Analysis of the Entropy of the Heart Rate Signal During the Creative Process

Ning Zhu
College of Landscape and Art Design, Hu'nan Agriculture University, Changsha 410128, Hu'nan, China

***Abstract*—Among the most important cognitive behaviors, creativity is essential for the flourishing of societies and mastery of various aspects of life around us. The effects of creative activities on the brain have only been examined in a few limited studies to date. The effects of such activities on the autonomic system have not been extensively studied. In this study, the changes in the heart rate signal before and during creative activity were examined using methods based on extracting chaotic and non-linear features from the heart rate signal. In particular, this study explores the qualitative changes in entropy during creative thinking and compares them with the resting state to determine whether or not creative activity is progressing. Based on analyzing the heart rate signals of 52 people while performing the three activities of the Torrance creativity test and comparing them with the resting state, the amount of approximate entropy and fuzzy entropy increased with the progress of the creative process. In contrast, comparing each stage of creativity to the previous stage during each activity in both types of entropy shows an increase in the average value at the end of each activity. The comparison of these steps with the last step two minutes ago shows completely incremental changes in activity 3 of both entropies. These entropies increase as the signal becomes more irregular and complex during the creative process. Our findings reveal significant increases in both approximate entropy and fuzzy entropy during creative activities compared to the resting state, suggesting heightened complexity and irregularity in heart rate dynamics as creativity unfolds. These results not only advance our understanding of the physiological correlates of creativity but also highlight the potential of heart rate entropy analysis as a tool for evaluating and enhancing creative abilities.**

***Keywords*—Heart rate signal; creative process; entropy; autonomous signals**

I. Introduction

Heart rate signal entropy analysis during creative thinking has emerged as a promising avenue of research in the field of cognitive neuroscience. The investigation of heart rate variability during creative tasks provides valuable insights into the physiological mechanisms underlying creative thinking processes [1-3]. By examining the complex patterns of heart rate fluctuations, researchers have been able to gain a deeper understanding of the dynamic interplay between the autonomic nervous system and cognitive processes involved in creative thinking [4-6].

The concept of entropy, borrowed from information theory, has been widely used to quantify the complexity and randomness of physiological signals, including heart rate variability. Entropy analysis allows researchers to assess the level of irregularity and disorder in the fluctuations of heart rate, reflecting the adaptability and flexibility of the autonomic nervous system. By examining the entropy of heart rate signals during creative thinking tasks, researchers aim to uncover potential associations between physiological dynamics and creative cognitive processes.

In recent years, many researchers have been interested in detecting cardiac behavior such as stress [7-9], anger and fear [10] or psychiatric diseases [11-13] by applying ECG signals processing. Using an electroencephalogram (EEG), Amin et al. [14] investigated brain behavior and dynamic neural activity during Raven's Advance Progressive Matrices (RAPM), which require strong cognitive reasoning to select a solution. Several studies have explored the relationship between heart rate signal entropy and creative thinking, providing valuable insights into the underlying mechanisms. For instance, a study conducted by Zakeri et al. [15] investigated the entropy of heart rate signals during a divergent thinking task. The results revealed a significant increase in heart rate entropy during periods of high creative output, suggesting a heightened autonomic response during creative thinking. These findings support the hypothesis that creative thinking is associated with increased physiological arousal and cognitive flexibility. In another study, Bakhchina et al. [16] examined the relationship between heart rate entropy and creative problem-solving. The researchers found that individuals with higher heart rate entropy demonstrated greater ability to generate creative solutions to complex problems. This suggests that heart rate entropy may serve as a potential biomarker for creative thinking abilities, providing a quantitative measure of the flexibility and adaptability of the autonomic nervous system.

An innovative method to distinguish between creativity states and electrocardiogram signals has been developed by Zakeri et al. [17]. In order to detect creativity states, 19 linear and nonlinear features of the cardiac signal were extracted. According to our results, the SVM was able to distinguish all three tasks from each other, particularly task 1, and reached a maximum accuracy of 99.63% in the linear analysis. Using the Alternative Uses Task adapted for EEG recording, Camarda et al. [18] investigated the relationship between functional fixedness and alpha-band power changes in the frontal and temporoparietal regions during creative idea generation. In the recent years, research has extensively explored the analysis of entropy in heart rate signals, particularly in the context of creative cognition. Studies have highlighted the application of entropy metrics, such as approximate entropy, symbolic entropy, and spectral entropy, to assess heart rate variability (HRV) in individuals with different cardiac conditions [19-21]. Additionally, the introduction of phase entropy has provided a novel method to quantify the complexity of HRV signals, offering better discriminatory power and stability compared to traditional entropy measures [22]. Furthermore, the nonlinear analysis of HRV using entropy-based parameters has shown promise in predicting adverse cardiovascular events in hypertensive patients, enhancing diagnostic accuracy and providing complementary information to linear indexes [23]. This interdisciplinary approach to understanding the relationship between entropy, physiological signals, and cognitive processes underscores the potential for entropy studies to unify cognitive science and cultural evolution [24]. Bieth et al. [25] examined EEG activity during an adapted version of a classical insight problem task, the Remote Associates Test in which three words must be connected by finding a word between them. We were able to explore remoteness in semantic connections (by varying the remoteness of the word in the solution across trials) and insight solving. Cao et al. [26] used EEG to investigate neural activity patterns of designers with higher and lower fixation levels during creative idea generation. This was done with the goal of determining the neurological basis of design fixation. From a neuroscience perspective, these results may reveal the different neural activities involved in the occurrence of higher and lower degrees of design fixation. Recently, Eskine [27] investigated the activation of these networks after participants listened to music that was previously shown to enhance creativity. Using resting state electroencephalograms, they provide novel methodologies for investigating network activation in a creative cognition framework by activating networks deemed important in the creative process.

The exploration of heart rate signal entropy during creative thinking holds significant implications across education, psychology, and neuroscience. By identifying the physiological markers linked to creative processes, researchers can formulate interventions and training programs aimed at enhancing creative skills. Additionally, combining heart rate entropy analysis with other physiological and neuroimaging techniques may offer a holistic understanding of the neural mechanisms that underpin creative thinking. In conclusion, analyzing heart rate signal entropy during creative thinking provides a unique perspective on the interplay between physiological dynamics and cognitive processes. Investigating heart rate variability and entropy yields valuable insights into the adaptive nature of the autonomic nervous system during creative tasks. By examining the relationship between heart rate entropy and creative thinking abilities, researchers can deepen our understanding of the physiological foundations of creativity and potentially develop novel interventions to enhance creative thinking skills.

Creativity is a pivotal cognitive function that drives societal progress and enhances individual adaptability in various life domains. Despite its importance, the physiological mechanisms underpinning creativity, particularly within the autonomic nervous system, have not been extensively studied. Prior research has primarily focused on the neurological aspects of creativity, with limited investigation into how creative processes influence autonomic signals, such as heart rate variability.

This study aims to bridge this gap by employing approximate entropy and fuzzy entropy analyses to explore the changes in heart rate signals associated with creative thinking. We hypothesize that creative activities induce distinctive patterns of heart rate variability, reflecting the adaptive responses of the autonomic nervous system. By analyzing heart rate signals from 52 participants engaged in the Torrance creativity test, we seek to identify entropy-based markers that differentiate creative states from resting states and track the progression of creativity across different stages of the task. It is evident from examining the history of the subject that the EEG signal has always been of interest to researchers because of its creative activity. Due to the lack of sufficient research in the field of autonomous signals and its relationship with creativity, the present study has been conducted in order to fill a part of the existing gap in this field. In the process of developing creative thinking in the brain, the functioning of the brain affects other parts of the body, as well as the autonomic nervous system. In turn, this system is divided into two areas, sympathetic and parasympathetic, in which the parasympathetic nervous system has a significant influence on the cardiac signal. This study examines the complexity and behavior of the heart rate signal during creative thinking, after it has been extracted from the cardiac signal. This study aims to determine the amount of irregularity in the heart rate signal by analyzing two types of entropy. This study is organized as follows: Introduction is given in Section I. The method of data collection and the method of conducting the study are described in Section II. Discussion is given in Section III. Finally, Section IV concludes the paper.

II. Research Method

In this study, a 16-channel Powerlab data acquisition device was used to record ECG data. The electrocardiogram signal of 52 people was recorded simultaneously with the Torrance creative thinking test and with a sampling rate of 1000 Hz from lead 2. The output signal from the device was amplified and displayed in LabChart software, which is supporting software for displaying and processing different types of physiological data. Fig. 1 shows a view of the PowerLab device. All the subjects were right-handed, and they were asked to refuse to eat coffee before the recording process and to have enough sleep to prevent fatigue. Torrance's creative thinking test is a 30-minute test and includes three activities; each activity consists of 10 minutes. The whole test consisted of 32 minutes, which included two minutes of resting and 30 minutes of performing the test. Then, Labchart software was used to extract the heart rate signal. After processing, the 10-minute heart rate signal was divided into five two-minute periods to examine and compare each stage of the Torrance creative thinking test with the resting state. The characteristics of the subjects are recorded in Table I.

A. *Torrance Creativity Test*

As a general rule, creativity refers to the ability to generate new, useful, and impactful ideas or products. Divergent-thinking tests such as the Torrance Tests are widely used and validated and, therefore, are the natural choice. The word can be expressed in two ways: figuratively and verbally. For this study, we used verbal form B as a method of data collection. A written informed consent ensuring voluntary participation and confidentiality of data was obtained from subjects before they completed the English version of the TTCT-Verbal (Form B) [28]. A total of six activities were included in the instrument: Activity 1 – Asking (posing questions about the pictured action for 2 minutes); Activity 2 – Guessing causes (making predictions about the cause of the action, 2 minutes); Activity 3 – Guessing consequences (predicting the consequences of the action, 2 minutes); Activity 4 – Product improvement (developing ideas for improving a toy monkey, 2 minutes); Activity 5 – Unusual uses (finding new uses for bottles, 2 minutes); and Activity 6 – Just suppose (thinking of potential ramifications for an improbable situation, 2 min) [29]. Under the supervision of trained research assistants, the instrument was administered collectively. Fluency (number of relevant responses generated), flexibility (number of categories reflected in responses, according to the categories outlined in the scoring manual), and originality (based on the frequency of responses). Responses generated by less than 2% of the sample were awarded two points, responses generated by 2% to 5% of the sample were awarded one point, and responses generated by more than 5% were awarded zero points) [30, 31].

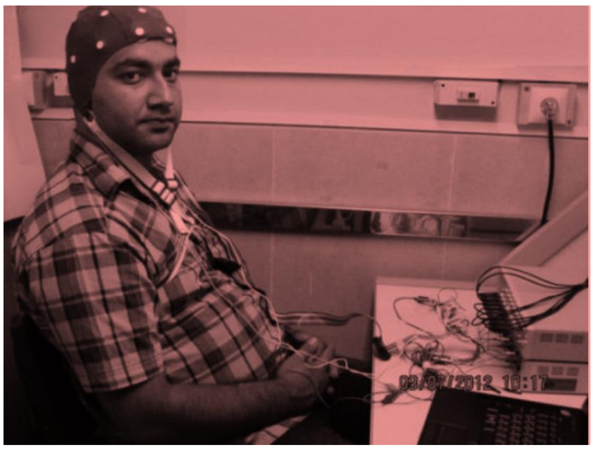

Fig. 1. A sample of ECG signal recording with 16-channel Powerlab device.

TABLE I. PERSONAL CHARACTERISTICS OF THE PARTICIPANTS IN THE TORRANCE CREATIVITY TEST (VERBAL FORM B)

Sample number	52
Age	19-25
Age average	22±1.4
Situation	Health, Right-hand

B. Approximate Entropy

Approximate entropy analysis provides a means to quantify the regularity and complexity of heart rate signals during creative thinking. By assessing the variability and unpredictability of heart rate dynamics, ApEn offers insights into the autonomic nervous system's adaptability during creative tasks. Understanding these physiological patterns through ApEn analysis can reveal the underlying mechanisms that support creative thinking. Additionally, integrating ApEn analysis with other physiological and neuroimaging techniques can enrich our understanding of the neural and physiological correlates of creativity, leading to the development of targeted interventions to foster creative abilities. Statistically, approximate entropy measures the degree of predictability of fluctuations in a time series [32]. A relatively higher value of approximate entropy reflects the likelihood that similar patterns of observations are not followed by additional similar observations. The approximate entropy shows the amount of disorder and complexity of the signal, which was first introduced by Pincus et al. [33]. This entropy has been used as an extension in the analysis of cardiac domains. The degree to which the occurrence of a value depends on the previous values in the input is measured by approximate entropy. Low values of this entropy indicate order, while high values indicate low predictability and disorder. The resistance and insensitivity of the approximate entropy to small and large artifacts makes it suitable for use in the biological field.

A technique called approximate entropy (ApEn) is used in statistics to quantify the degree of regularity and predictability of fluctuations over time series.

The theoretical foundations of Approximate Entropy are explained in a comprehensive step-by-step tutorial [34]. It consists of the following steps:

Step 1: Assume a time series of data $x(1), x(2), \ldots, x(P)$. These are P raw data values from measurements equally spaced in time.

Step 2: let $m \in \mathbb{Z}^+$ be a positive integer, with $m \le$ P, which represents the length of a run of data (essentially a window).

let $r \in \mathbb{R}^{+}$ be a positive real number, which specifies a filtering level.

let $p = P - m + 1$.

Step 3: Define $\boldsymbol{u}(i) = \{x(i), x(i+1), \ldots, x(i+m-1)\}$ for each i where, $1 \le i \le p$. In other words, $\boldsymbol{u}(i)$ is an m m-dimensional vector that contains the run of data starting with x(i).

Define the distance between two vectors x (i) and x (j) as the maximum of the distances between their respective components, given by:

$$d[\boldsymbol{u}(i), \boldsymbol{u}(j)] = \max_k(|\boldsymbol{u}_k(i) - \boldsymbol{u}_k(j)|) = \max_k(|u(i+k-1) - u(j+k-1)|), 1 \le k \le m \tag{1}$$

Step 4: Define

$$\phi^m(r) = \frac{1}{p}\sum_{i=1}^{p} log[C_i^m(r)] \tag{2}$$

where, log is the natural logarithm, and for a fixed m, r, and p as set in Step 2.

Step 5: Define approximate entropy (ApEn) define as

$$ApEn(m, r, P)(u) = \phi^m(r) - \phi^{m+1}(r) \tag{3}$$

It is recommended that m be equal to 1, 2 or 3 and r between 10% and 25% of the standard deviation of the data in applications related to heart rate. In this study, approximate entropy parameters m=1 and r=0.2*std (data) were selected.

C. Fuzzy Entropy

The fuzzy entropy is applied to the seal impression problem to measure the subjective value of information under the condition of uncertainty. It is a new method that replaces the fuzzy membership function with the single-step function to find entropy. This type of entropy combines local and global similarity in time series and provides good separation for time series with intrinsic complexity. The three primary parameters m, r and P should be considered when calculating fuzzy entropy.

Fuzzy entropy considers vectors of length m. x_i^m and x_i^{m+1} defined for all $1 \leq l \leq N-m$. For the time series of $\{u(t): 1 \leq l \leq N\}$, the shape of the vectors is expressed according to the following equation.

$$x_i^m = \{u(i), u(i+1), \ldots, u(i+m-1)\} - u_0(i), i = 1,2, \ldots, N-m+1 \tag{4}$$

where, x_i^m represents m consecutive values of u. Starting from the starting point i and discarding the baseline, we will have:

$$u_0(t) = m^{-1} \sum_{j=0}^{m-1} u(t+j) \tag{5}$$

It calculates the similarity degree vector from its neighborhood vector, which is defined by a fuzzy function according to the following relation.

$$D_{ij}^m = \mu\left(d_{ij}^m, r\right) \tag{6}$$

where, d_{ij}^m is the maximum absolute value of the difference of the corresponding scalar components x_i^m and x_j^m. For each averaging vector of $x_i^m (i = 1,2, \ldots, N-m+1)$, all degrees of similarity, we will have neighborhood vectors:

$$\phi_f^m(r) = (N-m-1)^{-1} \sum_{f=1, i \neq f}^{N-m} D_{ij}^m \tag{7}$$

By rewriting the equations, we will have:

$$\phi^m(r) = (N-m)^{-1} \sum_{f=1}^{N-m} \phi_f^m(r) \tag{8}$$

Then, the fuzzy entropy parameter of a time series is expressed as the following equation:

$$FuzzyEn(m,r) = lim[ln\, \phi^m\,(r) - ln\, \phi^{m+1}\,(r)]^{-1} \sum_{t=1}^{N-m} \phi_t^m(r) \tag{9}$$

For the data set with finite length N, this relationship is in the form of the following equation:

$$FuzzyEn(N,m,r) = ln\, \phi^m\,(r) - ln\, \phi^{m+1}\,(r) \tag{10}$$

Fuzzy entropy has relatively strong compatibility and is less dependent on data length. It has more freedom in choosing parameters and has high resistance to noise.

In this study, m=2 and r=0.2*std (data), where sdt represents the standard deviation, were chosen optimally.

The test used in this research, the Wilcoxon test [35, 36], is one of the statistical tests that is widely used in behavioral studies. A non-parametric test is used to compare the changes of two different conditions of a group of participants. If there is a systematic change between the two states, most of the high ranks belong to one state, and most of the low ranks belong to another state. If two situations are similar, the distribution of high and low ranks will be the same for both situations. These differences are expressed in the form of a probability (p-value). The p-value intuitively shows the significance of the differences between the two conditions, so the decrease of this number to less than 0.05 indicates a significant difference. In this research, we used the Wilcoxon statistical test because this test is non-parametric and does not need the normal distribution of the data. Also, it is not sensitive to the number of samples of groups.

III. Discussion

A. Approximate Entropy Analysis

Approximate entropy analysis is a method used to quantify the amount of regularity and unpredictability in time-series data, such as heart rate signals. In the context of creative thinking, approximate entropy analysis offers a valuable tool for examining the complexity and variability of physiological responses. Fig. 2 to Fig. 4 show the approximate entropy for a person at rest and the first to fifth 2-minute periods for activities 1 to 3. Analysis of approximate entropy for all three activities of Torrance's creativity test and comparing the first to the fifth 2 - minutes with resting state showed an increase in the range of this parameter at the starting point, with the progress of creative activity. As can be seen, the approximate entropy increased first at the starting point compared to the resting state, and then at the end of the creative activity, this parameter returned to its initial value; it means that the approximate value of the resting state is approaching. In the case of activity 3, this parameter had a decreasing rate at the starting point for some subjects.

In order to obtain a specific pattern and generalize it to all people, a box diagram of these values was drawn. These values are shown in Fig. 5 for 2-minute periods and for activities 1 to 3. The green graph shows the resting state, and the yellow graphs from 2 to 6 show the first to fifth two-minute periods, respectively.

Analysis of the patterns shows an increase in the average value for 52 subjects compared to the resting state. On the other hand, the comparison of each creative stage with the last two minutes of the previous stage shows constant changes in Activity 1. In activity 2, the average values increased in the second two minutes compared to the first two minutes, and for the third and fourth minutes, it follows decreasing changes. This amount in two minutes of the fifth; That is, the end of creative activity increases again. In activity 3, all the two-minute steps, except the third two minutes, follow incremental changes compared to the previous two minutes. Fig. 6 to Fig. 8 show the phase entropy for a person at rest and the first to fifth two-minute periods for activities 1 to 3.

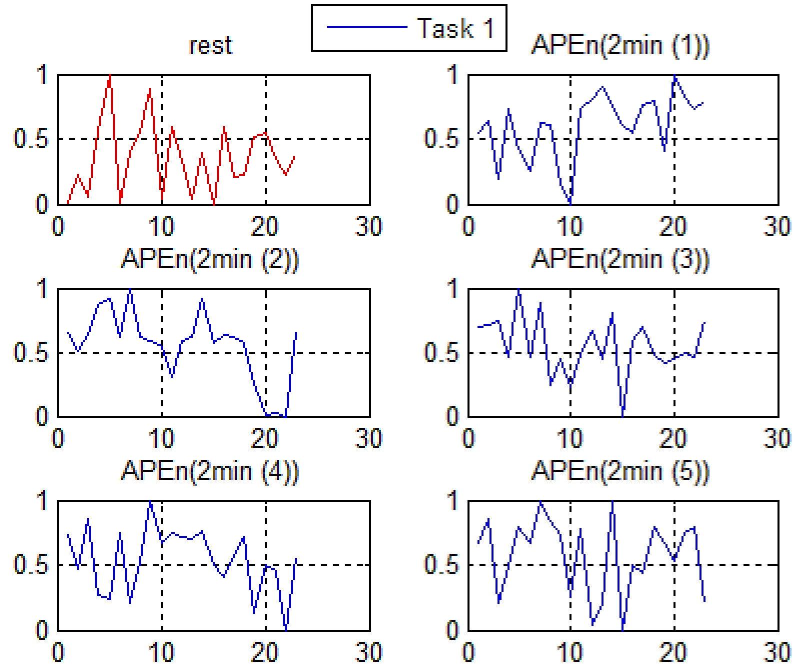

Fig. 2. The pattern of approximate entropy values in activity 1 in 2-minute periods (subject number 2), the vertical axis is the entropy range, and the horizontal axis is the number of windows.

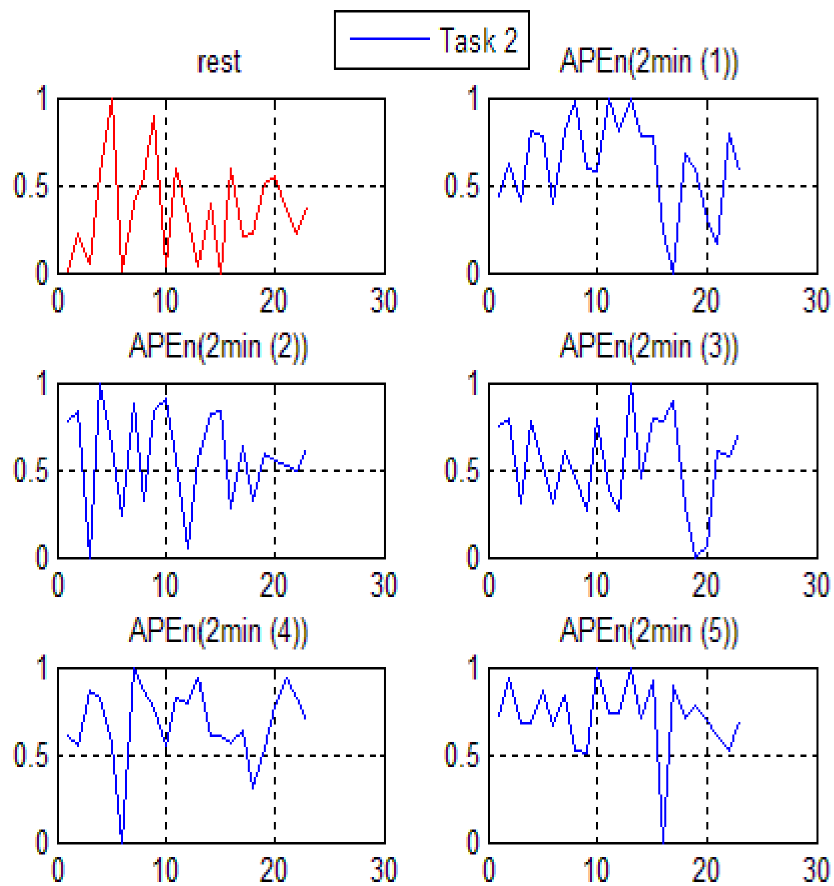

Fig. 3. The pattern of approximate entropy values in activity 2 in 2-minute periods (subject number 2).

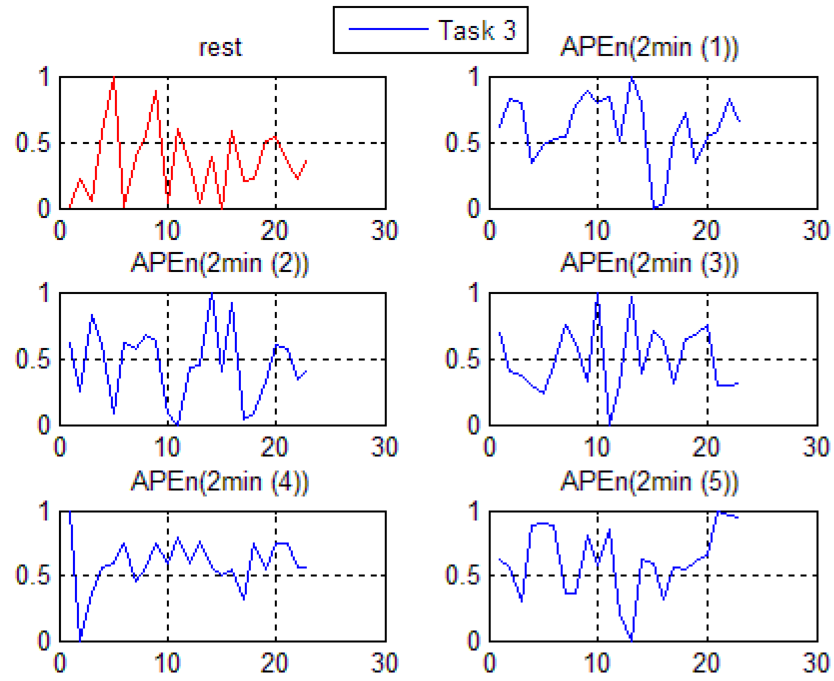

Fig. 4. The pattern of approximate entropy values in activity 3 in 2-minute periods (subject number 2).

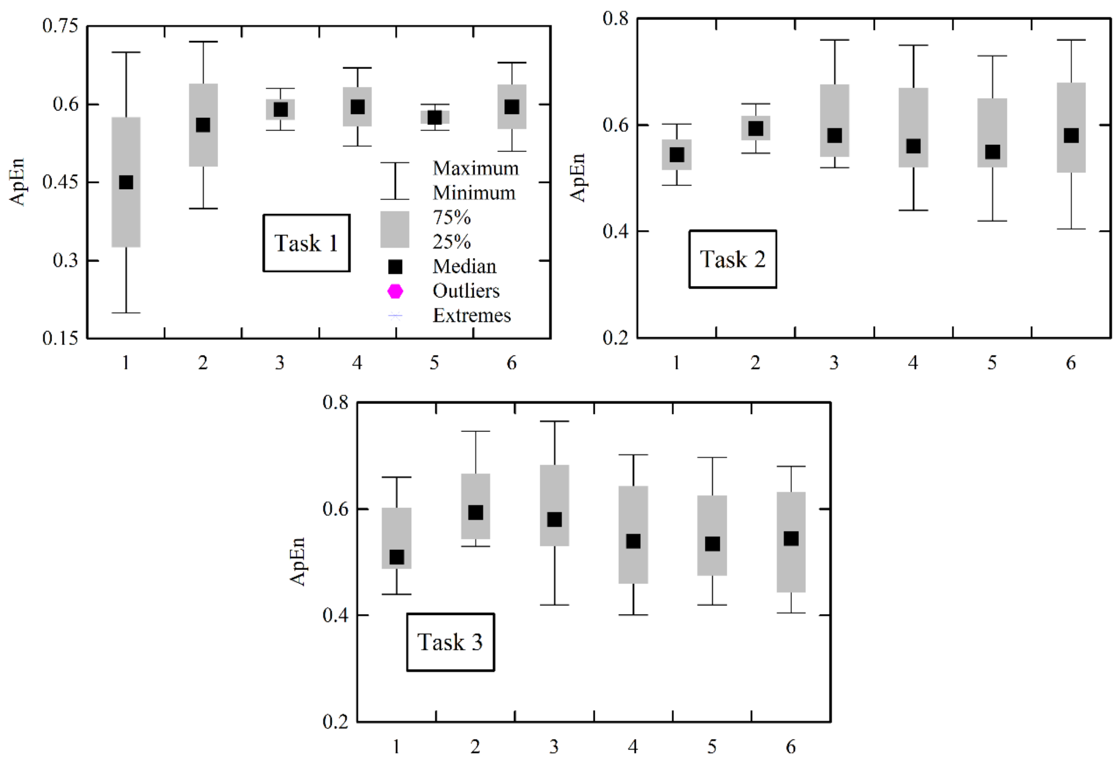

Fig. 5. Approximate entropy box diagram for 52 subjects in activities 1 to 3. The green diagram shows the resting state, and the yellow diagrams from 2 to 6 show the first to fifth two-minute periods, respectively. The vertical axis of the average and the horizontal axis of time means that each of the stages shows two minutes with rest.

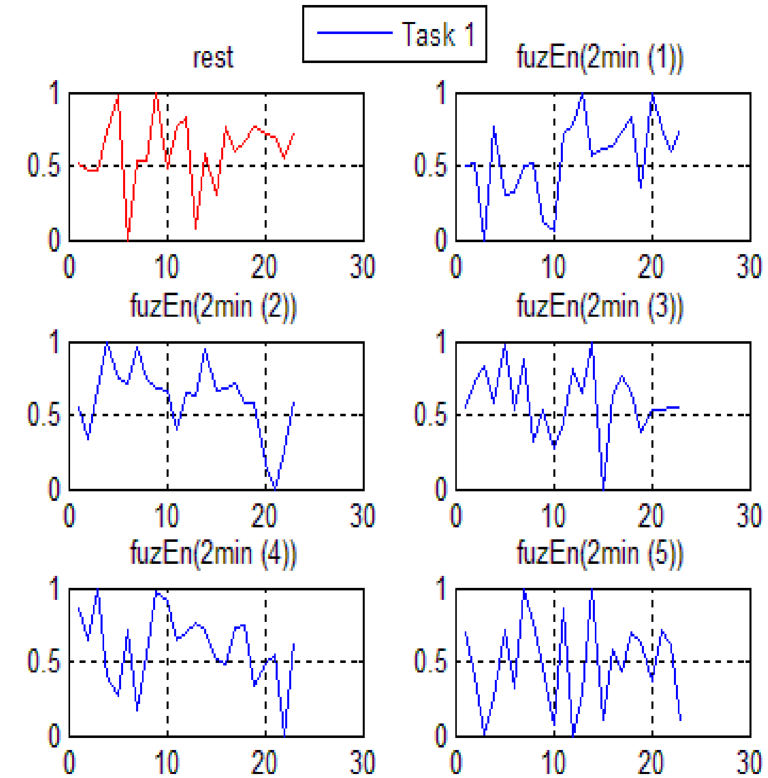

Fig. 6. The pattern of fuzzy entropy values in activity 1 in two-minute periods (subject no. 2), the vertical axis shows the entropy range and the horizontal axis shows the number of windows.

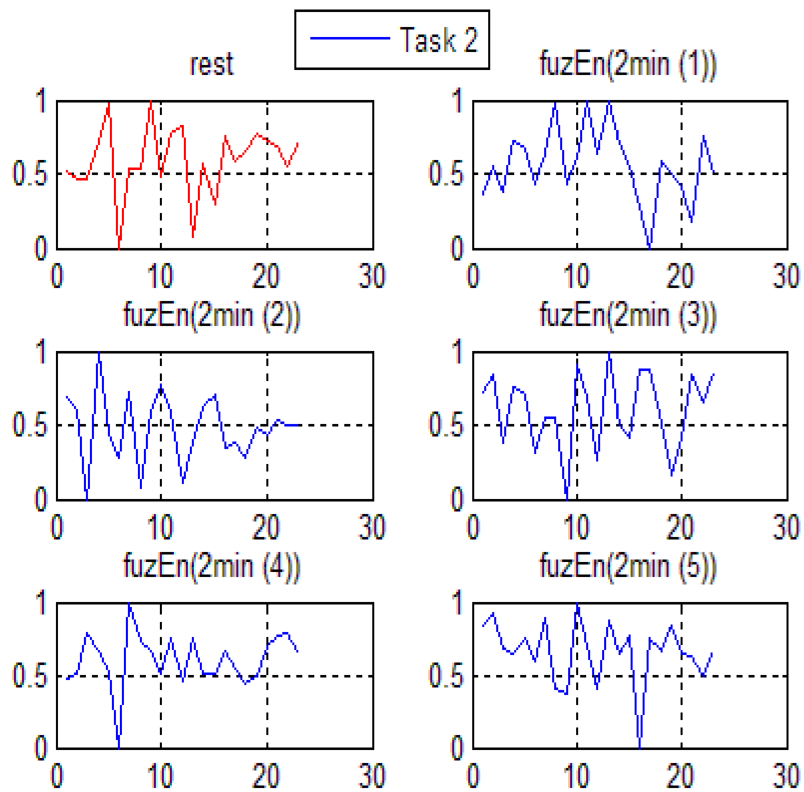

Fig. 7. The pattern of fuzzy entropy values in activity 2 in two-minute periods (subject no. 2), the vertical axis shows the entropy range and the horizontal axis shows the number of windows.

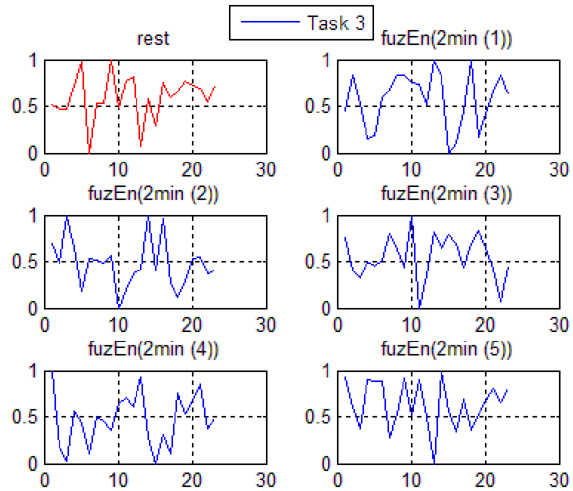

Fig. 8. The pattern of fuzzy entropy values in activity 3 in two-minute periods (subject no. 2), the vertical axis shows the entropy range and the horizontal axis shows the number of windows.

Box plots of fuzzy entropy for all three activities and 52 subjects are shown in Fig. 9. The analysis of the fuzzy entropy shape in 52 subjects showed incremental changes in the mean of the feature in the creativity state compared to the rest time. By comparing the two entropies, it can be concluded that creative activity in most subjects shows itself as the growth of the entropy range at the starting point of the pattern. However, phase entropy does not have such a development in most subjects despite incremental changes in the mean of the feature. The second two minutes did not change compared to the first two minutes of activity 1, while the average value decreased in the third two minutes and followed this decreasing trend in the fourth two minutes, and finally, this value increased in the fifth two minutes of the activity. The changes in the two-minute stages compared to the previous stage in Activity 2 have an increasing and decreasing pattern, and in Activity 3, this pattern is completely incremental for each two-minute stage compared to the previous stage.

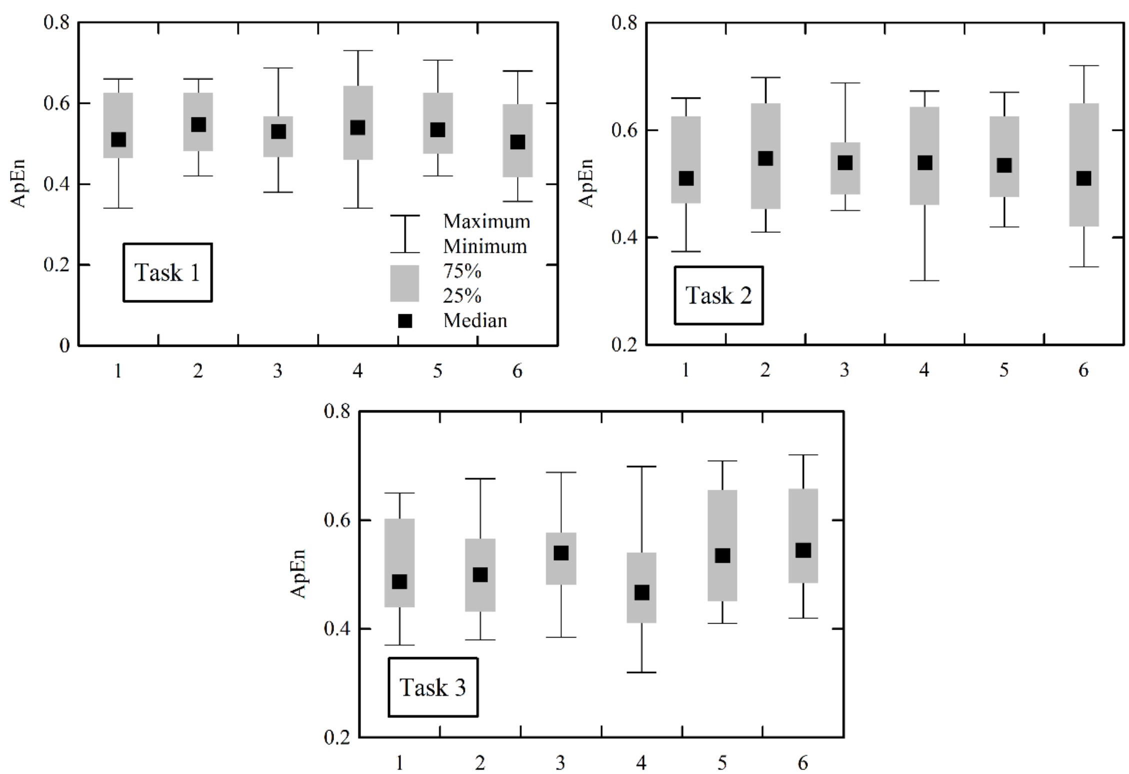

Fig. 9. Box diagram of phase entropy for 52 subjects in activities 1 to 3. The green diagram shows the resting state, and the yellow diagrams from 2 to 6 show the first to fifth two-minute periods, respectively. The vertical axis of the average and the horizontal axis of time means that each of the stages shows two minutes with rest.

B. Wilcoxon Statistical Test

For the purpose of determining the significance of the difference between the activities, the Wilcoxon statistical test was used, and the results are shown in Tables II and III. These tables present p-values for approximate entropy and fuzzy entropy between the resting state and Torrance's creative thinking activity. Based on the Wilcoxon statistical test, Table II shows the significant values for many states of creative thinking as compared to the resting state. For all three activities, these values are significant when compared to the resting state and the second and fifth minutes.

Statistical analysis of the phase entropy values for the resting state, the second and fifth two minutes of all three activities found significant results for the p values. Furthermore, a statistical test showed significant results for Activity 1's resting state and the first two minutes, as well as Activity 3's resting state and the fifth two minutes. According to Tables IV and V, the differences between each of the two-minute steps and the previous two minutes are explained. A comparison of the two-minute stages for both types of entropy is presented in Tables IV to V, with the most significant values being found in Activity 3 and transitioning from Activity 4 to Activity 5, two minutes during Activity 1 for both types of entropy. Significant results have been obtained. The value of approximate entropy was not significant for activity 2, which had two types of entropy.

In study [37], it was observed that there is a synchronization between high alpha brain waves and the illusion of an improvised dance during the imagination of a standard waltz dance. Gruzelier et al. [38] investigated the alpha/theta EEG band alongside HRV in a group of dancers in training. Their study revealed that an increase in HRV, influenced by autonomic nervous system activity, led to symptoms such as shortness of breath, rapid breathing, irregular heartbeat, tremors, feelings of fear, dry mouth, and increased nervous tension. These symptoms contributed to heightened stress, intolerance, irritability, inability to remain calm, and disorganized responses in young dancers. Guilford's test on alpha and theta waves showed no significant differences. Forte et al. [39] argued that concentration during cognitive tasks is associated with a decreased heart rate. Belli [40] found a significant difference in heart rate when individuals solved efficient versus inefficient problems. Additionally, individuals participating in group activities exhibited higher levels of creativity compared to those who did not. Brain imaging studies, including fMRI, PET, and SPECT, have shown that frontal lobe activation is more pronounced in highly creative individuals compared to those with lower creativity levels [41]. Stimulation of the vagus nerve (sympathetic) has been associated with increased heart rate and disturbances in testing processes, resulting in decreased creativity [42]. In an experiment conducted by Velázquez et al. [43] on 53 pairs of twins, it was found that the T gene significantly contributed to creativity in over 70% of participants. Research on individuals with Parkinson's disease indicated that the type of disease—right-hemispheric onset (RHO) or left-hemispheric onset (LHO)—affects creativity levels differently. Specifically, individuals with RHO experienced a significant decrease in creativity within three months [44].

Furthermore, comparing each stage of creativity with the previous one shows an increase in the average entropy value by the end of each activity, with significant incremental changes observed in the final stages. These findings indicate that heart rate signal entropy analysis can effectively differentiate between resting and creative states, offering a novel approach to evaluating individual creative abilities. Indeed, it is crucial to acknowledge the limitations of our study to ensure a comprehensive understanding of the findings. While our research contributes valuable insights into the relationship between heart rate entropy and creative thinking, it is essential to recognize certain limitations. These include the relatively small sample size and the lack of diversity in participant demographics. These factors may affect the generalizability of our results. Additionally, our study focuses specifically on the Torrance creativity test, which may not capture the full spectrum of creative activities. We acknowledge these limitations and recommend that future research endeavors address these concerns through larger and more diverse participant samples, as well as by exploring a broader range of creative tasks. Such efforts would enhance the robustness and applicability of findings in this field.

TABLE II. REPORT OF P-VALUES OF APPROXIMATE ENTROPY BETWEEN RESTING STATE AND TORRANCE'S CREATIVE THINKING ACTIVITY

	Activity 1	Activity 2	Activity 3
Rest & 1st 2-minit	0.0556	<0.05	<0.05
Rest & 2nd 2-minit	<0.05	<0.05	<0.05
Rest & 3rd 2-minit	0.0624	<0.05	0.0674
Rest & 4th 2-minit	<0.05	0.1279	<0.05
Rest & 5th 2-minit	<0.05	<0.05	<0.05

TABLE III. REPORT OF FUZZY ENTROPY P VALUES BETWEEN RESTING STATE AND TORRANCE'S CREATIVE THINKING ACTIVITY

	Activity 1	Activity 2	Activity 3
Rest & 1st 2-minit	0.13205	0.0678	<0.05
Rest & 2nd 2-minit	0.0824	0.2694	<0.05
Rest & 3rd 2-minit	0.1356	0.0684	0.8621
Rest & 4th 2-minit	0.0568	0.1924	0.3410
Rest & 5th 2-minit	<0.05	0.1782	0.2872

TABLE IV. APPROXIMATE P-ENTROPY VALUES BETWEEN THE TWO-MINUTE STEPS OF TORRANCE'S CREATIVE THINKING

2-minit	Activity 1	Activity 2	Activity 3
1st and 2nd	<0.05	0.3452	0.7452
2nd and 3rd	<0.05	0.9521	0.6782
3rd and 4th	0.5658	<0.05	0.8521
4th and 5th	<0.05	0.8924	<0.05

TABLE V. FUZZY ENTROPY P-VALUES BETWEEN TWO-MINUTE STAGES OF TORRANCE'S CREATIVE THINKING

2-minit	Activity 1	Activity 2	Activity 3
1st and 2nd	<0.0001	0.8523	0.1264
2nd and 3rd	0.0614	0.2026	<0.05
3rd and 4th	0.2358	0.5631	0.03421
4th and 5th	<0.0001	0.6740	<0.0001

IV. Conclusion

An analysis of nonlinear features of the heart rate signal during creative activity is presented in this article. As a result of this study, a gap in the literature has been filled regarding the response of autonomous signals to creative thinking. An examination of the approximate entropy and fuzzy entropy of the heart rate signal of 52 individuals during creative activity was conducted for this purpose. There were five stages in each of Torrance's activities, each of which lasted two minutes in length. As compared to the resting state, the approximate entropy values of each stage increased during creative activity. In terms of approximate entropy, a Wilcoxon statistical test indicated significant differences between creative activities and resting states. The highest significant values are associated with approximate entropy, followed by fuzzy entropy. As a result of comparing each two-minute stage to the previous stage, the 3rd activity in both types of entropy continually increased. Based on the results of the statistical test, a significant difference exists between the fourth and fifth minutes of Activity 1, indicating an increase in entropy at the end of the creative activity. During creative activity, the average values of these two types of entropy increase, indicating an increase in the complexity of autonomous signals. It is for this reason that the heart rate signal becomes irregular during creative activity. Although fuzzy entropy has advantages over the usual entropies, as mentioned before, the properties of the approximate entropy (the resistance and insensitivity of the approximate entropy to small and large artifacts) make it suitable for use in biological fields, especially heart rate signal analysis. Therefore, more appropriate to use approximate entropy than fuzzy entropy in this case.

Future research should focus on longitudinal studies to assess the impact of creative training programs on heart rate signal entropy over time and integrate these analyses with neuroimaging techniques like fMRI or EEG to better understand the neural correlates of creativity. Additionally, expanding studies to include diverse demographic groups can determine the universality of observed entropy patterns. Investigating task-specific physiological responses to different creative activities, employing machine learning for improved analysis accuracy, and exploring clinical applications for diagnosing and treating creativity-related deficits are also essential. Real-time monitoring systems using heart rate entropy analysis could provide immediate feedback in environments requiring continuous creativity, thereby advancing our understanding of the physiological underpinnings of creativity and developing practical applications to enhance creative thinking skills across various domains.

Statement on Ethics Approval and Consent:

I hereby include the following statement on ethics approval and consent:

This study was conducted with due consideration for ethical standards. Although the need for ethics approval may have been waived, I affirm MY commitment to ethical conduct and the protection of human subjects' rights.

Furthermore, should this manuscript contain any individual person’s data in any form, including individual details, images, or videos, we confirm that appropriate consent to publish has been obtained from the relevant individuals or their legally authorized representatives.

I am fully aware of the importance of respecting the rights and privacy of individuals involved in our research, and I assure readers that all necessary steps have been taken to adhere to ethical standards and obtain informed consent where applicable.

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