Crucial Events Identify Emotion Granularity from Long-Term ECG Recordings

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Abstract

The increasing interest in improving the accessibility and implementation of psychiatric solutions in diagnosing and treating mental and neurological disorders is driven by the need for real-time patient monitoring. One promising approach is emotion recognition using physiological signal complexity detection. Complexity measures involving crucial events, which are brief intervals of intermittent turbulence that resemble fractal-like behaviour and a part of temporal biosignals have been used to analyze physiological signals, with the assumption that healthy and pathological signals differ in their levels of complexity. However, there is limited knowledge about the relationship between physiological signals, and psychopathology. Changes in emotion are reflected in heartbeat variations, and valence and arousal are psychological features of emotion. Crucial events, patterns in the heart rate that identify instances of change, can be detected using the novel multiscaled modified diffusion entropy analysis (MSMDEA), which has been shown to distinguish healthy from pathologic cardiac signals and different types of pathologic signals at high statistical significance (p<0.0001) compared to using MDEA on its own.

1. Introduction

A mental disorder can be characterized as a clinically significant disturbance in an individual's cognitive functioning, emotional management, or behavioral tendencies. Typically, it is associated with the subjective sensation of distress or impairment [1]. In 2019, over 970 million individuals globally, experienced a mental health disorder. According to the study conducted by GBD (Global Burden of Disease) in 2022, anxiety and depressive disorders exhibited the highest prevalence rates among the various disorders examined [2]. Recent studies conducted by universities and hospital researchers in the emirates of the UAE revealed that more than 50% of the screened participants suffered from mental health disorders, of which the most common are anxiety and depression [3,4]. The global decline in mental health and the growing prevalence of anxiety and major depressive disorders is leading to an increased demand on mental health services. However, mental health services are limited leading to an increase of undiagnosed cases and lack of intervention. where treatment is not as effective [1, 3-5]. The current mental health questionnaires often rely heavily on self-reporting [5]. However, managing short-term and chronic mental or neurological disorders requires thorough follow-up and real-time monitoring due to their unstable nature, and this is not practical, inaccessible, and costly with the current methods [6]. A recently emerging active field of research that aims to bridge the gap between prevalence of mental health disorders and availability of clinical psychiatric practices is emotion recognition by wearable technology for at-home assessment. The focus of investigations in the scientific community has shifted to emotion recognition, especially with artificial intelligence and data mining having increased the opportunities and accuracy of identifying emotions in the wild [6-8]. This can be useful not only for clinical applications, but also for brain-computer interactions or human-to-computer interactions where robots can take the data from physiological variables such as heart rate and respond appropriately to the human they are interacting with [9]. For this to occur, accurate emotion granularity recognition in real-time is required.

1.1. Research Statement and Objectives

The research proposes that crucial events are an option to provide the foundational framework for this real-time information. Crucial events are brief intervals of intermittent turbulence that resemble fractal-like behaviour [10,11]. This study aimed to investigate an innovative approach for the classification of emotions defined by different levels of valence and arousal based on the complexity dynamics of ECG time series from healthy participants. The current data and part of the methods used for the preliminary analysis came from the Korean Advanced Institute of Science and Technology (KAIST), South Korea, and the University of North Texas (UNT), United States, respectively. The project's main objectives include:

1. Improving the current algorithm for detection of emotion granularity.
2. Validating and refining the proposed method on the

dataset provided by KAIST.

3. Developing a reproducible and reliable emotion detection system that could be applied in real-time settings for mental health assessment.

1.2. Background

Emotion recognition using physiological signals and artificial intelligence classifiers has been the topic of extensive research in the last decade [12]. Despite obtaining high accuracy, AI-based classification still has major limitations such as the heavy computational cost, lack of generalization and reproducibility, lack of data recordings captured in the wild, frequent need to update and retrain the data classifiers, constant need to obtain large sample sizes to train proposed models, achieving near-perfect results in the detection of only one dimension of emotion at low granularity, and some more found in the extensive reviews on this topic [6,13]. The proposed approach in this research which addresses these shortcomings is based on computing and analyzing complexity measures of physiological signals.

Complexity measures are valuable in assessing a range of psychological, neurological as well as physical conditions, as they may indicate an increase or decrease in the content of physiologic information as the basis of an individual's ability to adapt [14,15]. Complex systems such as the heart, exhibit statistical properties, including not only a mean heart rate and variance but also multiscaling and crucial events. Multiscale entropy analysis can quantify the complexity of physiologic time series, and a loss of complexity was shown to be a general characteristic of pathologic dynamics [16]. However, this type of assessment that relates features of crucial events and complexity to emotional or mental states has not been investigated and reported.

There are various methods for multiscaling analysis, including different entropy measures, threshold determination, and time coarse-graining approaches [17]. These methods aim to improve the analysis of shorter time series and can be useful for bedside diagnostics and dynamical models of biological control systems. Nevertheless, their impact on analyzing the diffusion entropy parameters used to detect crucial events is unknown [14]. Further research is required to understand and optimize the use of statistical indices characterizing crucial events, particularly in the context of nonlinear and nonstationary long-term ECG signals captured in the wild.

Crucial events are events characterized by changes in the complexity of the heart signal. The hypothesis that will be proven here states that determining crucial event occurrences in an ECG time series can identify significant characteristics in complex systems such as cardiac autonomic modulation of the heartbeat associated with emotional and mental states. Mathematically, crucial events have a waiting time distribution density with an inverse power law (IPL) index μ less than 3 and an IPL connected to 1/f noise derived from the diffusion entropy [18]. Multiscale Modified Diffusion Entropy Analysis (MSMDEA) is a modification of the diffusion entropy analysis (MDEA) proposed by Grigoloni [18,19] by adding a multiscaling component that has a higher sensitivity to changes in the heartbeat as well as providing additional information on physical characteristics of the heartbeat. MSMDEA optimizes the detection of crucial events to distinguish different emotion-labelled signals by computing the modified diffusion entropy at different temporal scales [20]. The development and refinement of methods such as MSMDEA can aid in accurately identifying and characterizing crucial events and provide novel markers of mental health and psychopathology and distinguish between different types of psychiatric pathology and monitor the progression of mental disorders.

2. Methodology

The heart signals dataset provided by the Korean Advanced Institute of Science and Technology (KAIST) involves ECG recordings, which were collected from a wearable chest strap sensor (Polar H10) worn by 90 participants over four weeks. Participants rated their daily emotions in terms of a seven-scale valence and arousal score using the experience sampling method (ESM) [21]. Five-minute segments of the labelled ECG time series were preprocessed using the Kaiser window filtering technique for the removal of signal artifacts [22], after which the MSMDEA was used for quantifying the complexity measures of the signal at multiple time scales. The method is a novel indicator of complexity in the field of physiological signal analysis and combines a second moment-based temporal multiscaling [23] with the modified diffusion entropy analysis (MDEA) [18]. Descriptive statistics were used to visualize the results, and inferential statistical tests such as the ANOVA/t-test were used to determine any significant differences between the complexity measures of the different groups of emotion-labeled ECG signals [20].

The KAIST dataset was aimed to develop the data analysis model and will be further used to optimize the technology as necessary.

3. Results and Discussion

In Table 1, the mean complexity index (μ) and standard deviation (SD) are provided for each combination of emotion dimension (high valence -HV, low valence -LV, high arousal -HA, and low arousal -LA) and temporal scaling factor (SF). The complexity indices of the ECG signals calculated by MSMDEA were averaged across 90 participants for 20 scaling factors (Fig. 1), of which the first 7 are demonstrated in Table 1. Overall, as the scaling

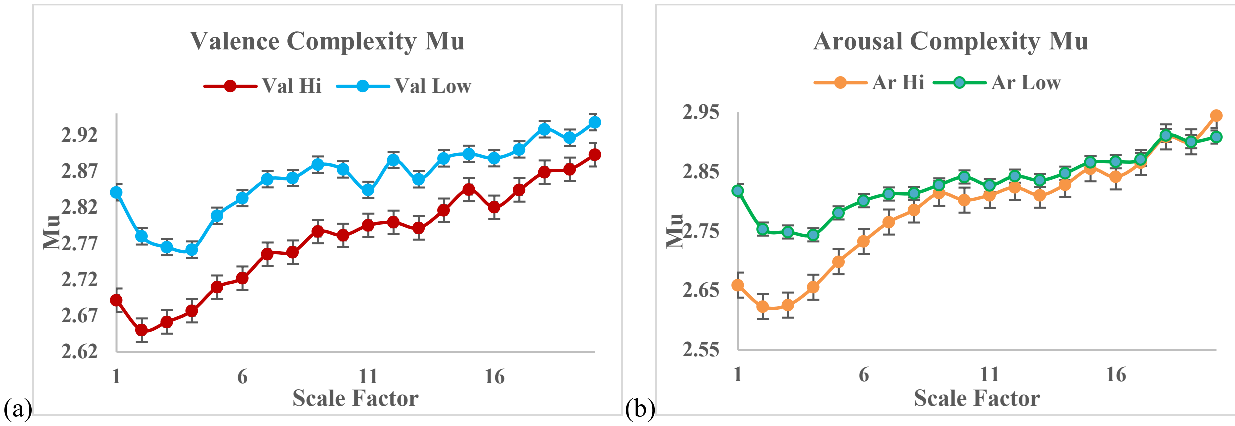

Figure 1. Overview of the difference between multiple states of emotion in terms of the averaged Mu (μ) on the y-axis across multiple temporal scales on the x-axis (a) High versus low emotion valence with high valence labels characterized by higher complexity (μ closer to its critical value of 2 which is the value reflecting maximum complexity [18]). (b) High versus low emotion arousal with high arousal labels characterized by higher complexity.

Table 1 shows the complexity metrics of the four dimensions of emotion (high and low valence and arousal) averaged across participants for the first seven temporal scaling factors.

	Mean Complexity Index μ±SD			
SF	HV	LV	HA	LA
1	2.69 ±0.4	2.84 ±0.5	2.66 ±0.4	2.82 ±0.6
2	2.65 ±0.3	2.78 ±0.4	2.62 ±0.3	2.75 ±0.4
3	2.66 ±0.3	2.76 ±0.4	2.63 ±0.3	2.75 ±0.3
4	2.68 ±0.3	2.76 ±0.3	2.66 ±0.3	2.74 ±0.3
5	2.71 ±0.3	2.81 ±0.4	2.70 ±0.3	2.78 ±0.4
6	2.72 ±0.3	2.83 ±0.4	2.73 ±0.3	2.80 ±0.4
7	2.76 ±0.3	2.86 ±0.4	2.77 ±0.3	2.81 ±0.4
Av	2.65	2.84	2.66	2.82

factor increases, the complexity index increases, which reflects the multiple levels of complexity within the ECG signal. The variations of the complexity metrics across the different dimensions of emotion may indicate that different emotional states have distinct effects on the complexity of ECG signals. This suggests that each state of emotion has a signature complexity index. The underlined complexity indices indicate the ones closest to the critical complexity value of 2, and they mostly occur from the 2nd to the 4th scale factor. The maximum SD values are found at the first temporal scale factor, after which they generally decrease as SF increases indicating the importance of temporal multiscaling for a more consistent characterization and comparison of the emotional states detected from ECG signals rather than looking at only one scale.

The MSMDEA detects the presence of crucial events in the signals translated through the complexity index inverse power law (μ) which is used to characterize and distinguish emotion labels. High and low classes of valence and arousal are distinct in their corresponding measures of complexity that lead to significant differences in crucial events (p-value<0.005) between the binary classes for each dimension of emotion across the different temporal scaling factors (Fig. 1). The high and low classes of valence are more significantly different (p<0.0001) than those of arousal (p<0.001), suggesting that the arousal aspect of emotions shows fewer temporal dimensions of complexity than valence, but they are enough to characterize and distinguish arousal labels from ECG.

These results show that the more positive emotions are (high valence and arousal), the closer they are to critical complexity (μ=2). Systems closer to the maximum complexity of μ=2 exhibit a healthy physiological and psychological function. However, the more negative emotions (low valence and low arousal) show a significant loss of the dynamics of complexity as the complexity indices diverge further away from the value of 2 and converge closer to the value of 3, which reflects a higher state of randomness in the system indicating a resemblance to pathological systems (Fig. 1). Since it was established previously that physiological systems consist of both Type I (Fractional Brownian Motion -based) and Type II (crucial events -based) 1/f noise [14], these results suggest that low valence and low arousal ECG signals lose more of their Type I FBM-based 1/f noise, leaving them with more Type II crucial events-based 1/f noise. On another note, the complexity index tends to approach 3 because the temporal scaling factor increases, as time coarse-graining at higher temporal scales reduces the length and thus, the complexity of analyzed signals, suggesting that group comparisons should be made at the same time scale rather than across different time scales.

The behavior of arousal complexity in these results agrees with another study that concluded the loss of complexity properties for negative arousal elicitation compared to the neutral emotional state [24]. The complexity measure used was approximate entropy (ApEn), and it showed a significant decrease during arousal elicitation at the lowest levels of valence in an experimental setup where 35 healthy participants were shown neutral and various degrees of unpleasant images. This supports the results of this paper which confirmed the loss of complexity dynamics at multiple time scales for negative emotions defined by their low valence (Fig. 1(a)).

4. Conclusion

The findings of the study have significance as they indicate that the complexity of electrocardiogram (ECG) signals exhibits variation across distinct temporal scaling factors and emotional aspects. The clinical significance of this knowledge lies in its ability to enhance our comprehension of the influence of emotional states on heart activity. Consequently, it holds promise for facilitating the diagnosis and monitoring of mental health disorders.

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