{(k,s)}\) and \(W_y^{(k,s)}\) that are integrated in the smoothing function. In the scale axis we integrate according to a limited function, described in Eq. (6), so the CWTs should be evaluated only in the points \(s \in [s_0 - \Delta s, s_0 + \Delta s]\), where \(\Delta s\) is a constant determined by the function in Eq. (6). However, in the time axis, we integrate according to an unlimited function, in Eq. (7). Anyway, since the components of the Gaussian become negligible after a certain threshold, we consider only the signal in a limited time interval, namely \(k \in [k_0 - \Delta_1(s), k_0 + \Delta_1(s)]\), where \(\Delta_1(s)\) depends on the scale \(s\), since the amplitude of the function in Eq. (7) depends on the scale. The value of \(\Delta_1(s)\) is computed as follows:

\[
\Delta_1(s) = \max \left\{ \eta \text{ s.t. } \frac{h_x(\eta)}{h_{\sigma}^{\text{max}}(\eta)} \geq \epsilon_1 \right\}.
\]

In this equation, \(\epsilon_1\) is a small threshold under which the component of the Gaussian can be considered negligible, and \(h_{\sigma}^{\text{max}}\) is calculated as

\[
h_{\sigma}^{\text{max}} = \max_{\eta} h_{\sigma}(\eta).
\]

This bound defines which samples of \(W_x^{(k,s)}\) and \(W_y^{(k,s)}\) we need to calculate the point \(C_{x,y}^{(k_0,s_0)}\). Now we analyze which samples of the signal \(x\) (and the corresponding samples for signal \(y\)) that we need to calculate the point \(W_x^{(k_1,s_1)}\). According to Eq. (1), each point of the wavelet transformation is obtained integrating all of the points of signal \(x\). Also in this case, the components of the Morlet wavelet in Eq. (3) become negligible after a certain threshold, making it possible to consider only the signal in a limited time interval, namely \(k \in [k_1 - \Delta_2(s_1), k_1 + \Delta_2(s_1)]\), where \(\Delta_2(s)\) is a function of the scale. The value of \(\Delta_2(s)\) is computed as follows:

\[
\Delta_2(s) = \max \left\{ \eta \text{ s.t. } \frac{|\Psi_{\sigma}(\eta)|}{\Psi_{\sigma}^{\text{max}}(\eta)} \geq \epsilon_2 \right\}.
\]

In this equation, \(\epsilon_2\) is a small threshold under which the component of the Morlet wavelet can be considered negligible, and \(\Psi_{\sigma}^{\text{max}}\) is calculated as

\[
\Psi_{\sigma}^{\text{max}} = \max_{\eta} |\Psi_{\sigma}(\eta)|.
\]

According to this rationale, in order to compute the wavelet coherence in the point \((k_0, s_0)\), we need all the samples \(x^{(k)}\) and \(y^{(k)}\) for

\[
k \in [k_0 - \Delta_T(s_0), k_0 + \Delta_T(s_0)],
\]

where

\[
\Delta_T(s) = \Delta_1(s) + \Delta_2(s + \Delta s).
\]

This means that we can calculate the value of \(C_{x,y}^{(k_0,s_0)}\) only after we have observed the signals at time \(k = k_0 + \Delta_T(s_0)\). This gives us a measure of the minimum delay required to have the requested level of accuracy.

## V. RESULTS: REAL-TIME COHERENCE

In this section we analyze the tradeoff between the delay after which we obtain the desired coherence representation, and the corresponding relative error, with respect to the coherence calculated a posteriori after observing the entire signal. We use the dataset collected during a Kundalini yoga session performed on August, 2011 and we average the results among all the people that were present during that session.

Before analyzing the effects of the real-time technique on the accuracy of the coherence calculation, we observe in Fig. 3(c) the plot of the coherence between a pair of people during that Kundalini yoga session. We notice in particular that for activity A1 there is a strong coherence among all the people at the low frequency (LF), probably due to the synchronized breathing imposed by this activity. For activity A8, in the LF, we observe a significant coherence that is decreasing in frequency as a function of time, corresponding to an increase of the breathing period imposed during A8. In contrast, for activity A7 we instead have significant coherence among all the people at the HF, in concordance with the fact that for this activity the breathing period is shorter. There are other points of interest in the graph, e.g., at the beginning of activity A8 we observe coherence among all the people at the VLF, but the physiological meaning of this is unclear [9].

We start calculating the coherence at each point \(k\), considering the signals from 1 to \(k + d/\Delta t\), where \(d\) is the delay (in seconds) introduced in the calculation. We want to quantify, with an example, what is the effect of the delay in the coherence accuracy. Fig. 4 illustrates the relative error as a function of the delay introduced, i.e.,

\[
E_F(d) = \frac{\|\hat{C}_{x,y}^{(k,s)} - \hat{C}_{x,y}^{(k,s)}(d)\|_2}{\|\hat{C}_{x,y}^{(k,s)}\|_2},
\]

where \(\hat{C}_{x,y}^{(k,s)}(d)\) is the coherence calculated with a delay \(d\) with respect to the point of interest \(k\), \(F\) is the frequency range chosen, \(F \in \{\text{VLF}, \text{LF}, \text{HF}\}\), \(s\) is the scale that varies in the frequency range specified by \(F\), and \(\| \cdot \|_2\) is the 2-norm. From the figure, we notice that for HF we need a delay of approximately 30 seconds to have a relative error close to zero, for LF we need a delay of about 10^2 seconds, and for VLF, about 10^3 seconds. We notice also that for a delay shorter than 10 seconds we have a significant error in all three ranges of frequency. This gives us a bound on the smallest error
we can achieve with the given delay for the specific dataset considered.

The error shown in Fig. 4 is achieved by computing the coherence for every time sample and considering all the signal samples available at that time. We averaged the error among all the couples of people performing the Kundalini yoga meditation session. If we want to compute the coherence locally, considering only a limited number of signal samples, according to the rationale in Sec. IV, we should consider the delay $\Delta_T(s)$ from Eq. (13). This delay is a function of the scale $s$ and of the two thresholds introduced in Sec. IV, i.e., $\epsilon_1$ and $\epsilon_2$. In Fig. 5, we put $\epsilon = \epsilon_1 = \epsilon_2$ and we represent the delay $\Delta_T(s)$ as a function of the value of $\epsilon$, for the four frequencies at the boundaries of the three regions of interest (HF, LF, and VLF). We notice that for $\epsilon \leq 10^{-2}$ the delay increases very slowly as a function of $\epsilon$.

Finally, we apply the techniques presented in Sec. IV to the real data collected during the Kundalini yoga session. In Fig. 6 we represent the relative error as a function of $\epsilon$ for the three frequency ranges of interest, calculated as

$$E_F(\epsilon) = \frac{\| \tilde{\rho}(k,s) - \rho(k,s) \|_2}{\| \rho(k,s) \|_2},$$

(15)

where $\tilde{\rho}(k,s)$ is the coherence calculated imposing a value of $\epsilon = \epsilon_1 = \epsilon_2$. We notice that the error is reasonably small for a value of $\epsilon \leq 10^{-2}$, for all three ranges of interest. Indeed, as in Fig. 5, given the value of $\epsilon$ there are different values of the delay for the three ranges of frequency considered.

VI. CONCLUSIONS

In this paper we proposed a method to study the heart rate variability in real time among people involved in the same activity, in order to reveal the presence of entrainment among these people which is shown by a common frequency pattern in their heart rate. We analyzed the bounds of the real-time application, studying the performance accuracy as a function of the delay introduced to collect the data requested.

In future work, we plan to implement this real-time application in a portable device, in order to allow a single user to check his or her entrainment level during a group activity, and to enable the group leader to check for members who are not fully connected, so that s/he can help disconnected members get more in sync with the group.

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