

Exploring the Short-Term Memory of Heart Rate Variability through Model-Free Information Measures

Gorana Mijatovic¹, *Member, IEEE*, Chiara Barà², Riccardo Pernice², Tatjana Loncar-Turukalo¹, *Member, IEEE*, Giandomenico Nollo³, *Member, IEEE*, and Luca Faes², *Senior Member, IEEE*

Abstract—In this work, we perform a comparative analysis of discrete- and continuous-time estimators of information-theoretic measures quantifying the concept of memory utilization in short-term heart rate variability (HRV). Specifically, considering heartbeat intervals in discrete time we compute the measure of information storage (IS) and decompose it into immediate memory utilization (IMU) and longer memory utilization (MU) terms; considering the timings of heartbeats in continuous time we compute the measure of MU rate (MUR). All measures are computed through model-free approaches based on nearest neighbor entropy estimators applied to the HRV series of a group of 15 healthy subjects measured at rest and during postural stress. We find, moving from rest to stress, statistically significant increases of the IS and the IMU, as well as of the MUR. Our results suggest that both discrete-time and continuous-time approaches can detect the higher predictive capacity of HRV occurring with postural stress, and that such increased memory utilization is due to fast mechanisms likely related to sympathetic activation.

I. INTRODUCTION

Heart rate variability (HRV) series exhibit memory effects that determine to a different extent their predictability depending on cardiac autonomic regulation, cardiovascular mechanics, circadian rhythms and other physiological factors. Such memory effects are typically deployed over multiple different time scales: while long-range correlations are detected from HRV recordings lasting several hours [1], the so-called *short-term* HRV refers to memory effects spanning time scales in the order of a few minutes [2]. Short-term HRV is typically investigated using spectral analysis or, in the time domain, using linear parametric or nonlinear model-free measures of predictability [3]. The latter approach is often preferred because it allows to detect memory effects related to complex mechanisms of physiological regulation which may result in nonlinear correlations. The non-parametric analysis of HRV and other physiological time series is typically performed using information-theoretic measures such as the information storage (IS) [4], which allows to detect virtually any type of interaction and offers the flexibility to

define measures able to capture specific aspects of the investigated dynamics. In this regard, information measures applied to physiological variability series have been used to infer the relevance of short-lag and longer memory effects respectively related to fast and slower physiological mechanisms, possibly associated to sympathetic and vagal short-term regulation [5].

The short-term memory of HRV is typically investigated using measures of information storage computed for discrete-time processes where the variable of interest is the interbeat interval [4]. However, continuous-time formulations have recently emerged to compute measures of coupling and causality which work for continuous processes where the variable of interest is an event (in the case of HRV, the heartbeat) [6]–[9]. In this context, in a recent preliminary work we have proposed an approach to quantify the rate of memory utilization in simulated heartbeat dynamics reproducing HRV [10]. The aim of the present study is to compare this continuous-time estimator of the predictive capacity of HRV with the model-free discrete-time estimator of the IS, also considering a decomposition of the latter into quantities measuring short-lag and longer memory effect. The work is focused on understanding the cardiovascular control mechanisms leading to HRV and on providing information about their latency in different physiological conditions (here, supine rest and postural stress).

II. INFORMATION-THEORETIC ASSESSMENT OF THE MEMORY OF HEART RATE VARIABILITY

In this work, we consider the cardiovascular system as a dynamical system whose activity is described by two types of random processes: a continuous-time point process R described by the times of occurrence of the heartbeats (times of each R peak in the electrocardiogram, ECG), and a discrete-time random process X described by the duration of the heartbeat intervals (heart periods). An exemplary realization of these processes is reported in Fig. 1a, showing the events t_i of the point process R and the observations x_i of the process X ($i \in \mathbb{Z}$, t_i is the time of the i^{th} heartbeat and $x_i = t_{i+1} - t_i$ is the duration of the i^{th} heartbeat interval). In the following, we formulate measures of the predictive capacity of the observed dynamical system defined in discrete time for the process X (information storage [4] and its decomposition into short- and long-memory effects) and in continuous time for the process R (memory utilization rate [11]).

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¹G. M. and T. L-T. are with the Faculty of Technical Sciences and CEVAS, University of Novi Sad, Serbia, email: gorana86@uns.ac.rs; ²C. B., R. P and L.F. are with the Department of Engineering, University of Palermo, Italy, ³G. N. is with Department of Industrial Engineering, University of Trento, Italy.

A. Discrete-time Formulation

The discrete-time process X is defined at each heartbeat time t_i , and quantifies the duration x_i of the i^{th} R-R interval. The capability of this process to keep predictable information over time is quantified by the so-called *information storage* (IS), an information-theoretic quantity defined for a stationary process as $S_X = I(X_i; X_i^-)$, where X_i is the random variable sampling the process at the current time t_i , $X_i^- = [X_{i-1}, X_{i-2}, \dots]$ is the infinite-dimensional variable covering the past history of the process sampled at the times t_{i-1}, t_{i-2}, \dots , and $I(\cdot; \cdot)$ denotes mutual information (MI).

The quantity S_X measures the amount of information about the present state of the process that can be explained by its own past states. As such, it reflects the predictability (regularity) of the process dynamics resulting from the presence of memory. Interestingly, the IS can be decomposed to evidence the separate contributions of "immediate" (one-lag) and longer-memory effects to the overall memory of the process X , exploiting the chain rule for MI to get:

$$S_X = I(X_i; X_{i-1}) + I(X_i; X_{i-1}^- | X_{i-1}) = I_X + M_X. \quad (1)$$

In (1), the term $I_X = I(X_i; X_{i-1})$ quantifies the information shared by the current R-R interval X_i and the interval X_{i-1} immediately preceding it, while $M_X = I(X_i; X_{i-1}^- | X_{i-1})$ quantifies the information that the past intervals $[X_{i-2}, X_{i-3}, \dots]$ share with X_i but not with X_{i-1} ; these two measures are denoted as *immediate memory utilization* (IMU) and *memory utilization* (MU). These three measures can be expressed evidencing marginal and conditional probability distributions of the heartbeat intervals using the expectation operator $\mathbb{E}[\cdot]$ as follows:

$$S_X = \mathbb{E} \left[\ln \frac{p(x_i | x_i^-)}{p(x_i)} \right], \quad (2)$$

$$I_X = \mathbb{E} \left[\ln \frac{p(x_i | x_{i-1})}{p(x_i)} \right], \quad (3)$$

$$M_X = \mathbb{E} \left[\ln \frac{p(x_i | x_i^-)}{p(x_i | x_{i-1})} \right]. \quad (4)$$

In sum, the decomposition (1) shows how the IS, quantified as the information carried by the present state of the observed system which is attributable to its past states, can be split into a contribution measuring the immediate usage of memory occurring within one single time step (i.e., the IMU) and a contribution measuring the usage of memory attributed to time lags longer than one (i.e., the MU).

B. Continuous-time Formulation

In this section, considering that event-based processes like the heartbeats are more naturally described by continuous-time point processes [9], [12], we describe the formalism introduced in recent theoretical works to compute measures of information dynamics in continuous time [11]. These works have highlighted the importance, when continuous-time information-theoretic measures are computed analyzing

discrete-time processes in the limit $\Delta t \rightarrow 0$ (where Δt is the sampling time of the discrete-time process), of normalizing the measures by Δt so as to obtain *rates* quantified in [nats/sec], providing in this way their convergence. However, when the analysis aims at quantifying the predictive capacity of continuous-time processes, the same works have shown that a convergent rate of the IS does not exist; moreover, considering the decomposition (1) applied to information rates, the divergent properties of the IS rate are inherited solely by the IMU rate term, while the so-called *memory utilization rate* (MUR) is convergent and quantifies the active memory usage of the process as it is understood in an intuitive manner [11].

Importantly, when the analyzed continuous-time process reduces to a point process, the MUR measure can be formalized in a way that allows its practical computation [8], [9], [11]. In particular, following the formulations in [11], the MUR of the heartbeat point process R for which N heartbeats occur in a period T , can be defined as

$$\dot{M}_R = \bar{\lambda}_R \mathbb{E}_{p_t} \left[\ln \frac{\lambda_{R,t_i | R_{t_i}^-}}{\lambda_{R,t_i | R_{t_i}^1}} \right], \quad (5)$$

where $\lambda_{R,t_i | R_{t_i}^-}$ and $\lambda_{R,t_i | R_{t_i}^1}$ are the instantaneous event-rates of R evaluated at the time of its i^{th} event t_i (i.e., the i^{th} heartbeat), conditioned respectively on its whole past history and on its previous event only, and $\bar{\lambda}_R = N/T$ is the average event-rate of R (i.e., the mean heart rate). The instantaneous event rate at the generic time u is defined as

$$\lambda_{R,u} = \lim_{\Delta u \rightarrow 0} \frac{p_u(N_{R,u+\Delta u} - N_{R,u} = 1)}{\Delta u}, \quad (6)$$

where $N_{R,u}$ is the number of events occurred up to time u ; p_u is a probability density evaluated in continuous time (i.e. at any time u), which differs from the probability p_t in (5) which is evaluated at the target events t_i . Then, substituting (6) in (5), making a Bayes inversion and noting that $\lim_{\Delta u \rightarrow 0} p_u(\cdot | N_{R,u+\Delta u} - N_{R,u} = 1) = p_x(\cdot)$, the MUR can be rewritten as [8]

$$\dot{M}_R = \bar{\lambda}_R \mathbb{E}_{p_t} \left[\ln \left(\frac{p_t(R_{t_i}^-)}{p_u(R_{t_i}^-)} \cdot \frac{p_u(R_{t_i}^1)}{p_t(R_{t_i}^1)} \right) \right], \quad (7)$$

where $R_{t_i}^1$ and $R_{t_i}^-$ denote the short-term memory of the process and its whole past history.

C. Estimation Strategy

This section describes how the discrete-time IS, IMU and MU measures defined in (2-4) and the event-based MUR measure defined in (7) were computed in practice from a series of heartbeat events. For both discrete- and continuous-time measures, the estimation strategy is based first on building realizations of the short (one-lag) and long (>1 lag) past histories of the process by using time-delay embedding, and then computing the quantities in (2-4) and (7) via nearest neighbor estimator of the entropy measures [8], [13].

The embedding strategies are illustrated in Fig. 1. For the quantities defined in discrete time (Fig. 1a) and referring

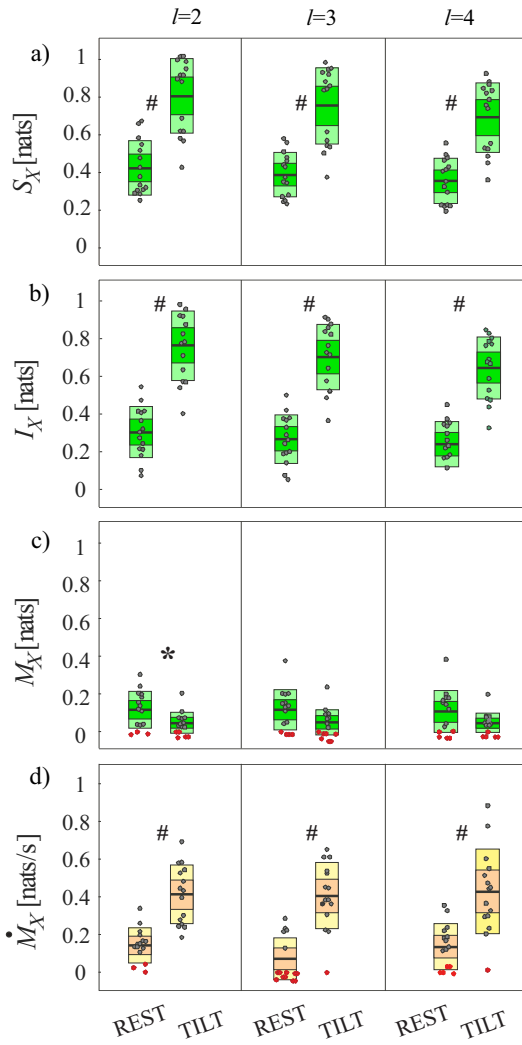


Fig. 2. Distribution and individual values of the IS, IMU and MU measures estimated in discrete time (a-c), and of the MUR measure estimated in continuous time (d), over fifteen subjects in the two analyzed experimental conditions REST and TILT. Red circles denote non-significant values detected by surrogate data analysis. Statistical analysis: *, $p < 0.05$, #, $p < 0.005$, REST vs. TILT.

The continuous-time analysis shows that the rate of memory utilization computed for the sequences of heartbeat times behaves similarly to the overall and immediate predictive capacity of the process computed for the series of heartbeat intervals. Indeed, the MUR measure shows a statistically significant increase while moving from the supine to the upright position (Fig. 2d), similarly to what observed for the discrete-time measures of IS and IMU (Fig. 2a,b). These findings provide an empirical confirmation of the fact that the MUR measure is able to capture fast memory effects, where a "fast" effect is here intended- at a discrete-time resolution- considering the interval preceding the current one.

IV. CONCLUSIONS

This study performed a comparative analysis between information-theoretic approaches for quantifying the concept of memory utilization in short-term HRV: the standard

discrete-time interval-based method, and a novel continuous-time event-based method. Our results indicate that the two approaches can detect equally well the increased predictive capacity of HRV occurring with postural stress, and that the event-based measure correlates with the interval-based measure of fast memory effects.

Future studies should better explore the link between discrete- and continuous-time approaches for the analysis of short-range correlations in HRV, particularly regarding the assessment of time-lagged interactions which can be associated to the latency of the physiological mechanisms evoked by different patho-physiological conditions.

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