Evaluating Valence Level of Pictures Stimuli in Heart Rate Variability Response

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Abstract

Low and high valence were induced in 20 male volunteers using two groups of pictures stimuli. Heart response was compared between two groups from RR series extracted from recorded ECG measurements. Mean heart rate and heart rate variability measures including time, frequency and Poincare domain were extracted. The results revealed that HRV triangular index, SDNN and SD2 were the only statistically significant parameters between groups ($p<0.05$). Mean heart rate and power in LF and HF bands were also different between low and high valence groups however level of significance was not reached. .

1. Introduction

Emotion is a complex psychophysiological experience of an individual's state of mind as interacting with environmental can influence emotions (1). People often behave in certain ways as a direct result of their emotional state, such as crying and fighting (2). If one can have the emotion without the corresponding behavior, then we may consider the behavior not to be essential to the emotion (3).

As all people express their emotions differently, it is not an easy task to judge emotions. A useful way to describe and recognize emotions is to have multiple dimensions or scales to categorize emotions (4). Instead of choosing discrete labels or words, observers can indicate their impression to each stimulus on several continuous scales, for example, pleasant-unpleasant, attention-rejection, simple-complicated, etc. (5).

One of the common scales for emotions is valence (6). Valence represents the pleasantness of a stimuli, with positive (or pleasant) at one end and negative (or unpleasant) at the other end (Figure 1) (6). Research in this field has shown that emotions can be distinguished depending on their valence level (6).

Valence, as used in psychology of emotions, capturing the attractiveness (positive valence) or aversiveness (negative valence) of an event, object, or situation which is also used to characterize and categorize specific emotions (7). For instance, emotions like anger and fear have "negative valence", on the other hand joy has "positive valence". Positively valenced emotions can be evoked by positive events, objects, or situations (8).

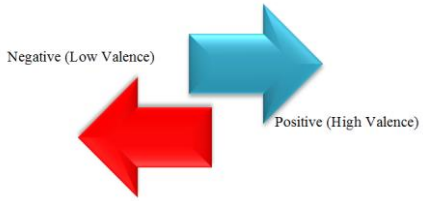

Figure1. Relation between valence level and positive and negative emotions.

The Autonomic Nervous System (ANS) is responsible for short-term regulation of heart rate (HR) and heart rate variability (HRV) (9). The sympathetic system is active during high activity situations and increases HR and reduces HRV (9). In contrast, the parasympathetic system which is active during rest can reduce the HR (9). Sympathetic and parasympathetic systems typically function in opposition to each other (10).

Emotional states in response to environment (e.g. color, picture, and video) can lead to changes in autonomic nervous system (ANS). HR and HRV have been successfully used in previous studies to capture ANS response to changes in emotional states (1, 11). Stress as a negative emotion has been known to have a physiological impact leading to an increase in levels of cortisol that can further lead to increase in heart rate and blood pressure and also decrease in HRV (12). During sadness, the power of VLF and HF frequency band both increase more than compared to other emotions. The power of LF is highest during pleasant state of mind and lowest during energetic state (11). The LF to HF ratio of the power is increased in joy and calm in comparison to others (11). Herbert et al., studied the effects of picture stimuli on stress and their results suggest that cardiac awareness is related to greater responsivity of the ANS during situations evoking autonomic reactivity (13).

The aim of the current study was to explore the potential of non-invasive HR and HRV measures to capture changes in autonomic nervous system (ANS) from pictorial stimuli.

2. Method and Material

2.1. Participants and Protocol

Two groups of pictures were used to induce positive and negative emotions in 20 healthy male volunteers (Age: 24.75±1.43). HR and HRV were measured using lead II ECG data recorded during the process. In order to relate valence level to positive and negative emotions validated Self-assessment Manikin (SAM) test was used (14). Between groups differences in HR and HRV parameters were quantified in time, frequency and Poincare domain. ECG data was recorded while participants were seated in a chair in front of a computer monitor and watched positive and negative stimuli pictures (presented for five minutes each). A 10 minutes break was given between each picture stimuli to cancel the effects of previous stimulation.

2.2. Emotion Assessment

After each stimulus, the subjects answered the SAM test. SAM test is a nonverbal, culture-fair rating system based on a three-dimensional system of emotion (valence, arousal, and dominance) that consists a series of pictograms to judge the affective quality of stimuli. (14).

In this study, the valence dimension of SAM is used to measure valence level of picture stimuli. As shown in Figure 2, the SAM figures range from frowning, unhappy to smiling, happy, on the valence dimension (14). The subject can select any of the five figures comprising scale (-2, -1, 0, +1, +2).

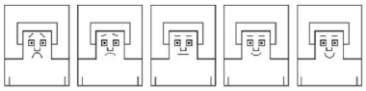

Figure2. Self Assessment Manikins (SAM Test) for assessing valence dimension. Figures range from frowning, unhappy to smiling, happy, on the valence dimension.

2.3. HR and HRV parameters

Pan–Tompkins algorithm was employed for QRS detection (15). Extracted QRS peaks were used for finding RR intervals.

For evaluating heart's reaction in response to picture stimuli, mean value of RR intervals (RR) and mean value of HR, and different HRV measures in time, frequency and Poincare domain were estimated from extracted RR intervals. A brief explanation of HRV measures can be found in the following subsections.

2.3.1. Time Domain Analysis

The analysis of HRV in time domain are the simplest to perform since they are applied directly to the series of successive RR interval values (16). Time domain parameters including SDNN, RMSSD, NN50, pNN50, HRV triangular index, and TINN were extracted from RR intervals (17).

The standard deviation of RR intervals (SDNN) reflects the overall (both short-term and long-term) variation within the RR interval series and is calculated as:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(RR_i - \overline{RR}\right)^2} \qquad (1)$$

where mean RR interval is shown by $\overline{RR} = E\{RR_i\}$.

The standard deviation of successive RR interval differences (SDSD) is used as a measure of the short-term variability.

$$SDSD = \sqrt{E\left\{\Delta RR_i^2\right\} - E\left\{\Delta RR_i\right\}^2} \qquad (2)$$

For stationary RR series, SDSD equals the root mean square of successive differences (RMSSD) given by (18):

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(RR_{i+1} - RR_i\right)^2} \qquad (3)$$

Another feature calculated from successive RR interval differences was NN50 which is the number of successive RR intervals differing more than 50 ms. By normalization of this parameter by total number of RR intervals, pNN50 can be estimated:

$$pNN50 = \frac{NN50}{N-1} \times 100\% \qquad (4)$$

The HRV triangular index was obtained from the integral of RR interval histogram divided by the height of histogram (19). TINN was calculated as the baseline width of the RR histogram (19).

2.3.2. Frequency Domain Analysis

Power spectrum analysis of heart rate variability is a useful non-invasive technique to investigate the neural mechanisms underlying cardiovascular regulation in the frequency domain (10). The main features in frequency domain were (11):

- Low Frequency (LF) power spectrum that ranges between 0.04 and 0.15 Hz and reflects both sympathetic and para-sympathetic activity. Generally, a strong indicator of sympathetic activity.
- High Frequency (HF) power ranging between 0.15 and 0.4 Hz measures reflects parasympathetic (vagal) activity.

- LF/HF Ratio indicates overall balance between sympathetic and parasympathetic systems. Higher values reflects domination of the sympathetic system, while lower ones shows domination of the parasympathetic system. This ratio can be used to help quantify the overall balance between the sympathetic and parasympathetic systems.

2.3.3. Poincare Domain Analysis

A typical Poincare plot of RR interval is shown in Figure 3. SD1 and SD2 are two standard descriptors of Poincare plot (21). SD2 is defined as the standard deviation of the projection of the Poincare plot on the line of identity (y = x), and SD1 is the standard deviation of projection of the Poincare plot on the line perpendicular to the line of identity (y = -x) (21). Given a time series RR = $\{RR_1,RR_2,\ldots,RR_n,RR_{n+1}\}$ the standard Poincare plot is a scatter gram constructed by locating points from the time series on the coordinate plane according to the pairing (x_i, y_i) in which (20),

$x = \{x_1,x_2,\ldots,x_n\} = \{RR_1, RR_2, \ldots, RR_n\}$ (5)

$y = \{y_1,y_2,\ldots, y_n\} = \{RR_2, RR_3, \ldots, RR_{n+1}\}$ (6)

and i = 1, 2, 3, …, n and n is the number of points in the Poincare plot which is one less than the length of the RR time series (21).

So we may define them as:

$SD1 = (Var(d1))^{1/2}$, $SD2 = (Var(d2))^{1/2}$ (7)

where Var(d) is the variance of d, and

$d1 = (x-y) / (2)^{1/2}$, $d2 = (x+y) / (2)^{1/2}$ (8)

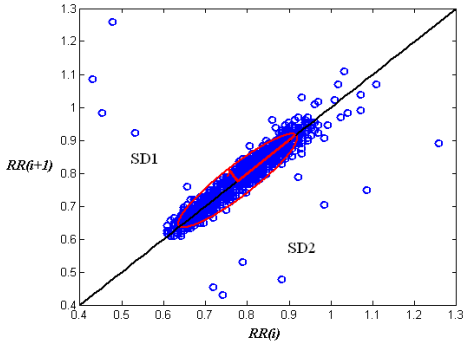

Figure 3. Poincare plot of RR intervals and its descriptors (*SD1* and *SD2)*

2.4. Statistical Test

In this study, Kruskal-Wallis test was used to evaluate between groups difference. The level of significant was set to 0.05.

3. Results

Mean and standard deviation of HR and HRV measures in low and high valence groups along with p values are reported in Tables1 and 2. By relating pictures to emotions according to valence level, the results show that the heart rate increased in response to the positive pictures while it had a decrease in response to negative pictures.

The LF power and HF power in normalized unit respectively increased and decreased in positive emotion (high valence) compared to negative emotion (low valence), Figure 4. HRV triangular index, SDNN and SD2 were significantly different between low and high valence groups ($p<0.05$).

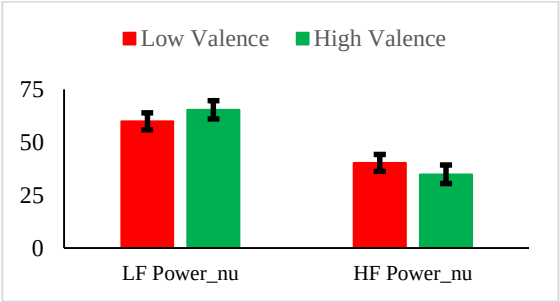

Figure 4. Power (normalized unit) in LF and HF frequency band for low and high valence groups (bars are the standard error)

Table 1. Mean±Standard Deviation of HRV parameters in time domain and Poincare domain along with p values

Parameter	Low Valence	High Valence	p-value
Mean HR	85.26±6.77	85.80±6.78	0.229
Mean RR	0.713±0.06	0.707±0.06	0.192
SDNN	0.058±0.02	0.048±0.01	**0.038***
Std HRV	6.71±2.12	5.77±1.71	0.117
RMSSD	0.044±0.037	0.037±0.025	0.337
NN50	63.15±54.51	49.07±46.80	0.311
pNN50	16.60±16.11	12.76±12.23	0.275
HRV triangular index	11.82±2.96	9.63±2.20	**0.024***
TINN	0.268±0.09	0.230±0.08	0.283
SD1	0.031±0.03	0.027±0.02	0.337
SD2	0.074±0.02	0.062±0.02	**0.016***

*: $p<0.05$

Table 2. Mean±Standard Deviation of HRV parameters in frequency domain along with p values

Parameter	Low Valence	High Valence	p-value
LF Power_nu	59.83±18.12	65.26±19.55	0.473
HF Power_nu	40.17±18.02	34.74±18.55	0.473
LF/HF Power	2.44±2.71	3.06±2.49	0.848

nu: normalized unit; LF: low frequency band; HF: high frequency band

4. Conclusion

In this paper, 20 participants were exposed to several pictures stimuli (negative and positive) and induced valence level was evaluated using SAM test and through changes in ANS. Results suggest HRV parameters can capture significant changes in ANS response to pictures stimuli. The findings of this research demonstrate the potential of using picture stimuli in conjunction with HRV parameters for utilization as a biofeedback training method to control emotions/emotional response.

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