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Evaluation of Pilots' Psychophysiological Condition Using Recurrence Quantification Analysis of Heart Rate Variability

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Abstract

Psychological discomfort or increased stress can negatively influence performing specific activities mainly concerning professions which are responsible for human lives. Such group of professionals includes aviation specialists, especially pilots. Psychophysiological state is indicated by certain physiological parameters by means of which it is possible to describe it. There is a wide range of methods for signal processing of measured physiological parameters which are, however, based on linear methods. This paper deals with application of non-linear method, the so-called recurrence quantification analysis for evaluation of psychophysiological state of pilots. For this purpose, R-R interval recording of pilots in training was conducted by the means of wearable telemetric system. Research sample consisted of 35 beginner pilots and measurements were performed during both simulated and real flights. Measured signal processing was done using standard time-series analysis (Mean R-R and SDNN) and also using recurrence quantification analysis. The results indicate that both standard and recurrence quantification analysis parameters were able to distinguish between two groups of measurements (simulated vs. real flights) at the significance level of $p < 0.05$. Apart from that, the results indicate considerable increase of heart rate frequency and decrease in its variability during real flights.
KEY WORDS: *recurrence quantification analysis, heart rate, piloting, pilot training, flight simulator*

1. Introduction

In the domain of aviation, air carriers are willing to achieve maximum comfort and safety of passengers. Achieving this depends on pilot, his co-pilot but also on various aviation employees or flight parameters. Flight parameters are influenced by the effect of environmental conditions on pilot and so it is flight safety. There are plenty of specific influences on human organism during flight, which depend on physical properties of surrounding environment, aircraft performance, demanding nature of required actions and on mutual effect of these influences on physiological functions of individual organs [1]. The goal of all human factor studies in aviation was and still is increase of flight safety. Owing to the acquired knowledge, awareness of pilot's stress load during flight is expanding also in terms of how to resist it or how to cope with it.

Individual aviation accidents statistics differ regarding the number of accidents caused by human factor. According to PlaneCrashInfo.com, 67.57% of aviation accidents are caused by human factors whilst almost 54% is caused by fatal piloting error. Majority of these errors emerges during approach and landing phase but almost 28% take place during routine flight phases [2]. Piloting errors are caused by various factors, for instance fatigue accompanied with reduced awareness, stress, flight crew's psychological state or inexperience in critical situations. The very pilot's state is indicated by his or her physiological parameters by means of which it is possible to evaluate his or her psychophysiological condition. In this field, majority of studies is focused on stress evaluation using heart rate variability (HRV) [3], [4]. The reason is that HRV reflects autonomic nervous system (ANS) modulation, which allows differentiating between connection of sympathetic and parasympathetic elements. With the help of ANS (sympathetic and parasympathetic) behavioural specification, it is possible to partly objectivise the effect of stress on human organism. From short-term perspective, the stress itself brings some benefits to organism. During long-term persistence, however, all benefits are lost and it can lead to fatigue or possible pathological consequences [5]. Such state is for pilots unacceptable.

As mentioned, most studies use HRV regarding identification of load, stress or more precisely adverse psychophysiological condition. Obtained signal evaluation methods are mainly based on time-series or spectral analysis

[6], [7], which are linear methods. Autonomic nervous system is characterised as non-linear deterministic system though [7]. The goal of this paper is to verify non-linear method application (recurrence quantification analysis (RQA)) on pilots' psychophysiological state evaluation. The concept of HRV evaluation using RQA is expanding but it was never used for pilots' evaluation.

2. Materials and Methods

For the purpose of verification of RQA suitability for its application on evaluation of psychophysiological state of pilots, heart rate frequency measurement was used for pilots in training. Research sample consisted of 35 subjects (27 men and 8 women) put in flight simulator (type TRD40) training and real flight training on Diamond DA40 aircraft. The pilots were students at Technical University of Kosice and at the age of 23 ± 4 years. Selection of research sample was conditional on medical fitness and theoretical knowledge of flight fundamentals. Specifications of the training are described closer in preceding study (see [8]). In essence, the point was to experimentally set the training for beginner pilots with the main emphasis put on simulator training with implemented real flights. Members of the sample completed continuous preparation covering 11 flight simulator hours followed by one flight hour on Diamond DA40 aircraft and then next 3 flight simulator hours were followed by another two flight hours finishing the training. Individual flights were uniform and consisted of series of precisely predefined manoeuvres. For the purpose of this study, it was the first transfer between simulated and real flying which was monitored. Estimated stress load was tracked and it was assumed that it would follow ascending trend concerning simulated and real flight comparison.

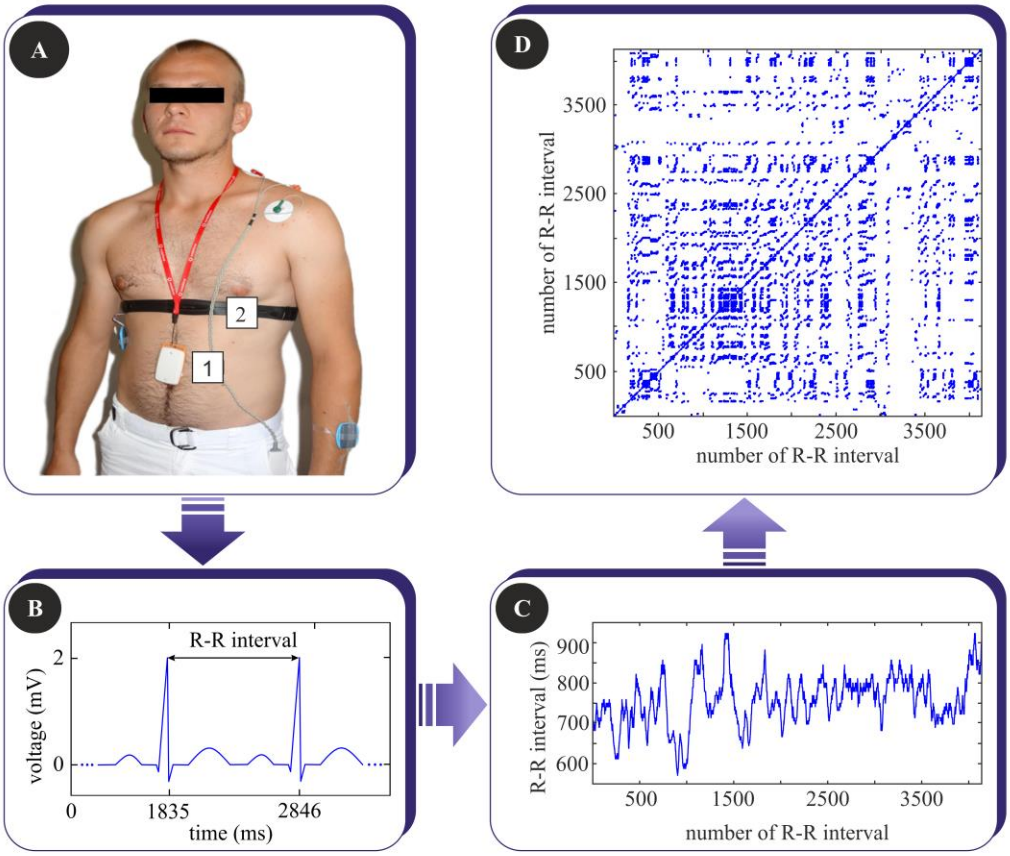

Fig. 1 Data processing: A - system FlexiGuard with central collection unit (1) and chest strap for heart rate monitoring (2); B – example of R-R interval; C – example of heart rate frequency signal in the form of R-R intervals; D – example of recurrence plot)

To verify the increase or decrease in stress load, ECG recoding was performed at 11th (simulated flight - SF) and 12th (real flight - RF) hour of training. FlexiGuard (FG) system (Fig. 1, A) was used for data recording. It is a wearable telemetric modular system designed for this purpose by Faculty of Biomedical Engineering, CTU in Prague (see [9]). The system is capable of continuous data recording of several physiological parameters but for the purpose of this study, only heart activity data were used, recorded by means of Garmin® chest strap. FG system recorded R-R interval data (Fig. 1, B) tracking time intervals between two characteristic ECG peaks. This concept is used mainly for heart rate variability evaluation, which could indicate various pathophysiological states such as stress [10]. R-R intervals measurement was performed during entire flight where the measurement begun at the time of take-off roll initiation and stopped at the time of touchdown.

The recorded signal (Fig. 1, C) was processed in two ways. The first way consisted of standard variables calculation used in clinical practice. Calculated were mean R-R, indicating average heart rate, and heart rate variability throughout standard deviation of N-N intervals (SDNN) which means SD of R-R intervals in our case [6]. This calculation was performed with regard to the verification of RQA suitability. The second way of data processing and evaluation consisted of procedures for creating recurrence plots (Fig. 1, D) which are essential for RQA. Detailed description of R-R interval signal processing by the means of recurrence analysis is presented below.

2.1. Signal Processing - Recurrence Analysis

In the domain of medicine research, non-linear analysis is becoming widespread. It is based on signal trajectory reconstruction in phase space [7]. One of non-linear analysis methods is recurrence analysis, which stems from theory of chaos. Recurrence analysis allows visualising recurrence of dynamic systems. For this visualisation, a time-series is needed with no requirements for its length, stationarity or distribution. It is possible to monitor dynamics of the entire system by means of this multidimensional method. First step is to establish multidimensional system, which relates to the original phase system. Phase space and distance matrix (DM) are to be computed here. Then points are identified which are distant in time but in terms of selected radius they are space neighbours. This creates recurrence plot (Fig. 1, D). The last step is evaluation of recurrence plot with the help of RQA.

Trajectory in phase space expresses dynamics of the entire system and with the help of several methods it can be reconstructed from just one scalar time-series. The most commonly used method is time delay embedding method, which prescribes following signal reconstruction [11]:

$$x(t_i) = \left[x(t_i), x(t_i + \tau), \ldots, x(t_i + (m-1)\tau) \right], \tag{1}$$

where i = 1...M; m is embedding dimension; τ is time delay and $M = N - (m - 1)\,\tau$, where N is amount of samples. Reconstructed phase space in this way is not identical with the original phase space but under certain conditions, dynamics of both systems are the same [11]. Basic condition for this is sufficient embedding dimension m and appropriate time delay τ. It was proved that for attractor of dimension D, the sufficient embedding dimension is $m \geq 2D + 1$. This knowledge works for infinite and accurate time-series which are, however, not measurable in practice. Because incorrect initial parameter selection can significantly affect the results and so the data may be misinterpreted, it is important to be careful when selecting m and τ.

For purpose of this study, time delay τ was selected so that the interactions between points of time-series would be minimised. This way is the attractor verified if it exists. Time delay τ states the distance between two neighbouring points of the time-series, which is to be reconstructed. For low τ is the difference between reconstructed vectors minimal and the information obtained about the dynamics of the system is not much enriched (it is so-called redundant state). Too much time delay causes the system's behaviour to become chaotic and complicated. In that case it is called irrelevant state. For optimal time delay τ setting, I was selected by means of minimal mutual information. It shows interdependence between two dependent quantities where the higher the dependence, the more information is obtained. Mutual information (I) calculation stems from entropy and is given by following:

$$I(A,B) = H(A) + H(B) - H(A,B), \tag{2}$$

where A and B are individual variables, $H(A)$ and $H(B)$ are their entropies and $H(A,B)$ is their combined entropy. The most appropriate time delay for measured signal was selected as the first minimum of mutual information. The first minimum of I corresponds to time step where measurement/observation $x(t_i + \tau)$ contributes on average with maximum information to the information which is already known from measurement/observation $x(t_i)$. If there is no minimum of mutual information, the value of τ was selected such where $(\tau) / I(0) = 0.2$, (see [11]).

The goal of phase space reconstruction was to ensure that there would be no trajectory intersecting. With small dimension, in majority of cases the trajectory intersects itself whilst increase in dimension causes the trajectory to cease this phenomenon. As a result of trajectory intersecting there are so-called false neighbours. One of the most commonly used methods for proper dimension m selection is method based on the number of false neighbours. It is about linear increasing of phase space dimension and monitoring of false neighbours. The disadvantage of this method is the selection of threshold at which two points are still considered as neighbouring. This problem was partly solved by Cao [12] who introduced following equation:

$$a(i,m) = \frac{\| x_{m+1}(i) - x_{m+1}^{NN}(i) \|}{\| x_m(i) - x_m^{NN}(i) \|}, \tag{3}$$

where $\|.\|$ is Euclidean distance; $x_m(i)$ is i-th reconstructed vector with dimension m and $x_m^{NN}(i)$ is his closest neighbour with non-zero distance from point $x_m(i)$. Cao also introduced $E(m)$ as average of all values $a(i,m)$ which can be calculated as:

$$E(m) = \frac{1}{N - m\tau} \sum_{i=1}^{N-m\tau} a(i,m). \quad (4)$$

From Eq. 4 it is apparent that first time delay is to be set. The difference between the number of false neighbours between two neighbouring dimensions is specified by comparison of values $E(m)$ and $E(m+1)$. This difference is given as a fraction $E_1(m)$ of individual averages (Eq. 5). At sufficiently high embedding dimension is the value of $E_1(m)$ stabilised at around 1.

$$E_1(m) = \frac{E(m+1)}{E(m)}. \quad (5)$$

By the above stated means, phase space with optimal time delay τ and embedding m dimension was reconstructed for each signal. For further processing it was necessary to create recurrence plot which characteristics were used for quantification analysis.

Recurrence plot (Fig 1-D) can be comprehended as two-dimensional depiction of N-dimensional phase space. The basis for recurrence plot (RP) creation is distance matrix (DM) which is squared matrix symmetric with respect to the main diagonal and from which the RP is obtained by thresholding. For DM calculation, Euclidian norm was used where the very prescription for DM is as follows:

$$DM(i,j) = || x(i) - x(j) ||, \quad (6)$$

where ||.|| is Euclidean distance, $x(i)$ and $x(j)$ are system's states in time i or j respectively and $i, j = 1,..., N- \tau(m-1)$, where N is the number of points, τ is time delay and m is embedding dimension. Recurrence matrix (RM), or more precisely RP as visualisation of RM, is derived from thresholding DM. RM can be described mathematically as follows:

$$R(i,j) = \Theta(\varepsilon - || x(i) - x(j) ||), \quad (7)$$

where Θ is Heaviside function (i.e. $R(i, j) = 0$ for $||x(i) - x(j)|| > \varepsilon$) and ε is distance threshold. Graphical depiction of RP is therefore binary coded, i.e. recurrence states are represented by points in RP. From Eq. 7 it is apparent, that thresholding directly influences the number of recurrence points. That implies that the threshold selection is one of the key factors of recurrence analysis. However, the optimal threshold setting is still subject of discussion. The most simple and used way for thresholding is selection of fixed percentage of recurrence points, i.e. such threshold setting which ensures the percentage value set for recurrence points in RP. When setting the threshold in this way there are several recommendations. One of them is that the recurrence points' percentage in graph should be kept at low values, i.e. no more than 5%. Other studies state that fixed recurrence points' percentage should be between 1.5% and 15% [7]. Because previous studies dealing with heart rate recurrence analysis often used fixed recurrence points' percentage set at 2.5% [7], this study used the same setting.

After recurrence plot creation (with selected thresholding), recurrence quantification analysis (RQA) was used for RP evaluation for each measured R-R interval signal obtained from heart rate measurements. Explicit mathematical definition for distinct RP properties allows in general analysing multidimensional, non-linear or noisy signals. The definition and procedures for RP structures quantification are based on horizontal, vertical and diagonal structures evaluation in RP. Currently, 9 variables are used for RP description. They are recurrence rate, which shows point density in RP, determinism (DET), laminarity (LAM), longest diagonal line (LMAX), divergence (DIV), average length of diagonal lines (AVDL), ratio between DET and recurrence rate (RATIO), Shannon entropy (ENTR) and maximal length of vertical line (MAXV) [13]. Because for the purpose of thresholding a fixed percentage setting for recurrence points was used, the parameter recurrence rate was discarded from the evaluation. Another reason for discarding this parameter was that it is covered in RATIO and so it would exhibit direct dependence. For the other above stated RQA parameters, which were calculated for each measured signal of R-R intervals, a statistical evaluation was performed.

For the above stated signal processing, an own-designed software in Matlab environment was used (MATLAB R2013a, MathWorks, Inc., Natick, MA, USA).

2.2. Statistical Analysis

Statistical analysis was used to evaluate the intergroup differences in standard parameters (Mean R-R a SDNN) and individual RQA parameters. The goal was to find those parameters, which were able to distinguish between the two groups of measurements during simulated and real flight. Statistical test selection was determined by probability distribution. Because the measured and tested data groups (represented by RQA parameters, Mean R-R and SDNN) obey normal distribution, Jarque-Bera test was used. Null hypothesis was that the data originate from normal distribution at the 5% significance level against alternative hypothesis that the data do not originate from normal distribution ($p < 0.05$). The testing did not indicate normal distribution for any data vector containing measured parameter. With respect to this finding, Mann-Whitney U nonparametric test was used for intergroup testing with null hypothesis stating that two samples originate from distribution with the same median at the 5% significance level. Alternative hypothesis stating that two samples originate from distributions with different median was accepted for p<0.05 and so it is possible to tell that between the two measured samples there is statistically significant difference.

Statistical testing was performed in Matlab environment (MATLAB R2013a, MathWorks, Inc., Natick, MA, USA).

3. Results

Graphical representation is realised in form of boxplots, where one boxplot demonstrates data distribution of measured parameter within measured group (SF or RF). Each boxplot shows (from lower horizontal line) minimum, first quartile, median (red), third quartile and maximum value of measured parameter in measured group.

The results of standard analysis, i.e. Mean R-R and SDNN evaluation, indicate statistically significant ($p < 0.05$) increase of average R-R interval values for SF compared to RP. Mean R-R value was 732 ms for simulated flights compared to 598 ms for real flights. This can be interpreted also by means of heart rate frequency in beats per minute (bpm) units (see Fig. 2). It is possible to tell that the average heart rate for researched sample of pilots is considerably lower for simulated flights than for real flights.

Significant differences between SF and RF were found also for heart rate variability by the means of SDNN. In case of SF, this was parameter 48 ms whereas for RF it was 32 ms. It is possible to see this considerable decrease in heart rate variability for RF compared to SF.

The results of statistical testing also indicated that there are significant differences ($p < 0.05$) between SF and RF between all measured RQA parameters. Statistically significant increase or decrease of measured parameters is depicted on Fig. 3. The importance of increase or decrease in respective parameters is the subject of discussion.

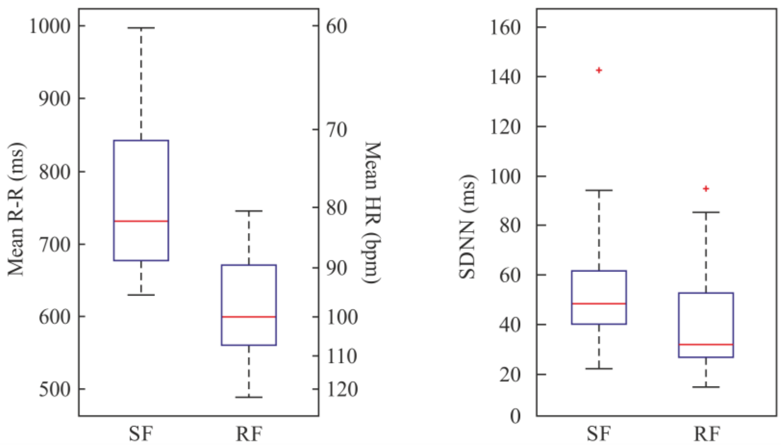

Fig. 2 Graphical representation of Mean R-R and SDNN distribution for pilots' heart rate during performing simulated (SF) and real flight (RF)

4. Discussion

The results of standard analysis demonstrated that in the research sample, psychophysiological stress load is higher in case of RF. During RF, significant increase in heart rate frequency with simultaneous decrease in heart rate variability was observed, what clearly indicates higher pilots' stress load [5]. This was in line with expectation.

RQA parameters support these finding. RP average length of diagonal line (AVDL) reflects average time during which two trajectory segments in phase space are close to each other (in distance =< ε). Regarding R-R intervals measurement, greater AVDL value indicates lower variability for group of subjects performing RF. In other words, RF group subjects exhibit less variance from mean heart frequency. LAM parameter indicates laminar state duration. It is a state where the dynamics of the system does not change or it changes only marginally. In case of a signal given by R-R intervals, the LAM parameter indicates decreased heart rate variability for RF.

DET (percentage of points comprising diagonal lines in RP) indicates that the system is more frequently returning to its previous states. The higher the determinism, the more frequently the system returns to its previous state. This is relates with system's foreseeability, i.e. the greater the DET the more foreseeable the system. Regarding the signals measured, DET indicates lower RF variability compared to SF.

RATIO is the ratio between DET and recurrence rate. In this case, DET is divided by constant (due to the fixed setting for percentage of recurrence points in RP) which means that, in terms of this study, the parameter has no special significance and its interpretation is similar to DET. In case of other type of thresholding (which will not ensure fixed setting for percentage of recurrence points in RP), the ratio between DET and recurrence rate could be used for revealing of hidden transitions [13].

ENTR parameter is derived from Shannon entropy where greater entropy means wider span of diagonal lines length (demonstrable in histogram) in RP. Greater ENTR value for RF group would mean greater variability in length but it is necessary to realise that average lines length for this observed group is greater thus more span for variation of diagonal lines length exists. In essence, this parameter points to previous findings concerning AVDL and DET. ENTR parameter is in case of this study a side-effect, complementing and confirmative figure. Information value of this parameter would be higher for system descriptions, where average length of diagonal line and number of points comprising diagonal lines would be comparable, i.e. statistically indistinguishable.

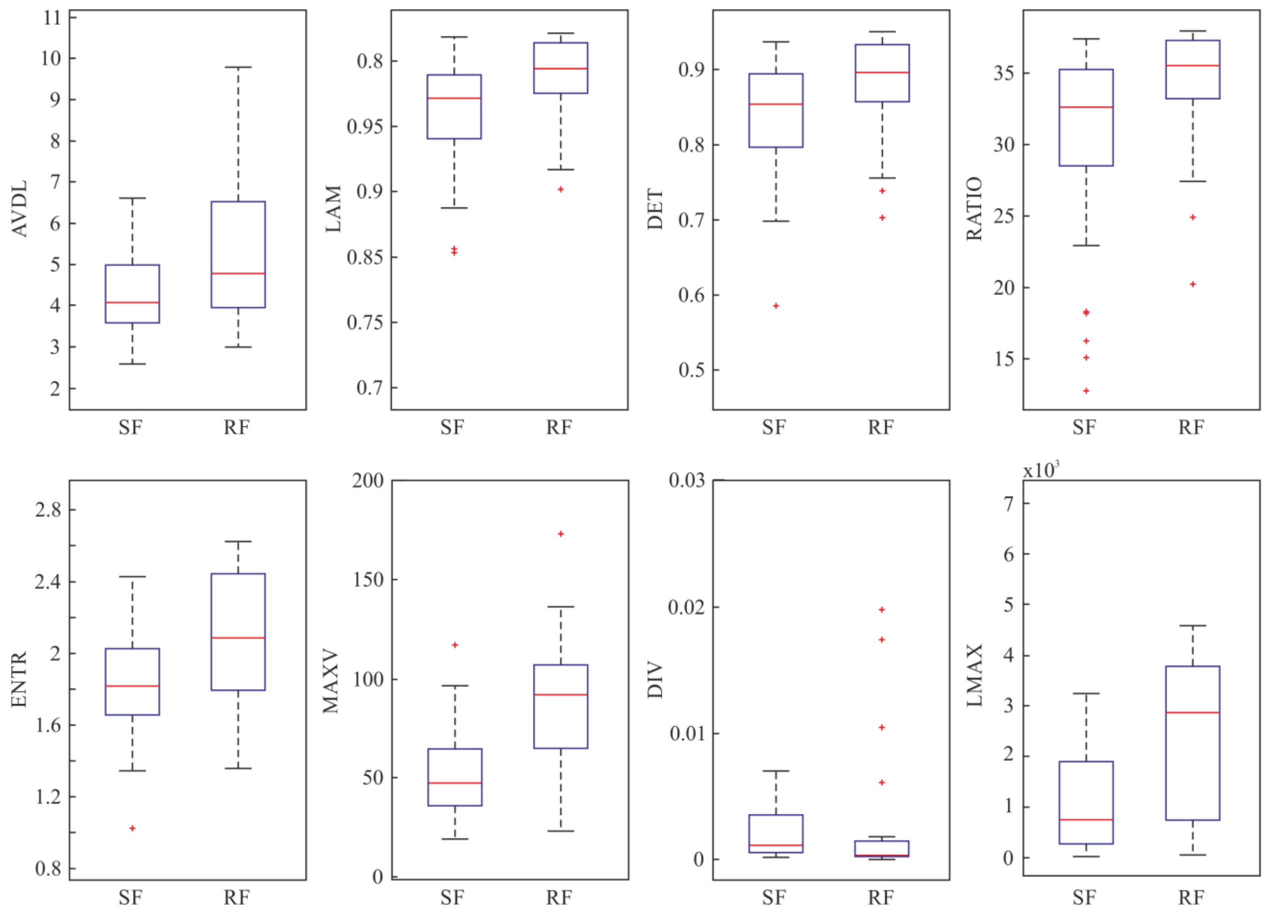

Fig. 3 Graphical representation of RQA parameters' distribution for pilots' heart rate during performing simulated (SF) and real flight (RF)

MAXV parameter denotes value of shortest vertical line. This value determines longest stay in specific state. In terms of evaluating signals of R-R intervals it is possible to tell that in case of RF the system remains in specific state longer compared to SF, what also indicates lower variability of heart rate for RF.

Maximal length of diagonal line (LMAX) in RP denotes longest time period during which the trajectory in phase space runs parallel to other segment (at distance =< ε). LMAX is closely related to divergence (DIV) where DIV is inverse value of LMAX. Both DIV and LMAX relate to the maximal Lyapunov exponent. Chaotic attractors are characteristic for their high sensitivity to initial conditions. It is possible to quantify the degree of chaotic nature by means of Lyapunov exponent. The exponent shows whether trajectories close to attractor converge or diverge. There are several of such exponents for each system or more precisely exactly one for each its dimension. The most important is the maximal one. In simple terms, maximal Lyapunov exponent is mostly influenced by long-term system behaviour and it is used as one of the indicators of chaotic nature. LMAX and DIV parameters then describe foreseeability of the system where greater DIV (lower LMAX) indicate lower foreseeability and vice versa.

Generally, the results in both cases (standard parameters and RQA parameters) demonstrate decrease in heart rate variability when performing real flights. Taking into account that at higher psychical or physical load, the heart rate increases with simultaneous decrease in its variability [5], it is possible to say that RQA parameters are capable of distinguishing such state. RQA parameters provide relevant information about psychophysiological condition of monitored pilots and they are able to describe complex system's behaviour based on R-R interval monitoring.

5. Conclusion

Aviation accidents are mostly caused by human factor, i.e. by pilot, co-pilot or the rest of flight crew. Due to this, it is suitable to monitor mental state of flight crew to ensure safety. The goal of this study was monitoring of pilots' psychic state during simulated and real flights using physiological data, i.e. ECG signal. Such monitoring can timely point out the change in pilot's physical state what makes it possible to prevent errors emerging for instance from higher mental load.

The study utilised standard ANS activity evaluation methods – mean R-R and SDNN. Non-linear data analysis RQA was used. The results indicate that during transition from SF to RF there is increased heart rate coupled with decrease in its variability what indicates higher stress load for RF. Identical results were achieved during all three types of analysis. This confirms suitability of RQA application for stress quantification. Although the RQA is not used for evaluation of pilots' mental state, compared to standard methods it provides the ability to monitor entire dynamics of the system, i.e. its behaviour description. RQA utilisation thus can lead to flight safety improvements.

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