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# Analyzing Autonomic Nervous System and Emotions with High-Resolution Data on ECG, Facial Expressions, and Respiration

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***Abstract*** **-** In the domain of emotional assessment, the predominant focus of numerous studies lies in elucidating the correlation between physiological indicators derived from electrocardiograms and facial expressions. However, there remains a scarcity of studies analyzing the correlation between autonomic nervous system indicators computed from electrocardiograms and emotions with high temporal resolution. In this study, we concurrently measured participants' facial images, capacitive electrocardiogram (cECG), and respiratory data. The cECG and respiratory data were sampled at 250 samples per second (sps), while facial images were captured at 5 frames per second (fps). By focus on respiration, our objective is to achieve a more nuanced understanding of the impact of emotions on the autonomic nervous system and the temporal sequence of responses. We devised a system to visually represent how elicited emotions are manifested in facial expressions, cECG, and respiratory data, with the aim of elucidating the intricate relationship among the autonomic nervous system, emotions, and breathing.

***Keywords*****:** cECG, Emotion, Respiratory, Autonomic Nervous

## 1. Introduction

In recent years, research comparing emotions and autonomic nervous system (ANS) indicators and establishing correlations between them has become increasingly active. In the healthcare field, research is dedicated to identifying emotions through ANS indicators [1]. In this domain, two models, the Discrete Emotional Model (DEM) and Affective Dimensional Model (ADM), are employed. DEM discretizes emotions, such as happiness, sadness, anger, etc. ADM captures emotions through Valence and Arousal. The advantages of these methods lie in evaluating and analyzing emotions through a unified approach, facilitating further progress in existing research, and enabling emotion analysis in diverse contexts. However, research analyzing the temporal relationship between the autonomic nervous system and emotions at a high resolution is still relatively scarce. Kwang Ho Choi et al. [2] used the International Affective Picture System (IAPS) [3] to investigate the effectiveness of HRV as a tool for evaluating emotions. Emotional assessment employed the Self-Assessment Manikin (SAM). They argue that it is only when visual stimuli elicit high levels of emotion that the assessment based on HRV might be applicable, their measurements are post-hoc, but with a high temporal resolution. However, the correlation between the autonomic nervous system and emotions, the order of reactions, and mechanisms remain unclear. Additionally, in the aforementioned studies, the timing of emotional experiences and the temporal changes in autonomic nervous indicators were not considered. Therefore, compared to previous studies where stimuli were administered before measuring emotional indices, we have developed a system capable of concurrently analyzing cECG, respiration, and emotional indices with high temporal resolution. This enables the exploration of the relationship between emotional indices and autonomic nervous system indices. In the experiment, respiratory measurements were taken simultaneously with the recording of facial expressions and electrocardiograms. As breathing is closely related to the autonomic nervous system, focusing on it allows us to understand its impact on changes in ANS indicators and the sequential relationship between emotions and the autonomic nervous system. In addition, this study focuses on the emotion of laughter, which is relatively easy to trigger. From a health perspective, laughter is a feasible health practice at the individual level. Literature [4] reports the contribution of pleasurable emotions, such as happiness, to longevity. Therefore, understanding the neural mechanisms of laughter associated with pleasurable emotions and their relationship with the autonomic nervous system is considered beneficial for society. We have developed a system for visualizing the response of emotions triggered in facial expressions, electrocardiograms, and respiratory data, aiming to clarify the relationship between the autonomic nervous system, emotions, and respiration.

## 2. Materials and Methods

The system consists of four main components. Firstly, there are the system circuits and testing equipment. Secondly, there is the setup of the environment for testing emotion data, cECG signals, and respiratory signals. Finally, there is the preprocessing of the acquired data and the ultimate data analysis. As illustrated in Figure 1, we will provide a more detailed explanation in this chapter.

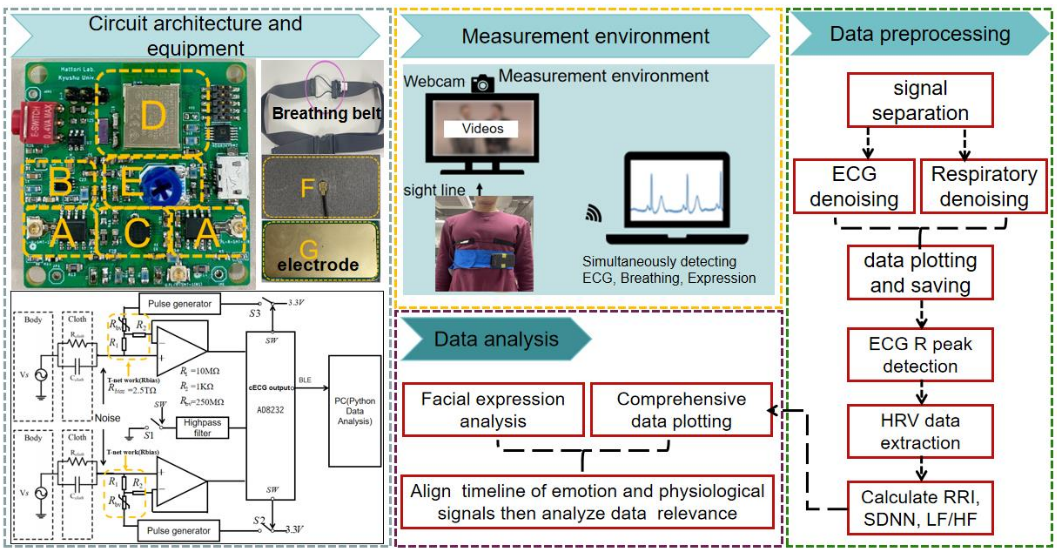


Fig. 1: Overall block diagram of testing and analysis system.

### 2.1. cECG Measurement Equipment and Respiratory Measurement Tape

Figure 1 shows the cECG measurement circuit and detection belt in this work. The circuit board includes the following four parts, A:the front-end detection circuit. B: Pulse generator, C: AD8232 Fast-recovering circuit. D: Bluetooth transmission circuit. E: Amplifier gain adjustment. The capacitive coupling electrode includes two parts, F:active guard side and G: measurement side. This circuit is equipped with a fast recovery function to reduce the possibility of QRS wave loss caused by oversaturation caused by motion artifacts during measurement. Figure 1 also delineates the respiratory belt employed in this study. The section highlighted with a purple circle features stretchable conductive rubber, while the remainder comprises non-stretchable materials. Previous investigations [5] have documented a positive correlation between chest range of motion and ventilation during deep breathing. Consequently, utilizing this respiratory measurement belt allows for a relatively predictive estimation of lung ventilation volume. During inhalation, the chest area expands, causing the conductive rubber to stretch, thereby increasing resistance and decreasing the measured partial pressure in series with it. Conversely, during exhalation, the chest area contracts, leading to the contraction of the conductive rubber and an increase in the measured partial pressure. Therefore, by analyzing voltage changes, we can discern the breathing patterns of the human body. Additionally, considering the potential impact of body movement on amplitude fluctuations, this article only supports measurements in a stationary sitting state.

### 2.2. Facial Expression Analysis Module

The Facial Action Coding System (FACS) theory, developed by Ekman & Friesen, enables the description of visible facial movements in humans [6]. It is a system that allows for the mechanical identification of human expressions based on the movements of specific muscle groups called Action Units (AU). Each AU represents the movement of a specific part of the face, such as the eyebrows, eyes, or mouth, and is assigned a unique number. A single expression is often composed of combinations of multiple AUs, allowing for a detailed analysis of the complexity of human expressions. In this study, we utilized this theory to analyze facial expressions.

Py-Feat (Python Facial Expression Analysis Toolbox) [7] is a facial information parsing library used in Python, based on the Facial Action Coding System (FACS). As mentioned earlier, FACS is a system that encodes subtle facial movements to represent specific emotions. Py-Feat utilizes this system to detect emotions from facial images and videos. It features facial landmark detection, classification, and emotion estimation, employing machine learning models to analyze various facial expression data and identify emotions such as joy, sadness, surprise, etc. Widely used in fields like psychology, marketing, user experience research, Py-Feat contributes to understanding human emotions. Figure 2 presents the results of analyzing sample images using Py-Feat. Py-Feat includes seven categories: anger, disgust, fear, happiness, sadness, surprise, and neutral, with all cumulative values summing to 1.0. In Figure 2, happiness has a value close to 1.0. In this study, we utilized this library to primarily analyze the subjects' happy expressions from facial images.

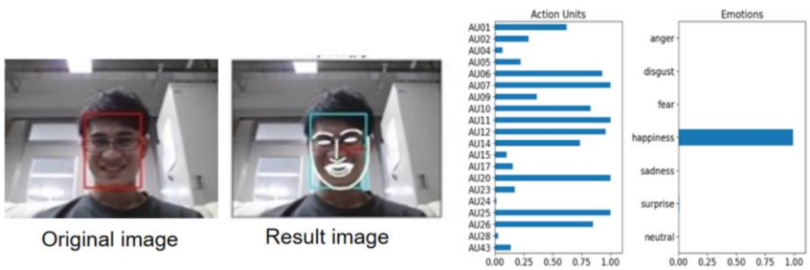

Fig. 2: Analysis results of sample images using Py-Feat.

### 2.3. Analysis Methods

We performed heart rate variability analysis on the recorded electrocardiogram, calculating RRI, SDNN, and LF/HF. Specifically, RRI, SDNN, LF/HF were computed every second, while facial expression values were calculated approximately every 0.2 seconds, ensuring each indicator could be tracked at least once per second. Furthermore, we referred to the cECG, instantaneous heart rate (IHR), and respiratory data to observe the response of respiratory and IHR data when a smiling expression occurred. This approach facilitated the visualization and assessment of IHR, smiling expressions, and respiratory data on a shared timeline.

Figure 1 depicts a schematic representation of the measurement setup. A monitor was positioned in front of the subject, accompanied by a network camera mounted above it. To induce laughter, we utilized videos with a duration of approximately 3 to 5 minutes, including sketches, comedian conversations, anime, and amusing animal behavior. Simultaneously, the participant wore a cECG measurement belt and a respiratory measurement belt for synchronous detection of cECG, respiratory signals, and facial images. The electrocardiogram was sampled at 250 [sps], while facial images were captured at 5 [fps (frames per second)]. Following data acquisition, we applied FACS theory to analyze facial expressions in the images, obtaining happiness values. Additionally, we preprocessed the cECG and respiratory signals for HRV analysis. The SciPy library's find_peaks function [8] identified QRS waves, and we calculated the time difference between adjacent QRS waves. SDNN and LF/HF utilized RRI from a 1-minute electrocardiogram for computation. The electrocardiogram range was shifted by 1 second increments from the beginning to the end of the measurement, allowing for the calculation of SDNN and LF/HF based on data from 30 seconds before and after each moment. This approach facilitated the comparison of happiness values at each moment with SDNN and LF/HF values.

## 3. Results and Discussion

The results of the preliminary experiments are illustrated in Figure 3. In the left image, in the time range of 75 to 95 seconds, a Happiness index below 0.2 is observed, followed by a surge to values exceeding 0.8 between 95 and 105 seconds. Additionally, LF/HF starts to rise from 75 seconds and increases to approximately 5.0 over 40 seconds, indicating sympathetic nervous system activation (when parasympathetic activity is suppressed or sympathetic activity is stimulated, values of 4.0 or higher are considered as indicative thresholds [9]). While previous reports have discussed the activation of the sympathetic nervous system through pleasurable emotions such as laughter [10], in this experiment, the Happiness index calculated from facial expressions momentarily surged from below 0.1 to around 0.8, while LF/HF, serving as an autonomic nervous system indicator, increased relatively slowly over approximately 40 seconds. Given that the LF/HF value is an average of the 30 seconds of electrocardiogram data before and after the time point, we consider the gradual rise in LF/HF to be reasonable. On the other hand, in the right image, the Happiness index exhibits multiple discontinuous surges, each of short duration, without a clear upward trend in LF/HF. Based on this result, it can be inferred that shorter durations of elevated Happiness do not lead to significant changes in LF/HF and sympathetic nervous system activation.

Furthermore, in in the right image, although LF/HF does not show an upward trend, it appears to influence the fluctuation pattern of RRI (approximately 225-250 seconds and 300 seconds). As mentioned earlier, we will focus on IHR (instantaneous heart rate), which represents a more immediate autonomic nervous system response, and compare it with the Happiness level for further discussion.

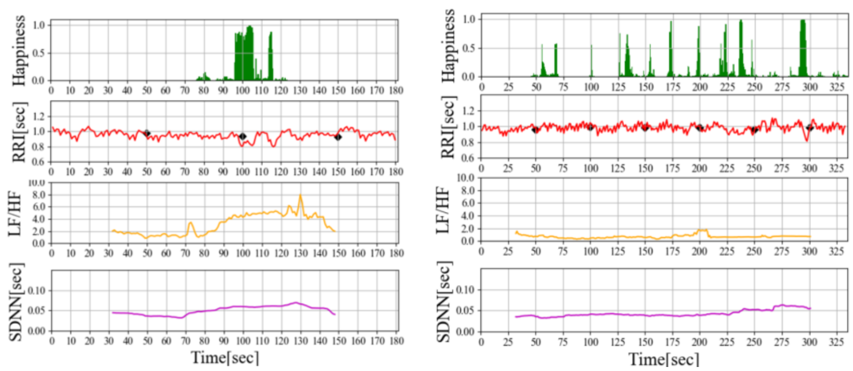


Fig. 3: Preliminary experimental results on the correlation between electrocardiogram data and emotional data.

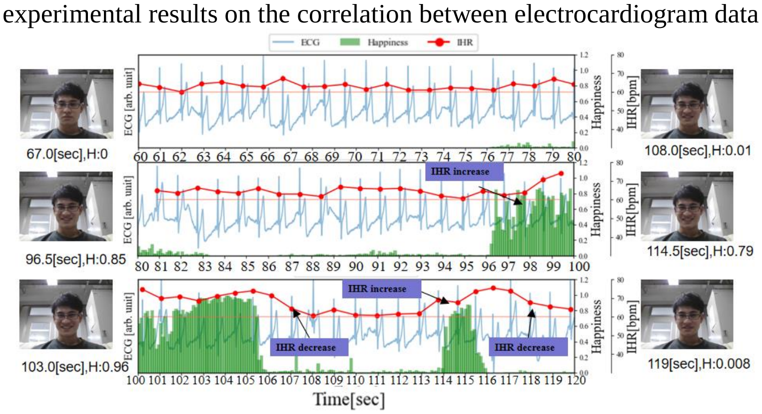


Fig. 4: The results of plotting cECG, IHR, and Happiness on the same timeline (with a high happiness index).

### 3.1. Relationship between Happiness Index and IHR during Emotion-Inducing Video Stimuli

Figure 4 illustrates the graph of the left side of Figure 3, where cECG, IHR, and Happiness are plotted on the same timeline. The horizontal line represented in burgundy indicates the Resting Heart Rate (RHR) during rest, serving as a reference baseline for IHR variations. Additionally, from 60 to 75 seconds, periodic increases and decreases in IHR can be observed. These fluctuations are considered Respiratory Sinus Arrhythmia (RSA), a common characteristic in healthy individuals. During the period from 76 to 95 seconds, the Happiness index generally remains below 0.2, and RSA can be confirmed. Between 96 to 106 seconds and 114 to 116 seconds, the Happiness index rises above 0.4 (reaching above 0.8 between 102 to 105 seconds), and during this period, RSA cannot be confirmed. Furthermore, with the increase in the Happiness index, IHR takes approximately 3 seconds to rise by about 15 bpm from the RHR value. Subsequently, with the decrease in Happiness, IHR takes around 3 seconds to drop by approximately 15 bpm. From these results, it can be observed that when the Happiness index reaches a certain value, RSA becomes less pronounced and affects heart rate variability. Figure 5 depicts a graph where the cECG, IHR, Happiness, and RHR from the right side of Figure 3 are plotted on the same timeline. During the periods of 120 to 126 seconds, 140 to 152 seconds, and 160 to 170 seconds, the Happiness index remains mostly below 0.1, and RSA can be clearly confirmed. On the other hand, during the intervals marked as (1), (2), and (3), there is a slight increase in the Happiness index, and the characteristics of RSA (the rise and fall of IHR) are subtle. Additionally, during periods (2) to (3), changes in the baseline of the electrocardiogram occur compared to other periods. Therefore, during this interval, respiratory may become shallower with the occurrence of laughter. During the interval marked as (4), the Happiness index reaches a maximum of around 0.6 and lasts for approximately 1 second. In the interval marked as (5), the Happiness index peaks at 1.0 and lasts for more than 4 seconds. Judging from the Happiness index and its occurrence frequency, it can be said that period (5) evokes stronger laughter than period (4). Moreover, the increase in IHR is also greater during this period.

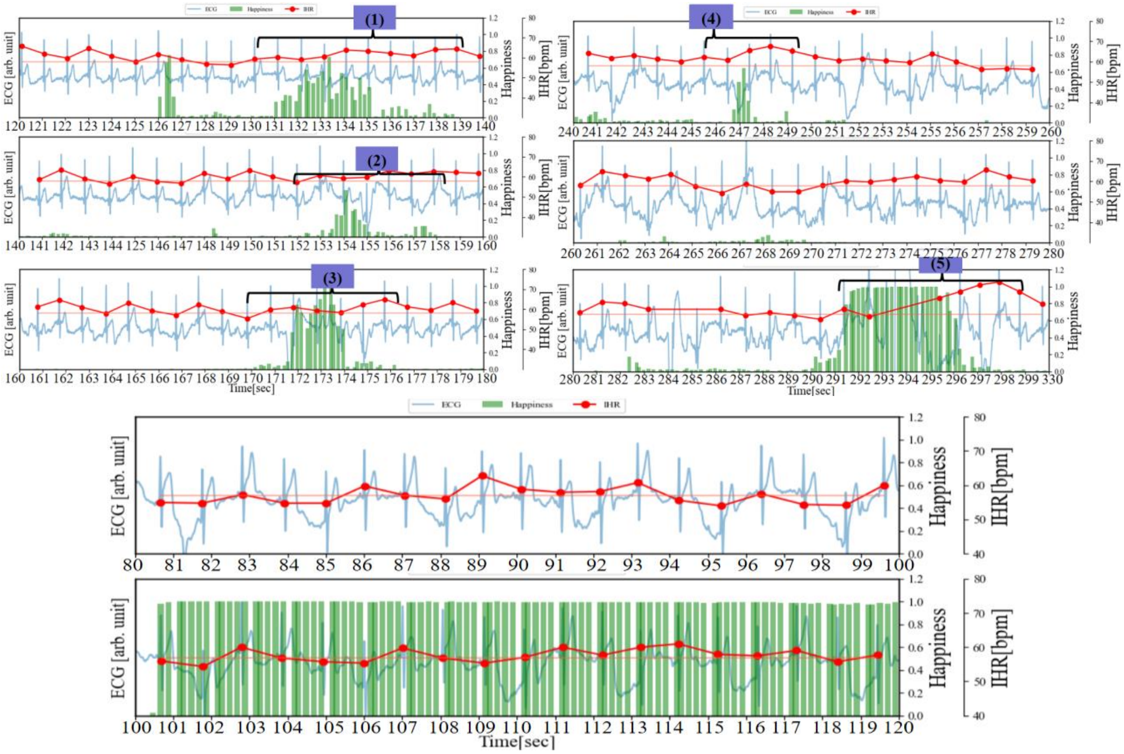


Fig. 5: The results of plotting cECG, IHR, and Happiness on the same timeline (with a low happiness index) compared with fake smiles.

As shown in the figure below in Figure 5, for comparison, participants were instructed to fake a smile while their electrocardiogram and facial images were measured, mirroring the procedure of the previous experiment. Participants commenced pretending to smile at 100 seconds and continued for 30 seconds. Between 60 and 100 seconds and after 100 seconds, there were no significant changes in IHR, despite the increase in the Happiness index caused by the fake smile. RSA remained observable. The distinct differences in RSA and IHR induced by genuine laughter and fake smiling through visual stimuli were clearly demonstrated. The significant presence of RSA indicates an increase in activity of the vagus nerve (a component of the parasympathetic nervous system) [11]. Additionally, as mentioned in literature [12], compared to fake smiling, spontaneous laughter is associated with more pronounced activation of the sympathetic nervous system, consistent with the findings of this study. Furthermore, we must consider another potential factor. During the occurrence of happiness, changes in human respiration may lead to the increase or decrease of IHR, thus rendering the features of RSA subtle. In the next section, we will utilize visualization of the respiratory state during the rise of happiness through respiratory waveform to further validate this.

### 3.2. Experiment Triggering Emotions with Video and Respiratory Data Integration

As illustrated in Figure 6, in addition to recording the electrocardiogram and facial images of the subjects while watching videos that induce laughter, we also collected respiratory data at 250 samples per second (sps). It is observed that the Happiness index steadily increases during periods (1), (2), (3), and (4), while the Instantaneous Heart Rate (IHR) increases by approximately 8 to 10 beats per minute (bpm) throughout the entire duration compared to the Resting Heart Rate (RHR). The data indicates a lengthening of the breathing time. Particularly during periods (3) and (4), each breath takes about 7 seconds (breathing waveform from 147 to 154 seconds and 162 to 169 seconds). From 200 to 236 seconds, the duration of Happiness is longer and the values are higher compared to the preceding periods. The IHR increases by approximately 10 bpm overall compared to RHR, reaching a peak of 23 bpm around 233 seconds (the maximum IHR in this experiment). Based on the amplitude variations in the breathing waveform from 220 to 234 seconds, it can be inferred that longer breathing cycles, with irregular rhythms, are induced compared to the periods of rest and shorter durations of Happiness. This is because during intense laughter, there is typically a series of short, shallow exhalations following a deep inhalation [13]. On the other hand, we conducted an inhalation test. As shown in the image below in Figure 6, even without visual stimuli, inhaling alone can cause an increase in IHR. After inhaling around 30 seconds, the IHR temporarily increases by 10 beats per minute (bpm) near 33 seconds, followed by an immediate decrease. Therefore, the phenomenon of the maximum IHR increasing by 23 bpm during the period from 220 to 234 seconds may also be related to the deep inhalation at that time.

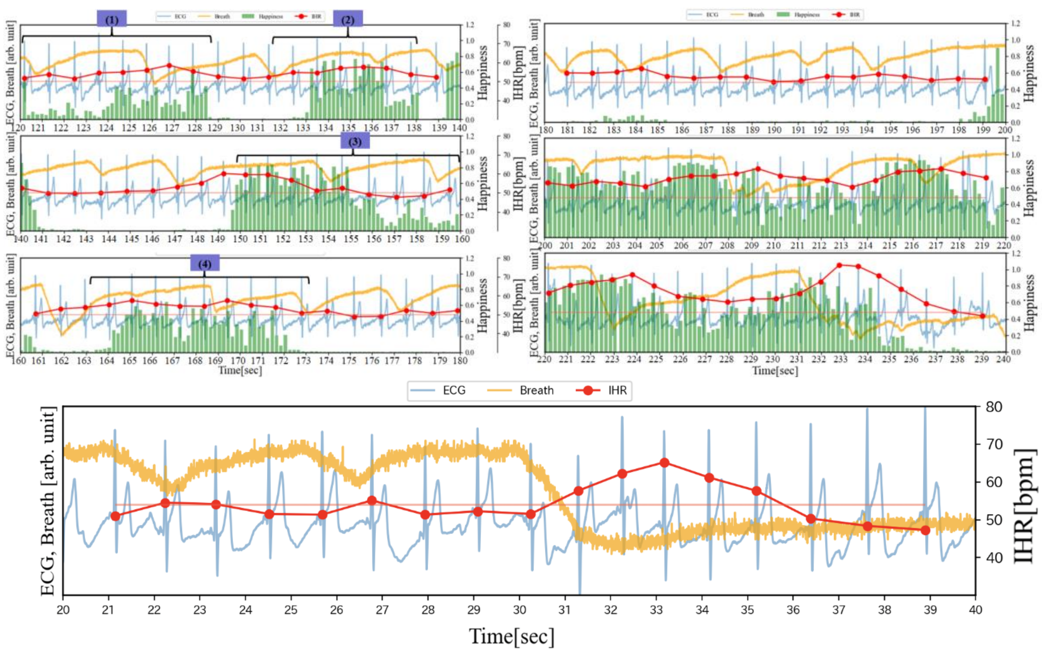


Fig. 6: cECG, respiratory data, IHR and Happiness results on the same timeline, and IHR response during inhalation.

### 3.3. Experiment Triggering Emotions with Video and Holding Breath

To further explore which relationship is more significant, between inhalation-induced increases in IHR and those induced by emotional arousal, we conducted an experiment where participants consciously held their breath while watching videos that elicited laughter.As depicted in Figure 7, participants inhaled at 40 seconds and 113 seconds respectively, holding their breath for 30 seconds each time. The difference lies in the absence of laughter-inducing stimuli in the former and its presence in the latter. According to reference [14], ceasing to breathe leads to a decrease in heart rate.

Consequently, we hypothesized that when the Happiness index increases, if the increase in heart rate variability (IHR) is more closely associated with emotion, then IHR will temporarily increase before decreasing but will not fall below the Resting Heart Rate (RHR). In the absence of visual stimuli, at 40 seconds, after inhaling and holding their breath, IHR temporarily increased by approximately 20 bpm from RHR, then decreased after about 3 seconds. During the 46 to 60-second interval, IHR was similar to RHR, while in the 60 to 80-second interval, IHR decreased by a maximum of approximately 9 bpm compared to RHR. On the other hand, after inhaling and holding their breath at 113 seconds, IHR temporarily increased by approximately 20 bpm, then decreased within 3 seconds. However, during the 120 to 133-second period, the Happiness index increased (emotional arousal occurred), and IHR increased accordingly. At this point, IHR exceeded RHR by approximately 10 bpm. Therefore, it can be concluded that although breathing affects IHR variation, the relationship between emotional arousal during an increase in the Happiness index and IHR increase is more pronounced.

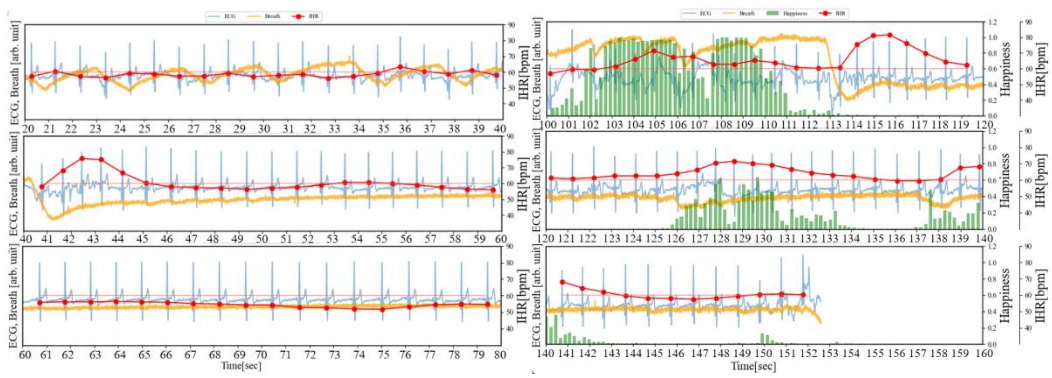

Fig. 7: The temporal changes of cECG, IHR, and happiness during inhalation and breath-holding under visual stimuli.

### 3.4. Discussion

The RSA effect refers to the increase in heart rate during inhalation leading to increased pulmonary blood flow and the decrease in heart rate during exhalation resulting in reduced pulmonary blood flow. The physiological reason why organisms have RSA is to improve gas exchange efficiency [15]. In other words, RSA is believed to regulate pulmonary blood flow based on lung capacity, thus conserving respiratory and circulatory energy during gas exchange. Additionally, it is known that RSA is more pronounced during reduced inhalation or decreased breathing frequency. Therefore, in our experiment, we observed an increase in IHR and a gradual weakening of RSA as the Happiness index rose. Regarding the interpretation of this result, firstly, with the rise in the Happiness index, emotional arousal (sympathetic nervous system activation) leads to an increase in heart rate (IHR). Physiologically, sympathetic nervous system activation causes the body to become tense, increasing cerebral blood flow, resulting in an elevated heart rate. Furthermore, the disrupted rhythm and reduction in amplitude of RSA during the increase in the Happiness index may be associated with irregular breathing. In an excited state, energy-saving mechanisms are less dominant, thus weakening the characteristics of RSA aimed at enhancing energy efficiency during gas exchange. Moreover, even after eliminating the factor of increased heart rate during inhalation in the breath-holding experiment, IHR still increased. Therefore, we believe there is a strong association between the rise in the Happiness index (sympathetic nervous system activation) and the increase in heart rate.

## 4. Conclusion

In this study, we developed a system capable of high temporal resolution data measurement. The cECG and respiratory data were sampled at 250 sps, while facial images were captured at 5 fps. This system was designed to investigate the relationship between physiological indicators obtained from cECG and facial expressions. During the experiment, participants watched videos designed to induce laughter, while their facial images, cECG, and respiratory signals were simultaneously recorded. Based on the collected data, we discussed the relationship between the autonomic nervous system and facial expressions. Additionally, control experiments were conducted to explore the impact of breathing on the autonomic nervous system. Initially, we observed that visual stimuli inducing an increase in the Happiness index also led to an increase in the IHR, accompanied by disruptions in RSA rhythm. Furthermore, inhalation also contributed to the increase in IHR. To further elucidate the potentially stronger association between the increase in Happiness index and the activation of the sympathetic nervous system leading to heart rate variability (IHR) elevation, we consciously stopped breathing during the viewing of video stimuli and conducted measurements. The results revealed that during breath-holding, when video stimuli caused an increase in the Happiness index, the IHR also increased simultaneously, exceeding the resting heart rate by approximately 10 bpm. Therefore, this reveals a positive correlation between the increase in Happiness index (sympathetic nervous system activation) and the rise in IHR.

## Acknowledgements

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