# Physiological Data Analysis for an Emotional Provoking Exergame


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***Abstract*—In this work we enhance our previously developed analysis method of provoked emotions in facial expressions through the analysis of physiological data. The presented work describes the integration of electrodermal activity, respiration and temperature sensors to enhance our exergaming system for emotional provocation. The combined analysis of facial expressions and physiological data is designed to evaluate physical and cognitive stress as well as emotional reactions. The experimental setup combines a cycling game controller with a 3D virtual cycling game to provoke emotions. A designed data recording framework collects frontal videos and physiological data as well as game and controller events. In this work, we found evidence that physiological data analysis enhances the previously developed analysis method. The system is able to evaluate individual differences of an entertaining and balanced workout program.**


## I. Introduction

Nowadays the paradigm of "healthy living" attracts growing worldwide attention. Exergames have the potential to support a healthy lifestyle [1]. Healthy living combines adequate nutrition and a well-balanced workout program, due to an increasing sedentary lifestyle [2]. The work of Biddle [3] links physical activity to emotions and mood, and Süssenbach [4] claims sports are crucial for well-being. The work presented in this paper encourages an ambient personal fitness program accompanied by entertainment content. Entertaining aspects can be used to enhance users' endurance and support a long-lasting fitness program. The perception of entertaining values and the emotional reaction to similar game elements is highly individual. This results in a different personal experience for each participant. Our system is designed to analyze these individual reactions and experiences. An ambient intelligent exergame application should be aware of any kind of stress the user might perceive, which in our application means physical or cognitive strain as well as emotional drain.

During our first case study, emotional provocation of facial expressions while exergaming was evaluated [5]. In this work, our previously developed event-based analysis method is extended by the analysis of physiological data, since mental strain leads to discriminative expressions in facial expressions [6] and self-reports [7]. This induces the necessity to integrate the analysis of physiological data into our system. Additionally, we integrate an electrodermal activity (EDA) sensor because electrodermal activity is part of the autonomous nervous system, which is known to be closely associated with the arousal of the participant [8] and may be applied for basic emotion recognition [9].

Measuring physiological data for tension recognition has a long tradition [6] because it is an interesting topic for various applications, such as supporting pre-hospital care [10] or driving [11]. Too much mental strain may increase negative emotions [12].

Our EmotionBike system is designed as a platform to conduct behavioral analysis studies. During a case study, the influences of the Big Five personality traits on specifically designed and crafted game elements were evaluated [5]. The system allows a situational context awareness due to a virtual game environment, the physical accessible exercise machine controller, and the smart home environment [13], [14] in which


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the system is located.

## II. Related Work

There are several related works for personal fitness management. For instance, Shih et al. [15] developed a physical fitness condition measurement system. In their work, they compare physiological data (body temperature, blood pressure and weight) with a person's body mass index. In our work, we integrate the emotional state of the user, as physical aspects combined with emotional states have a great potential to enhance user motivation and training effects. Süssenbach et al. [4] use a NAO[1] robot as a companion cycling instructor to perform motivation research in human-robot interaction. We do not focus on personal motivation but rather on individual differences in reactions to emotion provoking game elements.

The focus of our work lies on tasks which have a high physical effort, since physical activity is essential for the presented exergame. The aspect of performing physical activity has been studied in the research by Hong et al. [16]. Our exergame needs to sense all possible sources of stress the user might perceive, including physical or cognitive strain as well as emotional drain.

Common stressor tasks in related research are mental arithmetic, loud sounds and the cold water pressor test [16]. In our work, we analyze game elements as potential stressors. In addition, many studies induce stress by investigating public speaking tasks (e. g. [12], [17]–[19] ) since these tasks are known to be experienced as stressful [18]. Dickerson and Kemeny [20] have shown that social-evaluative threats are perceived as stressful. In a social-evaluative threat, the task performance might be perceived as being negatively judged by others. Our setup includes the presence of the experimenter and an independent observer, simulating an external judgment to the participants. The physiological system reacts not only to changes in stress, but also to changes in physical or mental conditions. The recognition of physiological responses during physical activity thus differs from recognition without movement [16]. Our work is based on the fact that it requires physical activity, thus we designed an event-based analysis of the collected data.

Previous work analyzed the measurement of physiological data in natural environments. For instance, Plarre et al. [21] found respiration features to be highly discriminatory of physiological stress.

An interesting research topic is the personality dimensionality that provides a basis to explain individual differences. Our previous findings [5] have shown individual differences in the facial expression of emotions. For one crafted game scene, ten out of eleven participants expressed joy while eleven showed sadness, but nine self-assessments and nine observer-assessments labeled frustration for this scene. Our observation of people smiling in situations of natural frustration has been reported by Hoque et al. [22]. In our work physiological data are analyzed to improve emotion recognition for frustrating game elements.

Giraud et al. [17] applied the Big Five Model [23], which is a widely used model of personality traits. It consists of five personality traits: Extraversion (E), Agreeableness (A), Conscientiousness (C), Neuroticism (N), and Openness (O) to experience. Brouwer et al. [24] investigated correlations between low neuroticism and high extraversion with stress sensitivity and assumed that there are measurable links between physiology and personality. Their results have shown that skin conductance correlated negatively with neuroticism, which was not what they expected [24]. They induced stress by negative feedback while gaming and measured by baseline differences, which is an often used technique because it has been shown that there are differences in skin conductance [6]. Our work is based on an event-based analysis method among individuals while playing games, but for the sake of completeness baseline differences have been evaluated as well. Schneider et al. [25], for instance, investigated resilience by using the appraisal ratio and examining the unique influence of personality on stress responses across multiple stressor outcomes, including affect and performance. As stimuli they used mental arithmetic tasks. They suggested that extraversion plays a role in the stress process because it uniquely predicted higher positive affect and lower negative affect in their study.

Walmik et al. [26] investigated the potential of an augmented helmet showing heart rate data in social context. They studied the engagement of cycling pairs and found that it can result in a social interplay which supports engagement with the exertion activity. Their work has shown that a biofeedback of physiological data can support social interplay and thus engagement with the exertion activity.

A form of gameplay where the current emotional state of the player leads to altering the game mechanics is called affective gaming [27]. In addition, Nacke et al. [28] use biofeedback in game design. Negini et al. [29] increase or decrease game difficulty by an analysis of galvanic skin response and Parnandi et al. [30] provides an adaptive game to electrodermal activity (EDA) measurements.

Affect recognition is an inherently multimodal task [31]. Nasoz et al. [32] developed an affectively intelligent adaptive car interface to facilitate a natural communication with the user. Their interface includes an affective user model created for each individual driver based on physiological measurements (galvanic skin response, heart rate and temperature).

Vachiratamporn et al. [33] have shown that survival horror games can be utilized to induce fear measured with physiological sensors and for affective gaming [34]. One of the presented game scenes has a fearful design characterised by a dark surrounding game environment.

## III. System Design and Experimentation Framework

Our experiment design provokes and measures emotions of participants during physical exercise on a gameplay augmented ergometer. Tailored game scenes feature game elements as

[1]https://www.ald.softbankrobotics.com/en

stimuli to trigger specific emotions. The measurement includes vision-based and physiological sensors consisting of electrodermal activity (EDA), respiration and temperature sensors. The experimental setup consists of a cycling game controller, vision-based and physiological sensors, a data recording system, and a virtual cycling game. Figure 1 shows the system overview. The experimental procedure embraces the ethical guidelines and the experimental task describes the conduct from the participant's viewpoint.

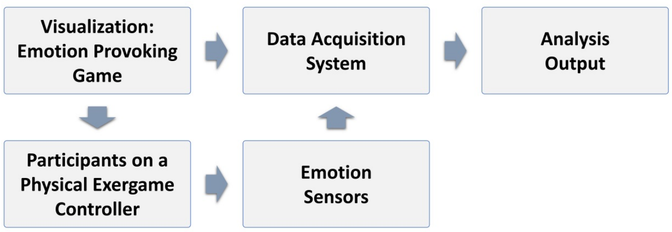


Fig. 1. Emotional Provoking Exergame System Overview

### A. *Experimental Setup*

The experimental setup consists of emotion sensors, a data recording framework, a physical exercise machine, and a game which is presented to the participants on a display in front of the bike (shown in Figure 2 and 3).

Fig. 2. Experimental Setup: Display Screen, Interactive Cycling Game Controller, Lighting

Fig. 3. Detailed View of the Experimental Setup: Rotatable Handlebar, Physiological Sensors connected to the Subject (EDA)

*1) Data Recording Framework:* Our data recording framework of different sensors uses components of a distributed system of multiple client computers loosely coupled using a message broker (Apache ActiveMQ) with a JSON-based protocol with the ability to log and replay all events and data (similar to [8]). A detailed description of the data recording system can be found in [5].

*2) Physiological Sensors:* The collected data includes respiration, body-temperature change, and galvanic skin conductance. Provided by a physiological data acquisition system, the Biopac MP36 operates at a rate of 500 Hz. The data are preprocessed by the device's internal hardware filters for gain improvement, noise reduction, and to apply low-pass filtering to discard the irrelevant frequencies. Additional software filtering and smoothing of the EDA input signal is achieved by a three-level cascade consisting of a digital low-pass Butterworth filter [35] ($4^{th}$ order, cutoff frequency = 5 Hz) in conjunction with two Moving Average Filters [36] (using boxcar and parzen kernels with a size of $375 = 0.75 \times$ sampling rate).

*3) Vision-based Sensors:* A Microsoft Kinect v2 camera records frontal images of subjects, showing the upper part of the body. The Kinect camera provides HD (1080P) and RGBD (518x388) images at 30 fps. Video files are collected on a data server for further analysis.

### B. *Experimental Procedure*

Before starting the experiment, the participants were briefed on the experimental procedure. They were informed about their right to abort the experiment at any time. In addition, they were informed about the aims of the project to provoke and measure emotions while doing physical exercises on an ergometer. The experimenter explained the measurement of vision-based sensor and mounted the physiological sensors for data acquisition. The EDA sensors were connected to the middle and forefinger of the participant's left hand if he or she stated right-handedness, as according to the procedure described by Boucsein [8]. During the experiment, all participants' facial expressions were assessed by an external observer and after completion of each level participants were asked to self-assess their emotions. The presence of the experimenter and an external observer may be perceived as a judgment and therefore acts as a social-evaluative threat [20].

At the beginning of each experiment, the participant was asked to fill out a questionnaire about personality traits, which was correlated with the other data as a part of the analysis, to evaluate personal differences. The applied validated questionnaire for the Big Five personality traits (openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism) was designed by Satow [37]. In addition, they were given a questionnaire about their fitness level and their game experience. The participants were informed that if they felt uncomfortable by answering a question they were allowed to skip. Following the completion of all tasks, they were asked about their physical strain perception in the range from 1 to 7, as defined by Borg [38].

To start the physical experiment, the participant had to mount the exercise trainer and the game was started and shown on a display in front of the bike. The game begins with a training level to get familiar with the interface mechanics and the game world.

Eleven people participated in the presented case study, comprised of three female and eight male participants aged between 19 and 41 with an average age of 27. A more detailed profile of the participants is described in [5].

### C. Experimental Task

The experimenter asked the participants to take a ride on the physical exercise machine with the virtual bicycle from the start line to the finish line through the designed game environment. During gameplay the experimenter guided the participants with pre-defined phrases through the game to explain critical parts and objectives. For example, in one scene the participants had the opportunity to skip to the next one after an exceeding number of trials because of the high difficulty in making it to the finish line.

## IV. Emotional Provocation for Exergames

The crafted virtual cycling game is designed similar to a car racing game and can be categorized as a fun racer, regarding the requirements of being intuitive, easy to learn, engaging, highly dynamic and enabling multiple forms of adaptation [30]. The cycling game has no ambition to be as physically accurate as a real world bicycle, because this game concept allows a broad range of gameplay mechanics and game events. The game is controlled by the player who has to physically accelerate and steer. The ergometer is used as a controller for the virtual bike. The input is directly transferred into the game and the virtual bike is simulated in near real-time. Game elements have been tailored to the needs of the experiment. Different scenes provides users with different objectives. Crafted scenes integrate game elements as stimuli for specific emotions. The exercising part of the experiment starts with a *Training Scene* to get familiar with the controls.

Game scenes were designed to provide different objectives to the participants. In the *Mountain Scene*, which is shown in Figure 4, the participants had to ride up a hill. The resistance of the ergometer pedals increases in percentage to the degree of ascent in order to analyze the influence of physical strain.

Fig. 4. *Mountain Scene*: Physical Effort

During a *Night Scene* the participants have to cross a dark forest. The only illumination is provided by the bicycle lamp. At the end of the scene, the user triggers a *Jump Scare Event*, as shown in Figure 5, where monsters spawn in front of the bike shouting a horrible sound and all player controls are disabled.

Fig. 5. *Night Scene*: *Jump Scare Event*

In a *Challenge Scene* the participants have to jump over a giant gap to see the finish line, as shown in Figure 6. The only way to achieve this aim is by crossing a booster gate, increasing the speed of the virtual bicycle. Due to the high speed, the steering is very sensitive which leads to a frustrating amount of trials. In most cases, the participants are not able to cross the finish line at all.

Fig. 6. *Challenge Scene*: *Falling Event*

A *Collection Scene* provides the participants with the objective to collect coins. All coins must be collected to fulfill the task. The positioning is designed as a parkour's traversal.

During a *Teddy Scene*, teddy bears are roaming on a street in the game environment. The participants have to decide if they want to avoid or hit the teddies. In the case of hitting a teddy, the *Teddy Hit Event* is logged into the system.

## V. Data Analysis

All timestamps for emotion provoking game elements are logged in a database. The sensor data near to provoking events are considered for the analysis. An appropriate analysis window is applied for each sensor.

### A. Facial Expression Analysis

The recorded facial expression data are analyzed with the Computer Expression Recognition Toolbox (CERT) [39]. CERT provides a probability for basic emotions (joy, disgust, anger, fear, neutral, sad, surprise and contempt). The analysis

TABLE I
CORRESPONDENCES FOR THE *Falling Event* IN THE *Challenge Scene* AND EDA PEAKS DETECTED (TOTAL MATCHES:70)

| Left Border (s) | Right Border (s) | Window Size (s) | Matches Found | Matched (%) |
|---|---|---|---|---|
| 1.0 | 4.0 | 5.0 | 60 | 86 |
| 1.0 | 6.0 | 7.0 | 64 | 91 |
| 1.0 | 8.0 | 9.0 | 66 | 94 |
| 1.0 | 10.0 | 11.0 | 68 | 97 |
| 2.0 | 4.0 | 6.0 | 62 | 89 |
| 2.0 | 6.0 | 8.0 | 66 | 94 |
| 2.0 | 8.0 | 10.0 | 68 | 97 |
| 2.0 | 10.0 | 12.0 | 70 | 100 |

TABLE II
CORRESPONDENCES FOR THE *Jump Scare Event* IN THE *Night Scene* AND EDA PEAKS DETECTED (TOTAL MATCHES:11)

| Left Border (s) | Right Border (s) | Window Size (s) | Matches Found | Matched (%) |
|---|---|---|---|---|
| 1.0 | 4.0 | 5.0 | 4 | 36 |
| 1.0 | 6.0 | 7.0 | 8 | 73 |
| 1.0 | 8.0 | 9.0 | 10 | 91 |
| 1.0 | 10.0 | 11.0 | 10 | 91 |
| 2.0 | 4.0 | 6.0 | 4 | 36 |
| 2.0 | 6.0 | 8.0 | 8 | 73 |
| 2.0 | 8.0 | 10.0 | 10 | 91 |
| 2.0 | 10.0 | 12.0 | 10 | 91 |

method is further described in [5]. In this paper the event-based analysis method will be enhanced by physiological data.

### B. Physiological Data Analysis

The EDA sensor data are evaluated in two ways. The first is an activity peak detection for the sensor data with a focus on the phasic component of the signal. The other tonic component is a baseline evaluation. The event-based analysis method was enhanced by a peak detection algorithm. The activity response in the skin conductance signal can be delayed by one up three seconds after an event. In addition, the rate of climb can take up to five seconds [8], thus we chose an expansive analysis window size. Table I shows the differences in recognized peaks for different analysis window sizes by occurrence of *Falling Events* during the *Challenge Scene*. Table II shows the differences in recognized peaks for different analysis window sizes for the *Jump Scare Event*.

### C. Analysis Results

The respiration rate during cycling exercises increase up to 50 breaths per minute [40]. In the case study we observed a maximum respiration rate value of 22 at the Mountain Scene due to moderate physical strain during the experiment. The aim was not high intensity training but rather an emotional provocation while exercising.

The mean respiration rate value did not increase significantly over the conduct duration (14.6 to 15.3) due to a moderate and not long-lasting experimental design.

*1) Training Scene:* Since no event occurs during the Training Scene, no emotional peaks were expected and thus facial expressions were not evaluated. Eight participants had a very high mean respiration rate at this scene, which might be explained by nervousness or the challenge of using the controls for the first time.

*2) Mountain Scene:* Physical strain is not included in the basic emotions and cannot be recognized with the applied CERT tool. The analysis of physiological data has shown that the respiration rate decreased in this scene in eight out of eleven participants, due to the increasing physical strain.

*3) Night Scene:* The *Jump Scare Event* triggered the most varying emotional response in facial expressions and is thus not very encouraging. The analysis of physiological data is much more promising. Ten out of eleven participants had a high peak after the *Jump Scare Event* occurred in the analysis windows of up to eight seconds after the event.

Seven participants had a positive peak in the temperature change data after the *Jump Scare Event*. Two participants exhibited a negative peak. Figure 7 shows an example of EDA data during the *Night Scene*.

*4) Challenge Scene:* In the case of an analysis window of 1 second before the event occurs and 10 seconds after the event, we have 97% matching performance in EDA data, which can be interpreted as tension due to the challenging objective.

Interesting findings were also observed in the participants' reactions in temperature data. In the analysis window for the *Boost Event*, which occurs by crossing the booster gate for the first time, there were seven participants with positive peaks and four with negative peaks. Figure 8 shows an example with positive peaks at the *Boost* and the *Falling Event*.

The emotion recognition from facial expressions was not that successful for this scene as discussed in [5] due to very individual reactions. For ten participants, a high probability for joy was recognized at least once; sadness was observed for eleven participants, but nine self-assessments and nine observer-assessments labeled frustration for this scene. Figure 9 shows that the combination of EDA and facial expressions is very promising because in our case a high tension was shown due to repeated occurrence of falling down the cliff.

*5) Collection Scene:* During the *Coin Collected Event*, seven participants had a high joy response at least once. In this scene, no significant results can be found in the electrodermal activity values. The respiration rate in this scene has the highest mean value compared to the other scenes, which makes this finding interesting.

*6) Teddy Scene:* The analysis of emotional responses in facial expressions has shown that eight out of ten participants felt joy during *Teddy Hit Events*. One participant did not hit a teddy due to successful avoidance, thus just ten participants can be evaluated. In one case, the teddy bumped into the bike from behind; the participant did not even recognize the *Teddy Hit Event* and thus exhibited no emotional peak at this point. Facial expression recognition showed promising results, while the peak detection for the electrodermal activity did not show significant results, thus confirming our expectations. The smile behavior for this scene differs from the *Challenge Scene* due to the lack of frustration provocation.

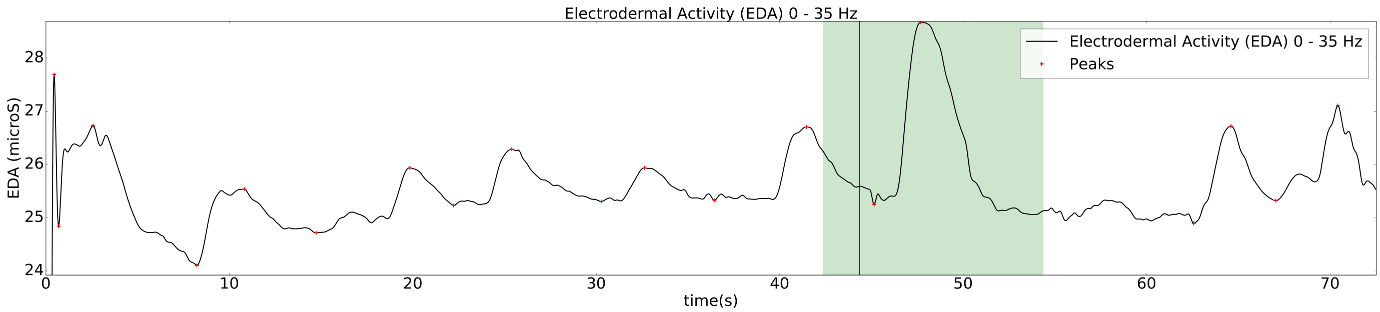


Fig. 7. Electrodermal Activity During Night Scene, for the *Jump Scare Event*

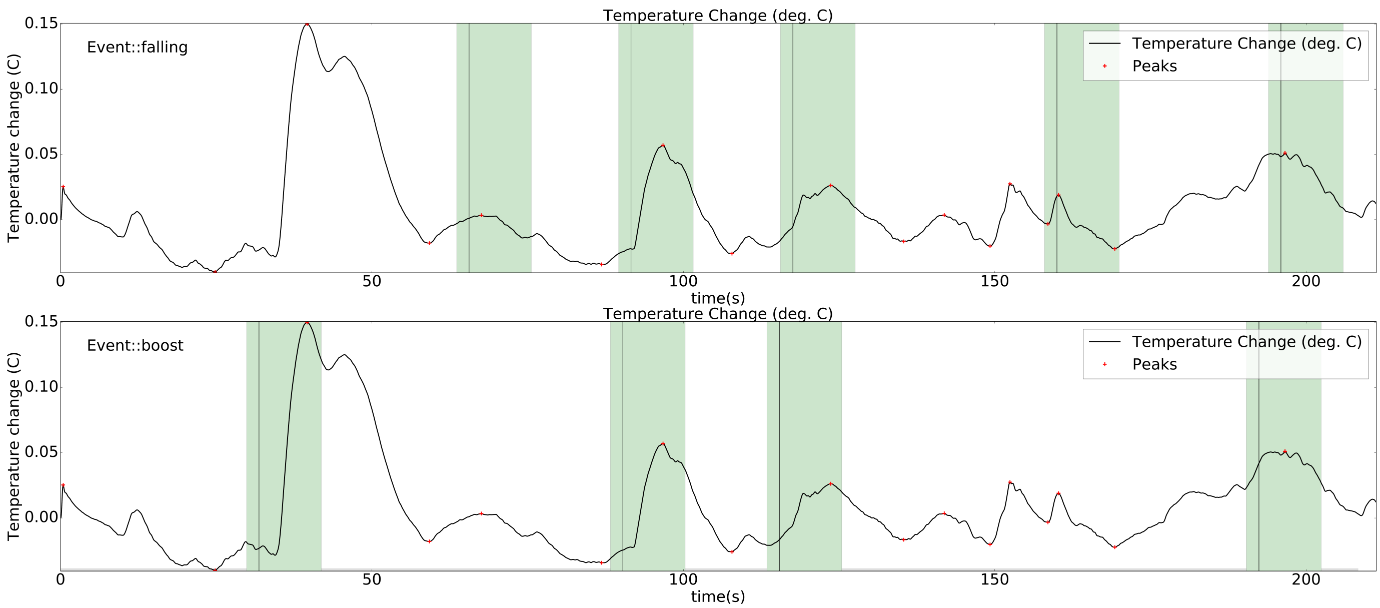


Fig. 8. Temperature Change During *Challenge Scene*, for the *Falling* and the *Boost Event*

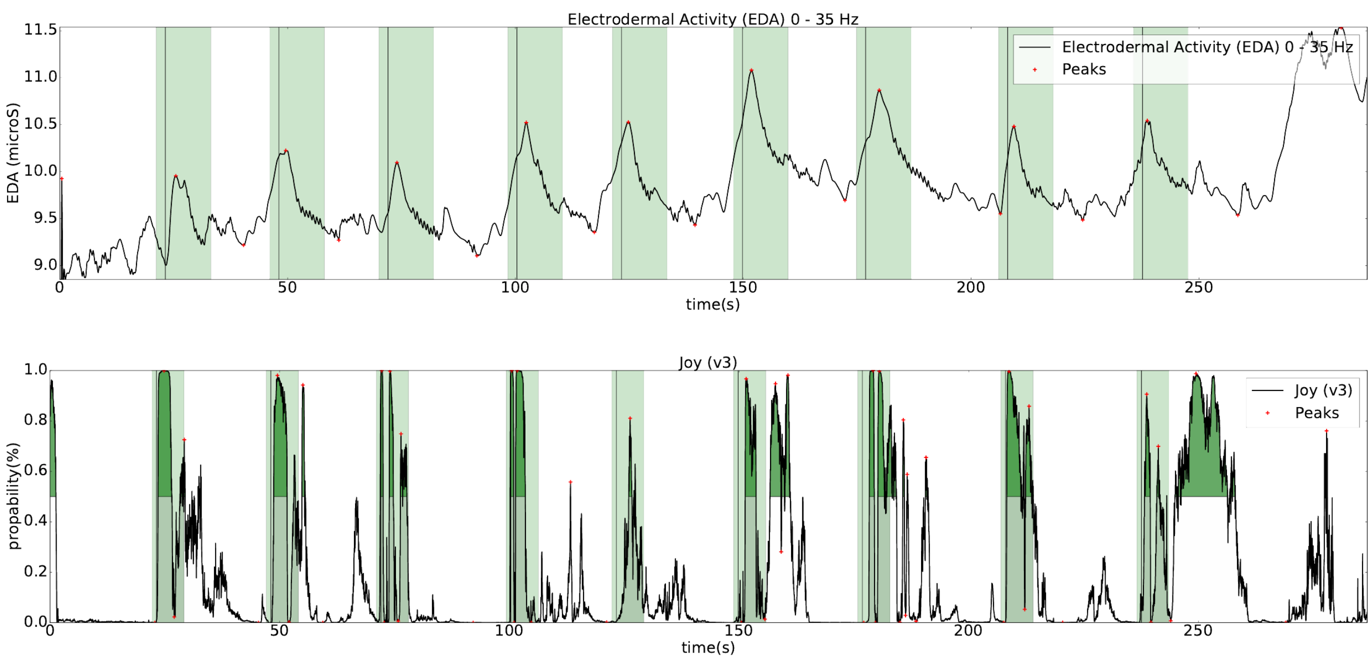


Fig. 9. Electrodermal Activity and Joy Output During *Challenge Scene*

*7) EDA Baseline:* The baseline of the EDA sensors increases over time from scene to scene, changing the absolute values for most participants due to the physical activity while exergaming. Our approach utilizes a peak event based approach and is robust to this changes due to the focus on the phasic component of the signal. Kächele et al. [31] stated a slow drift of the baseline over time. This tonic component of the signal is not highly diagnostic in our case due to the physical activity. Figure 10 shows the baseline results in detail.

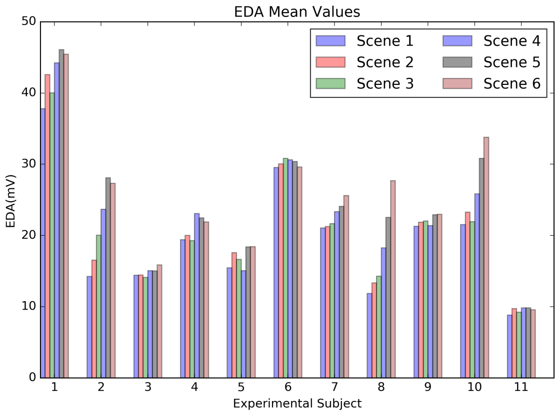


Fig. 10. EDA Baseline During Experiment

## VI. Discussion

The presented event-based analysis showed promising results in our case study. The provoked emotions shown in facial expressions were very individual for the crafted game elements and varied between the participants for some of the tailored events.

In this work we integrated physiological data into our event-based analysis method. In 97% of the *Falling Event* and 91% of the *Jump Scare Event* responses occurred in the EDA data. Thus the integration of physiological data into the *Challenge Scene* enhances the emotion recognition analysis; this helps to avoid for instance, false positives in joy recognition, because many people smile during natural frustration, as reported by Hoque et al. [22].

The highest peaks in electrodermal activity and facial expression recognition for the *Falling* and the *Jump Scare Event* were exhibited by extroverted participants. Three of the participants were classified as highly extroverted after the analysis of the personality questionnaire. One of these participants showed the highest values facial expression recognition and had the highest peaks during EDA analysis. Another participant who was classified as being extroverted showed very high values in facial expression recognition while the third participant had very high peaks in EDA analysis, which makes this finding interesting. For a further evaluation of this effect and to obtain significant results, an increase in the number of participants is planned for the future.

We found no negative correlation between skin conductance and neuroticism in our case study which has been reported by Brouwer et al. [24].

In this work it has been shown that the EmotionBike system is able to evaluate individual differences in perceiving entertaining game elements. The integration of affect recognition by physiological data into the system and a combination with basic emotion recognition by facial expression analysis magnifies the potential for ambient intelligent exergaming applications. In particular, the identification of individual differences in the perception of entertaining values between participants increased by adding a EDA data analysis.


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