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Adaptive Techniques for Extracting Mental Activity Phases from Heart Beat Rate Streams

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Abstract. The paper presents algorithms for automatic detection of non-stationary periods of cardiac rhythm during professional activity. While working and subsequent rest operator passes through the phases of mobilization, stabilization, work, recovery and the rest. The amplitude and frequency of non-stationary periods of cardiac rhythm indicates the human resistance to stressful conditions. We introduce and analyze a number of algorithms for non-stationary phase extraction: the different approaches to phase preliminary detection, thresholds extraction and final phases extraction are studied experimentally.

Due to very significant differences between streams obtained from different persons and relatively small amount of data common machine learning techniques do not work well with our data. Thus, we had to develop adaptive algorithms based on domain-specific high-level properties of data and adjust parameters based on the preliminary analysis of the stream, making the algorithms adaptive and thus able to capture individual features of a person.

These algorithms are based on local extremum computation and analysis of linear regression coefficient histograms. The algorithms do not need any labeled datasets for training and could be applied to any person individually. The suggested algorithms were experimentally compared and evaluated by human experts.

Keywords. small data, adaptive algorithm, non-stationary data stream, signal processing, mental activity phases, phase separation

1. Introduction

There is a large amount of research devoted to the usage of heart rate variability (HRV) measures for monitoring of physiological arousal, attention, stress and general cognitive workload of operators in the process of real or simulated professional work [1, 2].

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Still, the majority of time and frequency domain measures of HRV that have been used are coarse-grained and do not enable identification of moment-to-moment changes of operator mental state in the course of activity. However in many cases it is important not so much to measure the generalized level of physiological arousal of an operator during the performance of professional tasks, as to identify the moments in time when arousal sharply increases, which can be caused both by objective factors, such as increasing task demands, and by psychological factors, such as decision-making difficulties [3,4]. It is known, that people respond to the increase of cognitive workload with increasing of heart rate (HR) and reduction of heart rate variability (HRV) [1,2].

These periods of sudden changes of HR and HRV parameters are usually called the non-stationary (transitive, unsteady) phases (NSPh), in contrast to stationary periods, that are characterized by stability of HR and HRV parameters over time [5]. In a number of studies it has been shown, that time and peak characteristics of non-stationary phases, registered under physical or mental stress, can be considered as informative indicators of stress resilience [3,5]. Meanwhile, absence of reliable algorithms for detection and analysis of non-stationary periods of a heart rate essentially complicates the progress of studies in this area.

Technically, the problem may be characterized as “small data”, rather than BIG DATA. Specifically, this means that the amount of available data is relatively small; hence, it is hard to expect high performance on any machine learning algorithm. Further, the differences between phases to be detected may be lower than differences between individuals. Thus, we have to estimate parameters of algorithms (such as thresholds) on the fly, based on incoming data stream. Several attempts to use known techniques (such as change point detection etc.) were tried on the preliminary phases of this research, but everything failed. Thus, we use an adaptive approach that takes into account specifics of each individual.

The approach of this work is to identify high-level properties of data during a state of interest. These properties are somewhat fuzzy. To improve performance, a cascade of algorithms has been used: after preliminary identification of phase intervals, a set of thresholds is calculated, and then the intervals are finalized based on these thresholds.

The contributions of this research include:

- An adaptive approach to design of stream analysis algorithms.
- A number of algorithms for extraction of high-level mental activity phases from a stream of low-level sensor readings (such as heart beat rate).
- A comparative analysis of performance of the proposed algorithms.

This paper is a revised and extended version of [6]. The main improvements are:

- The concept of adaptivity has been explicitly introduced for this class of problems.
- The psycho-physiological background is extended significantly.
- The presentation has been improved.

The rest of the paper is organized as follows. Section 2 briefly outlines the psycho-physiological background. Section 3 contains a description of the problem and outlines the approach. Section 4 outlines the algorithms, sections 5 and 6 describe the experimental environment and results, respectively. Finally, section 8 contains a brief overview of related work. Section 9 summarizes the results of the research.

2. Psycho-Physiological Metrics

Russian applied psychophysiology has accumulated rich experience in using various physiological measures to assess stress response of operators during simulation-based training [3, 7, 8]. Since as early as 1970s, systems such as Physiologist-M were widely used in Russia (USSR) for monitoring flight skills acquisition by pilots during simulation-based training. Research by the Aerospace Medicine Research Institute (Moscow) has shown that most promising physiological measures for using in simulation-based technologies are: heart rate, minute ventilation or respiratory minute volume, muscular force applied to control-stick grips, right forearm flexor electromyogram amplitude, respiratory rate, and attentional resource measure (secondary task performance) [7, 8]. For training in realistic conditions, the authors recommended to restrict measurements to heart rate, respiratory rate, respiratory minute volume and attentional resource measure, this set of measures considered to be enough for reliable assessment of operator workload during training tasks on a simulator. The Physiologist-M system could register three of these measures: heart rate, respiratory rate and respiratory minute volume. Attentional resource measure was evaluated by measuring speed and number of correct responses in a secondary task (the task being, when visually presented with two numbers, to react in one of two predefined ways depending on whether the sum of the numbers is even or uneven) [7].

The problem with this approach was that psychophysiological standards had to be defined for various operator skill levels. It was assumed that there is an optimal level of physiological arousal which depends on training conditions and content specific to an activity and reflects the state of body's physiological systems which is adequate to current demands. The optimal arousal level was characterized by the following criteria [9]:

- high speed and accuracy of performing work operations;
- long-term working capacity;
- short warming-up period, i.e. quick attaining of required performance efficiency level;
- stable behavioral performance;
- high functional resilience (quick recovery of physiological resources after stress loads).

These criteria were used as preliminary goals when assessing physiological and behavioral performance of students during simulation-based training [7, 8].

Kozlovsky and Zhernavkov (1981) have proposed a simple method for assessing pilot's physiological responses by comparing work vs. rest values of physiological measures during different training scenario stages [7]. Normative values (in percent) and allowable deviations were defined for most informative physiological measures (heart rate, respiratory rate, respiratory minute volume, attentional resource) for main flight phases (take-off, ascent, level flight, descent, landing). This allowed to assess physiological cost, i.e. amount of effort expended by a student to complete these flight phases on a simulator.

A substantial drawback of this method is that averaging is performed over 3-5 minute intervals. It makes the method unsuitable for assessing short-term physiological responses to increased task demands or to stressors introduced during training.

Many studies focused on finding physiological criteria of skill acquisition by pilots during training [3,10]. It has been found that flight skills acquisition process has several stages. During initial stages of training, performing simulation-based tasks is associated with excessive physiological arousal. Amount of mental efforts expended by novices is usually inadequately high for task difficulty level, which results in high task physiological cost and thus low task performance efficiency. With skills improving, performance improves while task physiological cost gradually decreases. At final stages of training, students demonstrate high task performance efficiency, while their physiological responses reduce and stabilize [10].

3. The Problem and Approach

The data used for our computational experiments contain recorded streams of heart beat rate readings in a training center. Each file contains a recording for one individual during approximately half-hour training session. Each session consists of several periods when trainees were performing certain tasks (sometimes called work intervals below) interleaved with relaxation. The heart beat rate is recorded 4 times per second. Under the terms of the study, the moments of the beginning and end of work are known.

Psychologists found that during the execution of work and rest, the subject passes through phases of Mobilization, Stabilization, Work, Recovery (or rehabilitation) and the Rest. It is important to note that the phases of mobilization, stabilization and work are the steps of task execution, while the recovery phase and rest belong to repose stage. Figure 1 shows the heart rate of one subject with manually marked time intervals corresponding to the above phases.

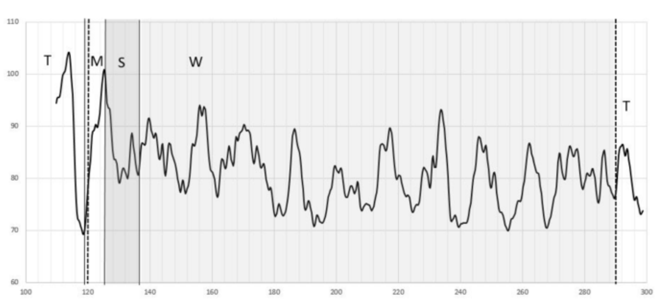

Figure 1. Example heart rate graph with automatically selected phases

The following high-level properties of heart beat rate stream were identified during preliminary analysis performed together with a team of psychologists [11, 12]:

- Mobilization (M)
  - heart rate stable increases (noticeable in comparison with normal fluctuations)
  - starts at task receiving (with possible short-term delay or advance)
  - the average value of the heart rate is higher than in the resting phase
  - the variation of the heart rate is lower than in the resting phase
- Stabilization (S)
  - the heart rate decreases
  - the average value of the heart rate is higher than in the resting phase
  - the Variation of the heart rate is lower than in the resting phase
- Work (W)
  - the average value of the heart rate is higher than in the resting phase
  - the variation of the heart rate is lower than in the resting phase
  - Ends at the time of the termination of task execution (with possible short-term delay)
- Recovery (R)
  - heart rate decreases
  - the average heart rate is higher than in resting phase
  - the variation of the heart rate is lower than in the resting phase
  - starts after the task execution has finished (with possible short-term delay)
- the Rest (T)
  - relatively low average heart rate (comparatively with other phases)
  - relatively large variation in heart rate (comparatively with other phases)
  - Ends at the time of assignment (with possible short-term delay or advance)

Although the properties listed above seem to be (and actually are) imprecise, vague, and fuzzy, they enable us to construct an algorithm extracting the most important phases with reasonable precision comparable with precision of human experts.

We focused on the selection of phases of mobilization, stabilization and work, because of task execution is more significant from the point of view of practical use.

4. Methodology

The adaptive approach enables us to obtain reasonable quality of mental phase identification without any massive training due to pre-defined high-level properties of phases to be extracted.

Our techniques for phase boundary consist of three main stages: preliminary allocation interval, the automatic determination of thresholds and refinement of intervals. A notable feature of our approach is its ability to automatically adapt to every particular person without any prior learning on other people; to take into consideration physiological characteristics of different people.

Due to non-stationary nature and in presence of measurement errors, as well as missing measurements, many traditional techniques for signal stream analysis, such as Fourier transformations, do not work well on available data.

4.1. Preliminary Interval Extraction

From all source points algorithm selects the most suitable for the phase boundary role, that is, the entire original time period is separated into preliminary segments for further processing.

No Straight The initial allocation interval is trivial, every point equally applies to the role of the phase boundary and is considered in the final stage.

Uniform partition The initial line segment is divided into a sufficiently large number of intervals of equal length — the preliminary intervals.

Local extremes Algorithm finds extremum inside the symmetric "window" of some length as local extremum. In the described experiments, the "window" length equals 21 (10 samples left and 10-right). Obtained local extremums were considered subsequently as the initial ends of the intervals.

4.2. Calculation of Thresholds

The goal of the second stage is to calculate thresholds to be used in the last stage as discriminators. Than is, the thresholds refine the imprecise properties of mental phases based on data specific for each trainee.

For example, it is necessary to find out which values of the slope of the linear regression should be considered as a significant increase (characterizing mobilization phase), and which values should be considered as slow descent, i.e., stabilization. To do this, the algorithm determines the lower and upper (sometimes — only the upper) thresholds of the coefficient of the linear regression of the work phase as it is characterized by a near zero coefficient of linear regression.

Clustering algorithms The algorithm calculates the lower and upper thresholds of the linear regression coefficient with clustering [13] values for all preliminary prefixes (the prefix with ends in a selected at the first stage points) clusters. The boundaries between the obtained clusters are upper and lower thresholds.

Histogram analysis The algorithm starts with building a histogram on values of the coefficient of the linear regression on all preliminary prefixes. Then we find maximum, since the most common value usually is close to zero and corresponds to the work phase — the longest phase. After that, all the neighboring intervals having non-zero height are concatenated into a single interval, whose ends are considered as the lower and upper thresholds of the coefficient of the linear regression of the work phase, respectively.

Coefficient of linear regression The algorithm constructs a histogram of the linear regression slope coefficients on the preliminary prefixes. Then we find the maximum point; as a rule, it is a small positive number that corresponds to "long" with the prefix ends in the second half of the task. Then to the right of the maximum point we calculate the minimum point of the histogram, which right boundary is the upper threshold of the phase of work.

4.3. Refinement of Intervals

At this stage, the preliminary intervals obtained at the first stage are processed using thresholds computed automatically in a second stage, for final selection of the phase boundary. This stage consists of two steps: extraction of boundary mobilization–stabilization and stabilization–work.

4.3.1. Mobilization–Stabilization boundary detection

The algorithm calculates the coefficient of linear regression on the preliminary prefix. The boundary between mobilization and stabilization is carried out at the right end of the prefix, which linear regression coefficient is greater than the threshold, determined automatically at the previous stage, and the heart rate value on the right end is maximal.

Let PI be a set of preliminary extracted points, $\beta_{\text{prefix}}(x)$ — linear regression coefficient for the first x points in seria and $\mathrm{HR}[x]$ — the heart rate value in the specified point. Denoting the threshold determined in the second stage as θ, we can determine the boundary between mobilization and stabilization as

$$\underset{x \,\in\, \mathrm{PI} \,\&\, \beta_{\text{prefix}}(x) \,\geq\, \theta}{\operatorname{argmax}} \mathrm{HR}[x].$$

4.3.2. Stabilization–Work boundary detection

Suffix The algorithm calculates the coefficient of the linear regression on the suffixes with the left ends at the points obtained at preliminary selection of the intervals. The intended separation between stabilization and work is done on the left border of the suffix of the coefficient of linear regression which has the minimum modulo.

If PI is a set of preliminary extracted points and $\beta_{\text{suffix}}(x)$ is linear regression slope coefficient for the last x points in seria, then stabilization–work boundary is

$$\underset{x \,\in\, \mathrm{PI}}{\operatorname{argmin}} |\beta_{\text{suffix}}(x)|,$$

Local minimum on prefix The algorithm calculates the coefficient of linear regression on preliminary prefix. We select the boundary of stabilization phase in the right end of the prefix, if the value of the coefficient is a local minimum among the coefficients of linear regression on the received prefixes. If we have several local minima, we select the leftmost inside the interval of the task executing (since minimum before working probably predates the growth of the HR during mobilization phase and refers to the resting phase).

Denote a set of preliminary extracted points as PI and the linear regression coefficient for the first x points in seria as $\beta_{\text{prefix}}(x)$. In this case we can compute the boundary using the following formula:

$$\operatorname*{argmin_{loc}}_{x\ \in \mathrm{PI}} \beta_{\text{prefix}}(x).$$

The techniques outlined above can be used on different modes depending on the amount of data used for calculation of thresholds. If the data stream is recorded, the entire file may be used in off-line mode. To process actual stream, a window must be specified for on-line mode. Note, however, that the window size must be at least greater than the duration of a task.

The off-line mode is expected to produce better results and is applicable in practical cases such as evaluation of trainees after a training session. Of course, the algorithms cannot be used for automatic evaluation of trainees, they only can find out who of trainees requires more attention of trainer or evaluator.

5. Experimental Evaluation

The purpose of the experimental study of these algorithms is to obtain information about the results applicability based on expert estimates. As a numerical characteristic of the algorithm quality, we used precision, defined as the proportion of tasks with properly selected phases.

All experiments were performed in off-line mode.

We evaluated algorithms with data containing the heart rate readings of 63 operators, each operator completed 5 tasks of MATB [14] and FTP [15] computerized aviation simulation tests. Heart rate was recorded 4 times per second, and the entire test lasted 1375 seconds, that means we had 5500 points for each person.

Data were obtained on three groups of operators (trainees):

- E0 — 15 specially trained "experts" having extensive experience in performing tasks;
- U0 — 25 "newcomers" who carried out tasks for the first time;
- U1 — 23 "newbie after training", a little trained but not specially prepared.

Table 2 contains mean, variance and range of data across these groups.

5.1. Preliminary Experiment

Because of variability at all stages of the proposed approach the number of combinations of algorithms is quite large, we must do initial testing on a smaller amount of data to reduce many of the methods discussed in further experiments. During these experiments, we assessed all possible combinations of realizations of the stages of the above algorithm applied to data of the first experiment all subjects from the group of experts to identify the most successful approaches for further work.

At the preliminary stage the data of experts were used, since this group has most clearly expressed phase activity due to the fact that they are the most trained of all operators and less prone to stress. This makes it easy to evaluate the results of the algorithms — the initial phase is usually visible to the layperson. So it's enough quite a visual analysis of graphics with a dedicated algorithm phases, to evaluate results without any additional expert assessments.

5.2. The Main Experiment

1. **No straight + local minimum on prefix:**
   Preliminary selection of the intervals is not performed, the boundary between mobilization and stabilization is determined with the threshold value of the coefficient of the linear regression is automatically determined by the method of coefficient of linear regression, and the boundary stabilization–the work is by finding the local minimum of the regression coefficient on the prefixes;
2. **Local extrema + suffixes:**
   the preliminary ends are at the points of local extrema, boundary mobilization–stabilization is determined with the threshold value of the coefficient of the linear regression is automatically determined by the method of coefficient of linear regression, and the boundary stabilization–work — by means of suffixes;
3. **Local extrema + local minimum on prefix:**
   The preliminary ends are at the points of local extrema, boundary mobilization–stabilization is determined with the threshold value of the coefficient of the linear regression is automatically determined by the method of coefficient of linear regression, and the boundary stabilization–the work is by finding the local minimum of the regression coefficient on the prefixes.

In this experiment, the algorithms were applied to all available data: five assignments of examinees for each of the three groups — using expert assessments for more detailed analysis of methods.

6. Results of Experiments

Table 1 shows the percentage of successfully selected phase among all tasks, the percentage of tasks where domain experts weren't able to identify phases, and the percentage of correct algorithmic identifications in the subset of successfully analysed manually by experts.

It should be emphasized that for some subjects, the experts were not able to identify phases in some tasks, so the table shows the estimation accuracy with and without these tasks.

Table 2 contains mean values of length and linear regression coefficient for mobilization (M), stabilization (S) and work (W) phases that were calculated with No straight + Local minimum on prefix. Table 3 contains mean values of length and linear regression coefficient for mobilization (M), stabilization (S) and work (W) phases that were identified by experts.

Table 1. Results of the algorithms

Group	Automatically detected phases	Not detected manually	Automatically detected among manually detected
No straight + Local minimum on prefix			
E0	0.57	0.14	0.67
U0	0.54	0.13	0.63
U1	0.58	0.32	0.86
Total	0.57	0.21	0.71
Local extremes + Suffix			
E0	0.08	0.15	0.09
U0	0.07	0.13	0.08
U1	0.07	0.32	0.10
Total	0.07	0.21	0.09
Local extremes + Local minimum on prefix			
E0	0.47	0.15	0.55
U0	0.34	0.14	0.40
U1	0.36	0.32	0.53
Total	0.38	0.21	0.48

Table 2. Phases characteristics (all calculated)

Group	E0		U0		U1	
	avg	median	avg	median	avg	median
Length of phase						
mobilization	13.75	13.20	17.15	16.95	13.46	12.58
stabilization	14.80	13.45	15.55	13.20	12.02	11.18
work	158.38	158.05	153.99	158.50	160.77	162.60
Linear regression coefficient on						
mobilization	1.70	1.73	1.81	1.81	2.12	1.76
stabilization	-1.16	-1.19	-1.34	-1.22	-1.75	-1.57
work	-0.0044	-0.0059	-0.0029	-0.0064	-0.0027	0.0017

7. Recalculating of the Thresholds

To study the impact of the previous tasks on the current performance results, we developed the following algorithms for calculating of the thresholds using previous task data. Table 4 contains mean values of length and linear regression coefficient for mobilization (M), stabilization (S) and work (W) phases that were identified by No straight + Local minimum on prefix algorithm using thresholds calculated with these recalculating algorithms.

7.1. Recalculating of the Thresholds for Every Tests Data

In this series of experiments the threshold of the coefficient of the linear regression on each task is computed without using the results of previous tasks.

Table 3. Phases characteristics (experts' approved)

Group	E0		U0		U1	
	avg	median	avg	median	avg	median
Length of phase						
mobilization	13.29	12.37	14.04	15.50	12.46	11.77
stabilization	13.87	14.75	15.96	12.83	11.70	10.75
work	159.99	158.56	156.83	160.88	161.98	163.28
Linear regression coefficient on						
mobilization	1.24	1.50	1.48	1.75	2.01	1.52
stabilization	-1.28	-0.87	-1.33	-1.04	-1.85	-1.17
work	-0.0030	-0.0059	-0.0027	-0.0065	-0.0036	0.0027

7.2. Using the First Calculated Thresholds

In this series of experiments the threshold of the coefficient of linear regression is evaluated once according the results of first task processing for each operator. Further, this threshold is used when selecting phases of all tasks of this trainee.

7.3. Use of the Thresholds, Calculated on the Previous Test Data

In this series of experiments the threshold regression coefficients for 2-nd etc tasks were obtained from the results of processing the previous task of current trainee. The 1-st threshold was calculated during the processing the first task.

8. Related Work

The HRV metrics were widely used in the psycho-physiological domain [7, 8] for stationary states, in contrast, we analyze non-stationary streams of HR recordings.

The problem of separation of the phases of mental activity belongs to the class of tasks in the study of brain activity, most of which are investigated on the basis of data analysis ECG, EEG, heart rate [16]. There are several different approaches to processing the above data and other streaming data: a wavelet transformation, machine learning techniques, finding points of change. The choice of approach is determined by the nature of processed data and the features of the task. In our problem the techniques listed above are not applicable due to high amount of noise, relatively small amount of data, and too high variability of data.

Specifically, for example, data processing of ECG and EEG is typically associated with the wavelet transform [17–19]. But such a transformation cannot be applied to heart rate due to the rapidly oscillating data, and also because of errors and failures in data that is highly sensitive Fourier transform.

Machine learning algorithms, most common approaches to data analysis, can be applied to the study of mental processes, for example, to classify brain activity [17, 20]. However, all previously used techniques are based on learning and, therefore, require a large amount of data labelled in advance, which makes them

Table 4. Phases characteristics (different thresholds recalculating algorithms)

Group	E0		U0		U1	
	avg	median	avg	median	avg	median
Recalculating of the thresholds for every tests data - length of phase						
mobilization	13.67	12.75	17.15	14.00	13.40	10.00
stabilization	14.73	11.75	15.55	10.75	11.69	9.75
work	158.38	162.35	153.99	161.75	161.27	165.25
Recalculating of the thresholds for every tests data - linear regression coefficient						
mobilization	1.70	1.23	1.81	0.98	2.02	1.22
stabilization	-1.16	-0.88	-1.34	-0.83	-1.80	-1.27
work	-0.0044	-0.0053	-0.0029	-0.0014	0.0036	0.0043
Using the first calculated thresholds - length of phase						
mobilization	23.95	13.50	18.23	13.00	22.34	10.00
stabilization	15.94	11.75	15.07	10.05	12.10	9.75
work	146.90	161.25	153.38	161.75	151.91	165.00
Using the first calculated thresholds - linear regression coefficient						
mobilization	1.49	0.84	1.70	0.97	1.97	1.12
stabilization	-1.21	-0.91	-1.33	-0.90	-1.75	-1.26
work	-0.0094	-0.0082	-0.0070	-0.0019	-0.0113	0.0026
Use of the thresholds, calculated on the previous test data - length of phase						
mobilization	19.75	13.25	22.88	16.75	20.49	10.00
stabilization	15.99	11.75	15.63	10.75	11.75	9.50
work	151.05	159.75	148.18	157.00	154.12	164.50
Use of the thresholds, calculated on the previous test data - linear regression coefficient on						
mobilization	1.58	1.15	1.50	0.72	1.94	1.12
stabilization	-1.14	-0.85	-1.27	-0.80	-1.81	-1.27
work	-0.0039	-0.0049	-0.0110	-0.0036	-0.0004	0.0034

not applicable in this problem because the nature of the behavior of heart rate varies between individuals and depending on the type of the job.

At the first glance, the algorithms for points of change (change point detection) [21–23] could be helpful for the problem of mental activity phase detection (since the behavior of the data at the boundary of two phases is changed). However, they are designed under assumption of more or less smooth behavior of the trend that is not valid for our data. An attempt to use these algorithms in our problem did not give meaningful results.

9. Conclusion

In this work, we propose adaptive techniques for analysis of small data and describe a number of algorithms for processing streaming data containing measurements of heart rate (HR) in performing the work, to identify the phases of mental activity taking into account individual psychophysiological characteristics of each subject. We proposed a three-stage algorithm to solve this problem without prelabeled data with only General knowledge about mental phases. The algorithm allows to distinguish the phase of mental activity considering the physiological and psychological characteristics of each person.

A comparison of several variants of this scheme was done by running algorithms on real data with subsequent assessment of their quality by specialists in the subject area. Best results were achieved by a method based on the analysis of the behavior of the coefficient of the linear regression, approximating the heart rate, on the prefix.

The proposed allocation algorithms phase metal activity are useful for many important practical applications, including:

- systems of automatic monitoring of mental status of different professional groups (air traffic controllers, pilots, etc.) when performing critical operations;
- adaptive human-machine interfaces and cognitive support systems of human activity;
- methods of assessing the level of fitness of personnel and their resistance to influence of factors of physical and mental stress;
- systems of diagnostics of disorders of mental activity in various neuropsychiatric diseases;
- online medical information assistance services [24];
- healthcare systems [25].

For future work an application of adaptivity to other small data problems combined with more sophisticated machine learning techniques may be investigated.

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