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ORIGINAL ARTICLE

Differences of Heart Rate Variability Between Happiness and Sadness Emotion States: A Pilot Study

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Abstract This pilot study investigated the differences of heart rate variability (HRV) indices between two opposite emotion states: happiness and sadness, to reveal the differences of autonomic nervous system activity under different emotional states. Forty-eight healthy volunteers were enrolled for this study. Electrocardiography (ECG) signals were recorded under both emotion states with a random measurement order (first happiness emotion measurement then sadness or reverse). RR interval (RRI) time series were extracted from ECGs and multiple HRV indices, including time-domain (MEAN, SDNN, RMSSD and PNN50), frequency-domain (LFn, HFn and LF/HF) and nonlinear indices (SampEn and FuzzyMEn) were calculated. In addition, the effects of heart rate (HR) and mean artery pressure (MAP) on the aforementioned HRV indices were analyzed for both emotion states. The results showed that experimental order had no significant effect on all HRV indices from both happiness and sadness emotions (all $P > 0.05$). The key result was that among all nine HRV indices, six indices were identified having significant differences between happiness and sadness emotion states: MEAN ($P = 0.028$), SDNN ($P = 0.002$), three frequency-domain indices (all $P < 0.0001$) and FuzzyMEn ($P = 0.047$), whereas RMSSD, PNN50 and SampEn had no significant differences between the two emotion states. All indices, except for SampEn, had significant positive correlations (all $P < 0.01$) for the two emotion states. Four time-domain indices decreased with the increase of HR (all $P < 0.01$), while frequency-domain and nonlinear indices demonstrated no HR-related changes for each emotional state. In addition, all indices (time-domain, frequency-domain and nonlinear) showed no MAP-related changes. It concluded that HRV indices showed significant differences between happiness and sadness emotion states and the findings could help to better understand the inherent differences of cardiovascular time series between different emotion states in clinical practice.

Keywords Emotion state · Heart rate variability (HRV) · Happiness emotion · Sadness emotion · Electrocardiogram (ECG)

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1 Introduction

Emotion recognition based on physiological signals has attracted more and more attention since physiological changes are linked with the autonomic nervous and endocrine systems [1]. Typical physiological signals used in emotion detection include electroencephalography (EEG), photoplethysmography (PPG), respiration (RSP), skin conductance response (GSR), skin temperature (SKT) and electrocardiography (ECG) [2–5].

In previous studies, different emotion states (happiness, sadness, disgust, surprise, anger, fear, etc.) have been reported to be linked with the different physiological features [1, 2, 4, 6]. Picard et al. used EMG, PPG, GSR, RSP and heart rate (HR) signals to identify eight emotion states and proved that it was feasible and reliable to use physiological features for emotion classification [1]. Ekman et al. recorded HR, left and right finger temperatures, skin resistance and forearm flexor diastolic signals to identify six emotion states: happiness, disgust, surprise, anger, fear and sadness, and compared differences of HR among the six emotion states [2]. Jang et al. studied the differences of three emotion states, i.e., boredom, surprise and pain, and reported that skin conductance level (SCL) and the average of skin conductance response (SCR) during pain emotion were significantly increased than that during boredom emotion [4]. Chang et al. adopted support vector regression (SVR) to classify three emotions (sadness, fear, and pleasure) and reported an average accuracy of 89.2% by analyzing physiological features extracted from ECG, GSR, BVP and pulse signals [6].

Heart rate variability (HRV), referring to the tiny variation of the interval between successive sinus heartbeats, contains abundant information of autonomic nervous response [7, 8]. HRV can reflect the balance between sympathetic and parasympathetic branches of individual autonomic nervous system by its spectral analysis [9, 10]. Time-domain, frequency-domain and nonlinear indices of HRV have been widely used as the marked features for emotion recognition. Kim et al. used time-domain and frequency-domain HRV indices to achieve an accuracy of 61.8% for classifying sadness, stress, surprise and anger emotions [11]. Mikuckas et al. developed a human computer system for stressful state recognition by analyzing multiple HRV indices from time-domain, frequency-domain and nonlinear, and reported that most HRV indices were sensitive to stress state [12]. Valderas et al. reported that there were significant differences in different HRV indices among relax, joy and fear emotion states [13]. Yu et al. employed support vector machine (SVM) to classify four emotions (neutral, happiness, stress and sadness) and exploited genetic algorithm (GA) to select HRV indices and achieved an average classification accuracy of 90% [14]. These related studies gave us a good basis for further exploring the changes in HRV indices between different emotion states.

In this study, we aimed to investigate the differences of multiple HRV indices between two opposite emotion states: happiness and sadness, to reveal the differences of the activity of autonomic nervous system under different emotional states. Meanwhile, the correlations of all indices between two emotion states were calculated to confirm the differences of HRV indices caused by the emotion states. In addition, the relationship between HRV indices and HR, as well as between HRV indices and blood pressure (BP), were also investigated separately in the two emotion states, in order to explore the effects from the HR and BP factor.

2 Method

2.1 Participants

Forty-eight healthy volunteers (25 females and 23 males), aged between 20 and 26 years, were recruited in this study. All volunteers were students from Shandong University and had no history of cardiovascular disease, mental illness, or alcohol records, confirming by their check-up reports from the Affiliated Hospital of Shandong University. All participants signed the informed consents before the experiment. The study received ethical permission from Shandong University and the Second Affiliated Hospital of Jining Medical College in China by the Committee for Ethical Affairs. Table 1 depicts the details for the involved participants.

2.2 Experiment Procedure

The experiment was performed in a quiet and temperature controlled (24 ± 2 °C) room. Standard limb lead-II ECG data were recorded. The locations attaching ECG electrode holder were wiped with a small amount of saline solution to ensure the good electrical conductivity.

Before signal recording, each participant had a rest for 10 min to permit the cardiovascular stabilization. Then ECG signals were recorded using the RM6240B signal recording system at a sample rate of 1000 Hz for each participant under two opposite emotion states: happiness and sadness. Two video stimuli (about 7 min) were used to evoke the emotion states: 'Joyous Comedy Person (a comedy sketch)' for evoking happiness emotion and 'I Want a Home (a touching movie)' for evoking sadness emotion. The reason of employing video stimuli is that they are more natural and reliable to evoke the inner feelings compared with other emotion stimuli such as images, sounds, etc. Video stimuli have the desirable properties of being readily standardized, involving no deception, and being dynamic rather than static. Video stimuli also have a relatively high degree of ecological validity, in so far as emotions are often evoked by dynamic visual and auditory stimuli that are external to the individual [15]. There was a 5-min gap between the two video playing sections, when the participant can sit quietly on the armchair to calm down their baseline emotions. Before the second video playing, each participant was asked for confirming he/she had restored calmness from the previous emotion state.

Table 1 Basic clinical characteristics of all 48 participants

Variable	Female	Male	Value
No.	25	23	48
Age (year)	23.7 ± 1.0	23 ± 1.3	23.5 ± 1.2
Height (cm)	162 ± 4	175 ± 6	168 ± 8
Weight (kg)	51 ± 5	66 ± 7	59 ± 10
Heart rate (beats/min)	71 ± 8	74 ± 9	72 ± 8
Systolic blood pressure (mmHg)	109 ± 10	126 ± 12	117 ± 14
Diastolic blood pressure (mmHg)	67 ± 8	73 ± 6	70 ± 8
Mean arterial pressure (mmHg)	81 ± 8	91 ± 7	86 ± 9

Data are expressed as numbers or mean ± standard deviation (SD)

In order to ensure the ECG signals were recorded under a certain emotional state, signals were not recorded at the first 2 min during each 7-min video playing, resulting in a 5-min ECG recording for each emotion state. Figure 1 shows the diagram of the experimental set-up and measurement process. One 14 inch laptop was used for playing the video stimuli and another 22 inch desktop was used for recording ECG signals with the connection to the RM6240B system. There was about 1.8 meters away between the laptop and desktop. The laptop was placed about 1 m in front of the participant. A dam-board was placed between the participant and the experimenter to ensure that participant was not influenced during the measurement and could express his/her emotion naturally.

HR and BP (systolic blood pressure, SBP and diastolic blood pressure, DBP) values of each participant were measured using the OMRON HEM-7051 electronic sphygmomanometer device before and after the signal recording (see Fig. 1). Mean arterial pressure (MAP) was calculated using the classic formula: $MAP = DBP + (SBP - DBP)/3$ [16]. HR and BP values measured before and after the signal recording were averaged to obtain the final results for each participant.

The order for playing the two video stimuli was random. Among all 48 volunteers, 25 participants (a random selection with mix of female and male) were first measured under happiness emotion then sadness emotion, and the other 23 participants used the reverse order.

2.3 Data Processing

Baseline drift and movement artifact in ECG signal were removed by using the sym8 wavelet decomposition [17]. High-frequency interference noise, resulting from the possible participant' movement during the measurement, was also removed. Adaptive difference threshold method was used to locate the R peaks and thus to construct RR interval (RRI) time series [18]. The RR intervals with ectopic beats were detected using the combination method and then were excluded [19]. In addition, we reviewed each recording and manually removed the detected RR intervals within the signal segments with strong movement artifacts

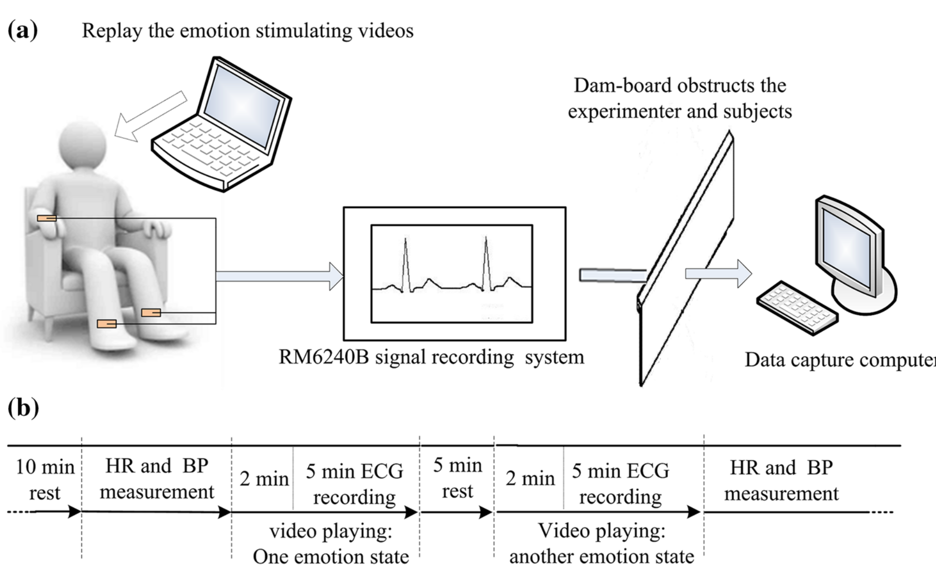

Fig. 1 Diagram of the experimental set-up (**a**) and measurement process (**b**)

due to laughing or crying. Figure 2 shows waveform examples of the recorded ECG signals under both emotion states and the corresponding RRI time series respectively.

2.4 HRV Indices Calculation

In this section, nine time-domain, frequency-domain and nonlinear HRV indices were employed to make a multiple HRV indices comparison between the two emotion states. The nine indices were chosen since many of the HRV measures are correlate closely with others and the selected indices are some of the most widely used HRV measures [7, 8].

2.4.1 Time-Domain Indices

For time-domain analysis, the first index was the mean value of RR intervals (MEAN), and the standard deviation of the RR intervals (SDNN) was used as the second index.

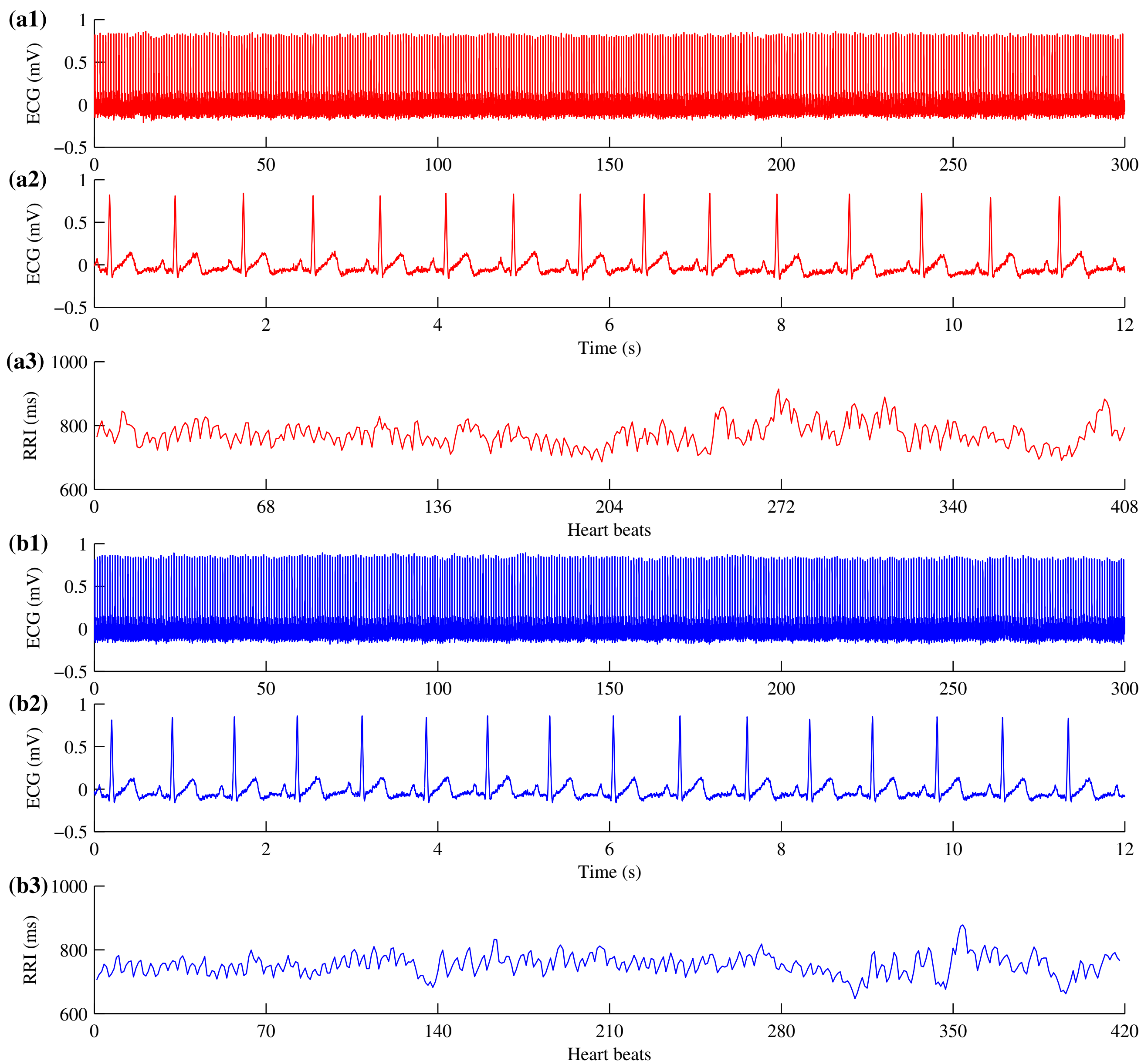

Fig. 2 Waveform examples of the recorded ECG signal for 5-min duration (**a1**, **b1**), 12-s duration (**a2**, **b2**) and the corresponding 5-min RRI time series (**a3**, **b3**) for the two emotion states: **a1**–**a3** for happiness emotion and **b1**–**b3** for sadness emotion

The RMSSD was defined as the square root of the mean squared differences of successive RR intervals $\left(\mathrm{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(RR_{i+1} - RR_i^2\right)}\right)$. The PNN50 referring to the proportion of differences between successive RR intervals greater than 50 ms was also calculated [7, 8, 20].

2.4.2 Frequency-Domain Indices

The frequency domain features of HRV series were calculated using the power spectral density. Prior to frequency-domain analysis, the spline interpolation was used to resample RRI time series evenly at 4 Hz. The HRV spectrum was produced by Burg's method with an order of 10 [21]. It was then decomposed into two separate frequency bands: a low-frequency band (LF) with spectral components from 0.04 to 0.15 Hz and a high-frequency band (HF) comprising frequencies from 0.15 to 0.4 Hz. The power of LF and HF were respectively normalized to the sum of LF and HF power, i.e., LFn and HFn, which represent the relative value of each power component in proportion to the total power minus the rest component. The representation of LFn and HFn emphasizes the controlled and balanced behaviour of the two branches of the autonomic nervous system. Moreover, normalization tends to minimize the effect on the values of LF and HF components of the changes in total power [7, 8]. The ratio of LF power to HF power (LF/HF) was also calculated.

2.4.3 Nonlinear Indices

Entropy is a non-linear measure for the complexity of physiological time series, especially for the short-term time series. Sample entropy (SampEn) and fuzzy measure entropy (FuzzyMEn) were used as non-linear indices in the current study. SampEn is the conditional probability that two short vectors of length m that match within an distance tolerance r will also match at the $m + 1$st point. [22, 23]. In the calculation process of SampEn, the vectors were determined as totally similar or dissimilar to a special vector based on the Heaviside function, i.e., the 0–1 determination. The rigid determination in the Heaviside function could induce the weak stability and consistency of SampEn [24, 25]. The calculation process of FuzzyMEn is similar to SampEn but using the fuzzy function rather than the Heaviside function. For the fuzzy function, this determination criterion exhibits the gentle boundary effect, while the traditional 0–1 judgment criterion from the Heaviside function is rigid in the boundary of parameter r. Thus FuzzyMEn method could reduce the sudden change of entropy values when the threshold r changes slightly and improve the statistical stability of SampEn [24, 25]. For the detailed calculation process of SampEn, please refer to [22, 23]. For the detailed calculation process of FuzzyMEn, please refer to [24, 25].

2.5 Statistical Analysis

Normal distributions of HR, SBP and DBP results were tested by the Kolmogorov–Smirnov test. Throughout all results, data were normally distributed. Hence, paired t-Student test was used to determine whether these results obtained from before and after the signal recordings had significant differences. A one way variance (ANOVA) was used to test the effect of experimental order (order 1 for first happiness emotion measurement then sadness and order 2 for first sadness emotion measurement then happiness) on HRV indices for happiness and sadness emotion states separately.

Normal distributions of all HRV indices of 48 participants were also tested by the Kolmogorov–Smirnov test. If the index meets the normal distribution, a paired t-Student test was used and otherwise, a Wilcoxon rank sum test was used, to determine the difference between two emotion groups.

Then, the Pearson correlation coefficients of HRV indices between two emotion states were calculated. The reason for the correlation analysis is that if HRV indices have significant differences between the two emotion states, we expect the majority of subjects output consistent higher or lower HRV results under one emotion state compared to another emotion state. So we expect the HRV indices between two emotion states have high correlation coefficients, to confirm the differences are due to the emotion state factor, not to the random individual factor. If the differences are mainly caused by the random individual factor, the low correlation coefficients are expected. The P-values and correlation coefficient R-values were reported.

In addition, the HR- and MAP-related changes of all HRV indices were also analyzed by calculating Pearson correlation coefficient and the fitting equations separately in the two emotion states, in order to explore whether the HR and MAP factors had significant effects on HRV indices and whether these effects for the two emotion states had significant differences. The fitting equations, P-values and correlation coefficient R-values were given.

Table 2 HR, SBP and DBP results from before and after the signal recording

Index	Before signal recording	After signal recording	P value
HR (beats/min)	72.4 ± 8.6	72.2 ± 9.1	0.8
SBP (mmHg)	118.5 ± 14.9	115.3 ± 14.1	<0.01[a]
DBP (mmHg)	70.7 ± 9.6	69.1 ± 7.8	0.1

Data are expressed as numbers or mean ± standard deviation (SD)

[a] Significant difference

Table 3 The effect of experiment order on HRV indices

Emotion state	Index	Experimental order 1	Experimental order 2	P-value
Happiness	MEAN (ms)	865 ± 85	831 ± 97	0.20
	SDNN (ms)	58 ± 12	52 ± 13	0.15
	RMSSD (ms)	43 ± 16	40 ± 16	0.49
	PNN50 (%)	24 ± 18	21 ± 16	0.52
	LFn	0.64 ± 0.17	0.63 ± 0.13	0.88
	HFn	0.36 ± 0.17	0.37 ± 0.17	0.88
	LF/HF	2.5 ± 2.1	2.1 ± 1.7	0.47
	SampEn	1.93 ± 0.28	1.92 ± 0.22	0.92
	FuzzyMEn	1.54 ± 0.37	1.54 ± 0.32	0.98
Sadness	MEAN (ms)	855 ± 64	814 ± 92	0.08
	SDNN (ms)	51 ± 16	47 ± 17	0.49
	RMSSD (ms)	42 ± 16	39 ± 18	0.52
	PNN50 (%)	23 ± 17	20 ± 18	0.55
	LFn	0.52 ± 0.18	0.49 ± 0.12	0.60
	HFn	0.48 ± 0.18	0.51 ± 0.12	0.60
	LF/HF	1.5 ± 1.6	1.1 ± 0.7	0.24
	SampEn	1.86 ± 0.15	1.91 ± 0.23	0.41
	FuzzyMEn	1.62 ± 0.29	1.65 ± 0.29	0.72

Data are expressed as numbers or mean ± standard deviation (SD)

Experimental order 1: first happiness emotion measurement then sadness, Experimental order 2: first sadness emotion measurement then happiness

SPSS software (Ver. 20, IBM, USA) was used to perform all statistical analyses above. A statistical significance was accepted at $P < 0.05$.

3 Results

Table 2 shows the HR, SBP and DBP results. SBP ($P < 0.01$) had significant difference between the measurements before and after the signal recording. However, HR ($P = 0.8$) and DBP ($P = 0.1$) did not show the statistical differences. Table 3 shows the effect of experimental order (order 1 for first happiness emotion measurement then sadness and order 2 for first sadness emotion measurement then happiness) on HRV indices from happiness and sadness emotions respectively. It was

Table 4 Results of HRV indices for all 48 participants between happiness and sadness emotional states

Index	Happiness state	Sadness state	P-value
MEAN (ms)[b]	849 ± 91	835 ± 80	0.028[a]
SDNN (ms)[b]	55 ± 13	49 ± 16	0.002[a]
RMSSD (ms)[b]	42 ± 16	41 ± 17	0.35
PNN50 (%)[b]	23 ± 17	22 ± 18	0.47
LFn[b]	0.63 ± 0.15	0.51 ± 0.15	<0.0001[a]
HFn[b]	0.37 ± 0.15	0.49 ± 0.15	<0.0001[a]
LF/HF	2.4 ± 1.9	1.3 ± 1.2	<0.0001[a]
SampEn[b]	1.92 ± 0.25	1.89 ± 0.21	0.37
FuzzyMEn[b]	1.54 ± 0.34	1.64 ± 0.29	0.047[a]

Data are expressed as numbers or mean ± standard deviation (SD)

[a] Significant difference

[b] Normal distribution

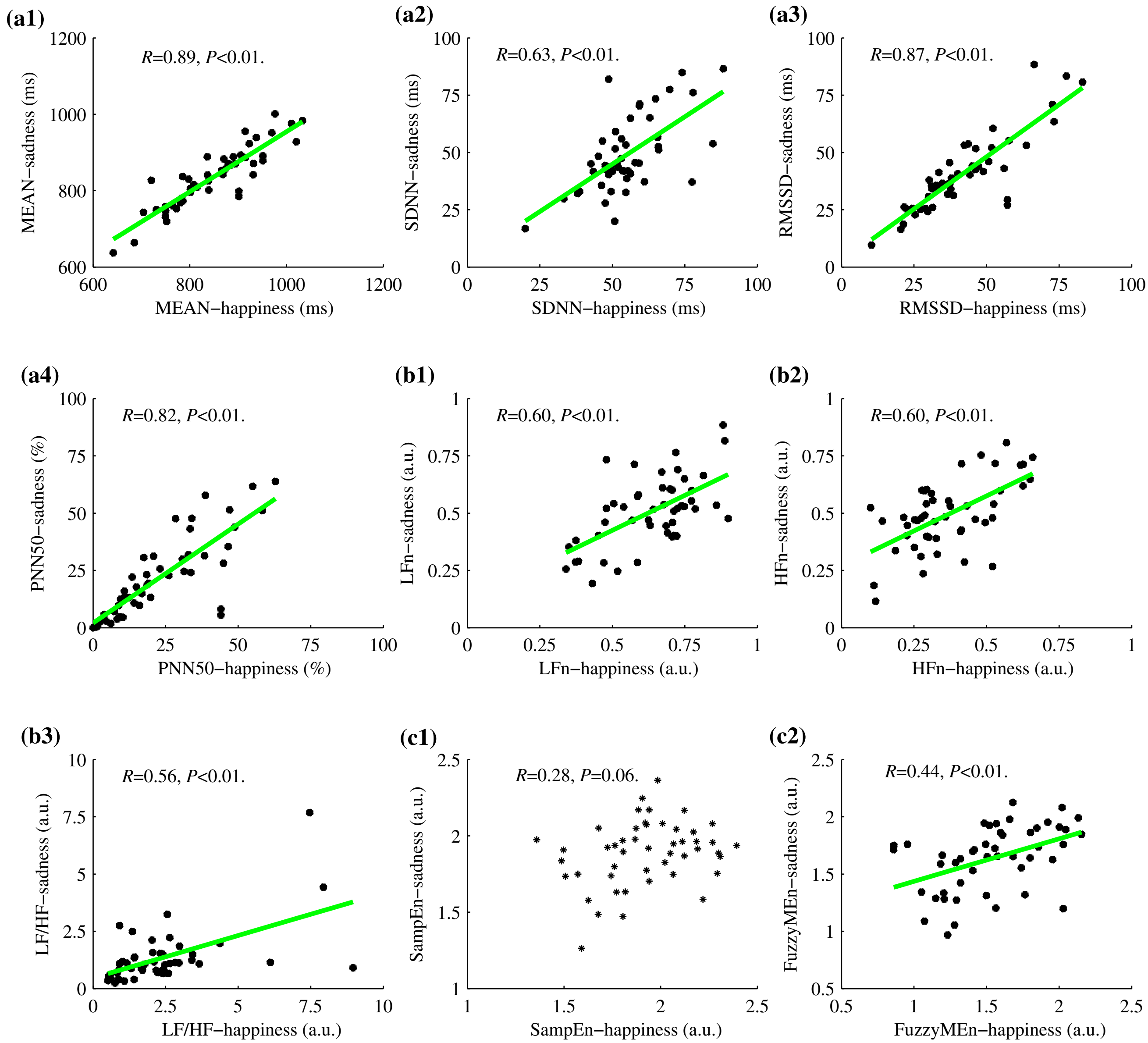

Fig. 3 Correlations of HRV indices between happiness and sadness emotion states. When the correlations are statistically significant, the corresponding fitting lines are also plotted. Time-domain indices: **a1** MEAN, **a2** SDNN, **a3** RMSSD and **a4** PNN50; frequency-domain indices: **b1** LFn, **b2** HFn and **b3** LF/HF; and nonlinear indices: **c1** SampEn and **c2** FuzzyMEn

confirmed that experimental order had no significant effect on all HRV indices (all $P > 0.05$) for both emotion states.

3.1 Comparison of the HRV Indices Between Two Emotion States

Table 4 shows the results of HRV indices for the two emotion states. Indices with normal distribution were marked. For time-domain indices, MEAN ($P = 0.028$) and SDNN ($P = 0.002$) were significantly greater in happiness emotion than those in sadness emotion, while the significant differences in indices of RMSSD ($P = 0.35$) and PNN50 ($P = 0.47$) disappeared. All three frequency-domain indices had significant differences between two emotion states (all $P < 0.0001$). For nonlinear indices, the significant difference was reported by FuzzyMEn ($P = 0.047$) but not by SampEn. ($P = 0.37$).

3.2 Correlation of HRV Indices Between Two Emotion States

Figure 3 shows the correlation results of all HRV indices for the two emotion states. The fitting lines and the corresponding R and P values are also shown when significant correlations were reported. R value is the Pearson correlation coefficient and is a statistic used to measure the strength of the relationship between two variables. As suggested, correlation coefficients (in absolute values) below 0.35 are considered as weak correlations, correlation coefficients between 0.36 and 0.67 are considered as moderate correlations, and those above 0.68–1.0 are considered as strong correlations [26]. All indices except for SampEn had significant positive correlations (all $P < 0.01$) between happiness and sadness emotion states. Strong positive correlation existed in time-domain indices of MEAN ($R = 0.89$), RMSSD ($R = 0.87$) and PNN50 ($R = 0.82$), and moderate positive correlation existed in SDNN ($R = 0.63$). Moderate positive correlation existed for frequency-domain indices, with $R = 0.60$ for both LFn and HFn and $R = 0.56$ for LF/HF. Moderate positive correlation also existed in FuzzyMEn ($R = 0.44$) while not in SampEn ($P > 0.05$).

3.3 Effects of HR and MAP on HRV Indices for the Two Emotion States

This section explored whether the HR and MAP factors had significant effects on HRV indices and whether these effects for the two emotion states had significant differences. The effects of HR factor on HRV indices for the two emotion states were summarized in Table 5 and Fig. 4. The fitting equations were also reported. Four time-domain indices significantly decreased when HR increased (all $P < 0.01$) for both happiness and sadness emotional states. However, frequency-domain and non-linear indices did not have HR-related changes (all $P > 0.05$) for the two emotion states. The effects of MAP factor on HRV indices were summarized in Table 6 and Fig. 5. None of the studied indices showed BP-related changes for either emotion state (all $P > 0.05$).

4 Discussion

Physiological changes under different emotion states mainly reflected the changes of autonomic nervous system activity. HRV analysis can quantify this activity and evaluate the power and balance of sympathetic and parasympathetic nervous system [9, 10, 27]. Previous studies have confirmed that the physiological features could change under different emotions and thus could be used in emotion identification and classification [1, 2, 4].

Ekman et al. reported happiness emotion gave an increased HR while Britton et al. reported the decreased result [2, 28]. Our results showed that compared with sadness emotion, happiness emotion output the decreased HR (i.e., an increased MEAN), which agreed with Britton et al.'s study but differed from Ekman et al.'s report. It has also been reported that HR during surprise emotion significantly increased than those during boredom and pain emotions [4]. Meanwhile, Mikuckas et al. found SDNN and PNN50 values increased during stressful emotion state while decreased during walking state, and RMSSD increased during stressful emotion state while marginally changed during walking state, and mean HR from 5-min RR interval time series decreased during stressful emotion state while increased during walking state [12]. Valderas et al. reported that HR was also significantly different between relax and fear emotions, and PNN50 showed significant difference between joy and fear emotions [13].

Table 5 Results of the effect of HR factor on HRV indices for the two emotion states

Index	Happiness state			Sadness state		
	Fitting equation: index =	R-value	P-value	Fitting equation: index =	R-value	P-value
MEAN (ms)	$-9.2 \times HR + 1513$	−0.85	<0.01[a]	$-8.1 \times HR + 1417$	−0.84	<0.01[a]
SDNN (ms)	$-0.84 \times HR + 116$	−0.56	<0.01[a]	$-0.91 \times HR + 115$	−0.47	<0.01[a]
RMSSD (ms)	$-1.02 \times HR + 115$	−0.53	<0.01[a]	$-1.04 \times HR + 116$	−0.52	<0.01[a]
PNN50 (%)	$-0.97 \times HR + 93$	−0.48	<0.01[a]	$-1.01 \times HR + 95$	−0.48	<0.01[a]
LFn	$0.0034 \times HR + 0.39$	0.19	0.20	$0.0040 \times HR + 0.22$	0.22	0.13
HFn	$-0.0034 \times HR + 0.61$	−0.19	0.20	$-0.0040 \times HR + 0.78$	−0.22	0.13
LF/HF	$0.049 \times HR - 1.2$	0.22	0.13	$0.032 \times HR - 0.78$	0.22	0.13
SampEn	$-0.0068 \times HR + 2.4$	−0.23	0.12	$-0.0025 \times HR + 2.3$	−0.21	0.15
FuzzyMEn	$-0.011 \times HR + 2.3$	−0.26	0.08	$-0.0091 \times HR + 2.3$	−0.27	0.07

[a] Significant relationship

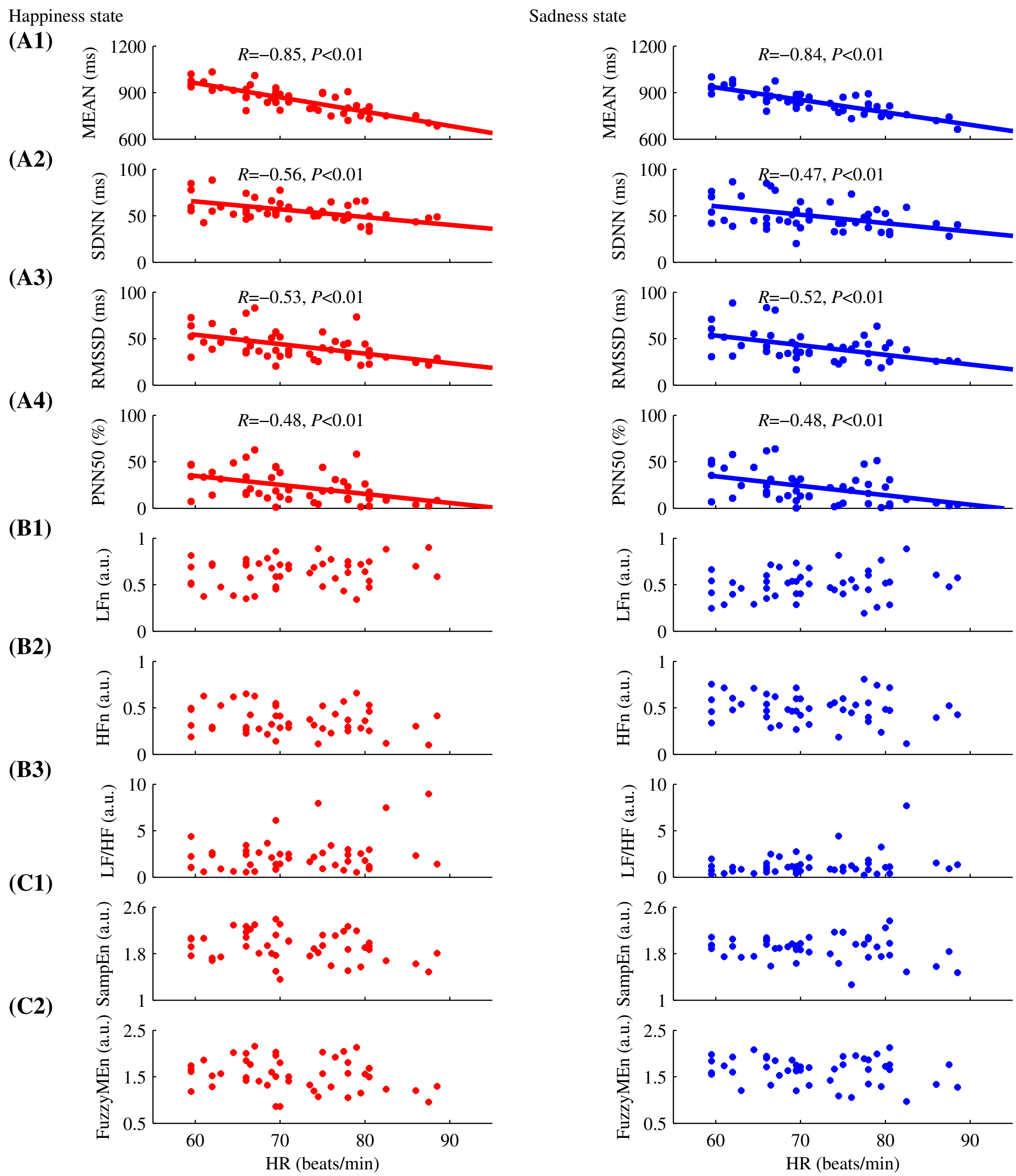

Fig. 4 HRV results plotted against HR. When the correlations are statistically significant, the *R* and *P* values and the corresponding fitting lines are shown. For each index, the left subfigure shows the results for happiness emotion and the right subfigure for sadness emotion. Time-domain indices: **A1** MEAN, **A2** SDNN, **A3** RMSSD and **A4** PNN50; frequency-domain indices: **B1** LFn, **B2** HFn and **B3** LF/HF; and nonlinear indices: **C1** SampEn and **C2** FuzzyMEn

In our study, we found a greater SDNN in happiness emotion than in sadness emotion. However, RMSSD and PNN50 had no significant differences between the two emotional states.

Frequency analysis of HRV can also reflect the inherent activity of the autonomic nervous system and they had clearer conclusion with the change of sympathetic and parasympathetic activities for short-term HRV analysis,

Table 6 Results of the effect of MAP factor on HRV indices for the two emotion states

Index	Happiness state			Sadness state		
	Fitting equation: index =	*R*-value	*P*-value	Fitting equation: index =	*R*-value	*P*-value
MEAN (ms)	$-1.2 \times \text{MAP} + 948$	−0.12	0.42	$-0.87 \times \text{MAP} + 909$	−0.10	0.49
SDNN (ms)	$-0.089 \times \text{MAP} + 63$	−0.07	0.65	$-0.076 \times \text{MAP} + 56$	−0.04	0.77
RMSSD (ms)	$-0.0063 \times \text{MAP} + 41$	0.004	0.98	$-0.0355 \times \text{MAP} + 44$	−0.02	0.89
PNN50 (%)	$0.0002 \times \text{MAP} + 23$	0.0001	1.00	$-0.046 \times \text{MAP} + 26$	−0.02	0.87
LFn	$0.0002 \times \text{MAP} + 0.62$	0.01	0.94	$-0.0001 \times \text{MAP} + 0.52$	−0.01	0.96
HFn	$-0.0002 \times \text{MAP} + 0.38$	−0.01	0.94	$0.0001 \times \text{MAP} + 0.48$	0.01	0.96
LF/HF	$0.0057 \times \text{MAP} + 1.9$	0.03	0.85	$0.0025 \times \text{MAP} + 1.1$	0.02	0.90
SampEn	$0.0068 \times \text{MAP} + 1.3$	0.26	0.08	$0.0060 \times \text{MAP} + 1.4$	−0.21	0.15
FuzzyMEn	$0.0035 \times \text{MAP} + 1.2$	0.09	0.52	$0.0044 \times \text{MAP} + 1.3$	−0.27	0.07

compared with the time-domain indices. LF mainly reflects the sympathetic and parasympathetic nervous activity while HF reflects the parasympathetic nerve activity [9, 10]. Mikuckas et al. found that LF and HF were very sensitive to coffee, alcohol and a physical load, and LF/HF increased in stressful emotion state [12]. Valderas et al. reported that LF, HFn, and LF/HF showed significant difference between relax and joy emotions, as well as between joy and fear emotions [13]. In the current study, LFn presented a significant greater level while HFn showed a significant low level under happiness emotion than sadness emotion, suggesting that compared with sadness emotion, happiness emotion output a greater sympathetic nervous activity and smaller parasympathetic nerve activity.

Indices of SampEn and FuzzyMEn, as the reflections of nonlinear dynamic characteristics, could evaluate the inherent complexities of RR interval time series under different emotional states [23–25]. Riganello et al. reported that there was a significant difference in SampEn between the healthy participants and vegetative state/unresponsive wakefulness syndrome (US/UWS) patients when listening to the Mussorgsky's music [29]. We found that there was a significant decrease in FuzzyMEn during happiness emotion, confirming that the decrease of complexity in RRI time series for happiness emotion.

Furthermore, the correlation analysis showed that all studied indices except for SampEn had significant positive correlations between two emotion states. These results are in our expectation. If HRV indices have significant differences between the two emotion states, we expect the majority of participant s output consistent higher or lower HRV results under one emotion state compared to another emotion state. So we expect the HRV indices between two emotion states have high correlation coefficients, to confirm the differences are due to the emotion state factor, not to the random individual factor. If the differences are mainly caused by the random individual factor, the low correlation coefficients are expected. The paired HRV results further confirm the differences are due to the emotion states rather than the participant's factor. The correlation results gave us more confidence on the confirmation of the accuracy of HRV calculation.

In addition, physiological factors, such as HR and blood pressure, have been shown to influence HRV parameters in hypertensive and normotensive participants [30, 31].This study showed significant HR-related changes for time-domain HRV indices but not for both frequency-domain and nonlinear HRV indices for the two emotional states, indicating that both frequency-domain and non-linear HRV indices were not sensitive to the HR changes. Moreover, none of the studied indices showed BP-related changes for either emotion state can be hardly influenced by the BP changes indicated that all indices were not sensitive to the MAP changes for the two emotion states.

Limitations of the current study should be revealed. First, only the HRV indices were considered and more physiological features, such as pulse transit time variability, will be considered in the future study. Meanwhile, although we did not find, the order of playing videos could have an effect on the emotion studies. This should be taken account in the future study. In addition, participants in this study only involved the healthy young people. To further investigate this concern, a large number of participants and patients with different emotion diseases will be studied.

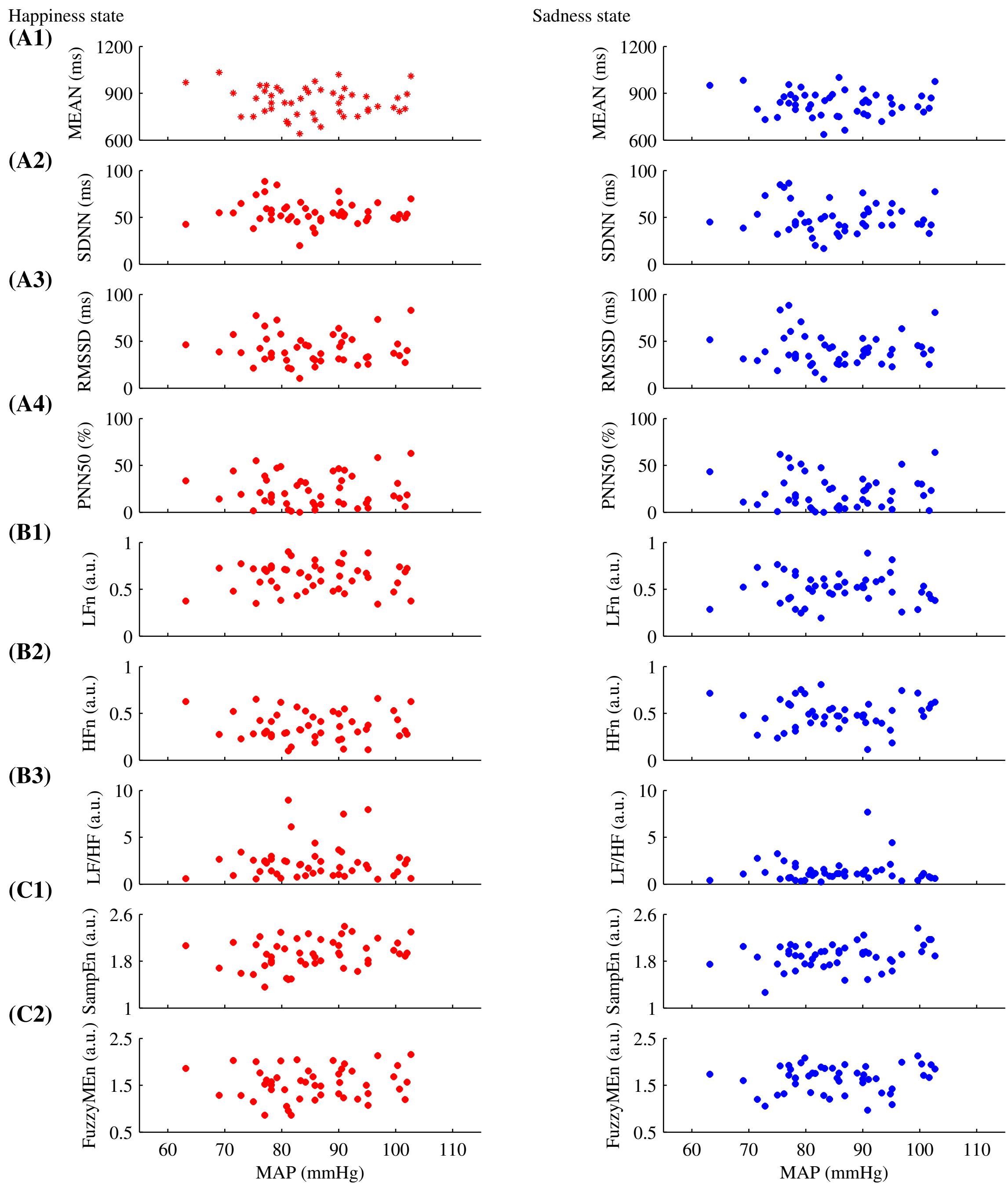

Fig. 5 HRV results plotted against MAP. For each index, the left subfigure shows the results for happiness emotion and the right subfigure for sadness emotion. Time-domain indices: **A1** MEAN, **A2** SDNN, **A3** RMSSD and **A4** PNN50; frequency-domain indices: **B1** LFn, **B2** HFn and **B3** LF/HF; and nonlinear indices: **C1** SampEn and **C2** FuzzyMEn

5 Conclusion

This pilot study investigated the multiple HRV indices between two opposite emotion states: happiness and sadness, to reveal the differences of autonomic nervous system activity under different emotional states. The results showed that most of the studied HRV indices had significant differences between happiness and sadness emotion states, and majority of them had significant positive correlations under the two emotion states. In addition, HRV time-domain indices significantly decreased when HR increased for both happiness and sadness emotional states whereas frequency-domain and non-linear indices did not have HR-related changes for the two emotion states. Moreover, none of the studied indices showed BP-related changes for either emotion state. This pilot study could help to better understand the inherent differences of cardiovascular time series between different emotion states.

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Compliance with Ethical Standards

Conflict of interest The authors declare no conflict of interest.

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