Differences of multiple heart rate variability indices between happiness and sadness emotion states: a pilot study

Hongyu Shi [a], Licai Yang [a,*], Lulu Zhao [a], Zhonghua Su [b], Xueqin Mao [c], Li Zhang [d] and Chengyu Liu [a,*]

[a] School of Control Science and Engineering, Shandong University, Jinan, 250061, China;

[b] Second Affiliated Hospital of Jining Medical College, Jining, 272051, China;

[c] Department of Psychology, Qilu Hospital of Shandong University, Jinan 250012, China;

[d] Department of Computer and Information Sciences, Northumbria University, Newcastle, UK.

***** Author to whom correspondence should be addressed; E-Mail: yanglc@sdu.edu.cn and bestlcy@sdu.edu.cn

Abstract

Research on emotion states based on physiological signals has attracted more and more attention. However, existing studies mainly focused on the classification accuracy tests based on different machine learning methods, without a comprehensive exploration for the inherent links between physiological features and emotion states. This pilot study aimed to investigate the differences of heart rate variability (HRV) indices between two opposite emotional states: happiness and sadness, to reveal the differences of autonomic nervous system activity under different emotional states. Forty-eight healthy volunteers were enrolled in the proposed study. Electrocardiography (ECG) signals were recorded under two emotion states with a random measurement order (first happiness 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. The results showed that experimental order had no significant impact on all HRV indices. Among all nine indices, six indices were identified

having significant differences between happiness and sadness emotion states: MEAN (P<0.05), SDNN (P<0.01), three frequency-domain indices (all P<0.01) and FuzzyMEn (P<0.05), whereas RMSSD, PNN50 and SampEn were reported having no significant differences among the two emotional states. All nine indices except for SampEn had significant positive correlations (all P<0.01) for the two emotion states. All indices showed no HR-related or MAP-related changes for each emotional state except that four time-domain indices decreased with the increase of HR (P<0.01). It concluded that HRV indices had 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.

Key words: Emotion state, Heart rate variability (HRV), Happiness emotion, Sadness emotion, Electrocardiogram (ECG)

1. Introduction

Emotion recognition based on physiological signals has attracted more and more attention since physiological changes are only controlled by the autonomic nervous and endocrine system but are hardly influenced by individual subjective consciousness[1]. Typical physiological signals used in emotion detection research 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 have been proven to be linked with the different physiological characteristics. Picard *et al* used ECG, PPG, SKT, 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. They also used the facial active and imagine tasks and demonstrated that compared with happiness emotion, HR increased in anger and fear while it decreased in disgust [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 98.9% 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]. HRV can reflect the balance of individual autonomic nervous system and the relax level of organism[8, 9]. Time-domain, frequency-domain and nonlinear indices of HRV have been widely used as the marked features for emotion recognition. Kim *et al* calculated time-domain (mean and standard deviation) and frequency-domain (low-frequency and high-frequency band) indices of HRV and reported an accuracy of 61.8% for classifying sadness, stress, surprise and anger emotions [10]. Mikuckas *et al.* developed a human computer system for stressful state recognition by analyzing multiple indices of HRV from time-domain, frequency-domain and nonlinear, and reported that most HRV indices were sensitive to stress state [11]. Valderas *et al.* reported that there were significant differences in different HRV indices among relax, joy and fear emotion states [12]. 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% [13]. However, the existing studies mainly focused on the classification accuracy tests based on the different machine learning methods, without a comprehensive exploration for the inherent links between emotion states and physiological features.

This paper 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. Nine widely used HRV indices, including four time-domain, three frequency-domain and two nonlinear indices, will be employed in this work.

2. Method

2.1. Subjects

Forty-eight healthy volunteers from Shandong University (25 females and 23 males), aged between 20 and 26 years (mean 23.5 years), were recruited in this study. They all have no history of cardiovascular disease, mental illness, or alcohol records. All subjects signed the informed consents before the experiment. Table 1 depicts the details for the involved subjects.

Table 1. Basic clinical characteristics of all 48 subjects.

Variable	Value
No.	48
Female/Male	25/23
Age (year)	23.5 ± 1.2
Height (cm)	168 ± 8
Weight (kg)	59 ± 10
Heart rate (beats/min)	72 ± 8
Systolic blood pressure (mmHg)	117 ± 14
Diastolic blood pressure (mmHg)	70 ± 8
Mean arterial pressure (mmHg)	86 ± 9

Note: data are expressed as numbers or mean ± standard deviation (SD).

2.2. Experiment procedure

The experiment was performed in a quiet and temperature controlled (24 ± 2 degree) room. ECG electrodes were attached to the right wrist and the right and left ankles to acquire the standard limb lead-II ECG recordings. The locations attaching ECG electrode holder were wiped with a small amount of saline solution to ensure the good electrical conductivity.

After a 10 min rest to assure the cardiovascular stabilization, ECG signals were recorded using the RM6240B signal recording system at a sample rate of 1,000 Hz for each subject under two emotion states: happiness and sadness. Two video stimuli (about 7 min) were used to evoke these two opposite emotion states. 'Joyous Comedy Person (a comedy sketch)' was used for evoking happiness emotion and 'I Want a Home (a touching movie)' was used for evoking sadness emotion. The reason of employing video stimuli is that they are more natural and reliable to evoke the inner feelings of the subjects compared with other emotion stimuli such as images, sounds, etc. The order for replaying the two video stimuli was random. There was a 5 min gap between the two video replaying sections. Figure 1 shows the diagram of the experimental set-up and measurement process. Two laptops were used during the experiment: one for replaying the video stimuli and another one for recording ECG signals with connecting to the RM6240B signal recording system. A dam-board was placed between the subject and the experimenter to ensure that subject was not influenced during the experiment and could express his/her emotion naturally.

HR and blood pressure (BP) values of each subject, including systolic blood pressure (SBP) and diastolic blood pressure (DBP), were measured using the OMRON HEM-7051 device before and after the signal recording. The mean arterial pressure (MAP) was calculated using

the classic formula: MAP = DBP + (SBP-DBP)/3 [14]. HR and BP values from the two measurements were averaged to obtain the final results for each subject.

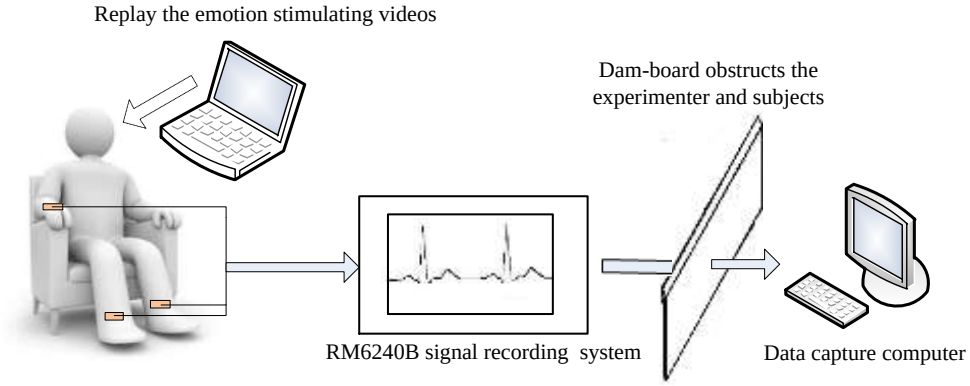

Figure 1. Diagram of the experimental set-up and measurement process.

2.3. Data processing

Wavelet transform (sym8 wavelet) was used for ECG pre-processing to remove baseline drift and high-frequency interference. Adaptive difference threshold method was used to locate the R peaks and thus to construct RR interval (RRI) time series. The RR intervals with ectopic beats were detected using the combination method and then were excluded [15]. Figure 2 shows waveform examples of the recorded ECG signals under two emotion states and the corresponding RRI time series respectively.

2.4. HRV indices calculation

2.4.1. Time-domain indices. The mean value of RR intervals (MEAN), standard deviation of RR intervals (SDNN), the square root of the mean squared differences of successive RR intervals (RMSSD), and the proportion of differences between successive RR intervals greater than 50 ms (PNN50) were used as time-domian indices [16, 17].

2.4.2. Frequency-domain indices. Prior to frequency-domain analysis, RRI time series were evenly resampled with a re-sampling frequency of 4 Hz by spline interpolation. Burg's

method with an order of 10 was used to produce the HRV spectrum [18]. It was then integrated into a low-frequency power (0.04 to 0.15 Hz) and a high-frequency power (0.15 to 0.40 Hz). The normalized low-frequency power (LFn), normalized high-frequency power (HFn), and the ratio of low-frequncy power to high-frequency power (LF/HF) were used as the frequency-domain HRV indices.

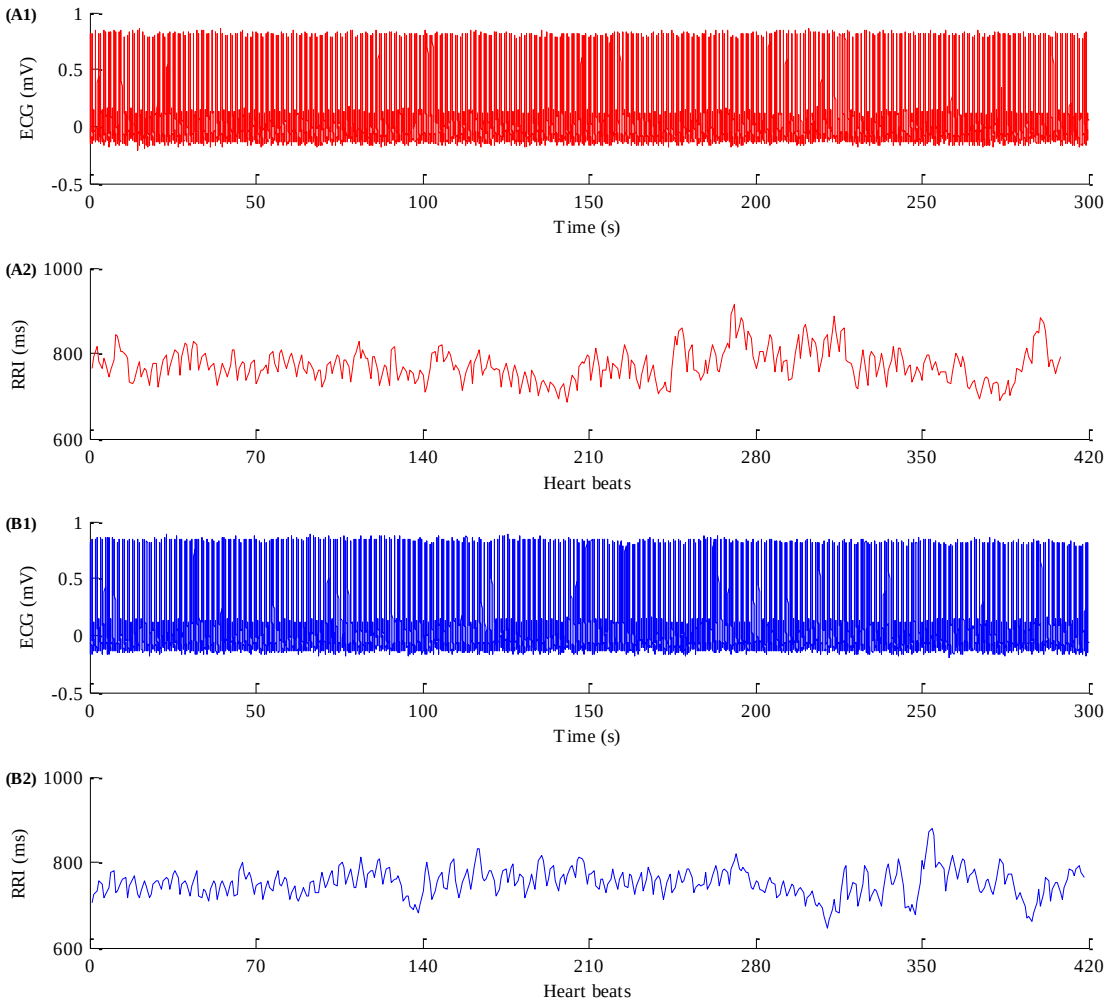

Figure 2. Waveform examples of the recorded ECG signal for 5-min duration and the corresponding RRI time series for two emotion states: (A1) ECG signal and (A2) RRI time series forhappiness emotion, (B1) ECG signal and (B2) RRI time series for sadness emotion.

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.

The calculation process of SampEn was summarized as follows [19, 20]:

For RRI time series $x(i)$ $(1 \le i \le N)$, given the parameters *m* and *r*, firstly form the vector sequences X_i^m:

$$X_i^m = \{x(i), x(i+1), \cdots, x(i+m-1)\} \quad 1 \le i \le N-m \tag{1}$$

The vector X_i^m represents *m* consecutive $x(i)$ values. Then the distance between X_i^m and X_j^m based on the maximum absolute difference is defined as:

$$d_{i,j}^m = d\left[X_i^m, X_j^m\right] = \max_{k=0}^{m-1} \left|x(i+k) - x(j+k)\right| \tag{2}$$

For each X_i^m, denote $B_i^m(r)$ as $(N-m)^{-1}$ times the number of X_j^m $(1 \le j \le N-m)$ that meets $d_{i,j}^m \le r$. Similarly, set $A_i^m(r)$ as $(N-m)^{-1}$ times the number of X_j^{m+1} that meets $d_{i,j}^{m+1} \le r$ for all $1 \le j \le N-m$.

Then SampEn is defined by

$$\text{SampEn}(m, r, N) = -\ln\left(\sum_{i=1}^{N-m} A_i^m(r) / \sum_{i=1}^{N-m} B_i^m(r)\right) \tag{3}$$

The calculation process of FuzzyMEn was summarized as follows [21, 22]:

For RRI time series $x(i)$ $(1 \le i \le N)$, firstly form the local vector sequences XL_i^m and global vector sequences XG_i^m respectively:

$$\begin{aligned} XL_i^m &= \{x(i), x(i+1), \cdots, x(i+m-1)\} - \bar{x}(i) \\ XG_i^m &= \{x(i), x(i+1), \cdots, x(i+m-1)\} - \bar{x} \end{aligned} \quad 1 \le i \le N-m \tag{4}$$

The vector XL_i^m represents *m* consecutive $x(i)$ values but removing the local baseline $\bar{x}(i)$, which is defined as:

$$\bar{x}(i)=\frac{1}{m}\sum_{k=0}^{m-1}x(i+k)\quad 1\le i\le N-m \tag{5}$$

The vector XG_i^m also represents m consecutive $x(i)$ values but removing the global mean value $\bar{x}$ of the segment $x(i)$, which is defined as:

$$\bar{x}=\frac{1}{N}\sum_{i=1}^{N}x(i) \tag{6}$$

Then the distance between the local vector sequences XL_i^m and XL_j^m and the distance between the global vector sequences XG_i^m and XG_j^m are defined as follows respectively:

$$\begin{aligned} dL_{i,j}^m &= d\left[XL_i^m, XL_j^m\right]=\max_{k=0}^{m-1}\left|(x(i+k)-\bar{x}(i))-(x(j+k)-\bar{x}(j))\right| \\ dG_{i,j}^m &= d\left[XG_i^m, XG_j^m\right]=\max_{k=0}^{m-1}\left|(x(i+k)-\bar{x})-(x(j+k)-\bar{x})\right| \end{aligned} \tag{7}$$

Given the parameters n_L, r_L, n_G and r_G, calculate the similarity degree $DL_{i,j}^m(n_L,r_L)$ between the local vectors XL_i^m and XL_j^m by the fuzzy function $\mu L(dL_{i,j}^m,n_L,r_L)$, as well as calculate the similarity degree $DG_{i,j}^m(n_G,r_G)$ between the global vectors XG_i^m and XG_j^m by the fuzzy function $\mu G(dG_{i,j}^m,n_G,r_G)$:

$$\begin{aligned} DL_{i,j}^m(n_L,r_L)&=\mu L(dL_{i,j}^m,n_L,r_L)=\exp\left(-\left(\frac{dL_{i,j}^m}{r_L}\right)^{n_L}\right) \\ DG_{i,j}^m(n_G,r_G)&=\mu G(dG_{i,j}^m,n_G,r_G)=\exp\left(-\left(\frac{dG_{i,j}^m}{r_G}\right)^{n_G}\right) \end{aligned} \tag{8}$$

Define the function $\phi L^m(n_L,r_L)$ and $\phi G^m(n_G,r_G)$ as:

$$\begin{aligned} \phi L^m(n_L,r_L)&=\frac{1}{N-m}\sum_{i=1}^{N-m}\left(\frac{1}{N-m}\sum_{j=1}^{N-m}DL_{i,j}^m(n_L,r_L)\right) \\ \phi G^m(n_G,r_G)&=\frac{1}{N-m}\sum_{i=1}^{N-m}\left(\frac{1}{N-m}\sum_{j=1}^{N-m}DG_{i,j}^m(n_G,r_G)\right) \end{aligned} \tag{9}$$

Similarly, define the function $\phi L^{m+1}(n_L,r_L)$ for $m+1$ dimension vectors XL_i^{m+1} and XL_j^{m+1} and the function $\phi G^{m+1}(n_G,r_G)$ for $m+1$ dimension vectors XG_i^{m+1} and YG_j^{m+1}:

$$\begin{aligned} \phi L^{m+1}(n_L,r_L)&=\frac{1}{N-m}\sum_{i=1}^{N-m}\left(\frac{1}{N-m}\sum_{j=1}^{N-m}DL_{i,j}^{m+1}(n_L,r_L)\right) \\ \phi G^{m+1}(n_L,r_L)&=\frac{1}{N-m}\sum_{i=1}^{N-m}\left(\frac{1}{N-m}\sum_{j=1}^{N-m}DG_{i,j}^{m+1}(n_G,r_G)\right) \end{aligned} \tag{10}$$

Then the fuzzy local measure entropy (FuzzyLMEn) and fuzzy global measure entropy (FuzzyGMEn) are defined by:

$$\begin{aligned}\text{FuzzyLMEn}\left(m,n_L,r_L,N\right)&=-\ln\left(\phi L^{m+1}(n_L,r_L)/\phi L^{m}(n_L,r_L)\right)\\ \text{FuzzyGMEn}\left(m,n_G,r_G,N\right)&=-\ln\left(\phi G^{m+1}(n_G,r_G)/\phi G^{m}(n_G,r_G)\right)\end{aligned} \tag{11}$$

Finally, the FuzzyMEn of RRI time series $x(i)$ is calculated as follows:

$$\text{FuzzyMEn}\left(m,n_L,r_L,n_G,r_G,N\right)=\text{FuzzyLMEn}\left(m,n_L,r_L,N\right)+\text{FuzzyGMEn}\left(m,n_G,r_G,N\right) \tag{12}$$

In this study, the local similarity weight n_L=3, global vector similarity weight n_G=2, and the local tolerance threshold r_L were set equivalent to the global threshold r_G, i.e., r_L= r_G =r. So the formula (12) becomes:

$$\text{FuzzyMEn}\left(m,r,N\right)=\text{FuzzyLMEn}\left(m,r,N\right)+\text{FuzzyGMEn}\left(m,r,N\right) \tag{13}$$

For both SampEn and FuzzyMEn, the entropy results were only based on the three parameters: embedding dimension *m*, tolerance threshold *r* and RRI time series length *N*. In the current study, the parameter *m* is set as 2 and *r* is set as 0.15 based on the recommendation of [23]. The parameter *N* is the number of RR intervals without any ectopic beats in RRI time series.

2.5. Statistical analysis

Normal distributions of all HRV indices for the two emotion states were confirmed by the Kolmogorov-Smirnov test. HR, SBP and DBP values from the two measurements, i.e., before and after the signal recordings, were tested by the paired *t* test. The effect of experimental order on HRV indices was analyzed using one way variance (ANOVA). The differences of all indices between two emotion states were compared by the paired *t* test. The Pearson correlation coefficients of all indices between two emotion states were also calculated. In addition, the HR- and MAP-related changes of all HRV indices between two emotion states were analyzed

by Pearson correlation. All statistical analyses were performed using the SPSS software (Ver. 20, IBM, USA). A statistical significance was accepted at $P<0.05$.

3. Result

Table 2 shows the results of HR, SBP and DBP values from the two measurements (before signal recording and after signal recording). There was significant difference for SBP ($P<0.01$) between the two measurements but no significant differences for HR ($P=0.8$) and DBP ($P=0.1$).

Table 3 shows the effect of experimental order on HRV indices. It was confirmed that experimental order had no significant effects on all indices (all $P>0.05$).

Table 2. Results of HR, SBP and DBP values from the two measurements.

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
DBP (mmHg)	70.7 ± 9.6	69.1 ± 7.8	0.1

Note: data are expressed as numbers or mean ± standard deviation (SD).

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

Note: Data are expressed as results or mean ± standard deviation (SD). Experimental order 1: first happiness then sadness, Experimental order 2: first sadness then happiness.

3.1. Comparison of the HRV indices between two emotion states

Table 4 shows the results of all studied HRV indices for two emotion states. For time-domain indices, MEAN (P<0.05) and SDNN (P<0.01) were significantly larger in happiness emotion than those in sadness emotion, while the significant differences in indices of RMSSD (P=0.4) and PNN50 (P=0.5) disappeared. For frequency-domain indices, all three indices had significant differences between two emotion states (all P<0.01). For nonlinear indices, the significant difference was reported by FuzzyMEn (P<0.05) but not by SampEn. (P=0.4)

Table 4. Results of HRV indices between happiness and sadness emotional states.

Index	Emotion state		*t*- value	*P*-value
	Happiness	Sadness		
MEAN (ms)	849 ± 91	835 ± 80	2.3	<0.05
SDNN (ms)	55 ± 13	49 ± 16	3.2	<0.01
RMSSD (ms)	42 ± 16	41 ± 17	0.95	0.4
PNN50 (%)	23 ± 17	22 ± 18	0.74	0.5
LFn	0.63 ± 0.15	0.51 ± 0.15	6.5	<0.01
HFn	0.37 ± 0.15	0.49 ± 0.15	-6.5	<0.01
LF/HF	2.4 ± 1.9	1.3 ± 1.2	4.6	<0.01
SampEn	1.92 ± 0.25	1.89 ± 0.21	0.90	0.4
FuzzyMEn	1.54 ± 0.34	1.64 ± 0.29	-2.0	<0.05

Note: Data are expressed as results or mean ± standard deviation (SD).

3.2. Correlation of HRV indices between two emotion states

Figure 3 shows the correlation of all HRV indices for two emotion states. The fitting lines and the corresponding R and P values are also shown when significant correlation is reported.

All studied indices except for SampEn had significant positive correlations (all $P<0.01$) between happiness and sadness emotional states.

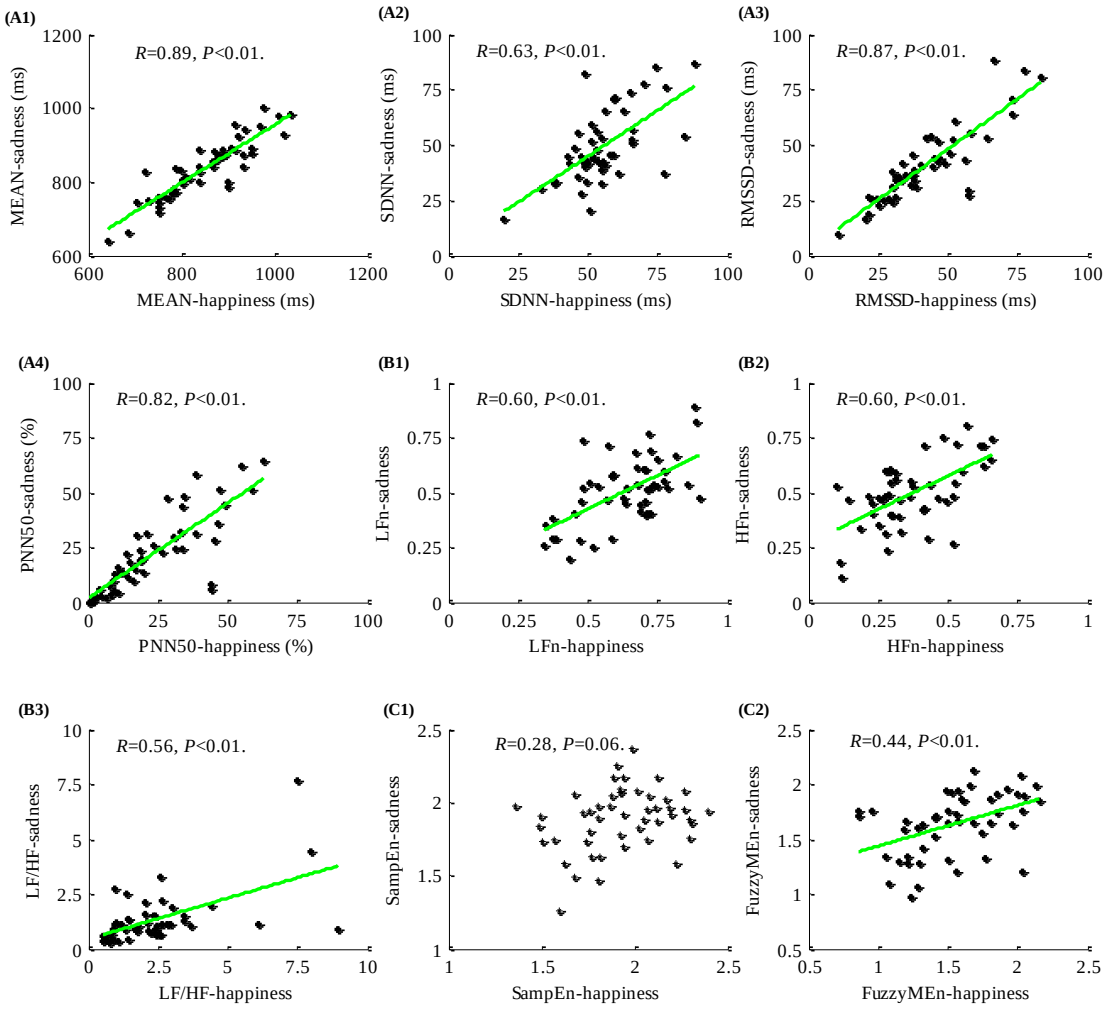

Figure 3. Correlations of HRV indices between happiness and sadness emotional states. The scatter plots represent values of all samples. The fitting lines and the corresponding *R* and *P* values are also shown when the correlations have statistical significance. Time-domain indices: (A1) MEAN, (A2) 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.

3.3. Effects of HR and MAP on HRV indices

Table 5 and Figure 4 show the effect of HR on the results of HRV indices for two emotion states. All four time-domain indices decreased with the increase in HR (P<0.01) for both happiness and sadness emotional states. However, all frequency-domain and non-linear indices had no HR-related changes (P>0.05) for the two emotions.

Table 6 and Figure 5 show the effect of MAP on the results of HRV indices for two emotional states. All indices showed no BP-related changes (P>0.05).

Table 5. Correlation coefficients (R values) and P values between HR and HRV indices for the two emotional states.

Index	Happiness		Sadness	
	R-value	*P*-value	*R*-value	*P*-value
MEAN (ms)	-0.85	<0.01	-0.84	<0.01
SDNN (ms)	-0.56	<0.01	-0.47	<0.01
RMSSD (ms)	-0.53	<0.01	-0.52	<0.01
PNN50 (%)	-0.48	<0.01	-0.48	<0.01
LFn	0.19	0.20	0.22	0.13
HFn	-0.19	0.20	-0.22	0.13
LF/HF	0.22	0.13	0.22	0.13
SampEn	-0.23	0.12	-0.21	0.15
FuzzyMEn	-0.26	0.08	-0.27	0.07

Table 6. Correlation coefficients (R values) and P values between MAP and HRV indices for the two emotional states.

Index	Happiness		Sadness	
	R-value	*P*-value	*R*-value	*P*-value
MEAN (ms)	-0.12	0.42	-0.10	0.49
SDNN (ms)	-0.07	0.65	-0.04	0.77
RMSSD (ms)	0.004	0.98	-0.02	0.89
PNN50 (%)	0.0001	1.00	-0.02	0.87
LFn	0.01	0.94	-0.01	0.96
HFn	-0.01	0.94	0.01	0.96
LF/HF	0.03	0.85	0.02	0.90
SampEn	0.26	0.08	0.27	0.07

FuzzyMEn	0.09	0.52	0.14	0.33

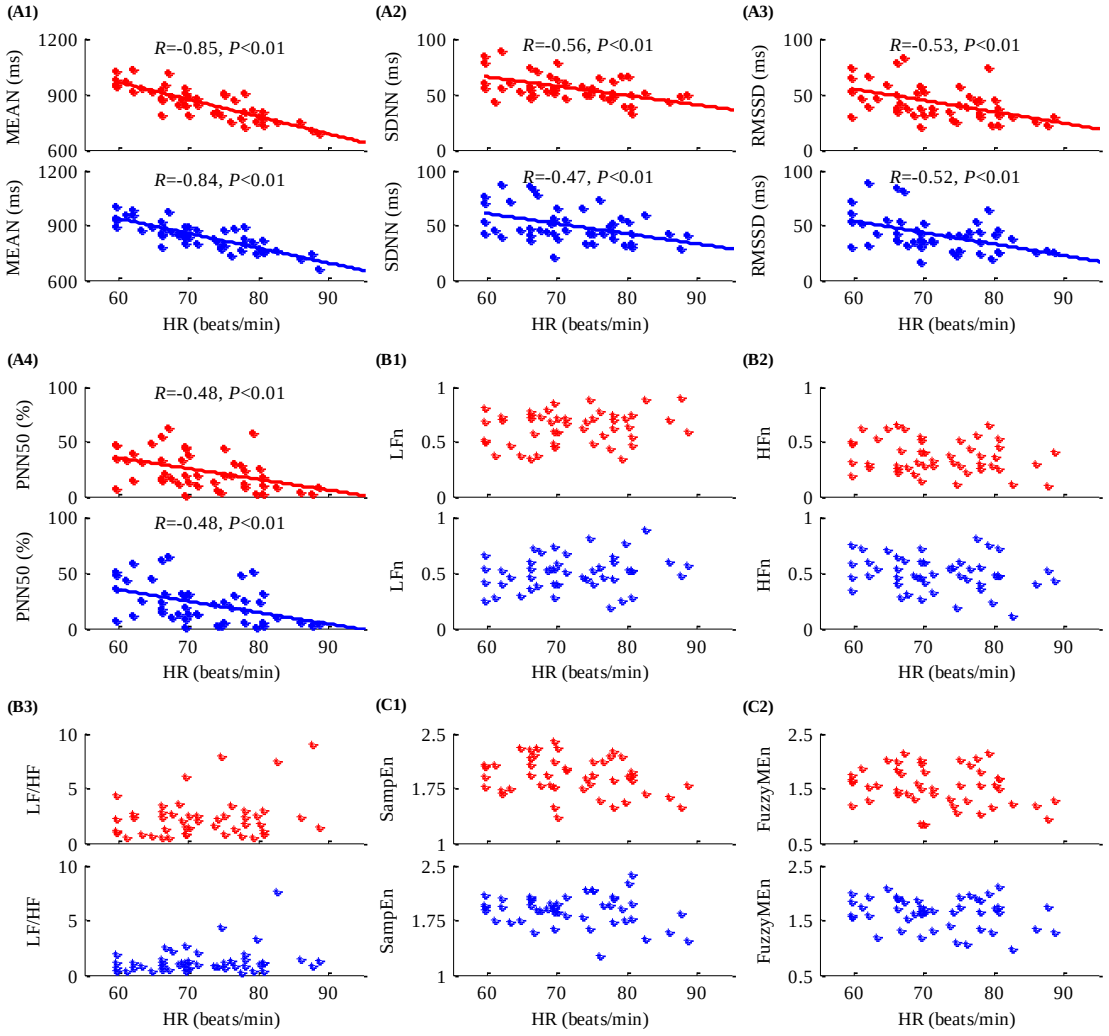

Figure 4. The analyzed time-domain (A1-A4), frequency-domain (B1-B3) and nonlinear (C1-C2) HRV results plotted against HR. The fitting line and the corresponding *R* and *P* values are also shown when the correlation has statistical significance. For each subfigure, the upper panel shows the results for happiness emotion and the lower panel for sadness emotion.

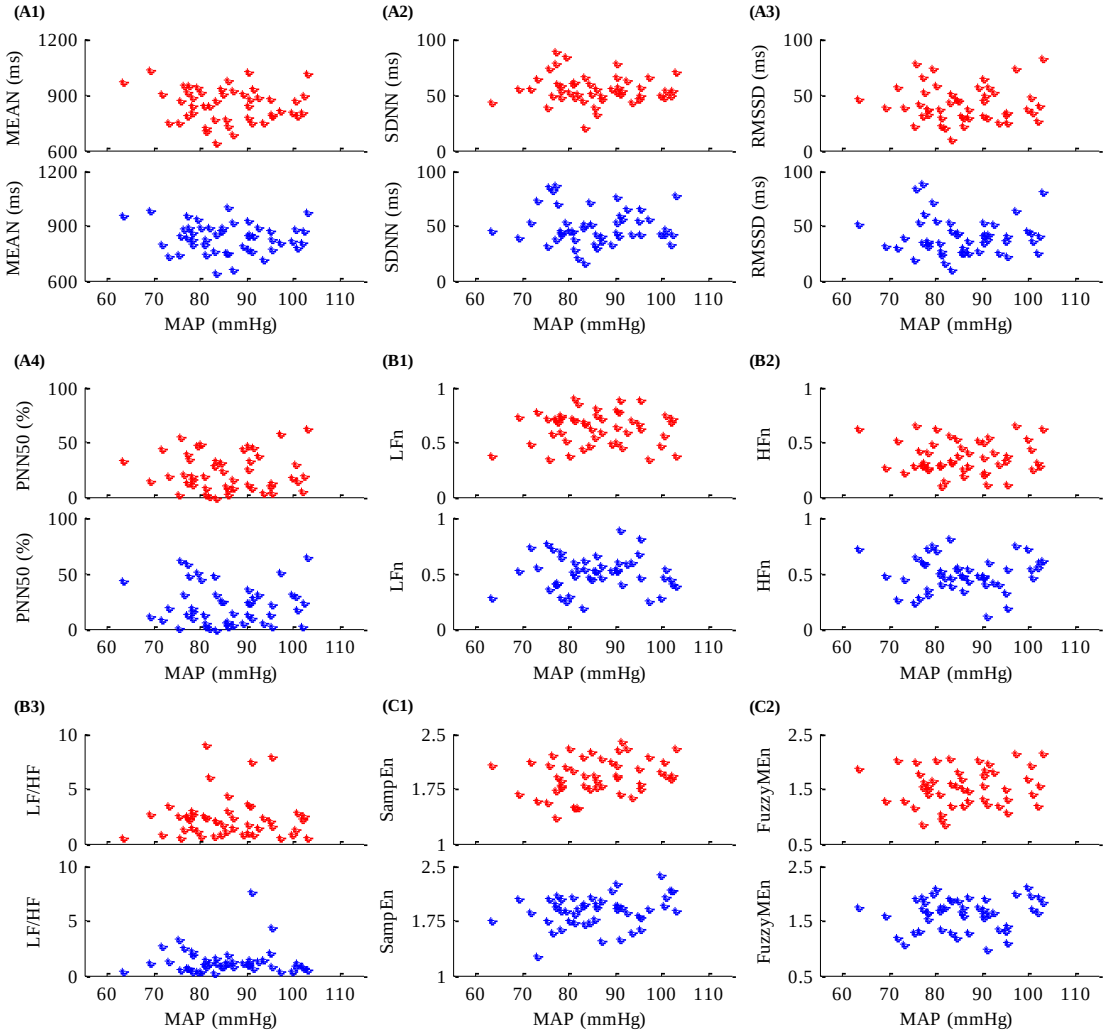

Figure 5. The analyzed time-domain (A1-A4), frequency-domain (B1-B3) and nonlinear (C1-C2) HRV results plotted against MAP. For each subfigure, the upper panel shows the results for happiness emotion and the lower panel for sadness emotion.

4. Discussion

Physiological changes under different emotion states mainly reflected the changes of the activity of the autonomic nervous system. HRV analysis can quantify the activity of the autonomic nervous system and evaluate the tension and balance of sympathetic and parasympathetic [7-9]. 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 decreased result [2, 24]. Our results showed that compared with sadness emotion, happiness emotion outputs the decreased HR (i.e., an increased MEAN), which agrees with Britton *et al*'s study but different with Ekman *et al*'s report. It has also been reported that HR during surprise emotion was significantly increased than those during boredom and pain emotions [4]. Meanwhile, Mikuckas *et al.* found SDNN, RMSSD and PNN50 values increased during stressful emotional state while decreased during walking state, and HR decreased during stressful emotional state while increased during walking state [11]. 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 [12]. In our study, we found an increased SDNN in happiness emotion. However, RMSSD and PNN50 had no significant differences between the two emotional states.

It has been proven that frequency analysis of HRV can reflect the volatility of the autonomic nervous system. Index of LF mainly reflects the sympathetic nervous activity while index of HF reflects the parasympathetic nerve activity [8, 9]. Mikuckas *et al.* found that LF and HF were very sensitive to coffee, alcohol and a physical load, and LF/HF increased in stressful emotional state [11]. Valderas *et al.* reported that LF, HF, and HF/LF showed significant difference between relax and joy emotions, as well as between joy and fear emotions [12]. In the current study, LFn presented a significant increase while HFn showed a significant decrease under happiness emotion, suggesting that the sympathetic nervous activity

increased while the parasympathetic nerve activity decreased for happiness emotion.

Indices of SampEn and FuzzyMEn, as the reflections of nonlinear dynamic characteristics, could evaluate the inherent complexities of RRI time series under different emotional states [20-22]. Riganello *et al.* reported that there was a significant difference in SampEn between the healthy subjects and vegetative state/unresponsive wakefulness syndrome (US/UWS) patients when listening to the Mussorgsky's music [25]. We found that there was a significant decrease in FuzzyMEn during happiness emotion, confirming the complexity of RRI time series for happiness emotion decreased.

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 since the paired HRV values from two emotion states should had the same trend of ups and downs. The correlation results gave us more confidence on the confirmation of the accuracy of HRV calculation.

In addition, this study showed significant HR-related changes for time-domain HRV indices but not significant HR-related variations for both frequency-domain and nonlinear HRV indices for two emotional states, indicating that both frequency-domain and non-linear HRV indices can be hardly influenced by the HR changes under the two emotional states. Moreover, all indices can be hardly influenced by the BP changes indicated by the slight MAP-related variations of all HRV indices.

5. Conclusion

This study suggested that multiple HRV indices had significant differences between happiness and sadness emotion states. The findings could help to better understand the inherent differences of cardiovascular time series between different emotional states. To further investigate this concern, a large number of participants and patients with different emotion diseases, such as depression and anxiety, will be required in future studies.

References

[1] R.W. Picard, E. Vyzas, J. Healey, Toward machine emotional intelligence: analysis of affective physiological state, IEEE Trans. Pattern Anal. Mach. Intell. 23 (10) (2001) 1175-1191.

[2] P. Ekman, R.W. Levenson, W.V. Friesen, Autonomic nervous system activity distinguishes among emotions, Science 221 (4616) (1983) 1208-1210.

[3] S.K. Hadjidimitriou, L.J. Hadjileontiadis, Toward an EEG-based recognition of music liking using time-frequency analysis, IEEE Trans. Biomed. Eng. 59 (12) (2012) 3498-3510.

[4] E.H. Jang, B.J. Park, M.S. Park, S.H. Kim, J.H. Sohn, Analysis of physiological signals for recognition of boredom, pain, and surprise emotions, J. of Physiol. Anthropol. 34:25 (2015).

[5] C.K. Wu, P.C. Chung, C.J. Wang, Representative segment-based emotion analysis and classification with automatic respiration signal segmentation, IEEE Trans. Affect. Comput. 3 (4) (2012) 482-495.

[6] C.Y. Chang, C.W. Chang, J.Y. Zheng, P.C. Chung, Physiological emotion analysis using support vector regression, Neurocomputing 122 (2013) 79-87.

[7] R.E. Kleiger, P.K. Stein, J.T. Bigger, Heart rate variability: measurement and clinical utility, Ann. Noninvasive Electrocardiol. 10 (1) (2005) 88-101.

[8] T.E. Brown, L.A. Beightol, J. Koh, D.L. Eckberg, Important influence of respiration on human RR interval power spectra is largely ignored, J. Appl. Physiol. 75 (5) (1993) 2310-2317.

[9] R. Furlan, S. Guzzetti, W. Crivellaro, S. Dassi, M. Tinelli, G. Baselli, S. Cerutti, F. Lombardi, M. Pagani, A. Malliani, Continuous 24-hour assessment of the neural regulation of systemic arterial pressure and RR variabilities in ambulant subjects, Circulation 81 (2) (1990) 537-547.

[10] K.H. Kim, S.W. Bang, S.R. Kim, Emotion recognition system using short-term monitoring of physiological signals, Med. Biol. Eng. Comput. 42 (3) (2004) 419-427.
[11] A. Mikuckas, I. Mikuckiene, A. Venckauskas, E. Kazanavicius, R. Lukas, I. Plauska, Emotion recognition in human computer interaction systems, Elektron. ir Elektrotech. 20 (10) (2014) 51-56.
[12] M.T. Valderas, J. Bolea, P. Laguna, M. Vallverdu, R. Bailon, Human emotion recognition using heart rate variability analysis with spectral bands based on respiration, in: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, Milan, Italy, 2015, pp. 6134-6137.
[13] S.N. Yu, S.F. Chen, Emotion state identification based on heart rate variability and genetic algorithm, in: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, Milan, Italy, 2015, pp. 538-541.
[14] C.Y. Liu, D.C. Zheng, L.N. Zhao, P. Li, B. Li, A. Murray, C.C. Liu, Elastic properties of peripheral arteries in heart failure patients in comparison with normal subjects, J. Physiol. Sci. 63 (3) (2013) 195-201.
[15] C.Y. Liu, L.P. Li, L.N. Zhao, D.C. Zheng, P. Li, C.C.w. Liu, A combination method of improved impulse rejection filter and template matching for identification of anomalous intervals in electrocardiographic RR sequences, J. Med. Biol. Eng. 32 (4) (2012) 245-250.
[16] M. Malik, J.T. Bigger, A.J. Camm, R.E. Kleiger, A. Malliani, A.J. Moss, P.J. Schwartz, Heart rate variability: standards of measurement, physiological interpretation, and clinical use, Circulation 93 (5) (1996) 1043-1065.
[17] J.P. Singh, M.G. Larson, H. Tsuji, J.C. Evans, C.J. O'Donnell, D. Levy, Reduced heart rate variability and new-onset hypertension: insights into pathogenesis of hypertension: the framingham heart study, Hypertension 32 (2) (1998) 293-297.
[18] J.J. Goldberger, M.W. Ahmed, M.A. Parker, A.H. Kadish, Dissociation of heart rate variability from parasympathetic tone, Am. J. Physiol.-Heart Circul. Physiol. 266 (5) (1994) H2152-2157.
[19] T. Zhang, Z. Yang, J.H. Coote, Cross-sample entropy statistic as a measure of complexity and regularity of renal sympathetic nerve activity in the rat, Exp. Physiol. 92 (4) (2007) 659-669.
[20] J.S. Richman, J.R. Moorman, Physiological time-series analysis using approximate entropy and sample entropy, Am. J. Physiol.- Heart Circul. Physiol. 278 (6) (2000) H2039-2049.
[21] C.Y. Liu, K. Li, L.N. Zhao, F. Liu, D.C. Zheng, C.C. Liu, S.T. Liu, Analysis of heart rate variability

using fuzzy measure entropy, Comput. Biol. Med. 43 (2) (2013) 100-108.
[22] C.Y. Liu, L.N. Zhao, Using Fuzzy Measure Entropy to improve the stability of traditional entropy measures, Computing in Cardiology, IEEE, Hangzhou, 2011, pp. 681-684.
[23] L.N. Zhao, S.S. Wei, C.Q. Zhang, Y.T. Zhang, X.G. Jiang, F. Liu, C.Y. Liu, Determination of sample entropy and fuzzy measure entropy parameters for distinguishing congestive heart failure from normal sinus rhythm subjects, Entropy 17 (9) (2015) 6270-6288.
[24] J.C. Britton, S.F. Taylor, K.C. Berridge, J.A. Mikels, I. Liberzon, Differential subjective and psychophysiological responses to socially and nonsocially generated emotional stimuli, Emotion 6 (1) (2006) 150-155.
[25] F. Riganello, M.D. Cortese, F. Arcuri, M. Quintieri, G. Dolce, How can music influence the autonomic nervous system response in patients with severe disorder of consciousness?, Front. Neurosci. 9 (2015).