Heart Beat Analysis for Estimation of Physical Load

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Abstract. The current physical load is proposed to be monitored and estimated by heart beat analysis based on the statistical analysis of accumulated and moving window data subsets with construction of kurtosis-skewness diagram. This approach was applied to the data gathered by the wearable heart monitor for various types and levels of physical activities, and for people with various fitness. The different physical activities, loads, and fitness can be distinguished from changes of heart beat distribution type on the kurtosis-skewness diagram. Some metrics for estimation of the instant and accumulated effect (physical fatigue) of physical loads were proposed that allow to derive models for explanation of the observed behavior by extreme value theory.

Keywords: Statistical Analysis, Physiological Signals, Heart Beat.

1 Introduction

Quantitative characterization and interpretation of the physiological signals is non-trivial task which attract attention of experts from various fields of science including medicine, biology, chemistry, electrical engineering, computer science, etc [1]. The main aim of this presentation report is to present the current work in progress that is dedicated to monitor and predict the type and level of physical load by the heart beat analysis during the physical exercises without information on limb and body accelerations in contrast to the widely used instant acceleration-based methods [2].

2 State of the Art

Estimation of the actual physical load and fatigue is of great importance nowadays in the context of human-machine interactions, especially for health care and elderly care applications [3,4]. Recently various techniques were applied to measure physical load, stress, and fatigue by heart-rate analysis, especially by measuring the heart period variability [5]. Usually, to recognize the type of the actual physical load the heart monitors are used along with other wearable sensors like accelerometers, power meters, etc [2], which give information on the instant state. To take into account the complex instant physiochemical and psychological state, the more complicated wearable devices like EEG-monitors and brain-computer interfaces are applied including various machine learning models [6-8]. In contrast, below the simpler and more available method for characterization of the actual physical load based on the heartbeat analysis by consumer gadgets is presented along with incentives for some models.

3 Preliminary Analysis

The proposed method is based on monitoring the human heart behavior in the simplest available way, namely, by heart beat/heart rate (HB/HR) monitor in consumer gadgets. Usually, HB/HR variability is high in a rest state, and it is much lower during an exercise, and this phenomenon is actively investigated to track and estimate stress states [5]. In contrast to the this well-known approach, the main idea of the method proposed here is to consider the time series of HB/HR values as statistical ensembles of values: a) accumulated from the beginning of the physical activity; b) contained inside the sliding timeslot window. These ensembles are processed by calculation of some parameters of statistical distributions (mean, standard deviation, skewness, and kurtosis). Finally, these statistical parameters are plotted on the Pearson (kurtosis-skewness) diagram (see below in Fig.1), where kurtosis values are plotted versus square of skewness [9]. The similar approach was successfully applied in various fields of science, including physics, materials science, finance, geoscience, etc. [9-11]. The measurements of heart activity during exercises were performed by Armour39 heart rate monitor by Under Armour with the attachment point at breast. For the initial feasibility study several persons of various fitness and age were involved in exercises like standing, walking upstairs, squats, dumbbells, push-ups.

4 Results

The time series of HB values were collected during various physical exercises and they were considered as statistical samplings. Then distributions of HB values in these samplings were analyzed (by calculation of mean, standard deviation, skewness, and kurtosis) and plotted on the Pearson diagram (Fig.1). For the better visualization the size of symbol grows with the time of experiment and the bigger symbols corresponds to the later time moments. The rose cloud of points denote the results of bootstrapping analysis in the standing position. In a standing position (red circles in Fig.1, left) the distribution of HB values is close to the normal distribution. Then with the start of the physical exercise (walking upstairs) the distribution of HB values (blue squares in Fig.1, left) moves away from the location of normal distribution (black asterisk in Fig.1, left), but confines itself in the region of beta-distributions (gray zone in Fig.1, left). After the end of exercises the HB distribution returns to the location of normal (black asterisk in Fig.1) and uniform (black triangle in Fig.1) distributions. The following metrics were proposed to characterize the accommodation and recovery levels during these exercises (Fig.2): the distance from the normal distribution (Metric1) and from the uniform distribution (Metric2) on the Pearson diagram.

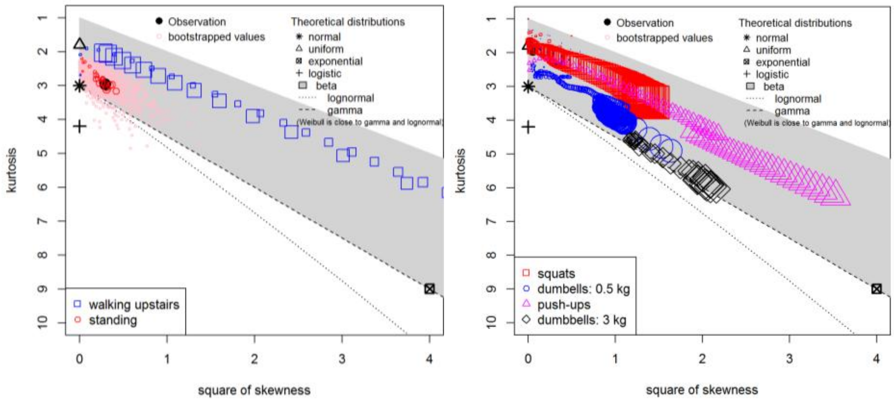

Fig. 1. The Pearson diagram for HB distributions vs. exercise time: for standing position and walking upstairs (left); for squats, dumbbells of various weights, push-ups (right).

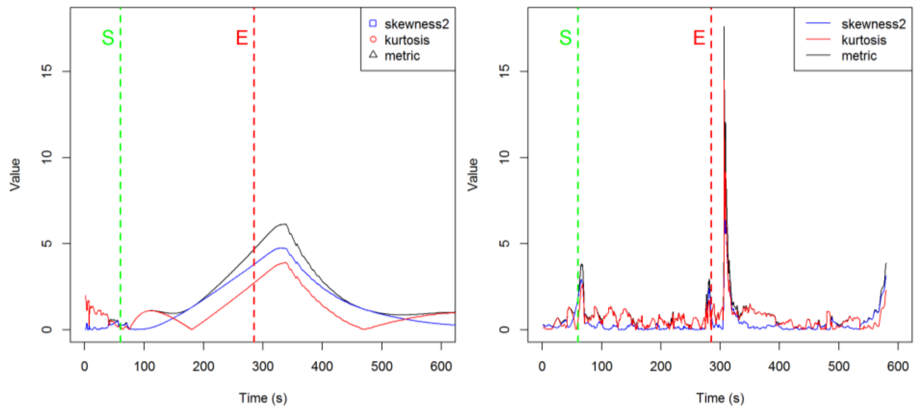

Fig. 2. Kurtosis, square of skewness, and Metric1of the HB distribution vs. exercise time: accumulated (left); contained inside the sliding timeslot window (right).

5 Discussion and Conclusion

The location of statistical ensembles of HB values is close to the location of the normal distribution in rest, but with time of exercises it moves away to others like beta-distribution, Weibull distribution, and gamma-distribution (Fig.1), and then return to the place of the normal distribution after the end of the exercises. From theoretical point of view this tendency can be roughly explained by the well-known extreme value models [11], where such change of distribution can be explained by appearance of correlation among neighboring events (HBs here) in contrast to normal distribution of HBs in a rest state. Now these results hardly have simple explanations especially as to influence of some specific experimental parameters (like age, gender, weight, fitness, mood, weather, etc.). But due to the recent success of various machine learning methods for analysis of the complex processes the incentive to apply some of them naturally appeared. The application of machine learning for the analysis of HB distributions is under work right now and the preliminary results will be published elsewhere in details [12]. But at this stage even the metrics proposed (Fig.2) can be used for monitoring and comparing levels of the physical loads and accommodation in addition to the well-known methods. The previous results shown that predictions are very sensitive to experimental parameters and the much larger datasets should be used. The further progress can be reached by sharing the similar datasets in the spirit of open science, volunteer data collection and processing [13-14]. In conclusion, the results on the change of HB distribution type under physical load allow to propose the new approach for monitoring and characterizing complex human activity patterns by widely available consumer gadgets, and give additional incentives for their modeling.

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