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# Psychophysiological assessment of emotions

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***Abstract.*** The scientific dispute concerning the identification of different psychophysiological patterns associated with specific emotions is still far to be settled. In this preliminary work we present new empirical data to foster the understanding of this topic. We report results related to cardio-respiratory indexes during the experience of autobiografical recall of emotions, namely: fear, anger, happiness and sadness, and show how it is possible to distinguish in a significant way between the different emotions and baseline conditions in 27 students. Of note, some indexes were even able to detect a significant difference between all four emotions. Although these preliminary findings refer to a partial sample of the ongoing research project, aimed at recording data from up to 60 subjects, the data support the possibility to detect specific psychophysiological patterns associated to the target emotions. A confirmation of these findings would foster the development of new tools for automatic recognition of affective states by means of cardio-respiratory signals.

*Keywords:* Affective Computing; Respiration; Heart Rate Variability, Emotion, Psychophysiology, User Experience.

## 1. Introduction

The scientific debate regarding the role of somatic activity in determining affective states started a long time ago. In 1894 William James (James, 1994) claimed that the peripheral afferent signals from viscera are the most important factor characterizing the experience associated with distinct emotions. In contrast, Cannon (1987) stated that the not quick, diffuse and unspecific visceral activity could not characterize the qualities of felt emotions (see also Cannon, 1931). The function of cognitive factors was highlighted by further theories claiming that peripheral activity only denoted the felt intensity of arousal and not the quality of the emotion experienced (Schacter and Singer, 1962). However, current studies provide evidence suggesting that cognitive factors contributing to determine affective states might be correlated with specific autonomic nervous activation (Kreibig, Gendolla and Scherer, 2012). This scientific dispute highlights the importance of defining the function of somatic states, represented by endocrine, visceral, musculoskeletal and behavioral response, during the experience of affective states. On one hand, James' original hypothesis claimed that emotions are correlated with different patterns of somato-visceral activity. On the other hand, the cognitive hypothesis affirms that the peripheral activation associated with affective states can be finally represented by a single dimension. There are previous researches that presented some evidence-based results supporting James' view. Distinct patterns of autonomic activity have been described across subjects when they were providing different emotional facial expressions (Ekman et al., 1983; Levenson et al., 1990), in response to visual (Collect et al., 1997), olfactory stimuli (Vernet-Maury et al., 1999), film clips (Christie and Friedman, 2004), and during autobiographical recall (Rainville et al., 2006). Performing a meta-analysis of the research investigations studying the physiological reactions monitored during the occurring of affective states provoked by a variety of methods, Cacioppo and his colleagues affirmed that the scientific literature presents only ambiguous evidence-based results supporting the existence of specific patterns of peripheral activity correlating with distinct affective states (Cacioppo et al., 2000). Even though Cacioppo's claim may be considered as conservative taking into account the existing data, it nevertheless advised the require for further studies about the correlation between somatic states and affective states. There are two main factors that can explain why it is quite difficult to detect specific psychophysiological patterns enabling to characterize different emotions. Firstly, the laboratory conditions are not the ideal setting where to elicit spontaneous emotional experiences, as emotions rise much easily during daily and private experiences. In laboratory settings, the "observation" research presence and/or technological apparatus (as sensors, wires, etc.) can strongly reduce the rise of authentic (and strong) emotional reactions in many subjects. A second key factor in characterizing the psychophysiological patterns of emotions is related to the mathematical and bio-engineering algorithms and analyses developed to process the biological signals from the autonomous nervous system. The first limit may be overwhelmed through the acquisition and analysis of psycho-physiological data when volunteers actually report to feel a target affective states, rather than just relying on stimulus or task-related reactions. In this study, we analyze data when subjects claim to feel a target emotion during an experimental procedure that requires the autobiographical recall and the re-evocation of the target emotion. This technique has been able to show some efficacy in inducing different patterns based on biological signals (Ekman et al., 1983). Progress in the characterization of psychophysiological patterns correlating with specific emotions may be carried out by monitoring different physiological signals simultaneously, or by refining the analysis of commonly applied physiological measures.

In this research we explored the first approach and applied a multidimensional analysis to evaluate cardiac and respiratory signals. In order to evaluate whether standard measurement techniques of heart rate variability and respiration during emotional states might be able to discern among the different target emotions.

### 1.1. Cardiorespiratory measurements

Cacioppo et al. (2000) claimed that the ability to characterize either the sympathetic or the parasympathetic reactions might increase the efficiency in discerning the biological patterns correlated with basic emotions. An important series of studies have been carried out in the last years where computational approaches have been applied on data collected in non-invasive ways, in order to define the autonomic process involved in the chronometric regulation of heart activity (e. g. Task force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996; Pagani et al., 1997)(Mainardi, 2009). These approaches can assess the activity of both of sympathetic and parasympathetic component by means of measuring modifications in the HRV. A tachogram measured in a continuous way can be obtained from the electrocardiogram through the calculation of distance between R-waves. From the derived RR-tachogram, it is possible to obtain different measures of HRV, for instance the mean or the standard deviation (time-domain indexes) of the RR-interval during a certain session or experimental condition. Another way to obtain HRV measures is to apply the Fast-Fourier Transform (FFT) to explore HRV measures in frequency domain (frequency-domain indexes, such as the spectral power for either the low frequency – more correlated with sympathetic activity – or the high frequency range – more associated with the parasympathetic activity. The parasympathetic activity is regulated by the vagus nerve and by the release of acetylcholine (Ach) at the neuro-muscolar junction, that is quite rapid since the Ach is rapidly deactivated by acetylcholinesterase in the extracellular space (Talman and Kelkar, 1993). The vagal activity can therefore be measured by a number of chronometric factors prone to be affected by high frequency modifications in the RR-interval. On the opposite, sympathetic activity is correlated with the release of adrenaline, that is quite slowly degraded. The diverse interactions between sympathetic and parasympathetic branches rely on the fact that the quick modifications in heart beat are regulated by parasympathetic activity, while slow modification are mediated by parasympathetic and sympathetic activity. Fast modifications in heart activity are also partially due to modifications in the respiration rhythms, since the raise of intra-abdominal pressure while inhaling provides the activation of baroreflector reflex and produces fast augmentation of heart beats regulated by vagal activity. The ensuing interaction is called respiratory sinus arrhythmia (RSA) and it is generally present in healthy heart activity. RSA is normally characterized by the amplitude of the RR interval changes associated with the respiratory cycle, normally reflected in the high frequency components of HRV. It is therefore important to consider both cardiac and respiratory signals.

## 2. Objectives

Cacioppo (Cacioppo et al., 2000) showed that the experience of different basic emotions is associated with modifications in heart rate. However, the role of heart rate during emotions has been well explored in fear. For instance, panic attacks were correlated with increased heart rate combined with important reduction in HRV (Yeragani et al., 1994). However, it is not evident yet whether this reduction is mainly due to respiration changes or generated by the affective state. There are few studies that already demonstrated the role of emotions in HRV modifications. One of them is the work by

McCraty (McCraty et al., 1995) that showed how the increase in heart rate during anger is mainly correlated with sympathetic activity, while the increase in heart rate during positive emotions is correlated with a predominant contribute from the high frequency domain, pointing at an increased influence from the parasympathetic branch.

In this study the aim is to explore the role of cardiorespiratory activity during different somatic states correlating with the experience of a target set of emotions on healthy human subjects. The hypotheses are: a) the cardio-respiration modifications correlating with target affective states might be defined according to the activity of sympathetic and parasympathetic branches (that can also be divided into 2 patterns: respiration coupled and respiration-uncoupled components; and: b) respiration can provide an additional contribute in discerning between the different affective states.

## 3. Material and Methods

The experimental protocol is inspired by a previous research work (Rainville et al., 2006), where subjects were asked to recall an autobiographical episode that strongly evoked the target emotions. The same protocol already provided evidence-based results showing different and quite robust cerebral activity patterns (Damasio et al., 2000).

### 3.1. Subjects

Twenty-seven normal subjects were voluntarily recruited from the student body of IULM University of Milan. Students were first contacted by phone and were scheduled to come at the Behaviour and Brain Lab for an interview were they had to let the researcher know whether they could recall one or two recent episodes where they felt each of the 4 target emotions: happiness, sadness, anger and fear. If positive, the researchers asked them to recall loudly while taking notes about all the episodes. After asking the subjects to judge the most vivid and intense episodes, they were scheduled for a second appointment to participate in the recording session. All the people who could not recall a vivid recent episode for each of the four emotions were not asked to participate in the research.

### 3.2. Experimental Procedures

Once subjects came at the lab for the experiment, they were asked to fill in a consent form, and then to sit down in front of a computer with an eye-tracking monitor. Then a researcher located all the sensors, and started the recording. After a baseline period (3 minutes), researcher helped the subjects in recalling the episode he/she described in the interview. Once he/she was saying to feel the emotion, the researcher asked to stay silent and without moving for 3 minutes. After the emotion recall, a rest of 3 minutes was provided before re-starting with the next emotion. The sequence of emotion to be recalled was randomly assigned.

### 3.3. Self-Reports

After each emotion recall, subjects were asked to fill in a short self-report about his/her feelings, expressing which emotion he/she felt during the recall, and in what extent he/she felt it on a scale from 0 (no intensity) to 4 (very intensive).

### 3.4. Physiological Measures

All physiological signals were recorded continuously using Flexcomp Infinity™ encoder (Thought Technology Ltd.; Montreal, Canada) with a sampling rate of 2048 Hz, while subjects sitting; all signals were then resampled at 256 Hz. Relative changes in both abdominal and thoracic expansion were measured using two bands provided of tension-sensitive latex rubber transducers; the abdominal band was placed over the lower floating rib, the thoracic over the upper part of the chest: both bands were adjusted individually to produce the maximal deflection during normal breathing in the pre-experimental set up phase; during this phase, the subjects were asked to exhale and inhale in a carefully sealed reservoir bag, i.e. to breath a constant tidal volume. This procedure was designed to calibrate the respiration signal and to cancel the effects of the different positioning by the experimenters and thoracic expansions of the subjects. ECG was recorded using a standard 3 leads montage (Einthoven lead 2 configuration). Reusable ECG electrodes (UniGel electrodes, Thought Technology Ltd.; Montreal, Canada) were attached on the right and left forearms. We recorded also: blood volume pressure with a photoplethysmography finger sensor; skin conductance with two electrodes placed on different fingers of a hand; EMG activity over the *currogator supercilii* muscles; EEG activity at the Cz position, according to the 10-20 system. These measures are not described further in this paper, which focuses on cardiorespiratory variables only.

### 3.5. Physiological signal processing

All signal were processed and analyzed with custom software developed using Matlab (The Mathworks, Inc.; Natick, MA) in order to detect the R peaks and calculate the RR series, i.e. the time interval between two consecutive R peaks. The respiratory signal was low-pass filtered and resampled in correspondence to the R waves occurrences. Data analysis was performed at the Neuroscience Statistic Research Laboratory, Department of Anesthesia of the Massachusetts General Hospital. From a RR series, the following parameters were obtained: the mean value of RR intervals in the recording period, the standard deviation of the RR interval (SDRR), i.e. the square root of variance. Since variance is mathematically equal to total power of spectral analysis, SDRR reflects all the cyclic components responsible for variability in the period of recording [1]; two of the most widely used measures derived from interval differences, the square root of the mean squared differences of successive RR intervals (RMSSD), and pNN50, the proportion derived by dividing NN50, i.e. the number of interval differences of successive RR intervals greater than 50 ms, by the total number of RR intervals. For both RR, thoracic and abdominal respiration series a parametric spectral analysis was performed, via autoregressive (AR) model coefficients estimation. The Levinson–Durbin algorithm (Franke, 1985) was used to obtain the coefficients of the autoregressive model. The AR power spectrum density estimate is given by (1):

$$P_{AR}(f\ ) = \frac{\sigma^2 \Delta t}{\left|1 + \sum_{k=1}^{p} a_k\, e^{-j2\pi f k \Delta t}\right|^2} \qquad (1)$$

where $\sigma^2$ is the variance of the white noise driving function and Δt is the re-sampling interval; the order $p$ was chosen according to the Akaike's Information Criterion (AIC), a standard figure of merit to measure model quality (Akaike, 1974). A spectral decomposition procedure was applied to calculate the power of the oscillations embedded in the series (Zetterberg, 1979). Accordingly to the standard measurements of heart rate variability (HRV) in both psychophysiological and clinical uses (Task force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, 1996), the power of each rhythm has been allocated to the corresponding frequency bands (very low frequency, VLF, <0.04 Hz; low-frequency, LF, from 0.04 to 0.15 Hz; high frequency, HF, from 0.15 to 0.45 Hz), and the central frequencies of LF and HF were calculated. The power of each components was expressed in normalized units [n.u.] (i.e., the relative value of each power component in proportion to the total power, minus the VLF component), considered more robust parameters, according to the recommendations reported in the literature; in addition, the LF/HF ratio was obtained.

### 3.6. Statistical analysis

All the parameters mentioned above were computed for each condition and a paired Student's t-test ($p<.05$) was performed to compare all the emotional states considered: Baseline, Happiness, Fear Anger and Sadness. In Table 1 it is possible to see the results.

***Table 1.*** *P-values for all experimental conditions. Balck: P<0.01; dark gray: 0.01<P<0.05; light gray: P ~ 0.05.*

| P-value | Baseline vs Joy | Baseline vs Fear | Baseline vs Anger | Baseline vs Sadness | Joy vs Fear | Joy vs Anger | Joy vs Sadness | Fear vs Anger | Fear vs Sadness | Anger vs Sadness |
|---|---|---|---|---|---|---|---|---|---|---|
| HRV | | | | | | | | | | |
| norm. LF power | 0.0256 | 0.0012 | 0.0037 | 0.0104 | 0.2336 | 0.2666 | 0.4830 | 0.4885 | 0.1904 | 0.2545 |
| frequency peak LF | 0.3374 | 0.0794 | 0.3025 | 0.2253 | 0.0621 | 0.0867 | 0.2893 | 0.0022 | 0.1983 | 0.0256 |
| norm. HF power | 0.0114 | 0.0004 | 0.0017 | 0.0057 | 0.1044 | 0.3030 | 0.4650 | 0.1401 | 0.0767 | 0.2792 |
| frequency peak HF | 0.4797 | 0.4176 | 0.3627 | 0.1885 | 0.4316 | 0.3714 | 0.2218 | 0.4253 | 0.2514 | 0.3180 |
| LF / HF | 0.2353 | 0.0535 | 0.0600 | 0.1746 | 0.1726 | 0.1513 | 0.4445 | 0.4616 | 0.1256 | 0.1526 |
| | | | | | | | | | | |
| RR | | | | | | | | | | |
| mean RR | 0.2074 | 0.0424 | 0.0147 | 0.0527 | 0.1257 | 0.0839 | 0.2303 | 0.3437 | 0.3761 | 0.2713 |
| st. d. RR | 0.2391 | 0.3688 | 0.3871 | 0.3629 | 0.4136 | 0.4025 | 0.1455 | 0.4747 | 0.2476 | 0.2661 |
| RMSSD | 0.4147 | 0.1449 | 0.0499 | 0.1982 | 0.0724 | 0.0300 | 0.1221 | 0.3547 | 0.3203 | 0.1898 |
| pNN50 | 0.1195 | 0.0177 | 0.3965 | 0.1567 | 0.1077 | 0.1349 | 0.4830 | 0.0136 | 0.1718 | 0.2023 |
| | | | | | | | | | | |
| Resp. (Thoracic) | | | | | | | | | | |
| norm. LF power | 0.0980 | 0.2268 | 0.0357 | 0.0343 | 0.3047 | 0.1502 | 0.2025 | 0.0735 | 0.0574 | 0.4455 |
| frequency peak LF | 0.2215 | 0.3616 | 0.2448 | 0.2334 | 0.0695 | 0.0502 | 0.0531 | 0.3515 | 0.3327 | 0.4606 |
| norm. HF power | 0.0502 | 0.0182 | 0.0182 | 0.0217 | 0.1215 | 0.1403 | 0.2248 | 0.4665 | 0.3385 | 0.3970 |
| frequency peak HF | 0.1287 | 0.0850 | 0.1947 | 0.4374 | 0.2615 | 0.4916 | 0.1137 | 0.2452 | 0.0480 | 0.1268 |
| LF / HF | 0.0505 | 0.2297 | 0.0697 | 0.0585 | 0.1684 | 0.3057 | 0.3996 | 0.1052 | 0.1050 | 0.3888 |
| | | | | | | | | | | |
| Resp. (Abdominal) | | | | | | | | | | |
| norm. LF power | 0.3275 | 0.3942 | 0.3192 | 0.1137 | 0.2078 | 0.4738 | 0.2452 | 0.1573 | 0.0379 | 0.2028 |
| frequency peak LF | 0.4589 | 0.4986 | 0.3198 | 0.3640 | 0.4411 | 0.2433 | 0.4050 | 0.2123 | 0.3565 | 0.1443 |
| norm. HF power | 0.2499 | 0.1999 | 0.2168 | 0.0782 | 0.3633 | 0.4164 | 0.2500 | 0.4244 | 0.3121 | 0.2609 |
| frequency peak HF | 0.2513 | 0.1117 | 0.1921 | 0.3490 | 0.1714 | 0.3261 | 0.1870 | 0.3376 | 0.0375 | 0.0756 |
| LF / HF | 0.2899 | 0.1264 | 0.4414 | 0.4938 | 0.0532 | 0.4016 | 0.3107 | 0.0831 | 0.0139 | 0.4108 |

## 4. Results

Self-reports of emotions are still under collection and they will be taken into account in further research reports, together with pupil dilation data and the other physiological signals that will be considered in further research papers. Regarding the cardio-respiratory data, we here present some preliminary results. About respiration, Figure 1 shows the different trends concerning the thoracic respiration normalized HF component for baseline and the four target emotions.

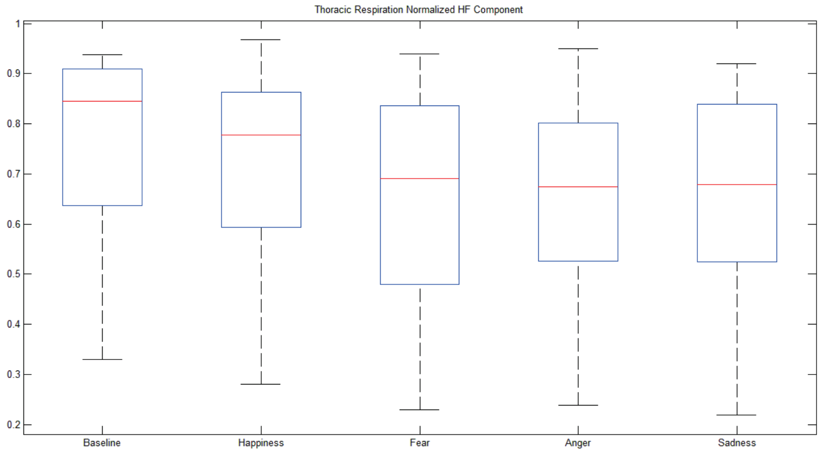


***Figure 1.*** *Thoracic Respiration Normalized HF Component for Baseline, Happiness, Fear, Anger and Sadness.*

In particular, in baseline we had the highest values, while for negative emotions (fear, anger and sadness) the lowest values are observed. The difference between baseline and the negative emotions is significant. Although the three negative emotions show similar trends for this index, it is during anger that the values are the lowest in comparison to sadness and fear. Happiness is showing values between baseline and negative emotions, and the difference between happiness and baseline was not significant for this index.

In figure 2, we show the trends of thoracic respiration normalized LF component. In baseline we now had the lowest values, while the highest ones are seen for anger and sadness conditions.

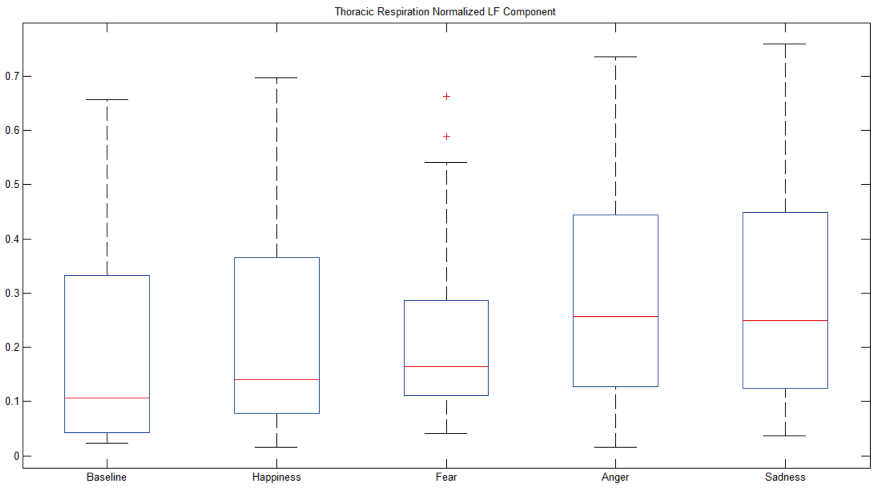


***Figure 2.*** *Thoracic Respiration Normalized LF Component for Baseline, Happiness, Fear, Anger and Sadness.*

Trend of HRV parameters are shown in Figure 3 and 4., In Figure 3, normalized HF power is shown: in baseline we had the highest values, while fear is characterized by the lowest ones. The three other emotions (happiness, anger and sadness) were in-between baseline and fear and very similar in values.

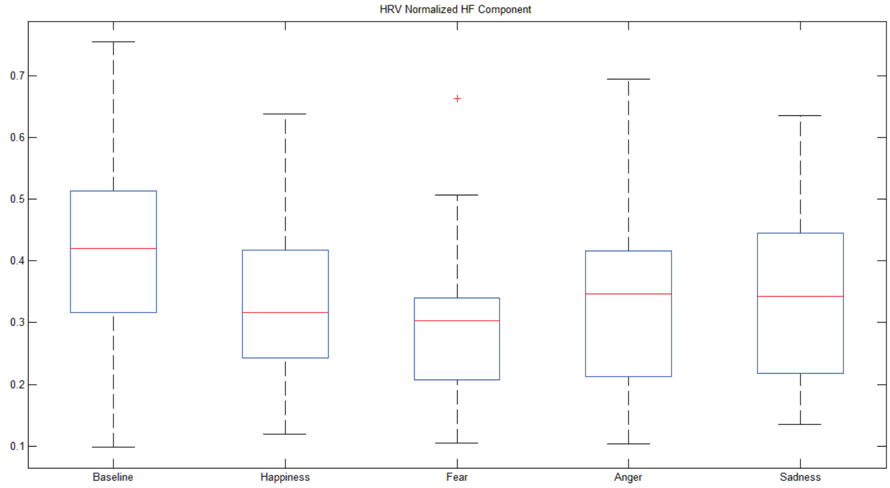


***Figure 3.*** *HRV Normalized HF Component for Baseline, Happiness, Fear, Anger and Sadness.*

In figure 4, we present the trends of HRV normalized LF component. For this measure the baseline is showing the lowest values, while fear is showing the highest ones.

Parameter values during every target emotion were compared with the baseline ones, in order to explore which factors might be more representative to identify significant different patterns. The list of dependent variables is reported in Table 1, where it is also possible to see the significant differences amongst the 5 experimental conditions. All target emotions are significantly different from baseline conditions when “normalized LF power”, and “normalized HF power” are considered. Conversely, respiration, subdivided into respiration thoracic and abdominal, is less robust in the discerning task in comparison to heart rate variability indexes above considered.

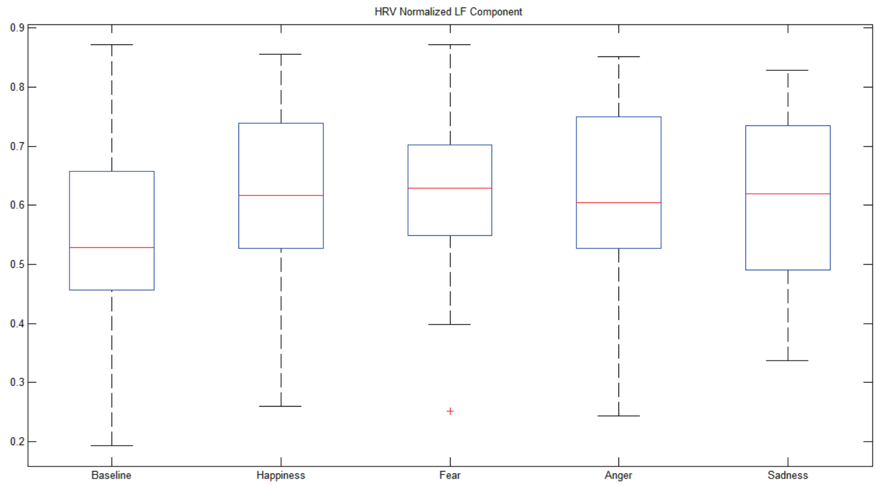


***Figure 4.*** *HRV Normalized LF Component for Baseline, Happiness, Fear, Anger and Sadness.*

For thoracic respiration, the index “normalized HF power” (as we already reported, only between baseline and happiness the respiration does not show significant differences, while it has been significant between baseline and the three other emotions) is performing better than the “normalized LF power” (where also the distinction between baseline and fear is not showing significant differences) in discerning between the different experimental conditions.

Considering the results about the possibility to discern between the four target emotions, it is possible to see in Table 1 how some indexes provided significant results. Between Happiness and Fear, no significant results are showed. The same for the comparison “Happiness vs Sadness”, where no significant results. For the comparison “Happiness vs Anger”, theRMSSD index is able to detect a significant difference between the two emotions. For the comparison “Fear vs Anger”, pNN50 index is able to discern between the two different emotions. For the column “Anger vs Sad”, we see that the index “frequency peak LF” can detect significantly between the two emotions. However, the best performance is for the column “Fear vs Sadness”, where we can see four indexes enabling the recognition task. In this case the four measures are all from respiration, one from thoracic (the “frequency peak HF”) and three from abdominal (the “power LF normalized”, “frequency peak HF” and “LF/HF”) that can discern significantly between the two emotions.

## 5. Discussion

Our preliminary results support the thesis that the four target emotions are correlated with different heart and respiration activities. Significant differences were found in discerning between baseline conditions and all four emotions. This finding underlines how the recognition task to evaluate whether a person is feeling a target emotion is feasible with these indexes. The detection task performed less efficiently when trying to detect differences amongst the four emotions. However, as somehow expected, the parasympathetic tone to the heart (HF power) is predominant during baseline and, on the opposite, is the lowest while subjects are experiencing fear. This confirms the concept that during baseline subjects are experiencing a rest state that allows slower heart rhythms, whereas fear elicits an automatic “fight or flight” response (Porges, 1997), activating the organism for a potential rapid reaction in order to attack or to escape the situation or the stimulus that generated fear. The opposite trends are shown in LF from HRV, making more robust the same “fight or flight” principles, as the LF power includes the influence of the sympathetic branch to the heart. In this second case we see that the lowest values are for baseline, while the highest are for fear, where the sympathetic contribution is supposedly much stronger in comparison to all other emotions. It is noteworthy that during anger the LF from HRV is not that evident, this finding is consistent with previous studies (MaCraty et al., 1995). Taking into account respiration, we see that anger is better characterized by the LF component, probably due to a more irregular ventilation activity of the lungs for this emotion in comparison to all the others, whereas for fear the ventilation activity seems to be more suppressed in comparison to anger. This results suggest that further considering indexes from the coupling between heart rate and respiration might yield better detection performance. Overall, these results support the idea that it is possible to identify at least one physiological index able to distinguish between the experimental conditions, even with the relatively small sample of experimental subjects here collected. For the moment only two conditions over ten failed to show at least one index with significant differences. Increasing the number of subjects might lead to more significant results, corroborating the encouraging findings already revealed by this study. In this research we applied a multidimensional analysis to evaluate cardiac and respiratory signals, although other physiological signals were also monitored in this study, as pupil dilation, electromyography of frontal muscles, skin conductance and electroencephalography activity. As subjects were heavily hooked-up with many sensors and wires, the results could be affected by the experimental setting, as some subjects could feel less prone to re-live the target affective states. However, the combination of cardio-respiratory patterns with other psycho- and neruophysiological signals might provide a better accuracy in characterizing amongst different mental states, both for affective and cognitive factors (Vecchiato et al., 2010, Mauri et al., 2010). Affective computing (Picard et al., 1995) is a promising field, the ability to implement an automatic recognition of emotions by means of cardiorespiratory patterns (or coupling them with other physiological or neurological measures) can open the way to the application of these research works to other fields, not only to more intelligent machines able to “understand” human affective states (Picard et al., 2001), but also to other disciplines as communication, advertising (Vecchiato et al., 2012), human computer interaction (Scotti et al., 2006), user experience (Yagyu et al., 1998) and so forth. Future work will be critical to be able to translate these basic research results into more applied fields.

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