Analysis of Heart Rate Monitors for Evaluating Student's Mental Working Capacity

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Abstract. It is necessary to develop smart e-learning systems that can evaluate in real time not only student's knowledge, skills and experience, but also his functional state. The learning load and intensity should not lead to a reduction of student's functional state, including learner's mental working capacity. Student's functional state can be evaluated by analysis of heart rate variability, since heart rhythm responds to all changes in the human body and environment. There are a lot of devices for measuring heart rate variability, which called heart rate monitors. In massive e-learning more accessible monitors should be used but such monitors may not be sufficiently accurate. This paper studies three devices that can be used to estimate student's mental working capacity.

Keywords: e-learning systems · Student's mental working capacity · Heart rate variability analysis · Heart rate monitors

1 Introduction

The sophisticated smart e-learning system should be designed and developed as a smart student-centered biotechnical system with certain features of smart systems (sensing, transmission, big data processing, activation of actuators) and levels of "smartness" (adaptation, sensing, inferring, learning, anticipation, self-organization) [1]. Capabilities of the system depends on kind of learning algorithms and dimension of feedbacks, which are needed to realize adaptive learning as well as to preserve the health of students and to reduce the cost of achieved learning outcomes.

A student is a key component of thee-learning system. He has specific abilities to read, write, infer, learn, retain and use knowledge. The optimization of these activities involves obtaining the maximum learning outcome in the minimum time. However, this process can be effective and optimal under the condition that student's psychophysiological state (student's functional state) is optimal [1, 2]. The functional state is a set of characteristics of physiological and psychophysiological processes in many respects determining the level of activity of functional systems, working capacity and behavior of a person; it determines a student's ability to carry out a specific activity.

The learning load and intensity should not lead to a reduction of student's functional state, including student's mental working capacity (MWC). Hence the e-learning system should make an impact on a student (learning, training, quizzes, etc.) on the

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basis of information not only about achieved learning outcomes, but also about the functional state (Fig. 1). In order to evaluate student's MWC the heart rate variability (HRV) analysis can be used. There are a lot of various heart rate monitors for measuring HRV. These monitors will make available various methods of HRV analysis in e-learning: adaptive e-learning, identification of students, smart classrooms, and smart environments for learning [3–7]. In massive e-learning more accessible monitors should be used but such monitors may not be sufficiently accurate. In the paper we study three types of devices that can be used to evaluate student's functional state, including student's MWC: ECG recorder, electrical HR monitor, optical HR monitor. ECG recorder is a more precision device. HR monitors with electrical and optical sensors were examined in comparison with this device.

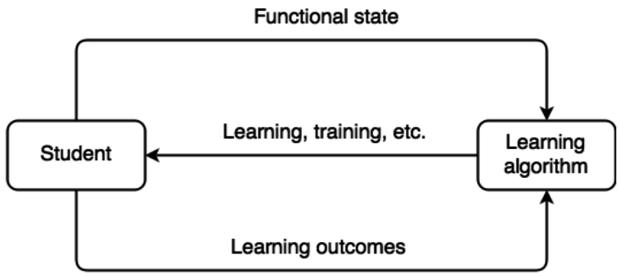

Fig. 1. e-Learning system

2 Student's Mental Working Capacity

In order to predict a reduction of student's MWC, it is necessary to distinguish the following MWC phases and corresponding degrees of regulatory mechanisms' tension:

(1) getting started with a certain tension of regulatory mechanisms;
(2) optimal MWC when the tension level of physiological systems corresponds to MWC;
(3) full productivity with possible initial signs of tiredness but without decrease of MWC;
(4) unstable productivity with clear signs of tiredness and decrease of MWC;
(5) progressive decrease of MWC with fast increase of tiredness and obvious decrease of learning efficiency.

HRV analysis is focused on monitoring of student's regulator mechanisms (a) before, (b) during, and (c) after learning. This method is based on (a) recognition and measurement of RR-intervals (Fig. 2) between the high-amplitude peaks of electrocardiogram (R-peak), (b) construction of time series of RR-intervals between two neighboring peaks, and (c) numerical analysis of obtained R-peak data. The most informative parameters of HRV analysis are (a) Heart Rate (HR), (b) Stress Index (SI), and (c) Index of Centralization (IC) [8].

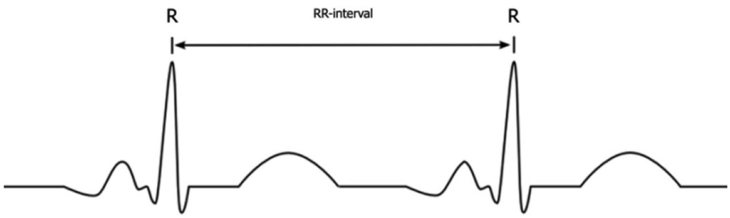

Fig. 2. RR-interval

The SI parameter is calculated based on the RR-intervals histogram:

$$SI = \frac{Amo \times 100\,\%}{2 \times Mo \times MxDMn},$$

where Mo – mode, Amo – mode's amplitude, MxDMn – variation range. The SI parameter is sensitive to increased sympathetic nervous system tone; as a result, a small physical, emotional or mental overload may increase SI values by 1.5–2 times.

The IC parameter is calculated based on the RR-intervals spectrum:

$$IC = \frac{VLF + LF}{HF},$$

where VLF – spectral density of RR-intervals in a very low frequency range, LF – in the range of low frequency, HF – in the high frequency range. It is associated with psycho-emotional stress and brain's functional state. Increasing IC means a rise in central control of heart rhythm.

As shown in [1, 2], parameters of student's psychophysiological state should be actively used in the advanced smart e-learning systems for more usability, higher efficiency of student's learning process, long-time retention of student's knowledge and learning outcomes. Based on obtained specific values of HR, SI, IC for a particular student for a particular learning assignment and range of "normal" values for this type of students the e-learning system will get additional useful criteria to smartly compile an individual learning trajectory for a student. In other words, it will be able to automatically generate an individual sequence of reusable information, learning objects and atoms, learning modules and assignments in order to provide maximum efficiency of student's learning process [9]. For example, each student in the online course gets a set of assignments for a new course topic on the specific level of complexity, and, if necessary, revised assignments for a previous topic in case IC parameter crossed the border (Figs. 3 and 4) [1].

3 Description of Heart Rate Monitors

The study included three devices that differ in types of sensors used and a number of estimated parameters: Varikard 2.51 (ECG recorder), Polar H7 (electrical HR monitor), and Mio Link (optical HR monitor). A comparison of the devices is shown in Table 1.

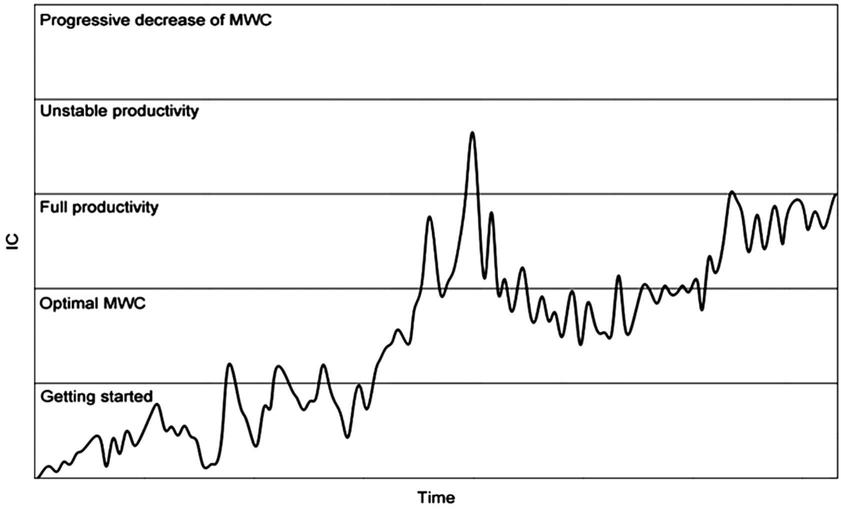

Fig. 3. Index of centralization

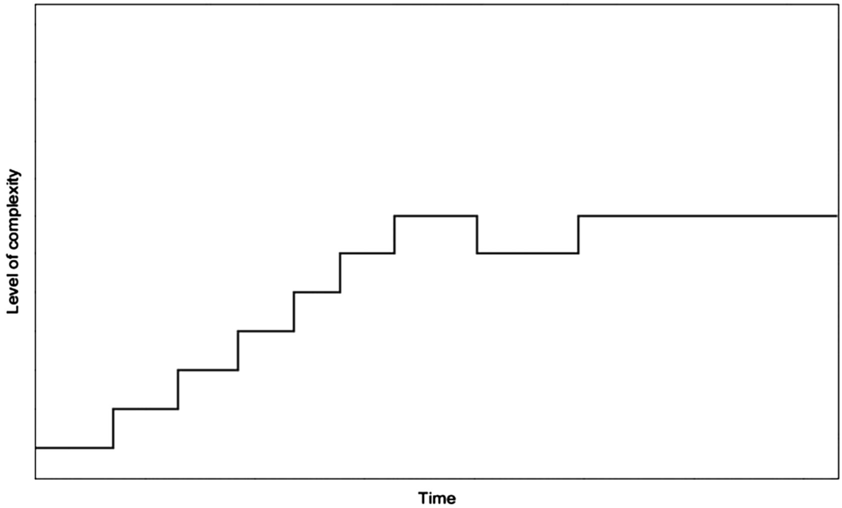

Fig. 4. Level of complexity

Table 1. Comparison of devices

	Varikard 2.51	Polar H7	Mio Link
Type of sensors	Electrical	Electrical	Optical
Connection type	Wired, USB	Wireless, Bluetooth	Wireless, Bluetooth
Data format	Electrocardiogram	Heart rate, BPM	Heart rate, BPM
Frequency data output	1200 Hz	1 Hz	1 Hz
Area of application	Medicine and science	Fitness and sport	Fitness and sport

The complex “Varikard 2.51”, which has been designed for the analysis of HRV, provides 40 various parameters that had been recommended by both Russian and European-American standards [8]. The complex is running under Microsoft Windows graphical operating systems, using the specialized software. It consists of a cardio amplifier associated with a computer via USB. Varikard provides the analysis of records with duration from several minutes to 24 h. At the same time some fragments of records which are needed to analyze HRV can be selected. The standard analysis is performed on the basis of five minute records. For measuring the potential difference electrodes are imposed on various parts of the body (Fig. 5). In order to improve an electrical contact with the electrodes a conducting gel is applied on the skin. The complex allows to obtain the RR-intervals and to carry out calculations of HRV in real time.

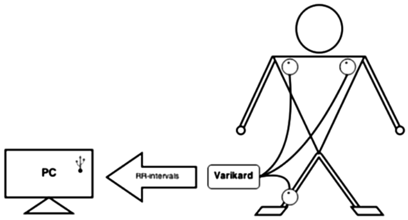

Fig. 5. Varikard 2.51

Polar H7 is the heart rate monitor that measures the electrical signals of the heart muscle. The electrode belt is fastened around the chest and transmits beats per minute (BPM) wirelessly via Bluetooth (Fig. 6).

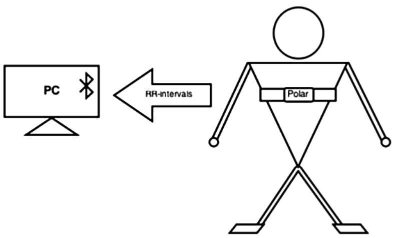

Fig. 6. Polar H7

Mio Link is the heart rate wristband. LED lights and an electro-optical cell sense the volume of blood under the skin. From there, sophisticated algorithms are applied to pulse signal so that heart’s true rhythm can be detected, even while running at performance speeds. BPM are transmitted via Bluetooth to a computer (Fig. 7).

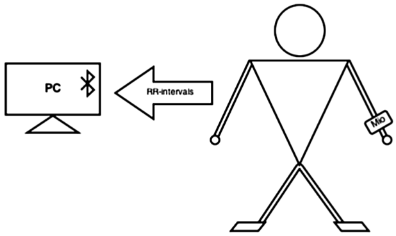

Fig. 7. Mio Link

Polar H7 and Mio Link heart rate monitors are compatible with Bluetooth smart devices that support heart rate service. These devices are used in fitness and sport in conjunction with exercise machines and fitness trackers.

4 Experimental Results

In the experiment nine subjects had participated. The timestamps and RR-intervals in milliseconds were received and stored from all three devices at the same time. Varikard 2.51 is considered as the most accurate source of RR-intervals. The obtained data shows that Polar H7 has slightly smoothed series of RR-intervals, and Mio Link has considerably smoothed series of RR-intervals in comparison with Varikard 2.51. And there is a time delay during transmission of the data from Polar H7 and Mio Link to a computer. For Polar H7 the time delay is 1 s, and for Mio Link – 6 s. In the experiment the data from all three devices were synchronized in time, i.e. the time delays of the devices were eliminated. For each subject and device the following parameters were calculated by using the data received during 300 s:

- Sample size – number of RR-intervals;
- Minimum – minimum value of RR-interval;
- Maximum – maximum value of RR-interval;
- Mean – mean of RR-intervals;
- Deviation– standard deviation of RR-intervals;
- SI – Stress Index;
- IC – Index of Centralization.

The calculations for some subject are shown in Table 2.

Two-sample t-test has shown that means of RR-intervals from the various devices for one subject are equal at the significance level at least 24 %. The mean probabilities, under the null hypothesis, of observing a value as extreme or more extreme of the test statistic are shown in Table 3.

The distribution of RR-intervals for the various devices corresponds to the normal distribution, but the form of the distribution for the various devices is slightly different (Fig. 8). Polar H7 and Mio Link provide a narrower range of RR-intervals, thereby showing a smaller standard deviation. To compare the distributions of RR-intervals a two-sample Kolmogorov-Smirnov test has been performed for all subjects under the

Table 2. Calculations of HRV

	Varikard 2.51	Polar H7	Mio Link
Sample size	327	300	300
Minimum	619	779	789
Maximum	1125	1090	1071
Mean	910	920	915
Deviation	91	64	53
SI	28	67	107
IC	2	8	12

Table 3. Two-sample t-test

	Varikard 2.51	Polar H7	Mio Link
Varikard 2.51	1.00	0.28	0.24
Polar H7	0.28	1.00	0.44
Mio Link	0.24	0.44	1.00

null hypothesis that the intervals of the various devices from the same continuous distribution. The mean probabilities of observing a value as extreme or more extreme of the test statistic are depicted in Table 4. The significance level was not less than 17 %.

Table 4. Two-sample Kolmogorov-Smirnov test

	Varikard 2.51	Polar H7	Mio Link
Varikard 2.51	1.00	0.66	0.17
Polar H7	0.66	1.00	0.23
Mio Link	0.17	0.23	1.00

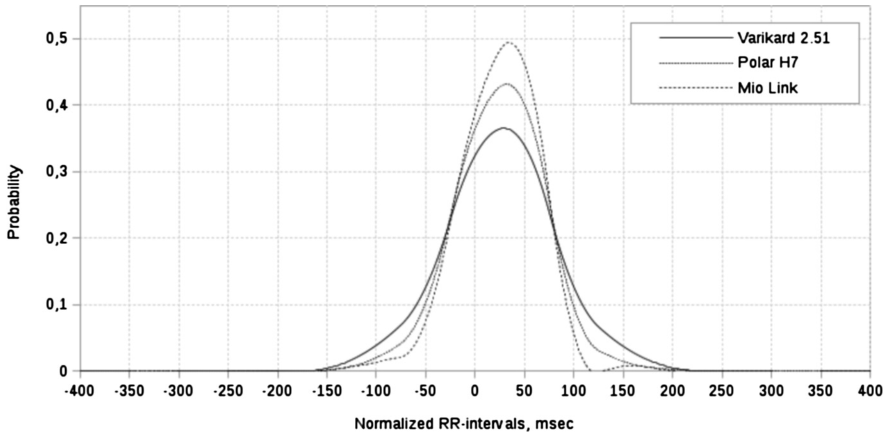

Fig. 8. Aggregated distributions of RR-intervals

Spectral analysis shows differences in the frequency characteristics of the output data for the various devices (Fig. 9). PolarH7 and Mio Link attenuate the signal in the high frequency range.

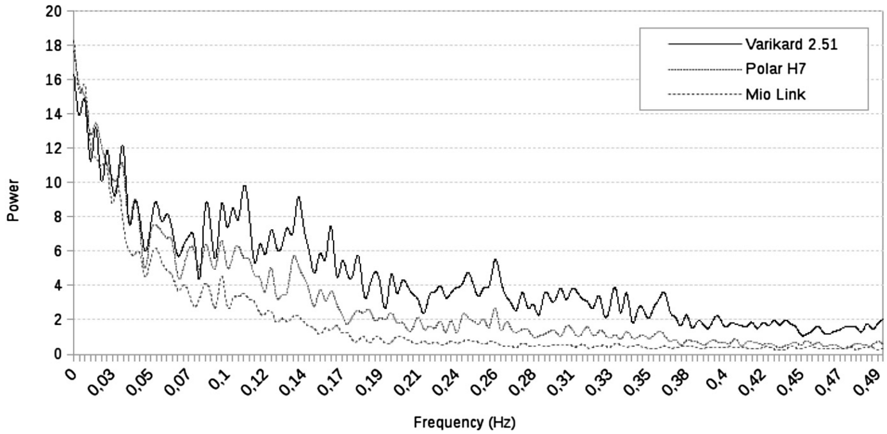

Fig. 9. Aggregated power spectral density

The comparative analysis of the dynamics in the indexes SI and IC which are calculated on the basis of the data from the various devices has shown a correlation between the indexes, although their values can vary considerably in numerical terms (Figs. 10 and 11).

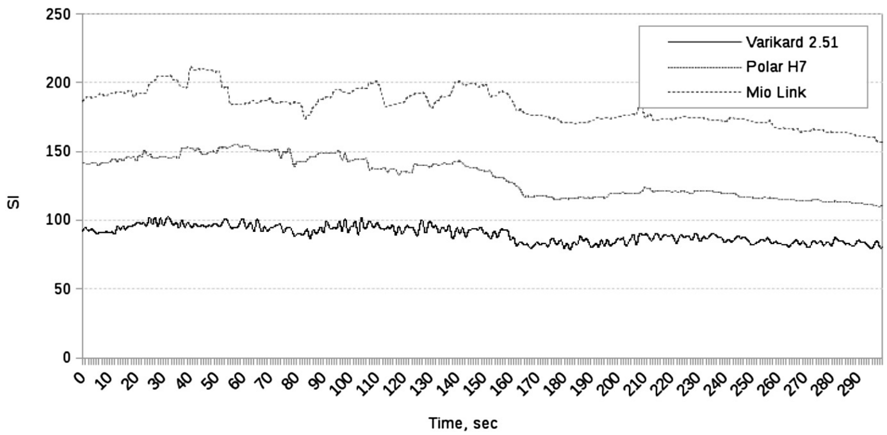

Fig. 10. Aggregated stress index

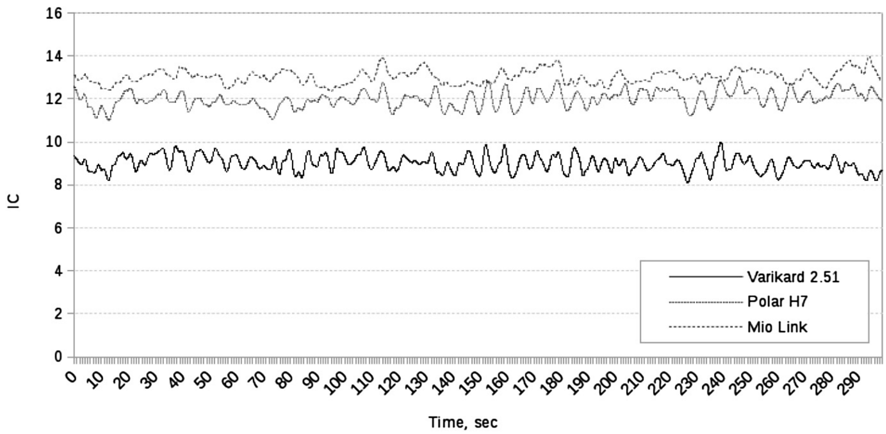

Fig. 11. Aggregated index of centralization

5 Conclusion

Based on the results of this study it can be concluded that the SI and IC that are calculated on the data from the various heart rate devices cannot be used at the same time. However, for the problem of measuring heart rate variability to provide biofeedback in the e-learning systems such devices as Polar H7 and Mio Link can be used. For this purpose, measuring background values of the indexes and then monitoring changes in values of the indexes over time with the same device are needed.

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