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

1. Introduction

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

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 physiological changes during driving such as drowsiness [4,5] 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 HRV measures have also been used to study the physiology of driving [4–6]. 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 [7]. 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 [8] (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 to running [8] and sleeping [9] with promising results, thus supporting further applications.

2. Data and preprocessing

We use the Physionet [10] database *"Stress Recognition in Automobile Drivers"* utilized also in Ref. [6]. It contains multi-parameter recordings including electrocardiogram (ECG) from healthy volunteers measured during automobile driving on open roads. The experimental protocol also included 15 min 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 [6].

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 Python using the GQRS algorithm [11]. An example of an incorrectly marked R peak caused by an artifact is visible

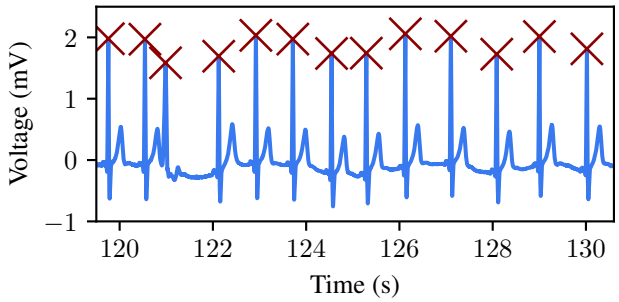

Figure 1. Example of electrocardiography recording with detected R peaks. See the text for details.

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. [12] for details).

3. Theory and methods

In the time-domain 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 [13] and then applying Lomb-Scargle periodogram [14]. These conventional HRV measures are calculated in 300 RR interval segments moving with a step of 10 intervals to obtain time-dependent measures. The mean values of these measures are computed separately for each rest and drive section.

The DDFA method [8] extends the conventional DFA [7] by yielding the scaling exponent as functions of both scale and time through the following steps:

1. Divide the time series into scale-dependent segments $\mathcal{S}_{s,t}$ with segment lengths $l(s) = 5s$, which yields good balance between temporal resolution and noise [8].
2. Compute the fluctuation functions in each segment at scales $\{s-1, s, s+1\}$ utilizing *maximally overlapping windows* (note that conventional DFA usually utilizes non-overlapping windows [7]).
3. Calculate the scale- and time-dependent scaling exponent $\alpha(s,t)$ with finite difference approximation from the logarithmic fluctuation function in each segment $\mathcal{S}_{s,t}$ [8].

For details and numerical validation of the method, see Ref. [8] and its Supplementary Information.

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 approximately 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 sympathovagal balance has been questioned [15]. Despite the general consistency of our results in Fig. 2 we point out that the variance amongst different subjects is large.

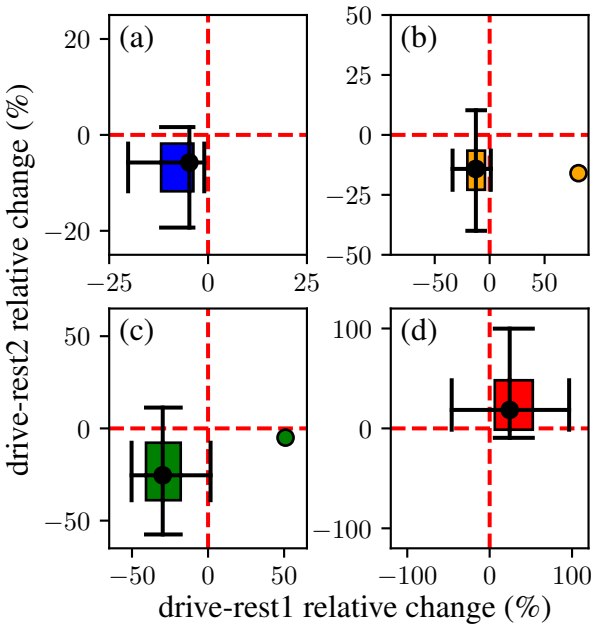

Figure 2. Relative differences in (a) mean RR, (b) RMSSD, (c) HF and (d) LF/HF ratio between driving and the first and second rest period, respectively. The whiskers represent data outside the interquartile range (IQR) by less than 1.5 times the IQR.

Figure 3 shows the DDFA scaling exponent (in color scale) during the complete measurement of a single subject (a), together with two zoomed parts from the first rest (b) and the drive (c) sections. The subject shows clear anticorrelations $\alpha(t,s) < 0.5$ in small scales (10–20) during 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 exercise [8] or cardiac

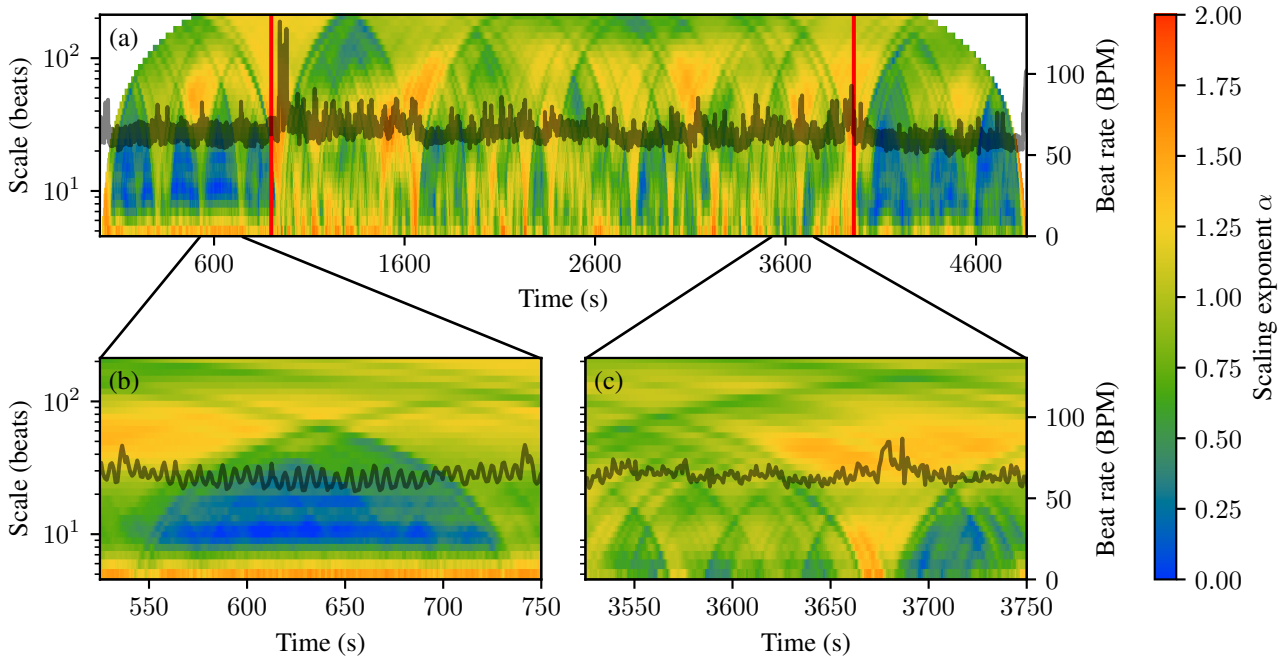

Figure 3. (a) DDFA results during the complete measurement (rest1-drive-rest2) for a single subject. The red vertical lines indicate the change of rest/drive sections. The black curve shows the heart rate. (b) Zoomed part of the first rest section. (c) Zoomed part of the drive section.

diseases [7], but in this example they are present during a resting period. We note, however, that the frequency of the oscillations would be compatible with relaxed breathing rate and Mayer waves [16], both of which could induce periodic modulations to the heart rate. Minute disturbances in the periodic modulation during resting are clearly visualized by DDFA, along with the greater short-scale variance during the driving. Intricate details such as these are revealed by DDFA that would remain hidden in the conventional HRV measures.

Not all subjects demonstrated as prominent differences between the different segments as in Fig 3. Indeed, in Fig. 4(a) we show the instantaneous heart rate for a subject where no significant differences were visually observed in the average RR behavior, as a function of time in the conventional HRV measures, or in the DDFA picture as in Fig. 3. However, the temporal fidelity of DDFA permits the study of scale-dependent *distributions* of the scaling exponent α, which are shown in Figs. 4(b–d). Discernible differences are found at the larger scales where the values are more condensed in the rest segments and α begins to decrease as a function of the scale, whereas it remains increasing during the drive segment.

Finally, in Fig. 5 we visualize the aggregate distributions of the DDFA scaling exponents over all the subjects during the different segments. The large individual differences between the subjects are evident as wide distributions that

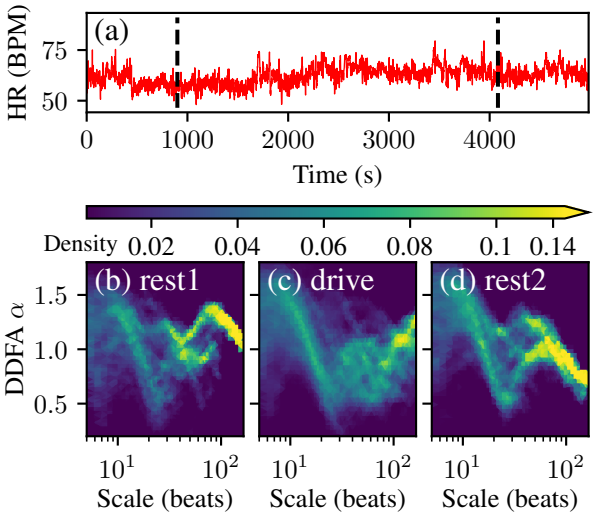

Figure 4. Instantaneous heart rate (top panel) and distributions of the DDFA scaling exponents as functions of the scale (bottom) for one subject in each section. In (a) the black dashed lines indicate the boundaries of the rest/drive sections. The color scale of the density is linear for densities 0–0.1 and logarithmic above this range.

partly mask the differences between the rest and drive segments. Overall the α values are slightly lower at each scale

in the rest segments compared to the drive segment, with the effect being more pronounced in the first rest segment. In contrast to the rest segments, anticorrelations ($\alpha < 0.5$) are practically non-existent during the drive segments. The distributions are also wider in the rest segments at smaller scales ($\lesssim 30$), which might be associated with people reacting differently to these controlled rest periods: some subjects might be calm and relaxed, while others are anxious and stressed about the experiment. At larger scales the qualitative trends that were observed in Fig. 4 for a single subject appear to persist through the individual variability in this overall data.

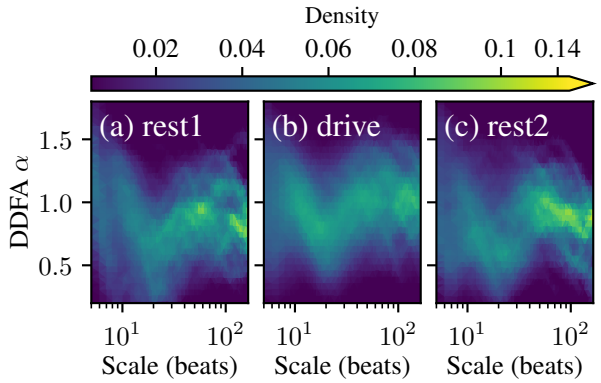

Figure 5. Aggregate distributions of the DDFA scaling exponents over all the subjects in rest1 (a), drive (b), and rest2 (c) segments. The color scale of the density is linear for densities 0–0.1 and logarithmic above this range.

5. Conclusions

Driving is a task that has highly individual effects on the HRV. Moreover, subjective responses to controlled rest periods complicate the establishment of reliable baselines. 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 reveal details and expose differences between the different segments overlooked by the conventional methods. Surprisingly, for some subjects the rest periods are characterized by anticorrelated behavior, which is commonly associated with physical exercise or cardiac diseases. However, DDFA reveals that these could be related to breathing and/or Mayer waves. It could therefore be worthwhile to complement conventional HRV measures with DDFA scaling exponents in forthcoming studies, particularly in cases where conventional methods do not yield discernible results.

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