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Heart rate variability monitoring for emotion and disorders of emotion

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Abstract

Background: Emotion is composed of cognitive processing, physiological response and behavioral reaction. Heart rate variability (HRV) refers to the fluctuations between consecutive heartbeat cycles, and is considered as a non-invasive method for evaluating cardiac autonomic function. HRV analysis plays an important role in emotional study and detection. *Objective*: In this paper, the physiological foundation of HRV is briefly described, and then the relevant literature relating to HRV-based emotion studies for the performance of HRV in different emotions, emotion recognition, the evaluation of emotional disorders, HRV biofeedback, as well as HRV-based emotion analysis and management enhanced by wearable devices, are reviewed. *Significance*: It is suggested that HRV is an effective tool for the measurement and regulation of emotional response, with a broad application prospect.

1. Emotion: definition, type and mechanism

The word 'emotion' was brought about by Thomas Brown in the early 1800s, but it was not widely recognized until about 30 years later when its modern concept emerged (Smith 2015). It is accepted as a general term for a series of subjective cognitive experiences, which represents the psychological and physical states produced by multiple senses, thoughts and behavior (Frijda 2008). Emotions can guide our decisions, further promote adaptive responses and their original roles were to motivate adaptive behavior that would have contributed to the survival of humans (Damasio 2003). The detection and regulation of emotions and disorders of emotion are thus essential to maintaining mental health and social functioning (Eisenberg 2001).

Discrete and dimensional are two approaches for emotional classification. Discrete emotion emphasizes the specificity and generality of emotional experience and expression and tends to ignore the global internal mechanism of the emotional process (Norman *et al* 2014). Green (1992) considers that emotions can be intuitively divided into positive and negative types. Positive emotions may be considered as any feeling where there is a lack of negativity, such that no pain or discomfort is felt, and predict increases in both resilience and life satisfaction (Cohn *et al* 2009), while negative emotions are related to the opposite. Many works suggest that there are several basic human emotions that can further be distinguished into different subcategories, as described by Shaver *et al* (1987) (see table 1). Some of the generally accepted basic emotions are happiness, surprise, fear, anger, disgust and sadness (Adolphs 2006). Recent research at the University of Glasgow investigated how the muscles in the face move when expressing a variety of emotions, and supports fewer emotion categories: four basic emotions of happiness, fear/surprise, disgust/anger and sadness (Jack *et al* 2014). Dimensional emotion focuses on the basic components of the emotional process (such as valence versus arousal and activation versus inhibition) without considering the discrete state. The circumplex model of affect proposes that all types of emotions are derived from two fundamental neurophysiological systems, relating to valence and arousal, respectively (Tseng *et al* 2014, Sharar *et al* 2016). Each emotion can be thought of as varying degrees of both valence and arousal (Valenza *et al* 2014).

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Table 1. Categories and subcategories of emotion.

Basic	Secondary	Tertiary
Love	Affection	Adoration, affection, love, fondness, liking, attraction, caring, tenderness, compassion, sentimentality
	Lust	Arousal, desire, lust, passion, infatuation
	Longing	Longing
Joy	Cheerfulness	Amusement, bliss, cheerfulness, gaiety, glee, jolliness, joviality, joy, delight, enjoyment, gladness, happiness, jubilation, elation, satisfaction, ecstasy, euphoria
	Zest	Enthusiasm, zeal, zest, excitement, thrill, exhilaration
	Contentment	Contentment, pleasure
	Pride	Pride, triumph
	Optimism	Eagerness, hope, optimism
	Enthrallment	Enthrallment, rapture
	Relief	Relief
Surprise	Surprise	Amazement, surprise, astonishment
Anger	Irritation	Aggravation, irritation, agitation, annoyance, grouchiness, grumpiness
	Exasperation	Exasperation, frustration
	Rage	Anger, rage, outrage, fury, wrath, hostility, ferocity, bitterness, hate, loathing, scorn, spite, vengefulness, dislike, resentment
	Disgust	Disgust, revulsion, contempt
	Envy	Envy, jealousy
	Torment	Torment
Sadness	Suffering	Agony, suffering, hurt, anguish
	Sadness	Depression, despair, hopelessness, gloom, glumness, sadness, unhappiness, grief, sorrow, woe, misery, melancholy
	Disappointment	Dismay, disappointment, displeasure
	Shame	Guilt, shame, regret, remorse
	Neglect	Alienation, isolation, neglect, loneliness, rejection, homesickness, defeat, dejection, insecurity, embarrassment, humiliation, insult
	Sympathy	Pity, sympathy
Fear	Horror	Alarm, shock, fear, fright, horror, terror, panic, hysteria, mortification
	Nervousness	Anxiety, nervousness, tenseness, uneasiness, apprehension, worry, distress, dread

Darwin put forward his theory of the nature of emotion in 1872 that the existence of emotional expression was the result of gradual adaptation during phylogenetic development (Darwin 1872). Twelve years later, James suggested that the subjective experience of certain emotions was the result of special changes in the somatic/visceral and behavioral response (James 1884). Their opinions laid the foundation for the controversy relating to the nature of emotions and their relationship with the patterns of somatic/visceral activity. Despite the fact that the debate still exists, most experts support the thinking that emotions are composed of cognitive processing, physiological reactions and behavioral responses (Thayer *et al* 2002). Although the generation of emotion is not just the result of physiological changes, their high correlation has been widely accepted (Levenson 2003) and has been emphasized in early emotion theory. As is known, physiological reactions are controlled by the autonomic nervous system (ANS), which is further divided into the sympathetic nervous system with excitatory effect and the parasympathetic nervous system with inhibitory function. These two types of nerves maintain mutual balance and a low degree of physiological arousal in the normal physiological state. When the individual is under physiological or psychological stress, the activity of the sympathetic nervous system becomes dominant, resulting in physiological arousal (e.g. an increase in heart rate, respiratory rate and pulse) to accommodate the pressure. However, there are obvious individual differences in the equilibrium state of autonomic nervous activity, which will in turn lead to diverse emotions. Individuals are prone to be tensive and excitable when sympathetic nervous activity is dominant, and the reverse response, such as patience, will emerge when parasympathetic nervous activity is predominant. In the brain regions, activities of the amygdala, anterior cingulate cortex and temporal lobe cortex, which reflect the effects of emotions on heart rate, are enhanced by emotional processing (Critchley *et al* 2005). Among them, the central nucleus of the amygdala is the generator of emotional autonomic activity, and the activity of the anterior cingulate cortex is related to the sympathetic autonomic response (Critchley *et al* 2013). Researchers also proposed another approach represented by the prefrontal cortex, which encoded stimulus information and transmitted it to other areas of the central autonomic nervous network, and

Table 2. Modal responses of ANS activation components for several common emotions.

Emotion	ANS activation component			
	α-adrenergic	β-adrenergic	Cholinergic	Vagal
Anger	+	+	+	—
Anxiety	(+)	(+)	+	—
Disgust mutilation	(N)	(+)	+	N
Fear	+	+	+	—
Sadness crying	(+)	/	+	N
Sadness non-crying	(+)	/	—	—
Sadness anticipatory	(+)	±	+	(−)
Sadness acute	/	—	—	+N
Amusement	+N	(−)	+	+
Contentment	(−)	(−)	—	±
Happiness	(+)	—	+N	—
Joy	N	±	+N	(+)
Surprise	/	/	(+)	/

Note: '+' indicates increase; ' − ' indicates decrease; 'N' indicates no change; symbols in parentheses indicate tentative response direction, based on fewer than three studies;and '/' indicates not mentioned in the literature.

even the brainstem, to produce a corresponding response (Ruizpadial *et al* 2011). Kreibig (2010) reviewed 134 studies of the relationship between emotion and peripheral physiological responses, and demonstrated that different emotions were associated with specific ANS response patterns with variable overlap (see table 2).

2. HRV: definition, mechanism and its relationship with emotion

Heart rate variability (HRV) refers to the fluctuations between consecutive heartbeat cycles. It is usually represented by the variation in RR intervals (the intervals composed of two adjacent R wave peaks of the cardiac cycle) collected from electrocardiogram (ECG) data (Task Force 1996) (see figure 1(A)), and any ECG lead signal is sufficient. A healthy heart corresponds to a certain inherent variability, and the loss of this variability is a precursor to heart damage (Goldberger 1990). The strict periodicity of the heart is not a sign of health, but is associated with pathological conditions (Pool 1989). Academic interest in cardiac rhythms may have emerged during the first half of the 18th century, and HRV, which can be used to characterize this rhythm, has attracted researchers' attention since the 1960s (Hon *et al* 1965, Berntson *et al* 1997). Studies in psychology and neuroscience have confirmed that periodic changes in heart rate are induced by the continuous interplay between the sympathetic and parasympathetic nervous systems, that can be reflected by HRV measurement. Consequently, HRV is considered to be an indicator of the adaptation to changing circumstances by the heart (Rajendra Acharya *et al* 2006), and is used as one of the main non-invasive methods for autonomic nervous function assessment (Task Force 1996). An increasing amount of psychological research supports the link between HRV and emotional response.

Anatomically, the heart is innervated by the sympathetic and vagal nerves—the two branches of the ANS (Jindal *et al* 2016). The somata of sympathetic postganglionic neurons lies in the stellate ganglion or cervical sympathetic ganglion. Their axons (belonging to the adrenergic fibers) form the cardiac plexus to innervate various parts of the heart, especially the sinoatrial node—the primary pacemaker of the heart. There are also some distinctions in the regulation of cardiac function between the sympathetic nerves from the left and right sides, in that the sympathetic fibers dominating the sinus node to realize the control of the heart rate mainly come from the right side, and the dominant fibers at the atrioventricular junction mainly come from the other side. In contrast, the somata of parasympathetic postganglionic neurons are located in the heart wall. Their fibers, which belong to cholinergic fibers, are shorter than sympathetic postganglionic fibers, and mainly innervate sinoatrial nodes, atrial muscle, the atrioventricular junction, etc. In addition, the two branches exhibit different functional and temporal effects of their variable signaling mechanisms. After being stimulated, the sympathetic nervous system plays a positive role in the heart by increasing heart rate, atrioventricular conduction and cardiac contractility, which is mediated by neurotransmission of norepinephrine. It exhibits a slow course of action on cardiac function, with the effect observed about a 5 s delay after stimulation and a final return to baseline about 20–30 s later. However, the parasympathetic effect on cardiac function, mediated by acetylcholine neurotransmission, is decreasing heart rate, atrioventricular conduction and cardiac contractility to ensure proper rest and energy reserves of the heart (Kawano *et al* 2003). Its effect on sinoatrial nodes appears rapidly, with the peak effect

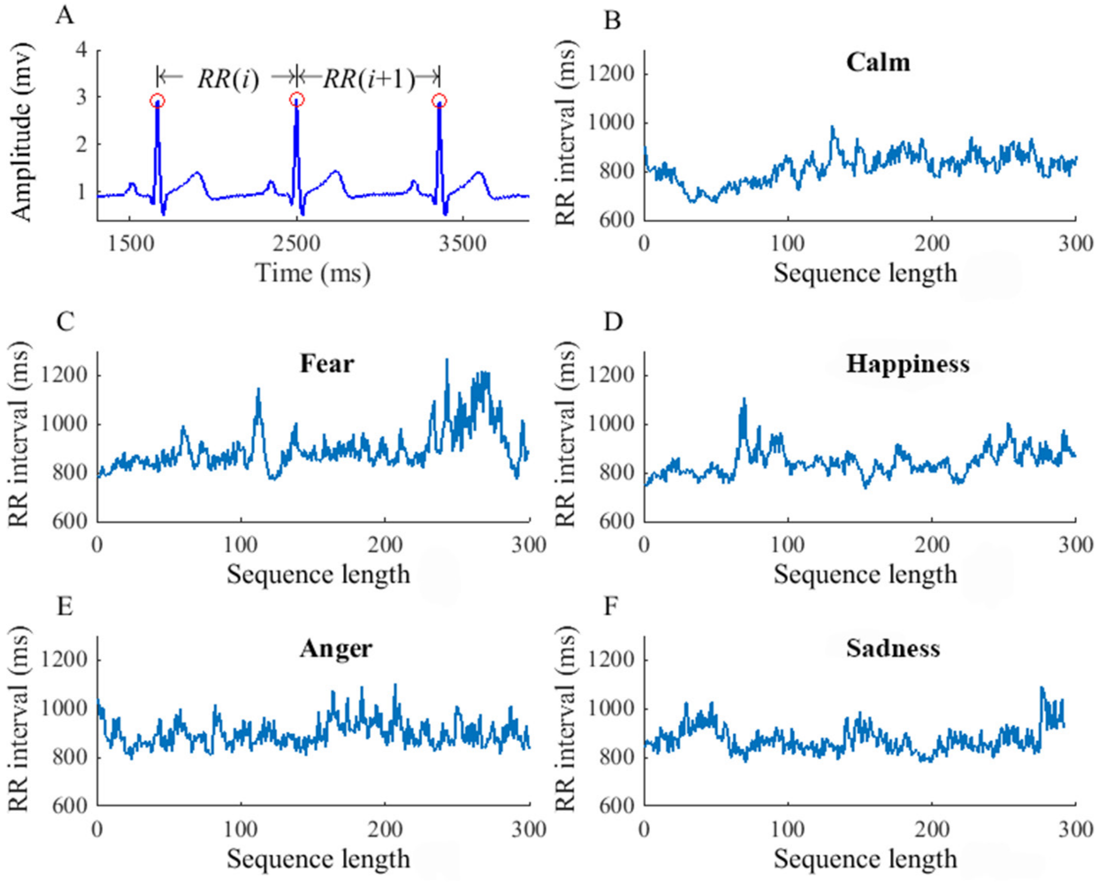

Figure 1. A construction of the an HRV series from the consecutive RR intervals in an ECG signal (A) and examples of the HRV series under calm (B), fear (C), happiness (D), anger (E) and sadness (F) conditions from a healthy subject.

observed after about 400 ms and a return to baseline within 1 s (Berntson *et al* 1997, Pumprla *et al* 2002), i.e. the peak response can be observed between two heartbeats. These significant differences between the effects of the two branches serve as the physiological basis of the low frequency (LF) band, which represents a mix of sympathetic and parasympathetic tension in spectrum analysis of HRV (Task Force 1996). In the normal physiological state of a human, sympathetic and parasympathetic nerves are under the opposite and unified tension state with a predominance of vagal tension, and their net effect is instantaneous heart rate.

ANS is further regulated by the central autonomic network, which consists of partial cortical (medial prefrontal and insular cortices), limbic (anterior cingulate cortex, hypothalamus, central nucleus of the amygdala, bed nucleus of the stria terminalis) and brainstem (periaqueductal gray matter, ventrolateral medulla, parabrachial nucleus, nucleus of the solitary tract) regions (Appelhans *et al* 2006). The central autonomic network can integrate the inputs from the internal physiological conditions and the external dynamic environment, then flexibly adjust the physiological arousal (including arousal associated with emotional expression and regulation) in response to these changes and further realize the regulation of the emotional reaction. The outputs can reach the sinus node through the ANS and affect the heart rate. Therefore, HRV reflects the instantaneous output from the central autonomic network and the ability of an individual to regulate emotional expression by the activity of sympathetic and parasympathetic nerves (Thayer *et al* 2002).

Research on HRV has exponentially increased in the last 30 years. Methods for HRV analysis have undergone extensive development, with time-domain analysis (e.g. SDNN, RMSSD, PNN50), frequency-domain analysis (e.g. LF, high frequency (HF), normalized LF, normalized HF, LF/HF) and non-linear analysis (e.g. entropy, Lyapunov exponent (LE), detrended fluctuation analysis (DFA), SD1 and SD2 from the Poincaré plot) (Rajendra Acharya *et al* 2006). These indices have been widely used as the marked features for emotion recognition (Shi *et al* 2017). Slight differences in signal preprocessing and abnormal rhythm detection during HRV sequence construction will lead to distinct results (Adriana *et al* 2018). To promote the repeatability of HRV indices, researchers have disclosed the toolbox and platform for HRV analysis, including methods for standardized data processing and index calculation, as well as a standard database (Adriana *et al* 2018, Behar *et al* 2018). The definitions of the HRV indices and their possible relationships with emotion have been summarized in table 3. Figure 1 demonstrates the HRV series under different emotional states (calm, fear, happiness, anger and sadness) from a healthy subject. The corresponding values of the HRV indices are exhibited in table 4.

Table 3. Definitions of the HRV indices and their possible relationships with emotion.

HRV index	Description	Relation with emotion
SDNN	Standard deviation of RR intervals	Correlate with LF (Kleiger *et al* 2005, Shaffer *et al* 2014)
RMSSD	Square root of the mean squared differences of successive RR intervals	Correlate with HF (Kleiger *et al* 2005)
PNN50	Proportion of differences between successive RR intervals longer than 50 ms	Correlate with HF (Kleiger *et al* 2005)
LF	Low frequency power	Reflects the activities of sympathetic and vagal nerves, mainly sympathetic activity (Taylor *et al* 1998)
HF	High frequency power	Reflects the vagal activity (Bloomfield *et al* 2001)
LFn	Normalized low frequency power	Similar to LF (Task Force 1996)
HFn	Normalized high frequency power	Similar to HF (Task Force 1996)
LF/HF	Ratio of LF to HF power	Reflects the balance between sympathetic and vagal activity; there is some debate (Task Force 1996, Billman 2013).
LE	Lyapunov exponent, an index to measure the degree of convergence and divergence around the phase space	Quantifies sensitivity of HRV series to initial conditions and characterizes the average divergence rate of adjacent trajectories in the series (Rajendra Acharya *et al* 2006)
DFA	Detrended fluctuation analysis, a method for determining the statistical self-affinity of a signal	Quantifies the fractal properties of short-term HRV series (Rajendra Acharya *et al* 2006)
SD1	Standard deviation of the distances of the RR intervals to the lines $y = -x + 2RR_{\text{mean}}$ in a Poincaré plot	Quantifies the fast beat-to-beat variability of the HRV series (Tulppo *et al* 1996)
SD2	Standard deviation of the distances of the RR intervals to the lines $y = x$ in a Poincaré plot	Quantifies the longer-term variability of the HRV series (Tulppo *et al* 1996)
Entropy	A family of statistics that can measure the complexity and regularity of RR interval series	Quantifies the complexity and regularity of short-term HRV series (Pincus 1991, Rajendra Acharya *et al* 2006), typically as approximate entropy (ApEn), sample entropy (SampEn) (Richman *et al* 2000), fuzzy measure entropy (FuzzyMEn) (Liu *et al* 2013), permutation entropy (PEn) (Xia *et al* 2018).

In this example, video stimuli were used to evoke the emotional states. Among them, the fear-inducing video might lead to greater heart rate fluctuations in the subject, especially during the period of heartbeat acceleration and holding of breath that the subject usually experiences during the fear-inducing process. Therefore, the SDNN and the other indices that reflect the fluctuations in RR intervals in the fear emotion have larger values. The sadness-inducing video can trigger complex emotional and cognitive judgments in the subjects. Thus SampEn, which reflects the intrinsic complexity of the sequence, is higher, while in fear emotion, it shows the lowest value. This might be because some of the intrinsic complexity information is obscured by the fluctuation of the sequence. These results suggested that different emotional states can be linked to different HRV indices, which is also the physiological basis of multi-feature emotion recognition.

3. HRV-based emotion study

3.1. HRV in emotions

Emotions require different patterns of autonomic activity for the purpose of body protection and behavior preparation owing to their distinct goals. HRV indices will also show a variety of performances in different emotions. Shi *et al* (2017) investigated the differences in HRV between happiness and sadness in 48 healthy volunteers. The results showed that the mean heart rate, SDNN, LFn and LF/HF in happiness were higher than those in sadness, while HFn exhibited the opposite result, which suggested greater sympathetic and smaller parasympathetic nervous activities in happiness. Valderas *et al* (2015) reported significant differences in HRV indices among relaxed, joy and fear emotional states in 25 subjects recorded during induced emotion experiments, even after Bonferroni correction. Compared with the calm-neutral state relaxed, HFn significantly decreased and LF/HF increased in the positive elicitation state, joy; the mean heart rate was augmented in the negative elicitation state, fear. In addition, LF/HF were higher and HFn was lower in joy than in fear (Valderas *et al* 2015). These results suggested a higher balance in the ANS during joy than during relaxed and fear. In the circumplex model of affect, arousal and valence are thought to be adequate parameters to identify specific emotions. Gaetano *et al* (2012) studied the neutral and arousal states in 35 healthy subjects, and the experimental results showed that HRV exhibited different behavior during the presentation of neutral images versus high arousal images; approximate entropy (ApEn) decreased when switching from the neutral session to the arousal session, and the LE was positive during the neutral session and negative during the arousal session, indicating a clear switching mechanism between regular and chaotic dynamics from neutral to arousal elicitation.

Table 4. The results of HRV indices under different emotions from a healthy subject (shown in figure 1).

	SDNN	RMSSD	PNN50	LFn	HFn	LF/HF	SampEn
Calm	64.56	35.43	18.78	0.65	0.35	1.83	1.84
Fear	86.44	60.96	32.45	0.60	0.40	1.47	1.64
Happiness	50.30	37.70	16.06	0.69	0.31	2.20	2.13
Anger	54.14	49.20	30.93	0.50	0.50	1.01	1.77
Sadness	40.04	40.74	23.17	0.45	0.55	0.82	2.48

3.2. HRV in emotion recognition

Emotion recognition is valuable in a great number of situations, such as medical applications where there is the need to identify the degree of pain while the patient is unconscious or unable to describe the undergoing pain, retail applications to determine whether a customer is really interested in buying a certain item, home applications by achieving emotional state detection and human-computer interaction to reduce the harm of chronic stress to residents, and so on (Alzoubi *et al* 2012, Mikuckas *et al* 2014, Jang *et al* 2015, Rakshit *et al* 2016). There are a variety of methods to carry out emotion recognition by speech (Pervaiz *et al* 2016), facial expression (Yu *et al* 2009), body movement (Zacharatos *et al* 2014), discourse (Kao *et al* 2009), etc. Nevertheless, these studies all suffer from the main drawback in that the results can easily be falsified by intentional gestures, actions and/or expressions of the participants. In recent years, researchers have paid great attention to emotion recognition based on physiological signals, among which the ECG signal with HRV is used most extensively (Kim *et al* 2004, Valenza *et al* 2012, 2014, Jang *et al* 2015, Yu *et al* 2015, Guo *et al* 2016, Rakshit *et al* 2016, Goshvarpour *et al* 2017).

A variety of emotion recognition systems based on HRV analysis have been introduced by researchers. Time-domain and frequency-domain indices are conventionally used. The accuracy can be improved by using non-linear dynamic methods owing to the non-linear characteristics of physiological signals. Guo *et al* (2016) combined time-domain, frequency-domain, a Poincaré plot and a support vector machine (SVM) classifier to discriminate two (negative and positive) and five (sadness, anger, fear, happiness and relaxed) emotional states in 25 healthy participants without psychiatric history, obtaining accuracies of 71.4% and 56.9%, respectively. When only time-domain or frequency-domain indices were used, both accuracies were lower than 55%. Yu *et al* (2015) also developed an emotion recognition system based on time-domain, frequency-domain and a Poincaré plot to classify neutral, happiness, stress and sadness emotions by SVM and a genetic algorithm, reporting a high classification accuracy of 90%. Valenza *et al* (2014) extracted the instantaneous spectrum, bispectrum and the dominant LE of HRV, then input them to an SVM classifier to recognize four emotional states; they obtained an accuracy of 79.29%, with 79.15% on the valence axis and 83.55% on the arousal axis. Goshvarpour *et al* (2017) used a Poincaré plot to distinguish five emotional states and obtained the best classification rate of 97.45%. Since photoplethysmography (PPG) signals can easily be detected by wearable devices such as a watch, Rakshit *et al* (2016) studied whether the HRV constructed from PPG could replace that from an ECG, and extracted time-domain and frequency-domain indices from the PPG signals to identify three emotional states (happiness, sadness and neutral), achieving an accuracy of 83.8% by an SVM classifier. Li *et al* (2017) also reported marked differences in time-domain and frequency-domain indices based on PPG signals between happiness and sadness states. Compared with happiness, HFn increased in sadness, while SDNN, LFn and LF/HF decreased. Several detectors have also been developed for applications. For example, the MediCore Company has developed a series of stress analyzers based on HRV methods and acceleration plethysmograms, which can detect the stress status of the participants. MIT has invented an emotion detector named the EQ-Radio and based on HRV and respiratory rate analysis, which can accurately detect four emotions: sadness, anger, happiness and joy, with an accuracy rate of 87% (Zhao *et al* 2016).

Many researchers also considered the effects of other physiological signals. Combinations of the conventional measures (LF and HF) of HRV and other physiological features from electrodermal activity and skin temperature were chosen to classify boredom, pain and surprise, achieving a classification accuracy of 84.7% using DFA (Jang *et al* 2015). Kim *et al* (2004) achieved accuracies of 78.4% and 61.8% when classifying three (sadness, stress and anger) and four (sadness, stress, surprise and anger) emotions, respectively, using an SVM classifier. Valenza *et al* (2012) combined deterministic chaos, recurrence plots and DFA measures in HRV, respiration activity and electrodermal response series analyses, and achieved an accuracy of 90% using the quadratic discriminant classifier.

3.3. HRV in emotional disorders

HRV analysis can not only distinguish between positive and negative emotions in healthy subjects, but it can also distinguish psychiatric emotional disorders. The significance arises from the fact that it can easily detect the sympathy-vagal imbalance, if it exists in these disorders.

3.3.1. Anxiety disorder

Anxiety disorder has become more common, especially among young people (Snyder *et al* 2009). Psychobiological theory suggests that resting vagal tension may be an important physiological indicator of anxiety disorders (Porges 2011). Chalmers *et al* (2014) carried out a meta-analysis based on 36 articles and found that anxiety disorders in adults were associated with decreases in time-domain and HF indices of HRV. Another meta-analysis of 44 studies in children and adolescents showed a similar direction (Graziano *et al* 2013). Research on the relationship between the resting vagal tone and anxiety in young people from samples in a non-clinical community obtained a negative relationship (Greaves-Lord *et al* 2007, 2010, Scott *et al* 2014) and no relationship (Elsheikh *et al* 2006, Wetter *et al* 2012), respectively. Time-domain and frequency-domain indices were evaluated in 28 women with premenstrual dysphoric disorder and 11 asymptomatic controls. The results showed that the SDNN and RMSSD in women with premenstrual dysphoric disorder were lower than those in asymptomatic controls, especially in the follicular phase. Supine HF—the most important vagal measure in the frequency-domain—also declined in the same phase, indicating premenstrual dysphoric disorder might be associated with decreased vagal tone (Landen *et al* 2004).

In another recent study, frequency-domain measures of HRV were chosen to evaluate the effects of therapeutic alliance on the anxious client, and the results showed that HRV might be used to measure the relationship between client anxiety levels and successful therapy in the future (Stratford *et al* 2014). Nevertheless, all of these studies only use time-domain and/or frequency-domain indices, which are not sufficient to capture the complex heartbeat information (Costa *et al* 2008). Therefore, Bornas *et al* (2015) explored the differences between adolescents with mild anxiety and severe anxiety by non-linear methods, and found the fractal dimension and SampEn in subjects with severe anxiety were significantly lower than those with mild anxiety, indicating the severity of anxiety was negatively correlated with HRV.

3.3.2. Depressive disorder

Clinical evidence has shown that depressive disorder is associated with increased cardiovascular events (e.g. cardiovascular morbidity and mortality), indicating that depression should be an independent predictor of the severity in patients with cardiovascular disease (Musselman *et al* 1998). Low HRV is a strong predictor of mortality in cardiovascular events. Therefore, studies on HRV have been focused on patients with depression or depression superimposed cardiac dysfunction (Carney *et al* 2001, Agelink *et al* 2002, Carney *et al* 2009, Kemp *et al* 2010, Borrione *et al* 2018).

Carney *et al* (2009) gave an overview of the literature about HRV in patients, with and without depression superimposed stable coronary artery disease or a recent acute coronary event (most of them reported declined HRV in depressed patients), and concluded that low HRV might play an important role in depression as a risk factor for coronary artery disease. They also studied post-myocardial infarction patients, with and without depression disorder, and found that the four frequency-domain indices of HRV significantly decreased in patients in the depression group. Further analysis showed no difference in HRV between patients with major versus minor depression, despite there being a decreasing trend from minor to major depression (Carney *et al* 2001). Another study compared the difference in HRV between patients with major depression and healthy controls, and observed similar results that RMSSD and frequency-domain indices observably decline in patients with depression, indicating a significantly lower modulation of cardiac vagal tone in patients (Agelink *et al* 2002). Although most of the HRV indices in patients in the moderate depressive symptoms group did not exhibit a significant reduction compared to the controls, they were in the expected direction. A meta-analysis based on 18 articles, comprising a total of 673 depressed participants and 407 healthy subjects also showed lower HRV in patients with depression, and the severity of depression exhibited a negative correlation with HRV, especially in the non-linear measures (Kemp *et al* 2010). These studies suggested that there is a direct negative correlation between the degree of depression and modulation of cardiovagal activity. Fraguas *et al* (2007) studied frequency-domain indices in eight patients with depression before and after treatment with drugs under four induced emotional states of happiness, sadness, anger and neutrality. It was found that the antidepressant reaction was positively correlated with the LF of sadness and the LF/HF ratio of happiness, suggesting the possibility of HRV as a potential predictor of the antidepressant reaction in induced emotion. In addition, Borrione *et al* (2018) found that melancholic features might be relevant in the association between major depressive disorder and HRV.

A reduction in HRV is also associated with some other negative emotions, such as panic disorder and post-traumatic stress disorder (PTSD). Prasko *et al* (2011) assessed the frequency-domain indices in patients with panic disorder before and after six-week therapy, as well as healthy controls. Autonomic activity was lower in panic disorder patients than in controls, and had a tendency to increase during the treatment. A study from Cohen *et al* (2000) also demonstrated that HRV significantly decreased in patients with panic disorder. Both these studies also found that PTSD patients had significantly higher heart rate and lower HRV values than the controls (Cohen *et al* 2000, Prasko *et al* 2011).

3.4. HRV biofeedback

HRV biofeedback (HRV-BF) is a relatively new form of psychological and physiological intervention, and is applied in training patients to change their heart activity in the variable and dominant rhythms (Wheat *et al* 2010). Over the past 20 years, it has gained increasing attention as an affordable and effective way to reduce symptoms of hostility, depression and anxiety (Keeney 2008, Jester *et al* 2019, Yu *et al* 2018) and to improve attention and executive function skills (Sutarto *et al* 2010). Yu *et al* (2018) assessed the depression and hostility scores in coronary artery disease patients with and without HRV-BF intervention at pre- and post-interventions and one-year follow-up. The results showed that compared with the control group, patients with HRV-BF intervention exhibited fewer all-cause re-admissions (12.00% versus 25.42% in the control group) and all-cause emergency visits (13.33% versus 35.59% in the control group). The LF in the HRV-BF group significantly increased at both post-intervention and one-year follow-up. Only the patients in the HRV-BF group had significantly decreased depression and hostility scores at post-intervention and one-year follow-up. Jester *et al* (2019) carried out HRV-BF intervention among community-dwelling elders (some of them were diagnosed with psychiatric disorders), and found that depression and anxiety disorders were significantly improved at the end of HRV-BF intervention, especially in the participants with psychiatric disorders, indicating that HRV-BF seemed to be effective in reducing these disorders in the elderly.

3.5. Wearable devices enhance HRV-based emotion analysis and management

With the rapid development of flexible electronics, the internet of things (IoT), machine learning and cloud computing, wearable devices have become powerful tools for people's daily health monitoring due to convenience and unobtrusive daily use (Malinin *et al* 2012, Matic *et al* 2012). Thus, they provide a potential improvement for emotion monitoring and regulation. Special sensor (Surrel *et al* 2015) and detection methods (Cheng *et al* 2017) have been developed to enhance the re-equipping of real-time and comfortable HRV-based emotion monitoring by wearable devices. Matic *et al* (2012) explored the emotional and other psychological responses of sedentary subjects using a Shimmer Wireless ECG sensor, and showed that subjects with sedentary working styles were more likely to have negative emotions. Music is recognized as playing a role in inducing strong emotional experiences, including positive and negative emotions (Hegde *et al* 2012, Ramasamy *et al* 2016). Hegde *et al* (2012) reported that HRV indices collected by e-bra showed marked differences from baseline to three different types of music conditions (happiness, sadness and peppy upbeat Hindi film song). In particular, the LF/HF under the sadness music condition decreased significantly, suggesting that the e-bra can be used to monitor cardiac physiology during music therapy. Ramasamy *et al* (2016) also described a preliminary study of emotion-based neuro-cardiology under music therapy.

Moreover, wearable devices have also been applied to HRV biofeedback systems that have emerged over the last few years (Gerasimov *et al* 2002, Zhang *et al* 2009, Wu *et al* 2012, Abtahi *et al* 2015). Zhang *et al* (2009) described a wearable respiration biofeedback platform for respiration guidance. Gerasimov *et al* (2002) introduced a type of wearable data acquisition system for stress monitoring and biofeedback training. Abtahi *et al* (2015) developed a wearable knitted garment with an HRV biofeedback system, which can help to improve the HRV and autonomic balance. Wu *et al* (2012) designed a wearable biofeedback system based on a multi-biosensor platform combined with a resonance frequency training biofeedback strategy for stress management and emotional control of unemployed people in daily life.

4. Outlook

HRV has been taken into consideration as an objective measure of emotional response, among which the polyvagal theory and the model of neurovisceral integration are the main supporting theories (Appelhans *et al* 2006). The reliability of wearable devices for HRV measurement in static posture has also been confirmed (Tsoi *et al* 2017). Therefore, a combination of wearable device and HRV-based emotion analysis can realize convenient emotion monitoring, and even promote the realization of real-time feedback regulation that will be of great significance; for example, an intelligent wearable system that can determine the emotional arousal and attention process of students during e-learning and further provide appropriate background music advice, which plays an important role in promoting innovative teaching methods based on network learning (Artífice *et al* 2017). Personalized wearable systems can detect the users' emotions and then select the appropriate emotion-regulating music (Chiu *et al* 2017) or HRV biofeedback (Mukhopadhyay *et al* 2015). The realization of real-time feedback regulation for relevant high-risk groups (such as the unemployed population, pregnant women, empty nest elderly, people with mental disorders, etc), or even ordinary individuals, is also valuable for avoiding the effects of negative emotion on physical and mental health.

An HRV-based emotion study is usually carried out when the participant is in the resting state. Mikuckas *et al* (2014) examined the impact of emotion and posture on HRV and found posture had a great impact on the HRV indices. The SDNN, RMSSD and PNN50 increased, while mean heart rate decreased during the resting state with stressful emotion. The RMSSD marginally changed. Mean heart rate increased while the other two indices declined during the walking state, indicating that the change in posture should be carefully considered during HRV-based emotion studies. In addition, aging, smoking and alcohol can also influence HRV (Melo *et al* 2005, Rajendra Acharya *et al* 2006). Gender, cardiovascular disease, diabetes mellitus and some other diseases can lead to variations in HRV (Rajendra Acharya *et al* 2006). Consequently, these factors, as well as the circadian rhythmicity (Kim *et al* 2014), should be taken into account in practical applications of HRV to ensure the accuracy of real-time emotion monitoring.

5. Conclusion

HRV reflects the activities of sympathetic and parasympathetic nerves participating in heart regulation, which is further regulated by the central autonomic network that adjusts the emotional response and physiological arousal. The physiological foundations of HRV, as well as its advantages of convenience and non-invasiveness, support it as an important tool for emotion study. A variety of studies have shown that the traditional time-domain and frequency-domain indices of HRV are able to characterize the autonomic activity among emotions, and the non-linear measures can help to improve the effectiveness. Recently developed wearable techniques enhance the practical requirement and implementability of HRV-based emotion monitoring. Therefore, HRV analysis has attracted wide attention with its broad application prospects in emotion recognition, emotion monitoring, mental disorder intervention and prognosis detection.

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