2025 International Conference “ROBOTICS & MEHATRONICS”
5 – 6 November, 2025, Sofia, Bulgaria

Distinguishing States of Rest, Fatigue, and Stress in Athletes Using HRV Geometric and Entropic Measures

Galya Georgieva-Tsaneva
Institute of Robotics
Bulgarian Academy of Science
Sofia, Bulgaria
galitsaneva@abv.bg

***Abstract*—Monitoring heart rate variability (HRV) provides valuable insights into autonomic regulation and recovery status in athletes. This study aims to distinguish between rest, fatigue, and stress states by combining geometric and entropic analyses of HRV. Short-term RR interval recordings were obtained from 14 competitive athletes before, immediately after, and two hours post-training sessions. HRV was assessed using Poincaré plots (SD1, SD2, and SD1/SD2 ratio), 3D phase-space attractors derived from time-delay embedding of RR intervals, and entropy-based indices including Sample Entropy and Shannon Entropy. The results revealed clear transitions from a comet-shaped Poincaré pattern at rest to more compact (fan-like) shapes during fatigue and torpedo-like distributions under stress. These changes were accompanied by progressive decreases in SD1, SD1/SD2, attractor volume, and entropy values, indicating reduced parasympathetic activity and increased sympathetic dominance. This integrated geometric–entropic approach offers a powerful tool for assessing training load, recovery, and early detection of functional overreaching in athletes.**

Keywords—Heart Rate Variability (HRV); Poincaré Plot; 3D Phase Space Attractor; Entropy; Sample Entropy; Shannon Entropy; Athletes; Autonomic Nervous System; Fatigue; Stress Monitoring.

I. INTRODUCTION

The autonomic nervous system (ANS) plays a key role in the regulation of heart rate by balancing sympathetic and parasympathetic activity. Analysis of changes in the R-R intervals of the heart rhythm [1,2] provides an assessment of the effectiveness of this balance, as well as the functional and health status of the body.

Heart rate variability (HRV) is the variation in the intervals between successive heartbeats (RR or NN intervals) and is a marker of the autonomic regulation of the heart.

Healthy cardiac systems show greater, more complex variations, which reflects flexibility and the ability to adapt to stressful conditions, while chronically reduced HRV is associated with increased risk and sympathetic dominance.

In sports and training regimens, HRV has been established as a useful marker for assessing training load, the degree of fatigue and recovery in athletes [3]. HRV measurements at rest, during exercise, and during recovery provide information about the body's adaptation to training, as well as the risk of excessive strain or functional overload (overreaching). Different HR and HRV measures can be useful for monitoring fatigue, recovery, and training effects. Studies of these measures justify the use of HRV as an indicator of training status and adaptation.

Severe fatigue is a prerequisite for a significant decrease in HRV parameters, leading to changes in muscle oxygen consumption even at rest [4]. For this reason, it is good to avoid overtraining and to personalize the training program.

At the same time, the studies presented in scientific publications on the effects of training are associated with methodological inconsistencies and/or incorrect interpretation of the data, and this provides scope for new studies to assess training status in order to address this issue as comprehensively as possible. More data are needed to assess the best practices for implementing HRV in sports [5]. In one respect, the literature is almost unanimous: analyses of 5-minute ECG/PPG cardiac recordings are probably the most useful monitoring tools.

The scientific literature uses a variety of methods for analyzing HRV—linear (time-domain, frequency-domain) metrics, as well as nonlinear and entropic measures. Nonlinear approaches (such as Poincaré plots, nonlinear entropic indices, and other dynamic attractors) allow for a more refined assessment of the complexity and irregularity of heart rhythm, which often cannot be well captured by linear analyses alone. Nonlinear methods can help to recognize subjective physical fatigue [6]. A recent study in wrestlers that used HRV measures to assess training load, fatigue, and stress showed that HRV measures can serve as sensitive indicators of recovery capacity and exercise tolerance [7].

The aim of the present study is to integrate geometric and entropic methods for HRV analysis to distinguish between resting, fatigue/stress and recovery states in athletes. Using Poincaré diagrams, Recurrence Plot and entropic indices, we analyze HRV parameters that can serve for monitoring workload and prevention of functional overtraining.

II. MATERIALS AND METHODS

The study was conducted on a group of 14 competitive wrestlers. Heart rate recordings were often made with Holter monitoring for about 10 min. In three states: before training (rest), after training (fatigue) and two hours after training

ACKNOWLEDGE THE FINANCIAL SUPPORT OF THE PROJECT WITH FINANCING AGREEMENT NO. PVU-44 OF 05.12.2024 UNDER PROJECT NO. BG-RRP-2.017-0011 "ECOLOGICAL COLLABORATIVE ROBOTS POWERED BY GREEN HYDROGEN" UNDER THE RECOVERY AND RESILIENCE MECHANISM FOR THE IMPLEMENTATION OF AN INVESTMENT UNDER C2I2 "INCREASING THE INNOVATION CAPACITY OF THE BULGARIAN ACADEMY OF SCIENCES (BAS) IN THE FIELD OF GREEN AND DIGITAL TECHNOLOGIES" FROM THE RECOVERY AND RESILIENCE PLAN, BULGARIA.

(recovery). The recordings are short-lived, and from the approximately 10 min recorded at rest, 5-minute series were separated and analyzed. The Holter recordings were processed by filtering artifacts and extreme values (ectopic beats).

Methods for analyzing HRV

Poincaré plot

A Poincaré plot is constructed by graphically displaying pairs of intervals (RR_i, RR_{i+1}) against each other [8]. The following parameters were calculated [9]:

$$SD1 = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\frac{(RR_i - RR_{i+1})^2}{2}}; \quad (1)$$

$$SD2 = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\frac{(RR_i + RR_{i+1} - 2\overline{RR})^2}{2}} \quad (2)$$

SD1 is the standard deviation of the projection perpendicular to the identity line, characterizing the short-term variability of heart rate.

SD2 is the standard deviation along the identity line [9]. Describes long-term changes in rhythm and may increase with fatigue, exertion or illness.

The ratio:

$$Ratio = SD1/SD2 \quad (3)$$

gives an indication of the balance between short-term and long-term fluctuations, is used as a general indicator of the harmony of cardiac dynamics — the higher it is, the better the autonomic regulation.

Quantitative calculation of the parameters SD1, SD2, and SD1/SD2 allows for an objective assessment of cardiac variability and is used in cardiological and sports analyses to monitor the physiological state.

Visual analysis. The shape and structure of the point cloud in the Poincaré plot carry information about the state of the system: "Comet" shape - narrow at the bottom and expanding upwards; characteristic of a stable and periodic rhythm; "Torpedo" shape - elongated and dense, usually indicating quasi-periodic or slightly chaotic behavior; "Fan" shape - a spread-out structure, indicating more chaotic dynamics or proximity to a transition to chaos. Complex or multilayered shape - may reflect a fractal structure and the presence of several dynamic states.

The symmetry of the points relative to the line y=x indicates the balance of autonomic regulation between the sympathetic and parasympathetic systems.

3D Poincaré method

Poincaré plot can also be constructed in three-dimensional space (RR_i, RR_{i+1}, RR_{i+2}). The three-dimensional method is an extension of the classical two-dimensional approach used to visualize the dynamics of successive RR intervals in the electrocardiogram.

While the traditional Poincaré plot depicts the relationship between two successive intervals, the three-dimensional version also includes the next interval, which allows a more complete representation of the dynamic structure of the heart rhythm. This forms a cloud of points in three-dimensional space that describes the transitions between three successive heartbeats.

The shape, orientation and dispersion of this cloud provide information about the complexity and stability of the rhythm.

- In a normal heart rhythm, the points are located close to the diagonal, forming a tight linear structure.
- In a variable or chaotic rhythm, the cloud expands in space and acquires a more complex, three-dimensional shape.
- Analysis of the geometric characteristics (e.g. volume, slope or orientation) of this cloud allows a more accurate assessment of the nonlinear relationships between successive RR intervals.

Recurrence Plot

Recurrence Plot (RP) is a graphical method for visualizing the dynamics of physiological signals, which shows the moments at which a system returns to states similar to previous ones. In the context of heart rate variability (HRV), RP is used to study recurring patterns and changes in the dynamic structure of RR intervals, which reflect the activity of the autonomic nervous system.

To make RP, the phase space of the time series is first reconstructed, with each moment of the signal represented by a set of values with a certain time delay. Thus, each point in this space describes the current dynamic state of the system. Then, all pairs of states are compared to determine whether they are close enough to each other according to a predetermined similarity threshold. If two states are close, a "recurrence" is marked in the corresponding position of the matrix.

The resulting two-dimensional matrix is visualized as a square graph, in which each black point represents a moment when the system was close to a previous state, and white indicates a lack of similarity. The main diagonal (from the upper left to the lower right) shows identical moments in time and is always filled. Diagonal structures parallel to it reflect repeatability and predictability in the signal, while vertical and horizontal lines indicate stagnant phases when dynamics temporarily slow down.

In HRV analysis, RP allows different physiological states to be distinguished. At rest, the graph usually shows a more scattered and complex structure, which indicates high variability and good autonomic regulation. In fatigue, longer diagonal lines appear, reflecting a more regular and predictable rhythm, while under stress the structure may appear chaotic, which is a sign of dominant sympathetic control and reduced complexity of the system.

The threshold ε defines the limit of similarity between the states of the system in the reconstructed phase space and controls the density of points in the Recurrence Plot. In the present study, the value of ε\varepsilonε was chosen as a fixed percentage of the maximum Euclidean distance between RR intervals, which ensures a balance between too loose and too tight structures. For comparability between different states (rest, fatigue, stress) the threshold was kept in a close range, ensuring comparable Recurrence Plots and stable RQA indicators.

RP is used both for visual analysis and as a basis for quantitative description through Recurrence Quantification Analysis (RQA) metrics that assess the degree of recurrence, predictability, chaoticity, and laminarity of the signal.

In **Recurrence Quantification Analysis**, several quantitative metrics characterize the dynamic structure of the time series of RR intervals. Recurrence Rate (RR) expresses the percentage of points in the recurrence matrix that repeat within a given threshold ε and reflects the overall degree of recurrence in the signal. Determinism (DET) determines the proportion of points forming diagonal lines and is related to the predictability and deterministic nature of the dynamics. Laminarity (LAM) is the percentage of points forming vertical lines, which indicates the presence of periods of stagnation or "laminar" states in the system. Trapping Time (TT) measures the average length of these vertical lines and describes the duration of stable states. Entropy (ENTR) assesses the diversity of diagonal line lengths, thus reflecting the complexity and degree of randomness of the time series.

Sample Entropy (SampEn) is a nonlinear measure of irregularity and complexity in time series, assessing the probability that given patterns of length m will remain similar when expanded by another value. Lower values of SampEn indicate higher regularity and predictability of the signal, while higher values reflect greater randomness and adaptability of the system. In the context of HRV, this allows an assessment of the dynamic balance between sympathetic and parasympathetic activity. Shannon Entropy, in turn, is a classical entropic measure from information theory that calculates the degree of uncertainty or probability distribution in the signal. High Shannon entropy corresponds to more diverse RR intervals and a richer information structure, while low values indicate reduced complexity and increased regularity of cardiac dynamics.

The **Hurst exponent** (H) is a fractal index that characterizes the degree of long-term dependence and self-organization in time series such as RR intervals. Its calculation is based on the method of rescaled range (R/S analysis), in which the dependence between the mean dispersion and the length of the observed segment is estimated. Values of H around 0.5 reflect stochastic, unpredictable behavior (similar to white noise), H > 0.5 indicate persistence and the presence of long-term correlation in the signal, while H < 0.5 indicate anti-persistence and a tendency to alternation of values. In HRV analysis, the Hurst exponent is used to assess the stability and fractal structure of the autonomic regulation of heart rate.

Statistical analysis

The comparison between the three states (rest, fatigue, recovery) was performed by T test analysis (each group against each). The level of P value<0.05 was accepted for statistical significance.

III. REZULTS

Table 1 presents the mean values and standard deviations of the main geometric, entropic and fractal parameters of HRV for the three studied states – rest, fatigue and recovery. A clear decrease in SD1 and SD2 is observed immediately after training, which reflects reduced short-term and long-term variability and increased sympathetic tone. The SD1/SD2 ratio is reduced, indicating a shift in the sympatho-vagus balance towards the dominance of parasympathetic activity.

The entropic indices SampEn and Shannon Entropy also decrease during fatigue, which indicates lower irregularity and information complexity of the heart rhythm. In the recovery phase, most parameters partially return to their baseline values, which indicates a reactivation of parasympathetic regulation and a return to a more balanced autonomic state. The values of the Hurst exponent remain relatively stable, which confirms the preservation of the long-term correlation structure despite temporary changes in short-term dynamics.

The results of the recurrence analysis show distinct changes in the dynamics of cardiac activity between the three studied states – rest, fatigue and recovery. The Recurrence Rate (RR) indicator remained relatively stable between the states (1.081 ± 0.14 at rest, 1.046 ± 0.22 at fatigue and 1.058 ± 0.19 at recovery), indicating a preserved overall degree of recurrence in the signal. In contrast, the parameters Determinism (DET), Laminarity (LAM), Trapping Time (TT) and Entropy (ENTR) increased significantly immediately after exercise – DET from 0.2981 ± 0.01 to 0.609 ± 0.04, LAM from 0.3637 ± 0.05 to 0.7426 ± 0.11, TT from 2.3053 ± 0.18 to 3.3017 ± 0.26 and ENTR from 0.5882 ± 0.09 to 1.178 ± 0.08. These changes reflect an increase in the determinism, stability and laminar nature of cardiac dynamics, accompanied by a reduction in chaoticity – a typical sign of increased sympathetic activity and physiological stress. Two hours after training, the values of all indicators decreased and approached baseline levels (e.g. DET = 0.3155 ± 0.04; LAM = 0.3936 ± 0.09; TT = 2.4209 ± 0.13; ENTR = 0.6228 ± 0.11), demonstrating restoration of autonomic regulation and a return to a more flexible, variable state of heart rate.

Significant differences ($p < 0.05$) were observed mainly between Rest and Fatigue for SD1, SampEn and Shannon Entropy (Table 2), confirming the influence of physical exertion on short-term variability and complexity of HRV. No significant differences were found between Rest and Recovery ($p > 0.05$), which corresponds to restoration of autonomic balance two hours after training. Between Fatigue and Recovery, significant differences were observed for SD1 and entropy indices, reflecting partial recovery of parasympathetic activity. Significant differences ($p < 0.001$) were observed between rest and fatigue, as well as between fatigue and recovery for all RQA indices, except RR. DET, LAM, TT and ENTR indices significantly increased during fatigue, reflecting increased determinism and laminarity of cardiac dynamics – typical signs of sympathetic dominance and reduced chaoticity. The lack of statistical difference between rest and recovery ($p > 0.05$) indicates recovery of dynamic flexibility and return to baseline autonomic regulation.

TABLE I. HRV PARAMETERS

Parameters	Studied groups		
	Rest* *N=14	***Fatigue* *N=14***	***Recovery* *N=14***
SD1 [ms]	31.1±9.38	22.33±7.41	29.67±8.09
SD2 [ms]	84.12±22.09	68.23±26.67	76.81±26.67
SD1/SD2 [-]	2.7±0.54	3.09±0.68	2.82±0.68
RR	1.081±0.14	1.046±0.22	1.058±0.19
DET	0.2981±0.01	0.609±0.04	0.3155±0.04
LAM	0.3637±0.05	0.7426±0.11	0.3936±0.09
TT	2.3053±0.18	3.3017±0.26	2.4209±0.13
ENTR	0.5882±0.09	1.178±0.08	0.6228±0.11
SampEn [-]	1.017±0.23	0.68±0.41	0.98±0.41

Parameters	Studied groups		
	Rest N=14	*Fatigue N=14*	*Recovery N=14*
Shannon Entropy [-]	3.8±0.48	3.32±0.21	3.67±0.17
Hurst[-]	0.79±0.22	0.75±0.18	0.78±0.31

TABLE II. P VALUE (T TEST)

Parameters	Studied groups		
	Rest vs Fatigue	*Rest vs Recovery*	*Fatigue vs Recovery*
Parameter	Rest vs Fatigue	Rest vs Recovery	Fatigue vs Recovery
SD1 [ms]	0.0108 *	0.6693	0.0189 *
SD2 [ms]	0.0979	0.4364	0.4024
SD1/SD2 [–]	0.1048	0.6095	0.3031
RR [–]	0.620	0.718	0.878
DET [–]	< 0.001 *	0.126	< 0.001 *
LAM [–]	< 0.001 *	0.287	< 0.001 *
TT [–]	< 0.001 *	0.062	< 0.001 *
ENTR [–]	< 0.001 *	0.371	< 0.001 *
SampEn [–]	0.0125 *	0.7707	0.0438
Shannon Entropy [–]	0.0165 *	0.5197	0.0488

* $p < 0.05$

2D Poincaré plot

Figure 1 shows Poincaré plots of the RR intervals of the studied athlete in the three states – before training (rest), immediately after training (fatigue/stress) and two hours after training (recovery). At rest, the scatter of points around the identity line is wider (SD1 = 31.38 ms; SD2 = 74.69 ms), which reflects high short-term and long-term heart rate variability and stable parasympathetic control. After training (SD1 = 18.87 ms; SD2 = 59.84 ms) the cloud of points narrows and orients along the diagonal, which indicates reduced variability, dominance of sympathetic activity and physiological stress. Two hours after exercise (SD1 = 18.41 ms; SD2 = 46.59 ms) the shape of the graph gradually broadens, which reflects partial restoration of autonomic balance and increased parasympathetic regulation.

3D Poincaré Plot

Figure 2 presents the three-dimensional Poincaré plots reflecting the spatial distribution of the RR intervals in the three studied conditions. Before training, the point cloud is widely scattered and fills a larger volume in the phase space, which indicates high variability and complex dynamics of the heart rate. After training, the distribution becomes highly concentrated around the identity line, with a clearly pronounced narrowing of the attractor — a characteristic sign of reduced dynamic flexibility and dominant sympathetic control. Two hours after training, the volume of the point cloud is partially restored, as the scattering increases again and the structure acquires a more diverse shape. This visually confirms the process of recovery and reactivation of parasympathetic activity, leading to a more balanced autonomic regulation.

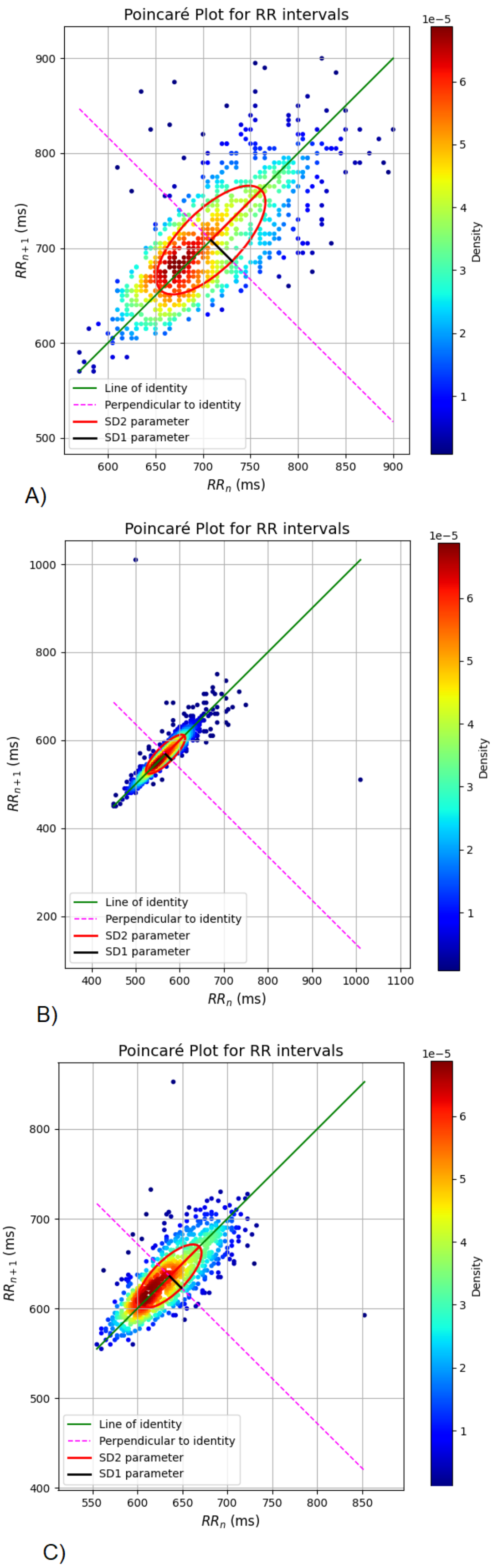

Fig. 1. Poincaré plot.
A) SD1 = 31.38 ms SD2 = 74.69 ms; SD1/SD2 = 0.42 ms
B) SD1 = 18.87 ms; SD2 = 59.84 ms; SD1/SD2 = 0.40 ms
C) SD1 = 18.41 ms; SD2 = 46.59 ms; SD1/SD2 = 0.32 ms

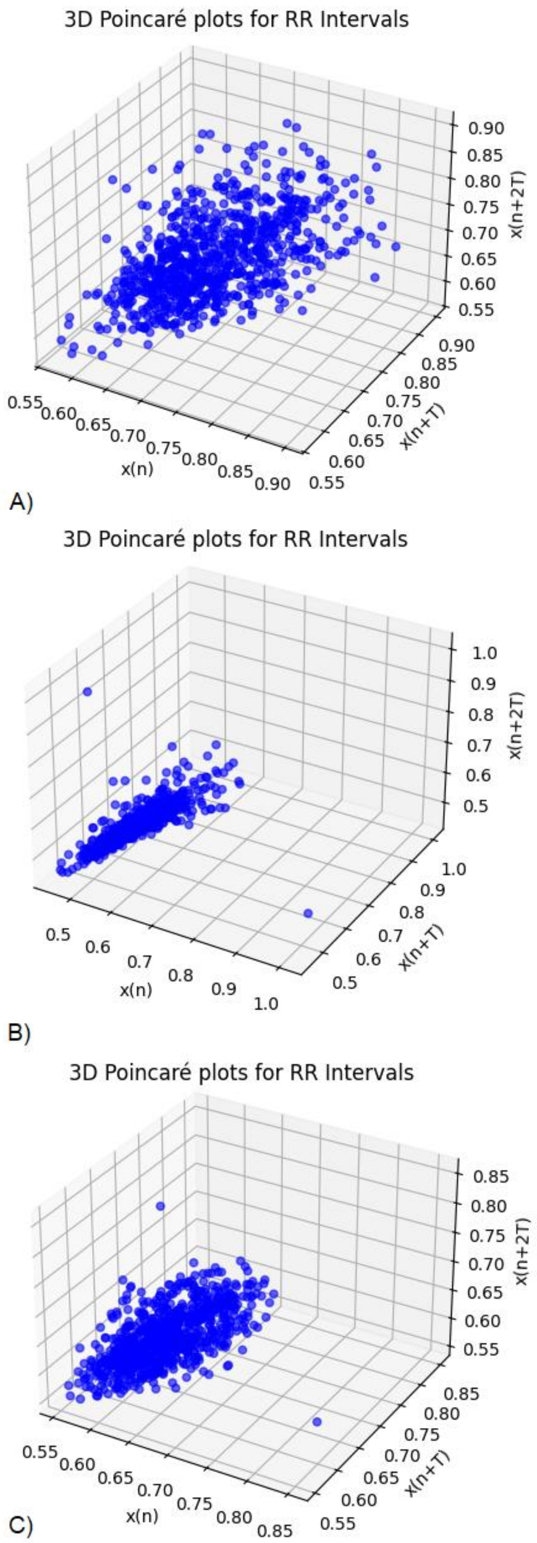

Fig. 2. 3D Poincaré plot. (A) праг ε = 0.5761;
(B) праг ε = 1.2622; (C) праг ε = 0.8399

Figure 3 presents the Recurrence Plots of the RR intervals recorded in the three experimental conditions: before training (rest), immediately after training (fatigue/stress) and two hours after training (recovery). At rest (ε = 0.5761), the RP shows a fine and uniform structure with many short diagonal and vertical lines, which indicates high variability and complexity of the heart rhythm, characteristic of a dominant parasympathetic control. Immediately after training (ε = 1.2622), the structure becomes significantly denser and more organized, with longer diagonals and compact areas of similarity - a sign of increased determinism and reduced entropy, associated with sympathetic activation and physiological stress. Two hours after training (ε = 0.8399), the RP regains its partially scattered appearance, with the density of recurrences decreasing and local patterns becoming more diverse again. This dynamics reflects the gradual reactivation of parasympathetic activity and the return to autonomic balance during recovery.

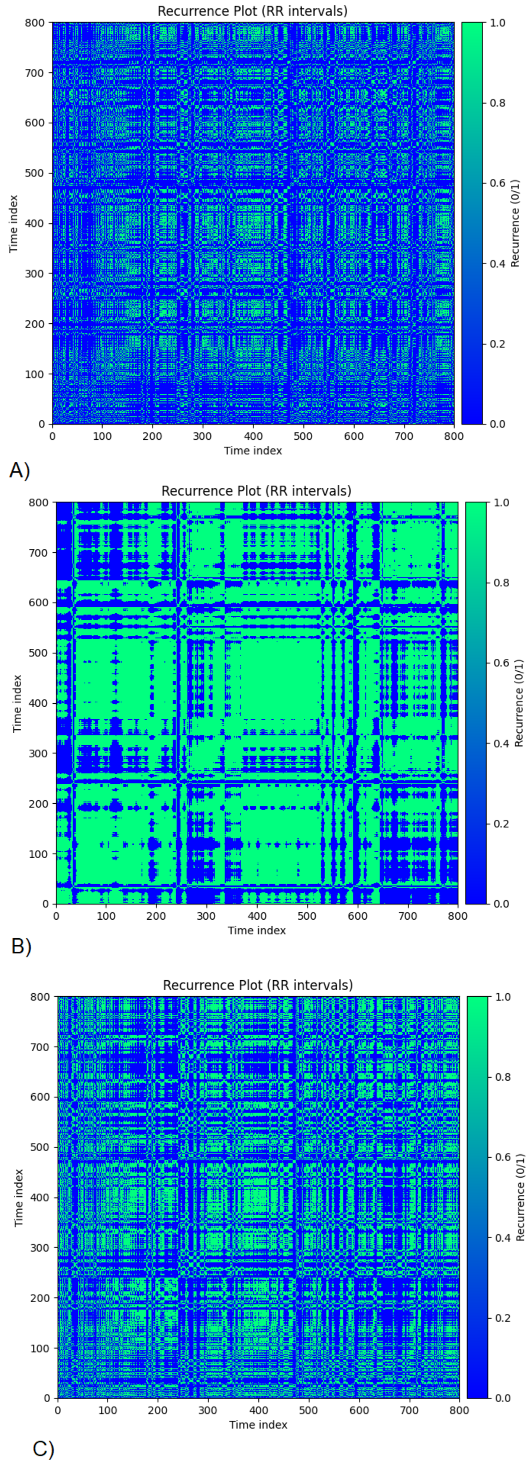

Fig. 3. 3D Recurrence plot.

Analysis of entropy and fractal indices

Before training, higher values of Sample Entropy (1.5297) and Shannon Entropy (3.7717) are observed, reflecting a high degree of irregularity and information diversity of the heart rhythm. The Hurst exponent (0.7887) shows moderate persistence and stable long-term correlation in the dynamics of RR intervals. Immediately after training, the values of Sample Entropy (0.8554) and Shannon Entropy (2.6169) decrease, which indicates reduced complexity and increased regularity of cardiac activity under the influence of sympathetic activation and fatigue. At the same time, the Hurst exponent decreases slightly (0.74), indicating reduced long-term correlation and more chaotic, anti-persistent behavior of the heart rhythm, characteristic of rapid adaptive changes in autonomic regulation after exercise. Two hours after training (Sample Entropy = 1.6214; Shannon Entropy = 3.2374; Hurst = 0.77) a restoration of the long-term structure is observed, indicating a return of autonomic regulation to a more balanced and physiologically stable state.

IV. Discussion

The present study demonstrates that combined geometric and entropic analyses of HRV provide information about the dynamics of autonomic regulation during training states in competitive athletes. The observed transformation of Poincaré and recurrent structures—from a widely dispersed pattern at rest to a compact, highly organized distribution during fatigue/stress—reflects a physiological shift from parasympathetic to sympathetic dominance. The simultaneous decrease in sample entropy and Shannon entropy indicates a loss of systemic complexity and adaptive variability immediately after training, while the gradual recovery of these indices two hours later illustrates the reactivation of vagal modulation and the restoration of homeostatic balance. These results support the interpretation that geometric and entropic measures are sensitive markers of short-term autonomic adaptations to exercise.

The findings are consistent with previous studies reporting reduced HRV complexity and short-term variability after intense exercise and gradual recovery during rest periods [2,3,6]. Similar patterns of reduced SD1/SD2 ratios and entropy values have been observed in endurance athletes experiencing acute fatigue, confirming that sympathetic activation reduces the dimensionality of cardiac dynamics, while recovery restores nonlinearity and fractal structure. The present results extend these observations by visualizing the temporal evolution of HRV through two- and three-dimensional geometric representations, providing a richer description of autonomic flexibility. Geometric and entropic markers can be used as indicators to monitor training load, optimize recovery periods, and prevent functional overload. The ability to detect changes in HRV parameters allows coaches to adapt training intensity based on each athlete's individual autonomic responses, thereby improving their training regimen. Integrating these analytics into wearable or IoT-based monitoring systems can further support personalized adaptive training protocols.

V. Conclusions

This study highlights the utility of integrating geometric, entropic, and fractal analyses of HRV to distinguish between resting, fatigue, and recovery physiological states in competitive athletes. The results show that geometric parameters such as SD1, SD2, and recurrent structures, together with entropic measures, provide additional information about autonomic modulation. After exercise, HRV becomes more deterministic, reflecting sympathetic dominance and reduced cardiovascular adaptability. Two hours after exercise, both geometric variance and entropy values partially recover, indicating reactivation of parasympathetic control and restoration of sympathovagal balance. The proposed approach, based on geometric methods and entropic parameters, offers a noninvasive framework for monitoring training load and recovery dynamics in athletes. These results support the possibility of application in sports science, where continuous monitoring of HRV may help to determine training load and prevent overtraining.

Acknowledgment

THE AUTHOR ACKNOWLEDGES THE FINANCIAL SUPPORT OF THE PROJECT WITH FINANCIAL AGREEMENT No. PVU-44 DATED 05.12.2024 UNDER PROJECT No. BG-RRP-2.017-0011 "ECOLOGICAL COLLABORATIVE ROBOTS POWERED BY GREEN HYDROGEN" UNDER THE RECOVERY AND SUSTAINABILITY MECHANISM FOR IMPLEMENTATION OF INVESTMENT UNDER C2I2 "INCREASING THE INNOVATION CAPACITY OF THE BULGARIAN ACADEMY OF SCIENCES (BAS) IN THE FIELD OF GREEN AND DIGITAL TECHNOLOGIES" FROM THE RECOVERY AND SUSTAINABILITY PLAN, BULGARIA.

References

[1] Malik, M.; Camm, A.J.; Bigger, J.T.; Breithardt, G.; Cerutti, S.; Cohen, R.J.; Coumel, P.; Fallen, E.L.; Kennedy, H.L.; Kleiger, R.E.; et al. Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. Eur. Heart J. 1996, 17, 354–381

[2] Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Front Public Health. 2017 Sep 28;5:258. doi: 10.3389/fpubh.2017.00258.

[3] Buchheit M. Monitoring training status with HR measures: do all roads lead to Rome? Front Physiol. 2014 Feb 27;5:73. doi: 10.3389/fphys.2014.00073.

[4] Vasquez-Bonilla, A.A.; Yáñez-Sepúlveda, R.; Tuesta, M.; Martin, E.B.-S.; Monsalves-Álvarez, M.; Olivares-Arancibia, J.; Duclos-Bastías, D.; Recabarren-Dueñas, C.; Alacid, F. Acute Fatigue Impairs Heart Rate Variability and Resting Muscle Oxygen Consumption Kinetics. Appl. Sci. 2024, 14, 9166. https://doi.org/10.3390/app14209166

[5] Addleman JS, Lackey NS, DeBlauw JA, Hajduczok AG. Heart Rate Variability Applications in Strength and Conditioning: A Narrative Review. J Funct Morphol Kinesiol. 2024 May 27;9(2):93. doi: 10.3390/jfmk9020093.

[6] Ni, Z.; Sun, F.; Li, Y. Heart Rate Variability-Based Subjective Physical Fatigue Assessment. Sensors 2022, 22, 3199. https://doi.org/10.3390/s22093199

[7] Georgieva-Tsaneva, G.; Tsanev, Y.-A.; Dechev, M.; Cheshmedzhiev, K. Impact on Competitive Performance and Assessment of Fatigue and Stress Based on Heart Rate Variability. Appl. Sci. 2025, 15, 10892. https://doi.org/10.3390/app152010892

[8] C. K. Karmakar, A. H. Khandoker, and A. Voss, “Sensitivity of temporal heart rate variability in Poincaré plot to changes in parasympathetic nervous system activity,” Biomed. Eng. Online, vol. 10, p. 17, 2011, doi: 10.1186/1475-925X-10-17

B. Wang, D. Liu, X. Gao, and Y. Luo, “Three-dimensional Poincaré plot analysis for heart rate variability,” Complexity, vol. 2022, Article ID 3880047, 2022, doi: 10.1155/2022/3880047.