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Abstract. Emotions are important mental and physiological states influencing perception and cognition and have been a topic of interest in Human-Computer Interaction (HCI) for some time. Popular examples include stress detection or affective computing. The use of emotional effects for various applications in decision support systems is of increasing interest. Emotional and affective states represent very personal data and could be used for burn-out prevention. In this paper we report on first results and experiences of our EMOMES project, where the goal was to design and develop an end-user centered mobile software for interactive visualization of physiological data. Our solution was a star-plot visualization, which has been tested with data from N=50 managers (aged 25-55) taken during a burn-out prevention seminar. The results demonstrate that the leading psychologist could obtain insight into the data appropriately, thereby providing support in the prevention of stress and burnout syndromes.

Keywords: Data visualization, Knowledge Discovery, EDA, BVP, HRV, Stress, low-cost sensor

1 Introduction

The value of emotion to the quality and range of everyday human experience is underestimated. It has a huge influence on the domains of cognition, in particular attention, memory, and reasoning [1]. An increasing problem in our western industrialized world is the Burnout Syndrome (BOS), which is a psychological state resulting from prolonged exposure to job stressors [2, 3]. In the past, many methods have been developed for measuring emotions, for a rapid overview refer e.g. to [4–7] and for a very short overview see [8], here a very brief summary: Electrodermal activity (EDA), aka Galvanic skin response (GSR), electro-dermal response (EDR), or skin conductance response (SCR) is basically the measuring of the electrical resistance of the skin and can be used as a sensitive index of the activity of the sympathetic nervous system. Another popular method to assess the psychophysiological activity is Heart-Rate Variability (HRV) (see details in Section 2), which can be derived from Electrocardiographic (ECG) or Blood Volume Pulse Data (BVP). Viewing these Biosignals on mobile devices is a current and increasing trend [9].

Research on stress recognition and classification with physiological signals has reached a good point (for an overview look at [10]. Nonetheless, because people are sensitive to this topic due the popularity about burnout, we must be careful with our affirmations. Today, algorithms are able to reach a high accuracy for modeling stress but we still can not fully trust them, there is always the danger of modeling artifacts. However, stress remains an important aspect of human health that we must learn to deal with. Until recognition and classification patterns become fully reliable, we will continue to retrieve any data available and provide information to the individual expert end users, enabling them to gain knowledge by interactive visualizations - intelligence remains the forte of the human brain [11]. Moreover, while people are often unable to clearly identify their own emotions; it can be iteratively learned.

We recognized that the participants involvement/acceptance of the evaluation process necessitated an clear and easy to understand visualization of the physiological data processing results, in order for them to learn something about their emotions or discuss them with an expert.

Therefore our central goal was to design and develop an interactive information visualization for our signal processing model, which 1) displays most of the important feature evaluations regarding stress, 2) displays the data in a way that it is easy to compare features between relaxing and activating situations; 3) displays the data in a way that can be helpful for a non-expert end user and 4) at least may be provided with average computer resources within a tolerable time.

In short, the visualization must provide a variety of information about individual physiological activities with the focus on stress, so that both the non-expert and the expert can analyze and discuss the data and, most of all, to obtain insight and new knowledge from it. All the data collection, evaluation and visualization should be done by one user interface. To ensure that the solution will be affordable for many people, we have used a low-cost-sensor, which is described in Section 3.

2 Background - Psychophysiological Assessment

Physiological events are involuntary activities for which our Autonomic Nervous System (ANS) is responsible. Two main nervous systems are relevant for stress, the Sympathetic and Parasympathetic Nervous Systems (SNS and PNS respectively). Stressful situations cause dynamic changes in the ANS whereby the activity of the SNS increases and of the PNS decreases. In short, the SNS dominates during restless activities and the PNS during resting ones. These two systems are important for our research, because they regulate the different physiological signals, such as heart rate variability (HRV), galvanic skin response (GSR), brain activity (EEG), blood pressure (BP) etc. Note that these systems are influenced by many different factors; two of them are eustress and distress. Eustress characterizes positive states and distress negative states, therefore, not all monitored stress should be perceived as bad stress. [12]

As Sharma and Gedeon showed in [10]-(Table 5) HRV and GSR are two good parameters for detecting stress. In our work we used GSR and BVP records from a low-cost sensor. The signal of the BVP can be used to compute the HRV and some other features explained in Section 1.

2.1 Electrodermal activity (EDA)

Electrodermal phenomena and the cardiac response are the most frequently assessed indices for the highly complex autonomic nervous system (ANS) activation in psychophysiology [13, 14]. The ease of obtaining a distinct electrodermal response (EDR) with inexpensive methods, the non-intrusiveness, and lenient field conditions are the major reasons for its popularity. Electrodermal recordings can use either external current (AC or DC) or the body's own electric current, the first are called exosomatic and second endosomatic. When an external current is applied to biological tissues such as skin, they act similar to electrical networks built of resistors and capacitors [13].

The term electrodermal activity (EDA) stands for all electrical phenomena of the skin, and was first introduced by Johnson and Lubin [15]. But there are also other frequently used terms, such as like Galvanic Skin Response (GSR). This electrical phenomena also includes all active and passive electrical properties which correlate to the skin and its extremities. The EDA has a central importance in biosignal acquisition and this concerns its psychological significance. Since the first research activities this response system has been closely linked with the psychological concepts of emotion, arousal and attention [14]. Basically it measures the hydration in the epidermis and dermis of the skin, which increases or decreases with the activation or inhibition of the sweat glands that are controlled by the sympathetic chain of the ANS.

Typically, this is recorded using two sensors placed at the surface of the hand or feet, since these are the areas of the body with higher seat gland density. In most cases the ring and middle finger are chosen and the most common unit used is μS.

The signal is a good indicator for stress, so that it helps to differentiate between conflict and non-conflict situations, but it is also a good indicator for dynamic activity. Usually a rapid rise of skin conductivity reflects a simple stress stimulus.

2.2 Cardiac activity

The main purpose of our cardiac activity is to maintain our organs activity by providing them with blood, , which is pumped around the body by the heart.

When we are under stress, the heart rate is increased by the SNS and after the stress has passed the PNS decreases it. . It is therefore obvious that we can evaluate stress by measuring the rate of cardiac activity. [16] Regarding stress, as in [17], acute stress causes the heart to contract with high force and increased frequency. It is also known that with more chronic stress, the mass of the heart is increased. However, the baseline cardiac activity depends on the fitness of an individual and his activity.

There are several methods of measuring the cardiac activity, one used in our work is blood volume pulse (BVP). Photoplethysmography (PPG) is a non-invasive monitoring technique that can be used to track changes in the cardiac system. A reflective finger PPG sensor converts the fluctuation in the blood volume within a region of the index finger into a continuous waveform known as the Blood Volume Pulse (BVP). Traditionally, the BVP period was used to determine the heart rate. Current research however, shows that the BVP is capable of reflecting more than just the heart rate. [18] With the BVP signal, we are able to compute the RR-Intervals (the time between two following heart beats) [19] and therefore the Heart Rate Variability (HRV). More information is provided in Section 4.

3 Experimental setup

Fifty healthy managers between the ages of 25 - 55 were recruited during a seminar and participated in our tests. Due to the pressure of time caused by testing this many participants during a seminar we had to design an experimental setup with a maximum time window of ten minutes. Therefore, the setup and introduction had to be fast and easy but without putting the participants under stress. Since we measured EDA and BVP, other requirements to our design arose. In order to have truthful signals, we had to ensure that there were no distracting or exciting elements in the room and also the temperature had to be kept at a pleasant level. In the past we experienced, some participants becoming nervous only because of a little blinking led on the notebook or the integrated webcam and sometimes the room temperature distorted our measurements.

As showed in [20] electrodermal and cardiac activity are both influenced by the physical activity of the participant. Both are strongly affected by anxiety and exercise [21] and in order to differentiate mental stress from other elicitations the activity also has to be considered. There are several solutions for this problem: firstly to add an accelerometer to the design, secondly to differentiate stress through feature extraction and preferably by reducing the physical activity as much as possible.

Another challenge we had set ourselves was to use low-cost sensors. Since the main purpose of our measurement is not to make a clinical analysis of the participants, but to visualize important information about their inner processes for discussion and learning, it is possible to keep the costs low.

Keeping all this in mind, we designed a hardware/software methodology that satisfies all these requirements.

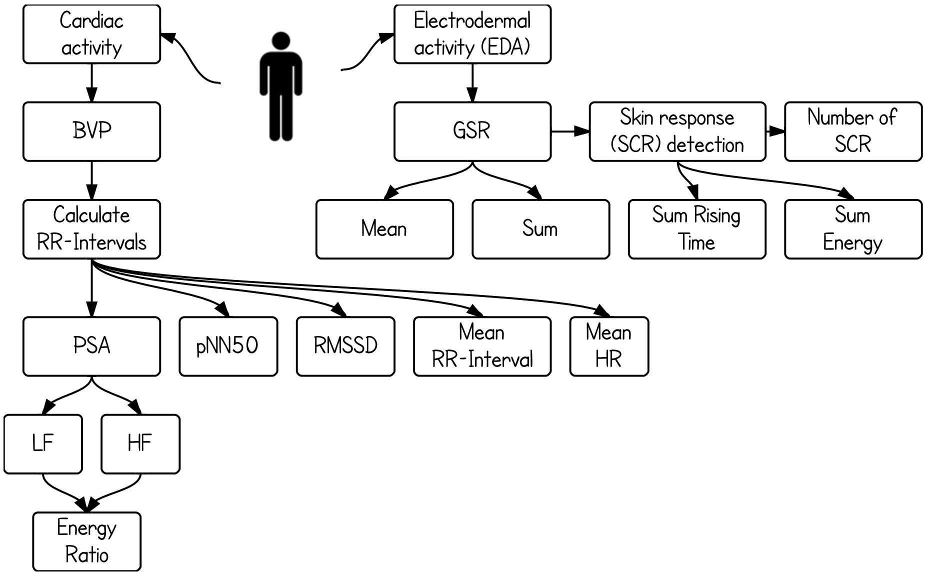

Fig. 1. Overview of extracted signal features

At the time we designed the system according to the requirements, we chose the IOM Device from Wild Divine [22] for the acquisition of physiological signals. The device has been connected to a notebook on which we run our software. This shows a video file, logs the raw data from the sensor and write it to a file. With a video consisting of three parts, we were able to reduce the physical activity to a minimum because the participants were only asked only to observe and move as little as possible. The first part showed a slowly moving picture of a sky so that the subject could relax, after a while a calm voice announced the second part and mentioned that it will be stressful, the second part showed some random stressful pictures and colors with noisy sounds, after 15 seconds the voice soothed the participants and the third part with a slowly moving grass video, followed. During all three parts, relaxing music played in the background.

The chronological order of the test session was as following: During the first part (Introduction and Setup - 2 min.), the participants were made familiar with the system and the tasks. We also gave them some information about the three parts shown in the video. Then we asked them to sit comfortably, keep their hands still and watch the video. To avoid measurement falsification we left the room and reentered after the end of the video. This second part (Videotest) lasted 5 min. and the third and last part was the feedback part (3 min.).

4 Feature extraction

In accordance with to many research reports about this topic [20, 23, 24], we chose to extract from our signals the features shown in figure 1. With a BVP signal, it is possible to calculate the RR-Intervals and from that we can compute the other features such as:

– Mean RR-Interval and mean HR: Each of them varies under stress and therefore reflects sympathetic or parasympathetic activities. Mean RR is significantly lower during a mental task than in the control condition. [25] A higher RR-Interval means a lower HR and vice versa. A significant change in the RR-Interval during stressful situations reflects a high HRV and therefore how well individuals are able to adapt to changes. [26]
– Power Spectrum Analysis: As in [27], the high frequency (HF) is thought to reflect parasympathetic tone, whereas the very-low-frequency (VLF) and low-frequency (LF) are thought to reflect a mixture of parasympathetic and sympathetic tone. Because VLF has been found to distort stress detection [16], we left this out. With LF and HF we can also compute the energy ratio (total LF over total HF), which increases if stress levels increase. [28]
– pNN50 and RMSSD: Both are time-domain related features that reflect parasympathetic activity [29, 30]. Since pNN50 is significantly lower with a mental task than in a control condition, it reflects mental stress. [25]

GSR is directly influenced by the ANS and therefore it is overall a good indicator for stress. Already, minimal calculations, such as mean and sum are strong features. The detection of the skin responses (SCR), in order to compute the other three features shown in figure 1-(under SCR), is more complex but provides us with further indicators of stress. [12, 28]

In total, we extracted twelve features and with this paper we suggest an easy to understand information visualization with the advantage of having a clear but deep insight into the data, in order to gain new knowledge.

5 Data Visualization

5.1 Related work

We have had experience with using Star Plot diagrams, which are suitable for mobile and touch computers [31]. Star Plots aka radar charts [32], also called spider web diagram, polygon plot, polar chart, or Kiviat diagrams [33], are graphical methods of displaying multivariate data in the form of a 2D chart of three or more quantitative variables represented on axes starting from the same point. Each multivariate observation can be seen as a data point in an n-dimensional vector space:

– Arrange N axes on a circle in $\mathbb{R}^2$
– $3 \leq N \leq N_{max}$
– Map coordinate vectors $P \in \mathbb{R}^2$ from $\mathbb{R}^N \to \mathbb{R}^2$
– $P = \{p_1, p_2, ..., p_N\} \in \mathbb{R}^N$ where each p_i represents a different attribute with a different physical unit
– Each axis represents one attribute of data

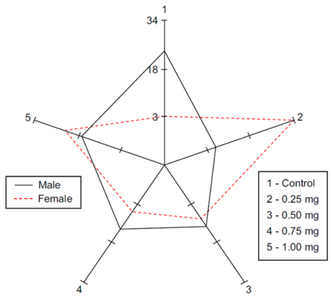

Fig. 2. A typical starplot diagram[34]

- Each data record, or data point P is visualized by a line along the data points
- A line is perceived better than just points on the axes

5.2 Our solution

During the measurements, the participants passed through three phases: First a relaxing, second a stressful and finally a relaxing/recovering phase. Consequently, our idea was to use this data and visualize the results corresponding to these three parts using three different colors. The idea becomes clear in figure 3. Unfortunately, it can be seen only in grey scales.

The upper half of figure 3 refers to the cardiac signal and the lower half to the electrodermal activity. Whereas the three smaller Star Plot diagrams show the feature values of the corresponding phase, the bigger spider diagrams with the darker areas on the right show the overall feature values. The values of each feature are only displayed if a user hovers a feature caption. As an example, here in the figure it is the mean HR. If a user hovers one caption, the corresponding value is shown in all four diagrams. If a user makes a right-click on a caption, they receive a short textual introduction to the meaning of this feature regarding stress.

Both the feature values of the four Star Plots of the cardiac signal and the electrodermal activity part are scaled the same way. The upper limit corresponds to the max overall value and the lower limit to the minimal overall value. This allows us to better compare the Star Plots.

6 Results and Discussion

In the EMOMES project, we have tested 50 participants so far and provided feedback to them after the test, only by showing them two diagrams: one for the heart-rate and one for the galvanic skin response. We noticed that most of them were very interested in such insights and, as far as they could understand

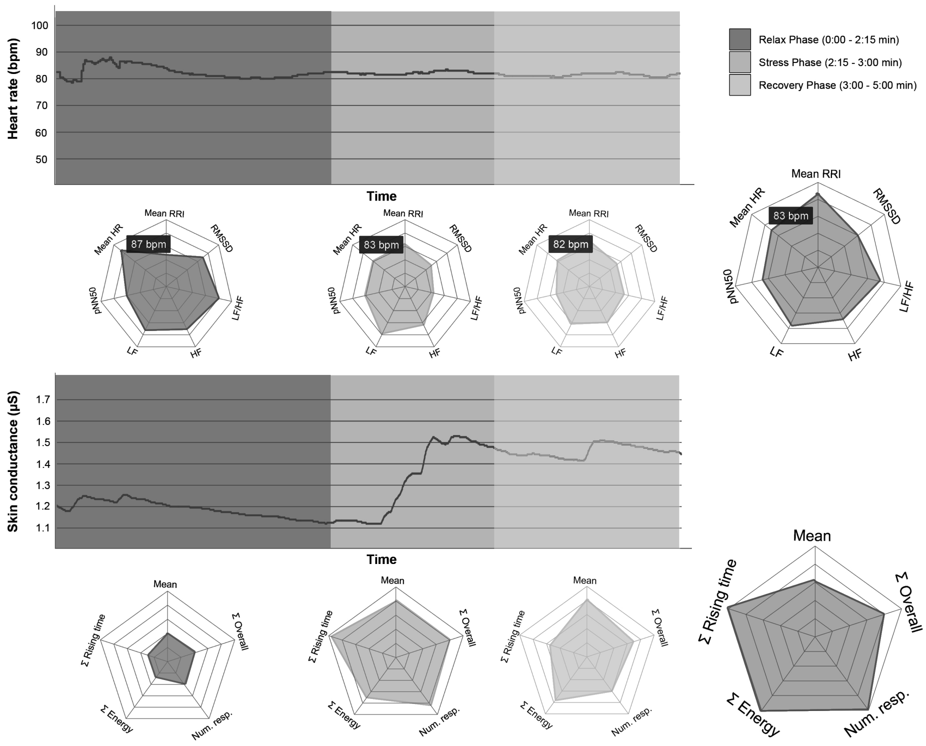

Fig. 3. Example of the information visualization screen

the theoretical concepts behind it within the short time frame given, some have provided supporting information for the signal interpretation and confirmed our hypothesis of the need of individual preliminary knowledge for the interpretation of the measured data. Just an interesting example: on one occasion, we noticed a high skin conductance response, which at first sight seemed similar to a measurement error, however, the participant told us that at that moment the music sounded like a mosquito and because he had a fight with one during the previous night, he got very nervous and flicked his finger.

In support of our hypothesis we extracted 12 features from the signals collected from these 50 participants. The signals were processed twice: once for the overall test and once for the three different parts. Therefore we divided the signals into three data entries each. With this data we provided the information needed by our visualization. The validity of the feature extraction is not given at this time as the low signal quality makes further examination necessary before all results can be confirmed, and only examples are offered. Nonetheless, because our focus is actually the visualization after the feature extraction, we had the necessary data structure for the visualization given in figure 3.

Feature	**Min**	**Mean**	**Max**
MeanRR (ms)	669	867	1114
MeanHR (bpm)	54	73	93
pNN50 (%)	24.80	49.44	76.90
RMSSD (ms)	46	111	265
LF (%)	23.90	40.69	56.70
HF (%)	16.50	39.13	68.30
LF/HF	0.364	1.2480	3.056
Sum GSR (μS)	-3.88	0.4640	3.09

Table 1. Results from our Signal Processing Model

Results from our signal processing model are shown in table 1 and are from all three video parts together. Actually, it is not possible to measure in this short time frame if someone has a BOS and therefore we can not claim that this visualization tells whether someone is afflicted by BOS or not. However, providing this clear overview to experts gives them a good objective insight about individual stress reactions and has been confirmed as a good starting point to discuss the autonomous stress behaviours and preventing stress and burnout syndromes in order to decide whether further investigations are necessary or not.

As mentioned in section 4 we can tell something about stress activity by looking at these features. As an example, if you look at the table 1 the sum of GSR tells us whether or not the participant was able to recover from the stress within this time frame. If this value is positive, it means that he had more SNS activity than PNS and vice versa. The same is for the LF/HF-Ratio. If it is high, it means the participant had a low HF activity and therefore less parasympathetic activity. By splitting up the feature extraction in three parts in correlation to the three video parts, we are able to compare them in more detail and have a deeper insight into the physiological activity. This provides us with the possibility to give more detailed feedback to the participants and a more profound basis for discussions and analysis.

7 Conclusion and Future Research

In this work, we described our lessons learned from testing 50 participants and we present a visualisation for providing insight into physiological behaviours regarding stress.

These goals were achieved to our satisfaction. The visualization displays most of the important feature evaluations regarding stress and displays them in a way that it is easy to compare features between the three parts and the overall features. It gives us a very clean insight into the data and offers good possibilities for knowledge discovery. With a minimum of support, a layman is able to understand the science behind it and can support us with useful information. Nonetheless there are some things that can be improved and expanded.

The low-cost sensor provided workable signals, but for more accurate studies the signal quality is too low. However there are still low-cost sensors that are promising, such the BITalino [35] and for better results for the visualization others will also be tried. After the completion of the processing, the evaluation of this visualization with a larger test group will provide further insight into our suppositions.

For a better insight for stress prevention, it would be helpful to include in our software a questionnaire like the Hamburger Burnout Inventory (HBI) that reflects the subjective sensation of the participants, especially looking at BOS. If the participants do this in advance of the test, at the end they have an objective and subjective insight.

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