Dynamical Heart Beat Correlations during Complex Tasks – A Case Study in Automobile Driving

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Abstract

Driving is a complex task that is known to cause highly individual stress responses. Here we study heart rate variability (HRV) during automobile driving compared with being at rest. We focus on time-dependent variations in the scaling properties of the RR intervals by applying a newly developed dynamical detrended fluctuation analysis (DDFA). In particular, we study whether DDFA brings additional insights to the HRV analysis carried out by conventional measures in the time and frequency domain.

We utilize the publicly available PhysioNet database for 16 drivers, whose ECG was recorded during 35-60 min of driving on public roads, preceded and followed by 15 min rest periods. The extracted RR intervals are then analyzed through the conventional HRV measures, followed by DDFA analysis that yields the time- and scale-dependent scaling exponents $\alpha(t, s)$. The temporal fidelity of the method permits accurate determination of distributions of $\alpha(t, s)$ in relatively short segments of data.

We find that even though all HRV measures show clear differences between driving and being at rest, the subjects exhibit highly individual cardiac responses to the experiment. In the individual level, however, DDFA gives detailed information on the dynamic changes in HRV which are often hidden in the conventional measures.

1. Introduction

Wearable heart rate (HR) devices are becoming widespread and highly accurate, allowing precise extraction of the interbeat intervals during different activities. Heart rate variability (HRV) analysis [1] has become a widespread tool to monitor, e.g, physical activity, recovery and sleep. Moreover, in a recent meta-analysis and literature review [2] it was pointed out that HRV is impacted by *stress*, and it could be used for assessment of psychological health.

Driving is a complex task that requires simultaneous use of sensory, motor and cognitive functions [3]. This complexity coupled with risks in traffic causes stress in many individuals. Thus, detecting and characterizing physiological changes in real time during driving could have relevant applications in improving road traffic safety.

Conventionally, HRV has been studied with time domain measures calculated from the RR intervals and frequency domain measures calculated from the power spectrum of the time series. These conventional HRV measures have also been used to study the physiology of driving [4]. HRV has also been studied with nonlinear methods quantifying the complexity and unpredictability of the RR intervals [1]. Detrended fluctuation analysis (DFA) is a commonly used nonlinear method describing the scaling properties of a time-series [5]. For HRV, DFA is commonly applied to obtain two scaling exponents for small (4-16) and large (16-64) scales, respectively.

Here we study HRV during driving by focusing our analysis on dynamic DFA [6] (DDFA) that enables accurate detection of continuous scaling exponents $\alpha(t, s)$ as functions of both time and scale. The continuous scaling exponents can detect real-time changes in the HRV, which can be utilized to better understand the physiology of driving. DDFA has been previously applied with promising results to running [6] and sleeping [7], thus supporting further applications to other activities.

2. Data and preprocessing

We use the Physionet [8] database *"Stress Recognition in Automobile Drivers"* utilized also in Ref. [4]. It contains multi-parameter recordings including electrocardiogram (ECG) from healthy volunteers measured during automobile driving on open roads. The experimental protocol also included 15 minutes rest periods before and after driving a predetermined route. During the rest periods subjects sat relaxed in an idling car inside the garage while keeping their eyes closed [4].

The database contains 16 measurements, but we discarded two of them as they lack parts of the ECG data in the middle of the experiment. Generally, however, the data quality is very good for a large fraction of the samples, enabling accurate R peak detection. Figure 1 visualizes the ECG and peak detection with WFDB software package for

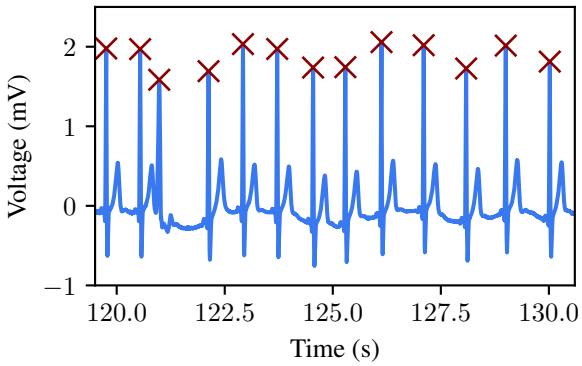

Figure 1. Example of electrocardiography recording with detected R peaks. See the text for details.

Python using the GQRS algorithm [9]. An example of an incorrectly marked R peak caused by an artifact is visible in Fig. 1 at 121 seconds. Such artifacts were removed as follows: (i) calculate the mean of last five correct RR intervals; (ii) check if the difference between the mean value and next RR interval exceeds a threshold (250 ms); (iii) remove those RR intervals without modifying the original time stamps of the RR intervals. In total, 1.8 % of the RR intervals were removed from the time series (see Ref. [10] for details).

3. Theory and methods

From the time-domain measures we consider the mean RR and RMSSD – the root mean square of successive RR interval differences. In the frequency domain we compute the absolute power of the high-frequency (HF) and low-frequency (LF) and their ratio (LF/HF). Transforming the RR interval time series into frequency domain is done by first detrending the time series with the smoothness priors method [11] and then applying Lomb-Scargle periodogram [12]. These conventional HRV measures are calculated in 300 RR interval segments utilizing overlapping windows with a step of 10 intervals. This segmentation is done separately for each rest and drive section. The mean value of each measure in each section is computed to get a single value for every section.

The DDFA method [6] extends the conventional DFA [5] by considering the scaling exponent as functions of both scale and time. In brief, DDFA consists of the following steps:

1. Divide the time series into scale-dependent segments $\mathrm{S}_{\mathrm{s,t}}$ with segment lengths $l(s) = 5s$.
2. Compute the fluctuation functions in each segment at scales $\{\mathrm{s}-1, \mathrm{s}, \mathrm{s}+1\}$ utilizing *maximally overlapping windows* (note that conventional DFA usually utilizes non-overlapping windows [5]).
3. Calculate the scale- and time-dependent scaling exponent $\alpha(s,t)$ with finite difference approximation [13].

For details and numerical validation of the method, see Ref. [6].

4. Results

In Fig. 2 we show the relative differences in (a) mean RR, (b) RMSSD, (c) HF, and (d) LF/HF between driving and the first and second rest period, respectively. All the results fall on the diagonal, which indicates that both rest periods (before and after) differ from driving in a similar manner. As expected, RR is decreased (HR increased) during driving on the average. RMSSD is decreased as well, which indicates increased dominance of the sympathetic nervous system during driving. Further, HF power is decreased, but LF/HF ratio is increased during driving. This could imply low vagal activation, even though the usefulness of LF/HF as a measure of sympatho-vagal balance has been questioned [14]. Despite the general consistency of our results in Fig. 2 we point out that the relative individual variations in the HRV measures are large.

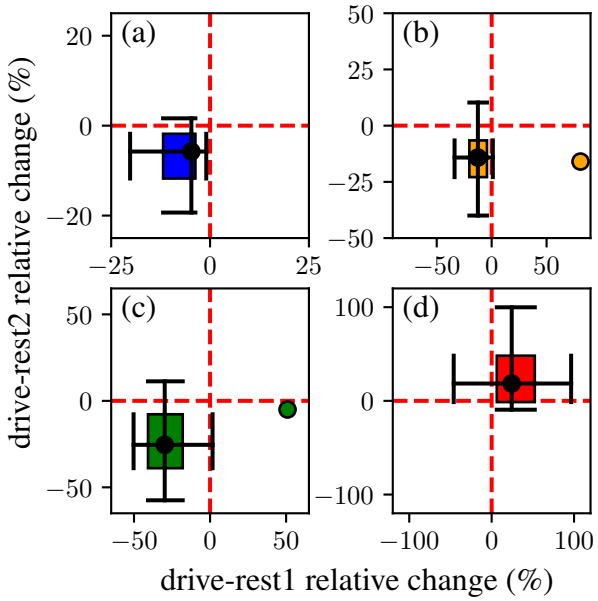

Figure 2. Relative differences in (a) mean RR, (b) RMSSD, (c) HF and (d) LF/HF ratio between driving and the first and second rest period, respectively.

Figure 3 shows the DDFA scaling exponent (in colorscale) during the complete measurement of a single subject (a), together with two zoomed parts from the first rest and the drive section (b-c). The subject shows clear anti-correlations $\alpha(t,s) < 0.5$ in small scales (10-20) during

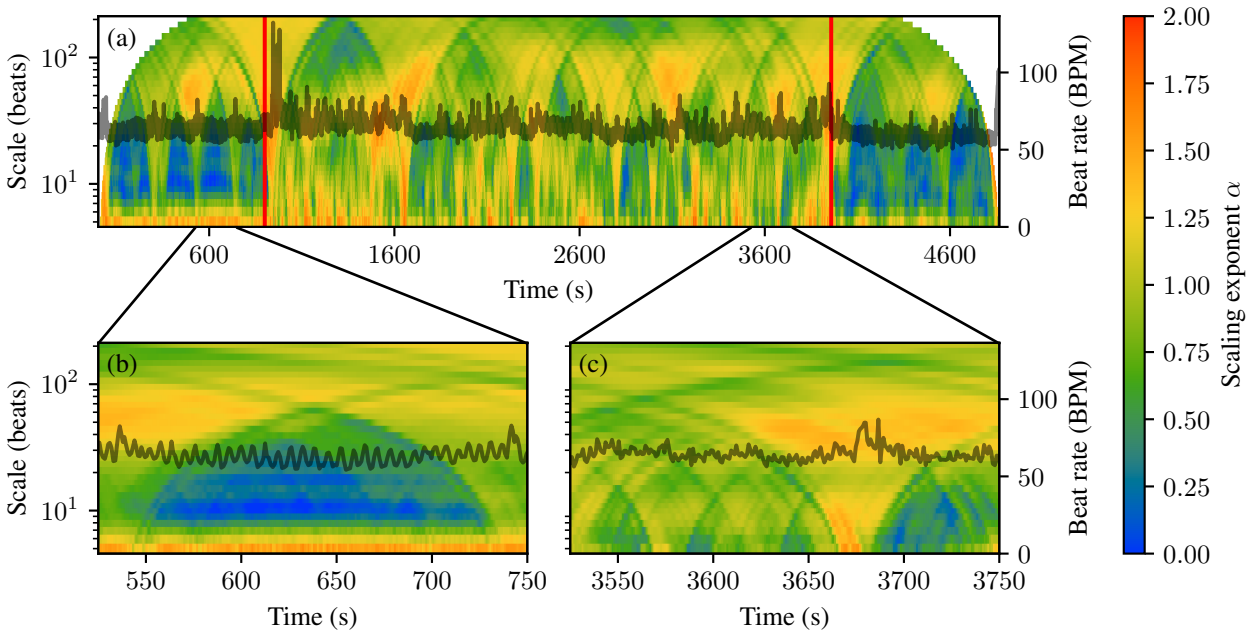

Figure 3. (a) DDFA results during the complete measurement (rest1-drive-rest2) for a single subject. The red vertical lines indicate the change of rest/drive sections. The black curve shows the heart rate. (b-c) Zoomed parts of the first rest section and the drive section.

the both rest sections. The anticorrelations are also visible in the HR in Fig. 3(b) as a sawtooth structure. The behavior is intriguing in the sense that previously anticorrelations have been associated with physical stress [6], and in this example they are present during a (supposedly) relaxing rest period. Nevertheless, we point out that the individual differences between the rest periods and driving are significant also in terms of the scaling exponent (see below).

Figure 3 further demonstrates that DDFA is capable to detect changes with high temporal resolution, whereas the use of conventional HRV measures on ultra short ($< 5\text{min}$) recordings have been criticized [15]. We also point out that in some cases, DDFA reveals differences between the sections that are not captured by conventional HRV measures (for details, see Ref. [10]).

Figure 4 shows the aggregated distribution of DDFA scaling exponents of all the subjects during the measurement. The distribution has a clearer shape, i.e., the scaling exponents are more consistent during the drive (c) than during the rest periods (b,d) – especially at small to moderate scales (5-30). This might be associated with people reacting differently to these controlled rest periods: some subjects might be calm and relaxed, while the others are anxious and stressed about the experiment. Driving can be thought as "shuffling" these rest periods in a relatively consistent fashion.

Finally, in Fig. 5 we visualize the normalized mean $\alpha(t, s)$ values aggregated over all the measurements. At small scales (5-16) the values during first rest period are consistently decreased, reflecting the observed anticorrelations in several cases. Both the second rest and drive sections show significantly increased variations. At large scales (17-100) all the segments show significant variations, and the mean α values are slightly higher during the drive section. Nonetheless, the results in Fig. 5 underline the large individual differences in the physiological effects of driving on the HRV.

5. Conclusions

Driving is a task that has highly individual effects on the HRV. Moreover, our results show that the anticipation of driving is highly subject-dependent. The conventional HRV measures during the driving show expected behavior compared to the rest sections, indicating that - on the average – the impact of the sympathetic nervous system increases during driving. The newly developed dynamic detrended fluctuation analysis (DDFA) is able to characterize the rest-drive transitions with excellent accuracy, thus complementing the conventional HRV measures. Surprisingly, for some subjects the rest periods are characterized by anticorrelated behavior, which is commonly associated with physical stress. In forthcoming studies, it could be

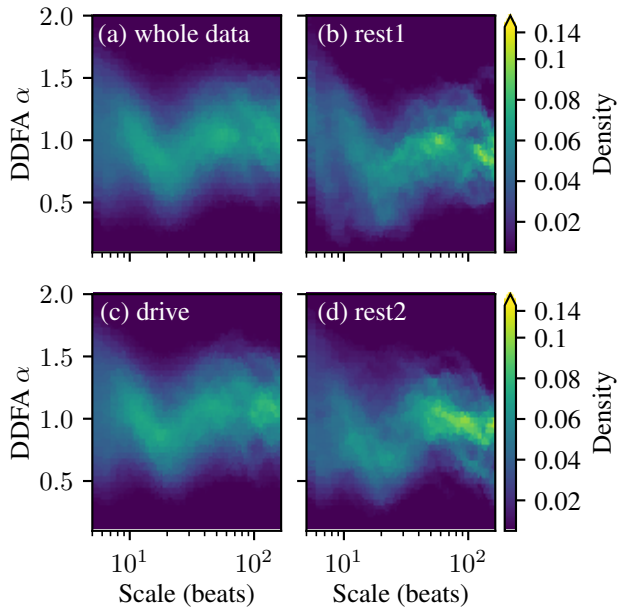

Figure 4. Aggregated distribution of DDFA scaling exponents for the whole data (upper left) and each section separately. The density in colorscale shows which proportion of the alpha values fall into each measurement bin. The scale of density is linear for densities 0–0.1 and exponential for values larger than 0.1.

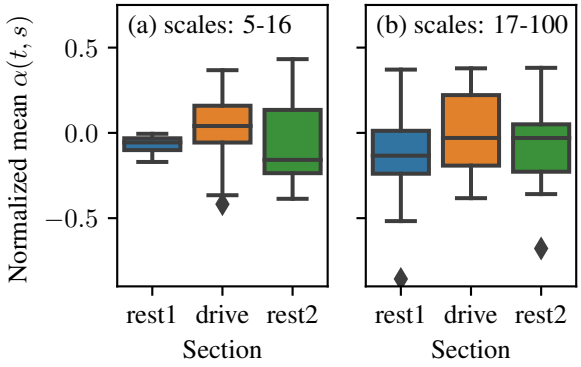

Figure 5. Aggregated box plot over all the measurements for normalized mean alpha values at (a) small and (b) large scales in rest and drive sections.

worthwhile to employ the DDFA scaling exponents as additional features in classification, in order to quantify the amount of new information that DDFA adds to the conventional HRV measures.

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