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Determining Importance of Physiological Parameters and Methods of Their Evaluation for Classification of Pilots Psychophysiological Condition

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Abstract— **At present, several studies exist describing the relevance of human factor in air transport with main focus on pilots and flight safety. Within such studies, monitoring of physiological functions is used. There are lot of physiological parameters and methods of their assessment; however, they are mostly based on principles originating from clinical practice. Yet, sensitivity and specificity of these methods with regard to assessment of aviation professionals - pilots is unknown. Therefore, this paper is oriented towards description of the most common methods for physiological parameters assessment. The paper also describes evaluation methods, which are on experimental level in terms of physiological data evaluation, namely recurrent quantification analysis. Within the research carried out, sample group of pilots was subjected to measurement for evaluation of their psychophysiological condition and performance. Selected evaluation methods were applied on the collected data and importance of those parameters and methods, which provided best classification for level of psychophysiological stress, was evaluated by means of statistical analyses. The results indicate that the most important physiological parameter for psychophysiological condition assessment of pilots is heart electrical activity where the possibility to perform signal processing whilst preserving its importance is provided by linear methods in the time and frequency domain, or alternatively by non-linear methods utilizing recurrent quantification analysis.**

Keywords— **air transportation; biomedical signal processing; biomedical telemetry; decision trees; nonlinear dynamical systems; regression analysis**

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I. Introduction

In the domain of aviation, whether military of civil transport, operators are making efforts to achieve maximum comfort and safety for passengers. Available statistical data dealing with aviation accidents are varying in the number of accidents and their causes, but it is possible to claim that pilot error contributed to 60 % of fatal accidents. For example, according to the statistics of PlaneCrashInfo [1], 58 % of aviation accidents from 1/1/1960 up to 12/31/2015 was caused by fatal piloting errors. Most of these errors occur during landing phase, but almost 28 % takes place during routine flight phases [1].

Piloting errors are caused by different factors, for example by fatigue accompanied with reduced attention, stress, pilots' psychical condition and also by insufficient experience with critical situations. Timely recognition of limit pilot fatigue, drop of situational awareness or stress by means of monitoring physiological parameters could prevent aviation accidents. This stems from the fact that during a flight, number of specific effects influence human organism and they depend on physical properties of the surrounding environment, aircraft technical properties, demanding character of required activity as well as mutual influence of the mentioned and other effects on physiological functions [2]. It is possible to obtain information about pilot's psychical and physiological condition [3] by measuring his/her physiological parameters.

There were lot of studies with the goal to improve safety and effectivity of military and civil aviation flying regarding its control and monitoring [4], [5]. In this sense, most of the studies were focused on mental and physical condition of aviation professionals (pilots, air traffic controllers etc.) by means of monitoring heart rate, breathing, blood pressure, blood saturation with oxygen, electrodermal activity etc. [6], [7], [8], [9]. Stress emerging from actual situation, which respective subject is confronted with, plays the key role [10]. Physiological function, such as heart rate, unfold from this condition, originating from human neural system. Part of the neural system is autonomic neural system (ANS), consisting of parasympathetic and sympathetic elements, which serve control of internal organs activities. Even small deviations from the so-called sympathovagal balance may be caused by stress situation. Therefore, it is important to timely identify changes in ANS and take adequate measures to reduce or eliminate stress situation and its negative effects on human activity.

In this way, many studies concentrate on individual parameters, which may have insufficient explanatory value, but the measurement of physiological parameters is more effective if multiple physiological measurements, which are mutually relevant, are merged. Analysis of such data and subsequent possibilities are extensive and there are many methods for biological signal processing; important is, however, which parameter is concerned, how to measure it and how to process such signal. Nevertheless, ordinary and clinically utilized systems appear not suitable for recording of such signal during performance of piloting activities. For majority of cases, the reason is their robustness and potential restrictions for working activities. With regard to this, mobile biotelemetry systems come to the fore which are, due to the mentioned reasons, used also in this study.

Based on the above-mentioned, experimental measurements were carried out to identify optimal usage of measured physiological parameters and methods of their evaluation to describe psychophysiological condition of pilots. Within the presented research concept, monitoring of piloting precision was used as comparative indicator of pilot’s stress and performance.

II. Materials and Methods

A. Participants

For the purpose of this study, selection of candidates from students of Technical University in Košice was performed. The goal was to select representative sample of subjects (consisting of beginners) with the largest level of uniformity possible. The selection was conditioned by meeting selection criteria, which consisted of successfully passing psychological and intelligence tests. Intelligence tests were focused on aviation regulations and basics of flight. Apart from that, participants had to meet the criteria for medical fitness according to Commission Regulation (EU) No 1178/2011, Annex IV [11] and could not be holders of a pilot license of any type (ULL, PPL or higher). This way, 35 subjects were selected (27 men and 8 women of average age 2 $\pm$ 4 years), who met the above-mentioned criteria.

B. Measurement Procedure

The general measurement methodology, regarding flight execution and evaluated subjects, was the same as in the previous study (see [12]). First part of the training took place on TRD40 flight simulator equipment, second (real flights) was executed on Diamond DA40 aircraft. During individual flights, the participants had to perform three precisely defined flight manoeuvres series during which they had to maintain prescribed flight parameters. Each of the series consisted of four flight tasks in predefined sequence: horizontal steady flight (HPL), horizontal 360° turn (H360) with 30° bank angle, 180° climb and descent turn with 15° bank angle and vertical speed of climb/descent equal to 500 ft/min. The entire flight consisted of the following: departure, three HPL series, H360, C180, D180 and landing. Obeying the prescribed flight sequence, uniformity of training and measurements was assured.

The entire training consisted of 17 flight lessons, where the above described series were repeated in each flight lesson. The subjects first finished the training part on flight simulator (11 lessons), then completed 1 real flight lesson followed by another 3 flight simulator training lessons and the training was finished by 2 lessons of real flying. Maximum time span between individual training lessons was 2 days. The entire training was done with analogue flight, navigation and engine gauges in the flight deck of both the simulator and real aircraft. For uniformity assurance, all flights were executed under uniform meteorological conditions with no or few clouds, ground visibility and in terminal manoeuvring area of Košice International Airport (ICAO code: LZKZ).

During selected flight lessons, a pair of measurements was conducted where piloting precision of individual manoeuvres was monitored and list of physiological parameters was recorded. Within the training, these measurements were conducted during lessons 2, 6 and 11 (simulated flights) and during lessons 12 and 17 (real flights), see Fig. 1.

Physiological parameters measurements were performed using modular telemetry system FlexiGuard [13], [14]. This system was conceptually aimed to build sensory network allowing wireless transmission of physiological and environmental variables measured on the body of its user. Sensory base for performing measurements was, owing to system modularity, adjusted for application purposes and based on typically measured variables [15], [16], heart rate, respiratory rate and myopotential measurement sensors were selected. The location of individual sensors was picked to acquire signal of the highest quality. Sensors location on test subject is depicted in Fig. 2.

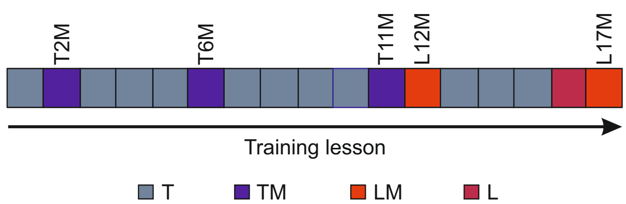

Figure 1. Training schedule (T – flight simulator, TM – flight simulator measurement, LM – flight measurement, L – flight).

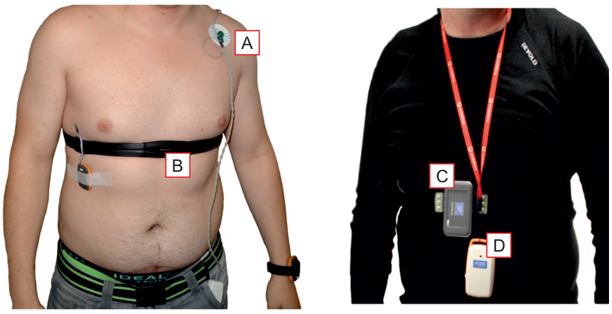

Figure 2. Location of FlexiGuard modular telemetry system sensors on test subject (A – myopotential sensor, B – heart rate sensor, C – respiratory rate sensor, D – modular sensing unit (MSU)).

On the figure, respiratory rate sensor is put on inner layer of test subject clothes because it did not require direct contact with skin.

C. Physiological Parameters Evaluation Methods

For heart rate data processing, only the values of RR intervals were used (time intervals between R peaks of QRS complex of ECG recording). Although the Flexiguard system offers data on heart rate also in bpm (beats per minute) units, the rate can be calculated using RR intervals, not to mention that most studies dealing with ECG processing use the above mentioned time difference between RR peaks [17].

RR intervals recording was evaluated using standard methods of time series analysis. Specifically, an average value of measured RR intervals, standard deviation of RR intervals (SDNN) and root mean square of the successive differences (RMSSD) [18] were calculated. Further, Kubios® software environment was used for data processing using spectral analysis [19]. Other output parameters were obtained as performance in frequency bands describing three basic spectral components: very low frequency (VLF), low frequency (LF) and high frequency (HF). The VLF band ranges between 0.01 – 0.04 Hz and describes the slow mechanisms of sympathetic system. The LF band is in the range of 0.04 – 0.15 Hz and characterizes both sympathetic and parasympathetic system, but, in general, it is considered as a strong indicator of sympathetic activity. The HF ranges between 0.15 – 0.4 Hz and reflects parasympathetic activity. Another parameter characterizing the spectral analysis is total performance (TP) which is an estimate of total spectral performance, i.e. all bands of 0.01 – 0.4 Hz, indicating overall ANS activity. However, the initial parameter is a low to high bands ratio (LF/HF) because it describes the total balance between sympathetic and parasympathetic component of ANS.

Data characterizing the number of breaths and myopotential activity were processed using standard analysis in time series domain, i.e. average respiratory rate and its variance were calculated. Pulse, respiratory rate and myopotentials data were also processed by recurrent quantification analysis (RQA). Recurrent analysis is one of the non-linear data analyses derived from chaos theory. Recurrence is an essential property of such dissipative dynamic systems. Recurrent graphs, the basic recurrent analysis tool, allow repetitive behaviour visualization of dynamic systems. The method is also suitable for non-linear analyses of short-term and non-stationary data [20]. This method of signal processing was used due to non-linear nature of autonomous neural regulation. Recurrent analysis procedure could be divided into three parts. The first step is, as for most of non-linear techniques [20], reconstruction of phase space. The second step is production of recurrent graph using threshold distance as an input parameter (see [21], [22]). Calculation of RQA variables is the last step of the analysis. It is a percentage of recurrent RR points, which form the recurrent graph. This parameter corresponds to the probability that particular condition will recur. Higher recurrence means a lower system variability and vice versa [23], [24]. Determinism DET is a parameter, that represents a percentage of recurrent points that form diagonal lines. Diagonal lines indicate that the system is returning to previous state at a different time. The determinism parameter is related to the predictability of dynamic systems. Laminarity LAM refers to the percentage of points that form vertical lines. This parameter is used for detection of laminar states, i.e. states, when the system does not change or it changes very little. Trapping Time TT is a parameter that labels an average length of vertical lines. This parameter denotes how long the system remains in a particular state and it includes information about frequency and length of laminar states. Low LAM and TT values indicate significant system complexity, i.e. the system returning to previous state only for a short period of time [24]. Other parameters of RQA include maximum length of diagonal line $Lmax$, divergence DIV (inverse value of $Lmax$), average length of diagonal line $AVDL$, ratio $RATIO$ (ratio between DET and RR), Shannon entropy $ENTR$ and maximum length of vertical line $Vmax$. To evaluate data using the described analysis, MATLAB environment was used to create software according to mathematical definitions [21].

D. Piloting Error Rate Evaluation

For piloting precision processing, two types of data sets were available, namely instructor notes and flight records.

Each manoeuver had prescribed flight parameters or more precisely rules, about which the subjects were informed during theoretical preparation. In case of HPL manoeuver and with regard to the precision, the most important was to maintain constant altitude whilst the altitude itself (its value) was not important. Further, it was important to maintain constant heading whilst the heading itself (its value) was again unimportant.

In case of H360 manoeuvre, the pilot was supposed to perform horizontal turn, whilst aircraft bank angle had to be constant at the level of 30°. The pilot had to maintain also constant altitude. During C180 or D180 manoeuvre, all subjects performed climb or descent 180° turn where the vertical speed of climb or descent was prescribed as constant to 500 ft/min and the prescribed bank angle was 15°.

The precision evaluation itself for data gathered from flight simulator was described in detail within conference paper named ”Evaluation of relationship between the activity of upper limb and piloting precision” [25]. The evaluation methodology relies on the assumption that in case of sufficient number of recorded values for respective flight parameter (n $\rightarrow \infty$), arithmetic mean of monitored parameter will approach real prescribed value. In essence, it is then possible to quantify error rate by calculating standard deviation.

The problem occurs when assessing real flights because for the research there were no data available from aircraft flight data recorder. This problem is partly resolved by instructor notes on piloting precision. Instructor manually recorded deviations during each individual manoeuvre. The deviations were recorded as maximal deviations from prescribed values (altitude, bank angle, vertical speed etc.), which were to be maintained by respective subject. In the previous study, piloting precision evaluation was compared with calculated deviations. Authors used the same data as in case of this work. The analysis showed that error rate calculated and evaluated by instructor mutually correlates and so it is possible to use only instructor notes for further evaluation.

For piloting precision evaluation, only instructor notes were used in this work. The data were divided into data sets describing precision when executing prescribed flight parameters and subsets defining measurements (T2M, T6M, T11M, L12M a L17M). In other words, all error rates from all subjects were included in the measurement categories. Within the statistical evaluation during the first phase, sub-data sets normality was evaluated by means of Kolmogorov-Smirnov test. The testing was performed on level of significance $p = 0.05$, where the hypothesis of normality was concluded with $p < 0.05$. Normal distribution was not identified in any case, i.e. for any sub-data set. Due to this, Wilcoxon test was used for further statistical evaluation to identify significant differences between groups. Hypothesis of significant difference between sub-data sets was concluded with $p < 0.05$, where all groups of measurements were compared with each other.

Overall progress of the training with regard to piloting precision as an indicator of performance, or more precisely pilot experience, is described more in detail within complex study dedicated to this issue [12]. For the purpose of this study, however, it was necessary and sufficient to consider normalized training progress. It was possible to calculate normalized progresses based on statistically significant differences between medians of individual training phases. These progresses were established based on error rate medians for specific manoeuvre and monitored flight parameter. They were then recalculated into single scale according to the maximum value from monitored data set. The normalization took place in line with equation:

$$N_i = \frac{med_i}{max(med_1, med_2, \dots, med_n)}, \tag{1}$$

where N_i is i-th normalized value, med_i is i-th median from monitored data set (where $i = 1 \dots 5$, for each measured training phase) and max is maximum of observed medians. Normalized progresses are depicted in Fig. 3 together with resulting average progress of piloting precision. The average progress was used as standard for evaluation of data gathered from evaluation of selected physiological parameters.

E. Statistical Analysis

Progressive regression method was selected for the choice of the most important parameters. The method performs the so-called stepwise regression, which is a systematic method for adding and removing terms from multilinear model based on their statistical significance in a regression. The method begins with an initial model and then compares the explanatory power of incrementally larger and smaller models. At each step, the p value of an F-statistic is computed to test models with and without a potential term. If a term is not currently in the model, the null hypothesis is that the term would have zero coefficient if added to the model. If there is sufficient evidence to reject the null hypothesis, the term is added to the model. Conversely, if a term is currently in the model, the null hypothesis is that the term has zero coefficient. If there is insufficient evidence to reject the null hypothesis, the term is removed from the model [26].

Basic classification criterion (or more precisely classification vector y) was, in case of addressing the mentioned issues, established based on piloting precision evaluation. Monitored parameters progresses, within statistical evaluation of piloting precision, pointed to behaviorality of tested subjects. To establish optimal classification vector y, median progresses for each monitored parameter were averaged and normalized. The result was vector $y = [0.7426\ 0.4041\ 0.2571\ 1.0000\ 0.6880]$. The values correspond to individual training phases, their progress

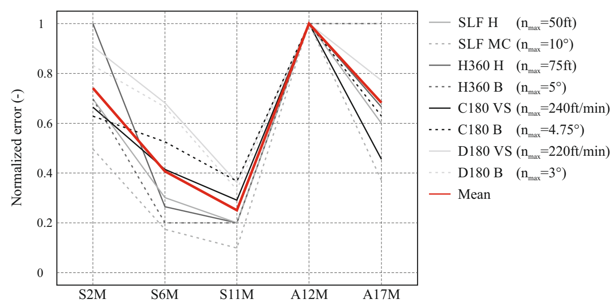

Figure 3. Depiction of normalized error rate courses for monitored flight parameters during executed flight manoeuvers (SLF – steady level flight; H360 – horizontal 360° turn; C180 – 180° climb turn; D180 – 180° descend turn; H – height; MC – magnetic course; B – bank angle; VS – vertical speed; nmax – normalization coefficient representing the maximum in given dataset) [12].

is logical and, in essence, it corresponds to logical assumption about the training. It is possible to describe the assumption as:

"All monitored training phases will exhibit statistically significant difference where the total psychophysiological stress during training on flight simulator will significantly decrease and during first flight on real aircraft then significantly increase compared to previous measurements. At the final stage, i.e. during second flight in real aircraft, psychophysiological stress will significantly decrease in comparison with the previous fight."

The above-mentioned classification criterion "y" is thus criterion established based on exact results from piloting precision evaluation and it also meets logical consideration, which can be named as base hypothesis.

The classification criterion was further used to select the most statistically significant parameters. The selection was performed in MATLAB environment using function stepwisefit. Based on the performed analysis and within the indicated steps, the parameters from data matrix listed below were selected as the most significant.

- Step 1, added column 1, $p = 2.5311 \cdot 10^{-06}$
- Step 2, added column 2, $p = 0.0416275$
- Step 3, added column 9, $p = 0.0170257$
- Step 4, added column 18, $p = 0.0302947$
- Step 5, deleted column 2, $p = 0.17803$
- Final selection of columns: 1, 9, 18

Column 1 represents Mean RR, column 9 is HR RATIO and column 18 is HF. SDNN parameter (column 2) was deleted by backwards elimination. The testing was conducted at the level of significance $p = 0.05$. Parameters, which will be used for further evaluation are thus Mean RR (mean value of R-R intervals, i.e. intervals between individual heart beats) or Mean HR (mean heart rate), HR RATIO (RATIO parameter for heart rate from recurrent analysis) and HF (high-frequency band spectral density for R-R intervals). From the nature of the processing, it follows that the selected parameters are linearly independent.

Subsequently, importance for the selected parameters was determined. Importance calculation was formulated by Friedman [27]. The calculation is based on frequency of variable for splitting and it is weighed by the squared improvement to the model, which is a result of each splitting followed by averaging across all trees. If needed, predictor importance was scaled according to their portion so that the total importance was 100 % [28].

III. Results

Tables presented below show the distribution of Mean RR parameter (average time between RR intervals – heart beats), which was marked as the most important by progressive regression. The parameter is presented as sample, due to the assumption of corresponding progress with other selected parameters, i.e. HR RATIO (RATIO from heart rate recurrent analysis) and HF (evaluation parameter of sympathovagal activity symptoms using frequency analysis). Interpretation of training progress based on psychophysiological condition is, therefore, comprehensively assessed using the example of Mean RR. Graphical representation of the results is in form of boxplots showing distribution of monitored parameter for all subjects from evaluated training phases (T2M, T6M, ...).

The tables represent results from Wilcoxon text in the form of p-values. The test was selected considering the normality of data (examined by Kolomorgov – Smirgov test), where the hypothesis about normality on the level of significance $p < 0.05$ was not concluded for all observed groups. Therefore, this condition determined non-parametric form of testing of inter-group similarity. The testing was done on level of significance $p = 0.05$, where values of $p < 0.05$ concluded the hypothesis about statistically significant inter-group difference.

When evaluating Mean RR parameter, significant differences between T2M and T11M, T2M and L12M, T6M and L12M, T6M and L17M, T11M and L12M, and T11M and L17M (Tab. I) were discovered. The interpretation of the discovery can be following. The mean RR interval increased between the first and second measurement on flight simulator. This increase, however, is not statistically significant, although the testing showed that resulting level of significance of inter-group difference is $p = 0.084$, which is a value not too different from 0.05. Subsequently, the median of average time between RR intervals decreased minimally. The decrease, however, is not statistically significant compared to T6M. On the other hand, statistical significance became evident in comparison to T2M measurement. During the first measured flight on DA-40 aircraft, rapid decrease in Mean RR parameter was recorded and this decrease exhibits statistically significant difference from previous measurements. Measurement L17M is, with regard to the evaluated parameter, on the same level as T6M measurement. Described progress is shown in Fig. 4.

Regression trees providing information about strength of classification predictor were used for backwards classification of subjects into individual groups. Testing and training group were randomly selected in a ratio of 70:30. In case of this analysis, the classification predictors were the above-mentioned selected parameters. The analysis was carried out with regard to verification of parameters significance and their capability to assign subjects into respective phase of training.

In the case presented in Fig. 5, the subjects were classified into individual groups. The importance of predictors

TABLE I
Wilcoxon Test Results for Heart Rate Mean RR Parameter

	T2M	**T6M**	**T11M**	**L12M**	**L17M**
T2M	1	0.0844	0.0318	0.0038	0.2447
T6M	0.0844	1	0.7177	0.0007	0.0207
T11M	0.0318	0.7177	1	$9.74\ 10^{-06}$	0.0021
L12M	0.0038	0.0007	$9.74\ 10^{-06}$	1	0.1719
L17M	0.2447	0.0207	0.0021	0.1719	1

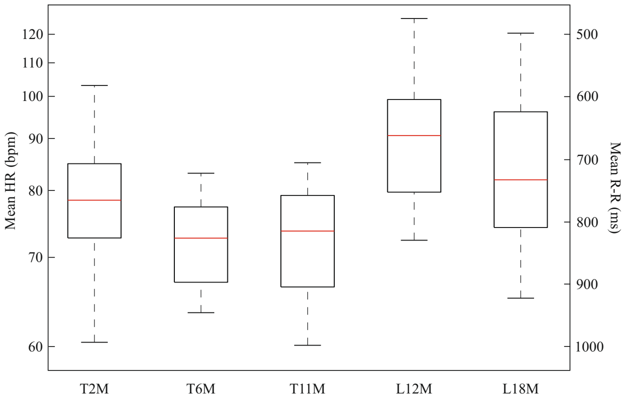

Figure 4. Mean RR and Mean HR parameters distribution for heart rate in the form of box-plots for each measured flight lesson.

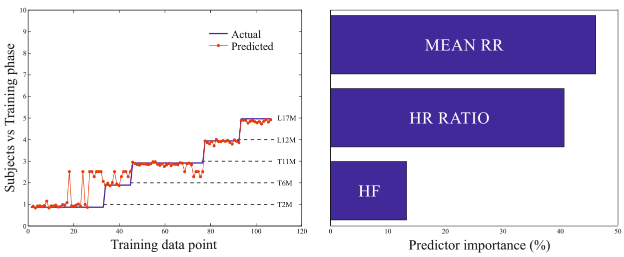

Figure 5. Backwards classification of subjects into groups using selected heart rate parameters (left) and their importance (%) (right).

was in the following sequence (from highest to lowest): Mean RR (or Mean HR), RATIO and HF.

IV. Discussion

The study results show that change of psychological stress was not reflected by each monitored physiological parameter but only by evaluated parameters based on heart activity. Based on the performed multi-regression analysis, no relationship between all monitored parameters was found, except between mean value of heart rate R-R intervals (Mean RR) or mean heart rate (Mean HR), RATIO parameter for heart rate from recurrent analysis and high-frequency band spectral density of RR intervals for heart rate.

Based on the results, monitored Mean RR parameter can be pronounced as characterizing pilot training progress with regard to psychophysiological stress, describing it as continuously decreasing during flight simulator training. The stress significantly increased during the first flight on DA-40 aircraft and during next flight lesson (L17M) it decreased to the level of T6M.

Interpretation of Mean RR parameter progress is the same as for Mean HR. Mean RR parameter is one of the main indicators of heart rhythm variability, which increase indicates higher psychophysiological stress [29]. It means that graphs presented in Fig. 4 exibit inverted progress compared to the progress of Mean HR.

The results also show that the parameters characterizing heart rate as an indicator of psychophysiological condition are more significant than all other parameters considered in this work. HF parameter itself reflects parasympathetic activity of autonomic nervous system of human organism. RATIO parameter represents return of the system to previous states, i.e. for RR intervals analysis this parameter reflects heart rate variability.

V. Conclusion

The goal of this study was to determine the utilization of selected physiological parameters and methods of their evaluation with regard to description of pilots psychophysiological stress. The measurements of physiological parameters of group of subjects undergoing flight training took place according to defined training methodology. To ensure measurement uniformity, research sample selection was performed based on psychological testing, comparable age, flying experience and health conditions of the subjects. During the training, data collection consisting of selected physiological parameters (respiratory rate, heart rate, myoelectric activity) and evaluation of piloting precision of selected flight tasks were carried out in accordance with training methodology.

Data evaluation was performed at two levels – assessment of piloting precision and evaluation of physiological parameters. Standard and experimental methods, regularly used for the purpose of physiological parameters evaluation, were chosen. From standard methods, methods for evaluation in the domain of time-series and frequency were used. In addition, a method not typically used for evaluation of physiological parameters was selected. It is called recurrent analysis and it is based on investigation of chaotic signals seasonality. Using statistical methods and approach, separation of the most important physiological parameters and methods of their evaluation was achieved. Also, importance of monitored parameters with regard to classification prediction was determined.

Based on the results, it was possible to determine suitable methods for evaluation of physiological parameters and to determine suitable physiological parameters serving as indicators of psychophysiological stress, which enables starting points for further practical research in this field.

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