MULTIFRACTAL ANALYSIS OF HEART RATE VARIABILITY IN SLEEP DEPRIVATION AND ALCOHOL INTOXICATION

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Abstract: We would like to present the results obtained from the signal of heart rate variability (HRV) in experiments motivated by practical needs of distinguishing the sleep-deprived individuals and individuals with alcohol intoxication from vigilant individuals with no sleep deficit. Namely these states are dangerous in traffic – accidents, car crushes are an epiphenomenon of tired, angry, sleep deprived or (in the worst case) drunken car drivers. Though some physiological signals may contain important information, classical methods (such a statistical or spectral analysis and also methods arising from low-dimensional chaos) do non imply unambiguous results; till this time no universal and easy to calculate descriptor for this purposes exists. We focused our attention to the heart rate signal, which is relatively easy accessible; both classical statistical and (multi) fractal HRV analysis was performed.

Introduction

It is clear that "degree" of sleep fatigue is measurable only indirectly, on the basis of measurement of a lot of signals carrying any information about fatigue. All symptoms extracted from these signals will be called the fatigue indicators. Especially in the last 10 years, statistical and spectral properties of inter-beat interval sequences (measured as the distance between two successive R-waves on an ECG record, RR) have attracted the attention of researchers, and it has been shown that heart rate fluctuations carry much more information about neuro-autonomic control that had previously been supposed.

Methods

In the experimental part, we have obtained 23 pairs of approximately 80 minutes long ECG records (sampling rate 500 Hz, resolution of the AD converter 16 bits). In each pair were one record from vigilant state and one record in alcohol intoxication or sleep deprivation. For the experimental and technical details see [3]; conceptual block scheme of our old experimental equipment with off-line data processing is shown on Figure 5. Original measuring equipment placed in car is shown on Figure 1, nowadays we are testing new miniaturized experimental version with real-time adaptive estimation of selected indicators.

Figure 1: Old experimental equipment with off-line analysis

The experimental data were preprocessed (filtration, segmentation) and heart rate variability signal was extracted. The basic idea of the fractal analysis of time-series is in quantification of self-similarity of rescaled segments of the signal. The integration (or accumulation) is the step that can be interpreted as the mapping of the original (bounded) series to the integrated signal with fractal behavior. In fractal signals the distribution is scale dependent and this dependency can be quantified using so called self-similarity indexes; in monofractal signals the dependency is exponential and it is possible to calculate one and only self-similarity exponent; on the contrary for the multifractal signals it's not possible and we must characterize signal using more local exponents of self-similarity.

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We have conducted classical statistical HRV analysis and then fractal and multifractal analysis. For this purpose we have used several different methods:

(1) classical statistical pNN50 and SDNN HRV indexes,

(2) the DFA-estimator - Detrended Fluctuation analysis, for details see, for example, reference [1].

(3) the WAV-estimator based on dispersion of the wavelet transform coefficients,

(4) the WTMM-estimator - Wavelet Transform Modulus Maxima, which represents so-called multifractal formalism.

Details on extraction of all computed parameters (algorithms) are summarized and described for example in [6].

Classical statistical methods for HRV analysis were insufficient, mono and multi-fractal analysis allowed rather distinctive differentiation of both states. The best results were given by the multifractal descriptor derived from the 3rd order distribution function. Well-known Gaussian formalism with the 2nd order statistical moments gives only the suboptimal results in case of heart rate fluctuations. We have not found significant mutual difference between the states of sleep deprivation and alcohol intoxication. The main advantage of introduced methodology may be in an automatic, absolutely noninvasive procedure and relatively easy accessible source signal (heart rate).

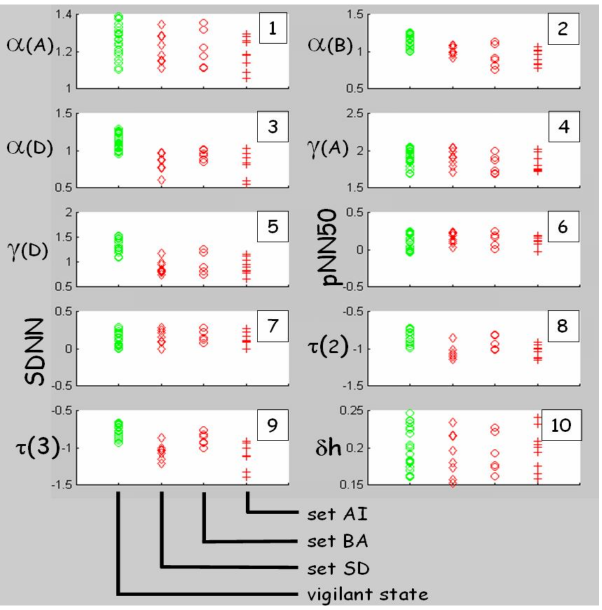

Figure 2: Discrimination ability of calculated HRV indicators, set AI – persons with alcohol intoxication (laboratory), set BA – sleep-deprived persons (3 days, laboratory), set SD – sleep-deprived persons (2 days, terrain experiment).

Results

(A) We present the results obtained from the signal of heart rate variability (HRV) in experiments motivated by practical needs of distinguishing the sleep-deprived individuals with alcohol intoxication from vigilant individuals with no sleep deficit (see [3] for details). Discrimination ability of such indicator is clear from Figure 2.

(B) We have designed, constructed and now we are intensively testing portable experimental equipment (partly on Figure 3), which will be able to utilize this theoretical methodology in practice. The system contains sensors for steering wheel movements, radial and axial acceleration of the vehicle and three types of sensors for heart rate detection.

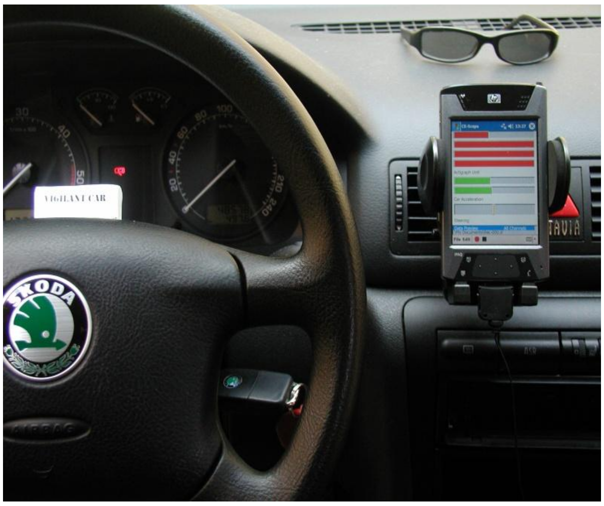

Figure 3: New experimantal equipment, real-time visualisation of estimated indicators.

The system is relatively simple to use and in the control unit of this system are implemented adaptive algorithms for early detection of mentioned dangerous states of the driver (alcohol intoxication or sleep deprivation); these algorithms are still under the development. Conceptual block scheme is on Figure 6; the algorithm of a block labeled 'classification' is currently derived from a classifier based on some parameters mentioned in [3]. The classifier is adaptive, with an adaptation time of not less than 40-60 minutes: the first approximately 15 - 20 minutes are necessary for the driver to adapt to driving under the given conditions, and the driver must undertake at least two 10-20 min. medium-term cycles, which can be seen in all measured parameters.

Such a classifier cannot be principally combinatorial because, as has been shown, a situation can occur when the current (short-term) value of a parameter on the classifier´s output is in such a position within the medium-term cycle that, e.g., a drowsy driver can be classified as alert (or vice versa). This fact is particularly important. We suspect that the slight

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inconsistency in the results of previous studies may be caused by this fact (known as aliasing). Now we will present a very brief description of an approach that we used to solve the mentioned problems: a fuzzy automaton (Figure 4) as interface between classifier and a visualisation unit.

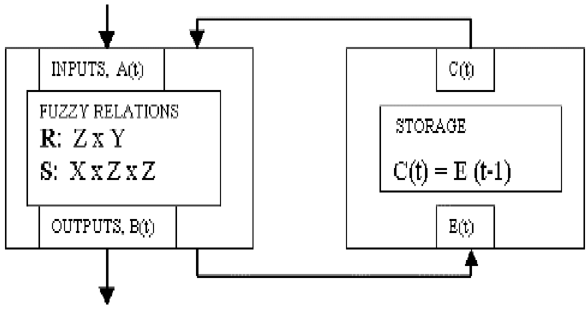

Figure 4: Block scheme of the fuzzy automaton. A=<X,Y,Z,R,S> , working frequency 60 s. X … set of input states, Y…set of output states, Z …set of internal states.

The main idea of this approach is based on the belief that most biological and bio-technical systems go through some "fuzzy" states during their lives. This means that the system must be in at least one state at the moment, but it can also be more or less in some other states (with another order of membership in "fuzzy" terminology). The current output of the fuzzy automaton depends on the past state and the current input through state-transition and output relations. Both fuzzy relations are represented by matrices and a simple max-min composition is used. In our case, specially modified values of the mentioned parameters (for example HRV indicators etc.) are used as input values of the fuzzy automaton. In our present simplified version, "special modification" means application of static threshold criteria and fuzzification. However, a much more sophisticated adaptive classifier can be used in this place.

The state-transition and output relations can be adjusted so as to obtain output states which correspond closely to the real evolution of the "fatigue states" of a driver (for example, if the automaton has passed the state which means a "high risk" of fatigue it cannot in the near future return to the "no risk" state, and must also be in some higher state not far from the "high risk" state). The number of internal states is not higher than 5; a major problem is that no exact method is available for determining the suitable state-transition relation. There are also some other problems with the functionality of the fuzzy automaton, e.g., the max-min composition that is used causes "bruising" of the fuzzy states, the setting of correct initial values to the fuzzy automaton is not easy, etc. On the other hand, software simulation of the fuzzy automaton is quite easy and fast (no more than 30 lines of C source code) and, likewise, the fuzzy automaton simulates the well known behaviour of many natural systems

Discussion

Our interpretation of the results of multifractal analysis of the heart rate concerns the configuration of biological regulatory systems. We used division into 3 levels of the control. This is not just theoretical construction but such procedure of multifractal analysis of the time arrays makes possible to quantify the crucial aspects which is documented by the comments for each of the control levels.

1. Strategical (planning) level. Characteristic lenght of the fluctuations of HR is hundreds to thousands of heart beats. Significant influence of sleep-deprivation and alcohol intoxication. No need for detail evidencing, long-term memory necessary. Localization: restricted areas in brain ?
2. Tactical (coordination) level. Characteristic lenght of the fluctuations of HR is tens to hundreds of heart beats. Low influence of sleep-deprivation and alcohol intoxication. Need for more detailed evidencing, earlier forgetting. Autonomous reflexive loops. Localization: modulla oblonghata, spinal cord ?
3. Operational (executive) level. Characteristic lenght of the fluctuations of HR is units to tens of heart beats. No influence of sleep-deprivation nor alcohol intoxication. Need for detail evidencing, immediate response in real time, early forgetting. Local feedback circuits, direct mechanisms. Localization: pacemakers, transmission heart system ?

This configuration leads to new understanding of physiological regulations different from compartment model for example, or from the homeostasis principle. In this new picture there would rather be the whole coordinated system of interrelated fluctuating regulatory loops that operates chaotically and far from the balance.

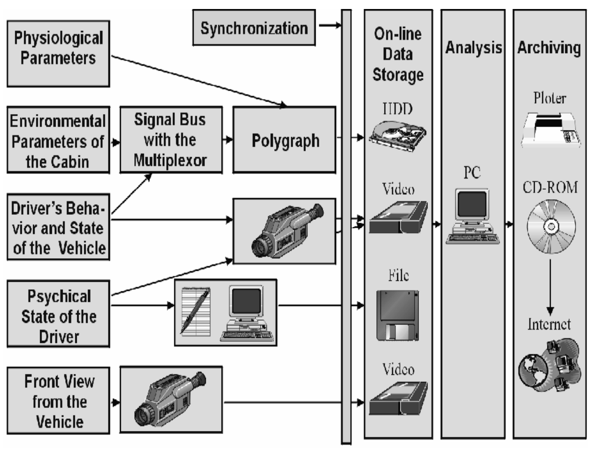

Figure 5: Conceptual block scheme of our old experimental equipment with off-line data processing.

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The multifractal analysis of HRV is a very convenient tool for inspecting the central nervous system, further investigations and development of this method will reveal more. It is clearly evident, for example, that adequate combination of selected indicators - on Figure 2 it were parameters τ(3) and α(D) – has better discrimination ability, see Figure 7.

Conclusions

Distinguishing between the vigilant and sleep deprived (or vigilant and intoxicated with the alcohol) persons using the fractal and multifractal analysis of heartbeat time series will be probably possible. On the other hand we have found no significant mutual difference between the states of sleep deprivation and alcohol intoxication. The length of fluctuations on which the discrimination occurs, coincides with the scales from hundreds to thousands heart beats. One important limitation emerges from this fact: at least 40-60 minutes of the ECG record are necessary for the sufficient discrimination.

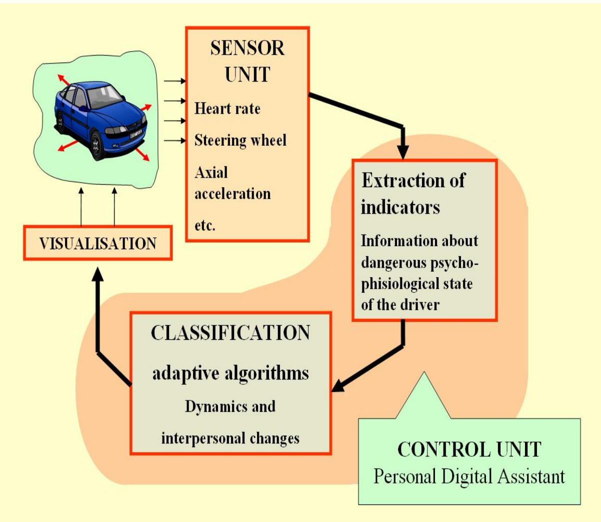

Figure 6: New experimantal equipment, real-time calculation and visualisation of estimated indicators.

Nevertheless we believe this methodology will be useful in practical situations in the traffic or industry. Proposed interpretation comes from the analysis of 23 independent datasets, so some (but no so far going) generalisations are convenient. In the near future it will be necessary to carry out more experiments in order to verify this methodology and, especially, its accuracy. For the first experimental group the results are quite promising.

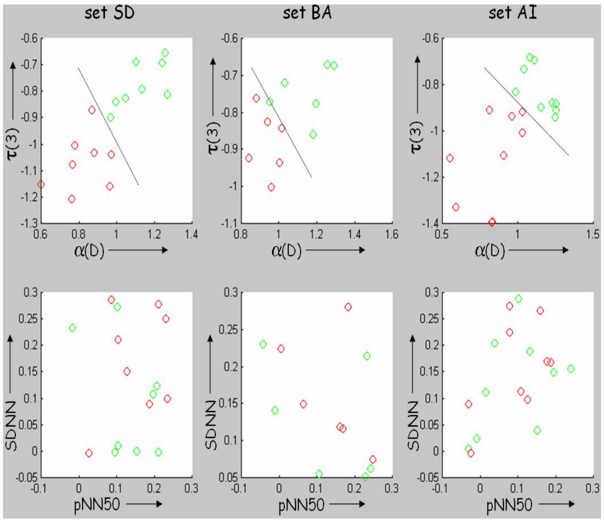

Figure 7: Combination of selected fractal indicators improved discrimination ability (up), in case of combination of classical statistical indicators the improvement was not evident (down).

Acknowledgement

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