Analysis of physiological signals for recognition of stress

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***Abstract*— People with limited communication capabilities, like people with a severe mental disability or dementia, are often not capable of expressing their emotions. This leaves these vulnerable people in many cases misunderstood and not always adequately helped. Better understanding of their emotions, feelings and unmet needs will strengthen the trust relation between the client and the caregiver. It will lead to better care for less costs and ultimately it will lead to increased quality of life and happiness. Mentech Innovation develops sensor technology that quantifies emotions to give these vulnerable people a voice.**

The aim of the study is to examine the body response to stress. Electrodermal activity (EDA) and heart rate (HR) signals were measured from thirteen participants while exposed to a stimulus of fear. This body response was recorded with the wristband Empatica E4 while the participants were exposed to a video scene with the fear predefined stimulus. The data set was used to derive a stress model based on in-depth variability analysis and deep learning algorithms to predict stress moments.

The results of study clearly indicate patterns in body responses to a fear stimulus, and provides statistical and a deep-learning models to recognize and predict stress.

I. INTRODUCTION

People suffering from mental disability or dementia sometimes face difficulties to express their emotions and feelings. It is in these cases difficult for caregivers to provide appropriate care. Sensor-based emotion recognition can contribute to a better understanding of their emotions, and therefore to better care and increased quality of life and happiness.

Mentech Innovation proposes sensor-based technology to solve this challenge. Wearable sensors measure body parameters such as skin temperature, heart rate, activity and skin conductance. The body response is subsequently analyzed with models and deep learning algorithms. Patterns are then derived from the data and used for emotion reading. For this, Mentech Innovation develops a model to assess arousal and the emotional well-being of people suffering from severe mental disability and communication limitations (see [1]).

This paper presents an overview of stress assessment using physiological signals. The paper is structured as follows. Section II presents the experimental study and the data collection, section III presents the data analysis, section IV presents a deep learning approach, section V presents a real application. Results and discussion are given in section VI.

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II. EXPERIMENTAL METHOD

A. Participants

Thirteen participants aged from 20 to 47 years, with different genders, nationalities and backgrounds, and without history of medical illness attributed to heart disease, participated in the study. The aim of the study was explained to the participants prior to the experiment. The content of the movie was however not revealed. The test persons were exposed to a relaxing environment (comfortably settled on a couch), while wearing the wristband Empatica E4 and beng exposed to the content of the movie.

B. Experimental procedure

The participants were exposed to an eight-minutes video, including different scenes: relaxing, unusual, relaxing, stress (stimulus), relaxing, unusual, relaxing, unusual. The emotion sensing is based on a distinct moment of fear caused by a sudden stimulus, among relaxing sequences. The video content is explained in details in appendix 1. The recordings were synchronized, and the heart rate, the inter-beat intervals and the skin conductance data were then collected for further analysis.

III. DATA ANALYSIS

The heart rate (HR) and the electrodermal activity (EDA) of each participant were synchronized with data treatment software (Visual Basic provided by Excel) to allow for correlation analysis.

A. Data visualization

EDA is a physiological signal that is measured from a person's body surface. It characterizes changes in the electrical properties of the skin because of the activity of the sweat glands. The EDA is a measure of the activity of the autonomic nervous system, and especially sympathetic nervous system, sensitive to arousal level [2]. EDA was measured with two electrodes, made of silver with a metallic core, via an alternative current of 8 Hz and a sampling frequency of 4 Hz [3].

The heart rate is determined from photoplethysmography (PPG). The principle is based on the exposure of light on the skin that is reflected by the blood in the vessels. The amount of light reflected on the photo-sensor depends on the flow rate of blood in the vessels, changing with the cardiac cycle [2]. The inter-beat interval and consequently the heart rate can be derived from the blood volume pulse. The PPG sensor uses two green and two red lights over a 15.5 mm^2 sensitive area, with a sampling frequency of 64 Hz [3].

The heart rate and the electrodermal activity of each participant are plotted figure 1 and 2.

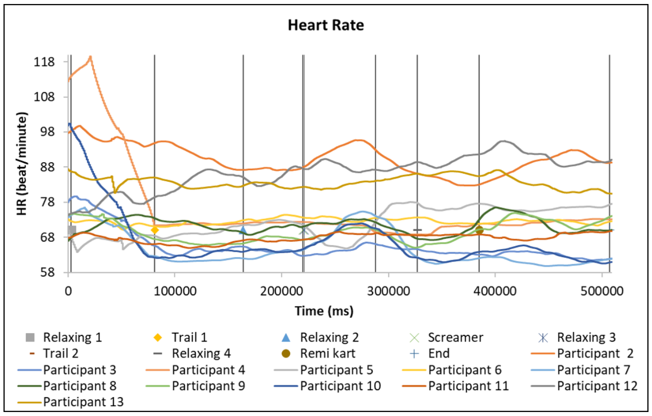


Fig. 1. Heart rate of all participants exposed to the video content.

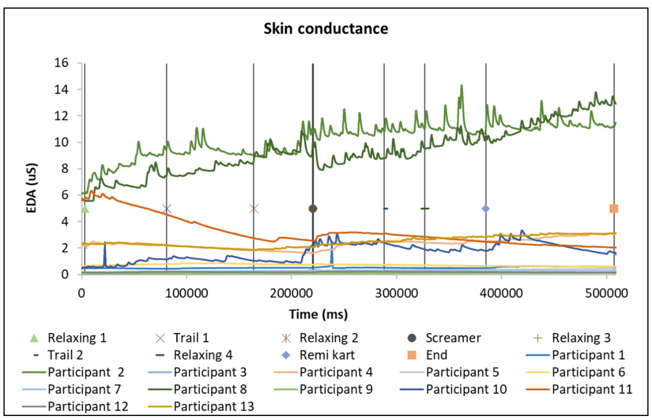
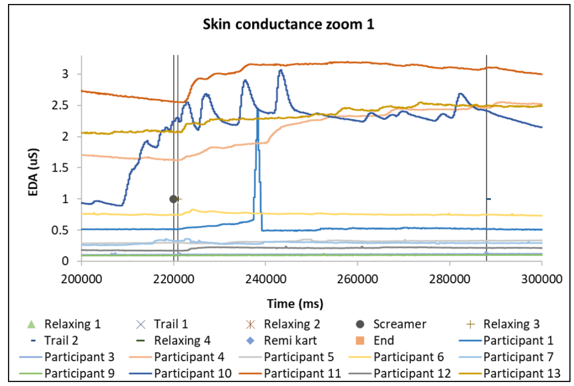


Fig. 2. Skin conductance of all participants exposed to the video content.

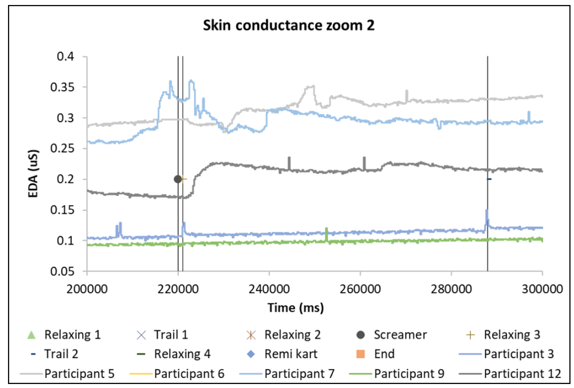
For every participant except participant 5, figure 1 shows that the heart rate increases at the moment of appearance of the stimulus (screamer). Figure 2 also shows that there is a step in the EDA after appearance of the stimulus, which can also be see in figure 3.

In order to analyze the patterns induced by the appearance of the stimulus, the heart rate and the electrodermal activity signals have been filtered with a moving average process, and normalized. Participants 7, 10 and 12 are taken as example and are plotted in figure 4. Their derivatives are plotted in figure 5.

This study points out a pattern in the body response after the appearance of a fear stimulus. A positive derivative relates to an increasing signal, a negative derivative relates to a decreasing signal. The heart rate increases before normalizing to its basic value, whereas the skin conductance has a steep increase. Figures 4 and 5 show that both HR and EDA increase after the the appearance of the fear stimulus. The delay is due to the somewhat slower body response. The electrodermal activity varies with the state of sweat glands



(a) Zoom 1



(b) Zoom 2

Fig. 3. Zoom in of the skin conductance.

in the skin. It measures the psychological arousal, since the activity of the sweet glands is controlled by the sympathetic nervous system. The screamer creates fear which produces sweat and increases the skin conductance.

B. Correlation analysis

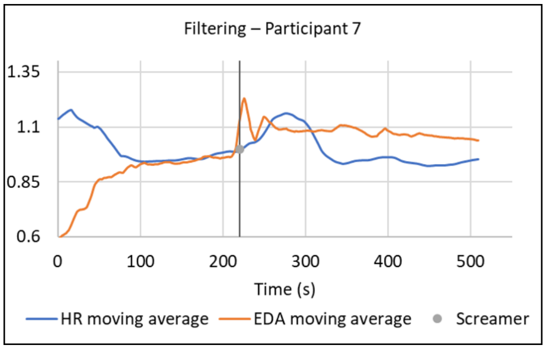
The study aims to model the body response to fear. The correlation analysis made with the software *R* highlights that the body responses of the participants are correlated.

The statistical procedure ”principal component analysis” has been applied on the heart rate data set (see fig.6) and on the electrodermal activity data set (see fig.7). The color represents the degree of accuracy of the representation in the plane at hand. The closer to red, the better the accuracy of representation. The angle between two red arrows is the correlation. The closer to 0, the better the correlation. A π angle between two arrows means an anti-correlation. A $\frac{\pi}{2}$ angle means no correlation.

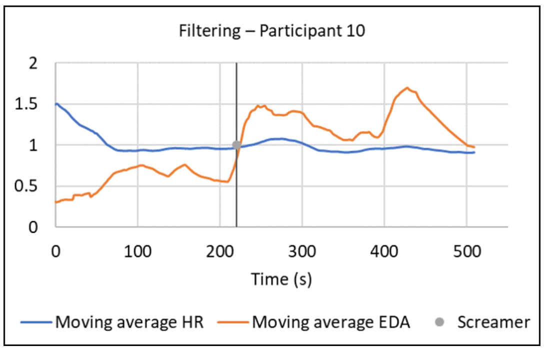
The HR correlations given in figure 6 illustrate that participant 3, 4, 10 are correlated and anti-correlated with participant 1, 12, 5. However, participant 11 is not correlated with the others.

The EDA correlations given in figure 7 show that there is a common trend in skin conductance responses. The closer the participants arrows, the more correlated they are.

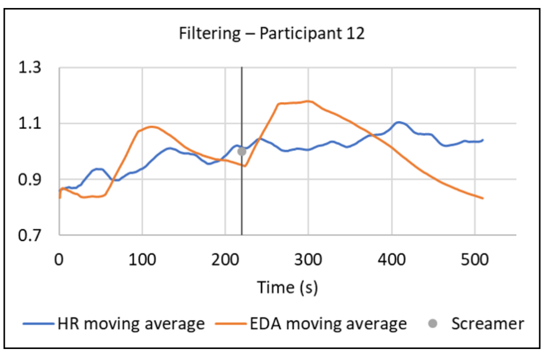
This correlation study points out a common body response pattern after a fear stimulus.



(a) Participant 7

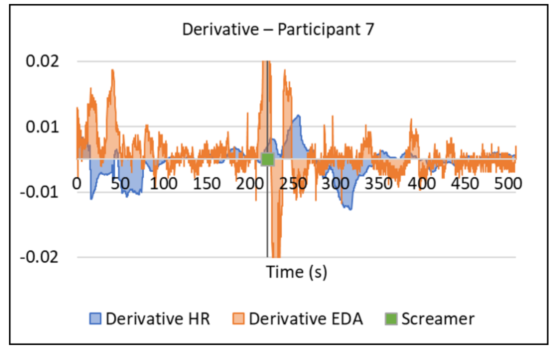


(b) Participant 10

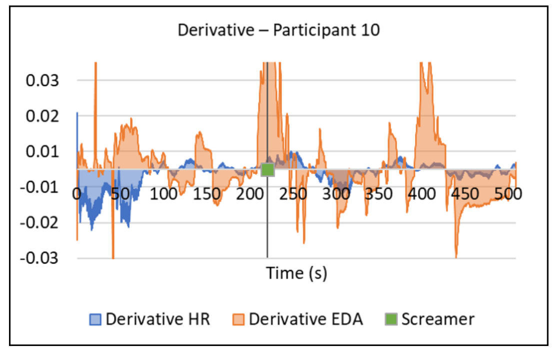


(c) Participant 12

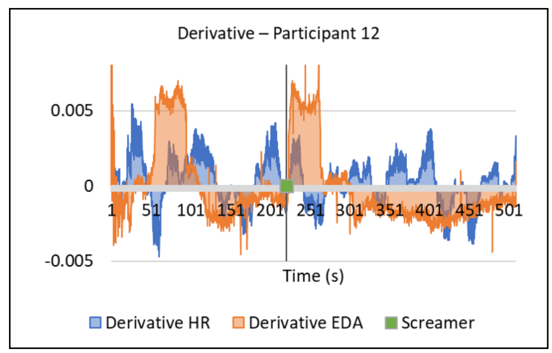
Fig. 4. Electrodermal activity and heart rate signals filtered and normalized.



(a) Derivative participant 7



(b) Derivative participant 10



(c) Derivative participant 12

Fig. 5. Derivative of HR and EDA filtered signals.

C. *Distribution analysis*

The stress can be computed by studying the distribution of cardio-intervals. The index uses the inter-beat interval data set provided by the Empatica measurement device.

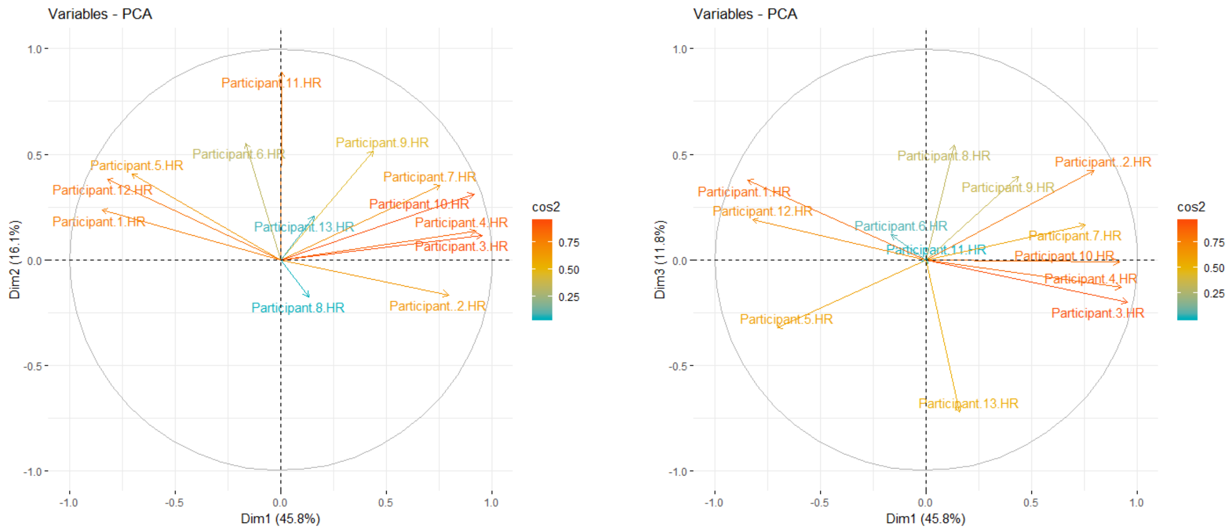
The video has been divided into three samples (see appendix for more details). The first sample is designed as a relaxing state, the second sample is designed a state with stress and the third sample is designed as a recovery state. Figures 8 and 9 illustrate the unequal inter-beat interval distributions between participants (participants 3 and 13 taken as example) and between samples.

Every participant has a different distribution, and the distribution also differ between the three different samples. The heart rate variability (HRV) is an analysis methodology based on the measurement of a consecutive series of the cardiac cycle duration, called inter-beat intervals. It is a method for the evaluation of autonomic regulation of the body. The sympathetic nervous system increases pulsation rate whereas the parasympathetic nervous system decreases it. The heart rate at normal heart function is in the range of 60-70 beats/min with a domination of the parasympathetic nervous system. Under stress, the sympathetic nervous system activity is intensified. That affects the inter-beat intervals duration and thus the heart rate. Geometric methods can analyze the inter-beat intervals shapes and distribution over the period of investigation and then evaluate quantitatively the stress level. A stress index can be computed from statistical analysis of the histograms [4]. The Baevskys stress index (SI) is calculated according to equation 1.

$$Si = \frac{AMo}{2 \times Mo \times MxDMn} \tag{1}$$

Where:

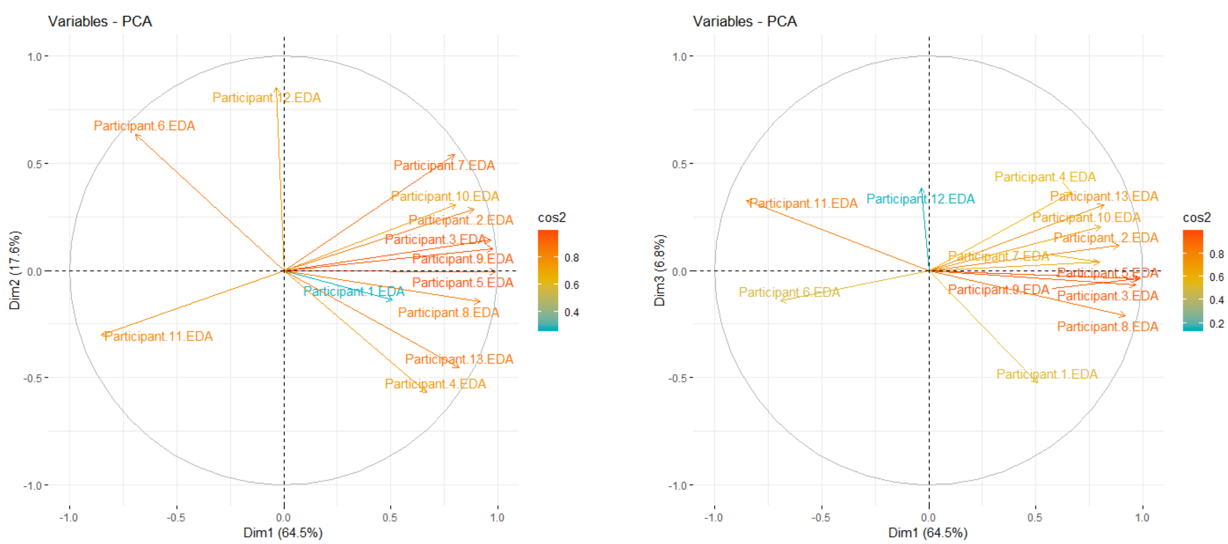
- Mo (Mode) is the value most frequently observed among the cardio-intervals. Mo is taken as the median



(a) Plane (1,2)

(b) Plane (1,3)

Fig. 6. Principal component analysis (PCA) applied on the heart rate of all participants.



(a) Plane (1,2)

(b) Plane (1,3)

Fig. 7. Principal component analysis (PCA) applied on the skin conductance of all participants.

of the inter-beat intervals.

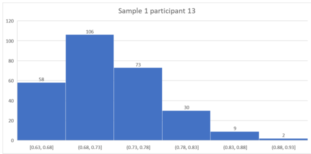
- AMo (Amplitude of a mode) is the percentage of cardio-intervals related to Mo value.
- MxDMn is the difference between longest and shortest. inter-beat intervals.

The stress indexes related to the three samples are plotted figure 10.

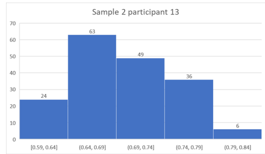
Participant 1 was removed from the data analysis because of missing inter-beat interval data. His heart rate has nevertheless been used in the above study because the Empatica provided values.

Most of the participants experienced more stress during the second sample, that is to say during the screamer scene. For some participants (5 and 7) the stress index is higher during the third sample, because they were expected another stimulus in the video.

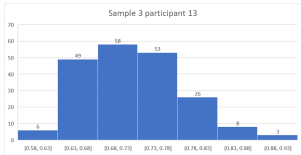
Finally, this model is accurate for 10 out of 12 participants, which corresponds to 91.7% accuracy.



(a) Sample 1

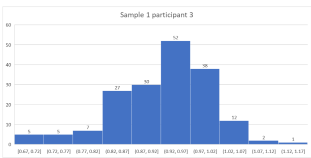


(b) Sample 2

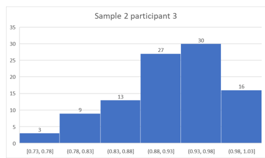


(c) Sample 3

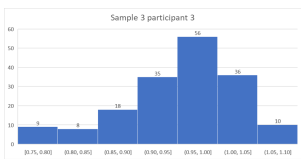
Fig. 8. Histograms representing the distribution of the inter-beat intervals of participant 13 for the three samples. Vertical axis: number of inter-beat interval. Horizontal axis: inter-beat interval.



(a) Sample 1



(b) Sample 2



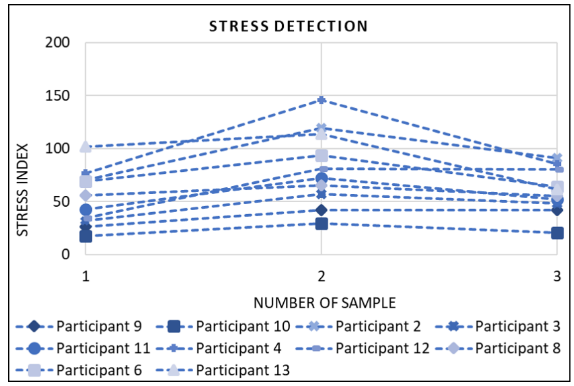
(c) Sample 3

Fig. 9. Histograms representing the distribution of the inter-beat intervals of participant 3 for the three samples. Vertical axis: number of inter-beat interval. Horizontal axis: inter-beat interval.

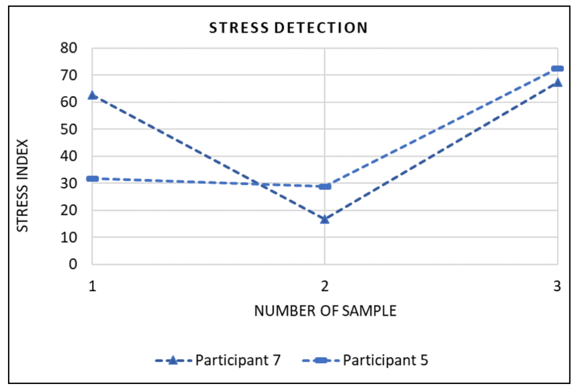
IV. DEEP LEARNING ANALYSIS

Deep learning algorithms are strong tools to derive patterns from data sets. Based on an extensive literature research, the most suitable algorithms for this particular use case was selected. These algorithms include: Nave Bayes (NB), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), K Nearest Neighbors (KNN), Decision Trees, Random Forest, Stochastic Gradient Descent (SGD), Multilayer Perceptron (MLP). Considering the case and the dimension of data sets, the algorithms used to predict the stress or calm states were linear SVM, NB and LDA.

After selection, the algorithms were applied on the car experiment data to retrieve the most accurate algorithms, SVM had a better accuracy (83%) in comparison to NB (81%) and LDA (78%). The deep learning model was therefore based on SVM. From the car experiment, the peak moments of stress and calmness (time frames is 7s with 20-25 rows of physiological data) were selected and used to train the algorithm for stress and calmness detection.



(a) Participants experience more stress in the second sample than in the first one.



(b) Participants experience less stress in the second sample than in the first one.

Fig. 10. Stress index of participants.

V. APPLICATION FOR REAL USE CASE

Mentech Innovation has a strategic collaboration with Severinus, a care organization in Veldhoven with care houses for mentally disabled people [5]. The derived stress and deep-learning models were applied to data sets acquired on clients with a severe mental disability. Following figures are three heart rate signals recorded on a patient of Severinus.

Figures 11 and 12 show the heart rate response of a client while watching an exciting movie. The emotional state of the client during this experiment was estimated from the judgment of a psychologist, who analyzed the recorded images. These observations are indicated as different colours in the figure: orange is stress, light blue is relax, dark blue refers to physical stress (during walking). Distinct periods of stress are identified, which correspond to exciting events during the movie. Emotion levels were also derived via the developed deep learning model, these are indicated as 0 (relax) and 1 (stress). The agreement between the observation of the psychologist and the arousal predictions of the deep-learning model is pretty good.

In addition, the deep learning model was applied to a HR response of a client during nursing time in the morning to predict the emotional state, see figure 13.

These experiments show that the support vector machine algorithm is able to detect quite reliably stress moments.

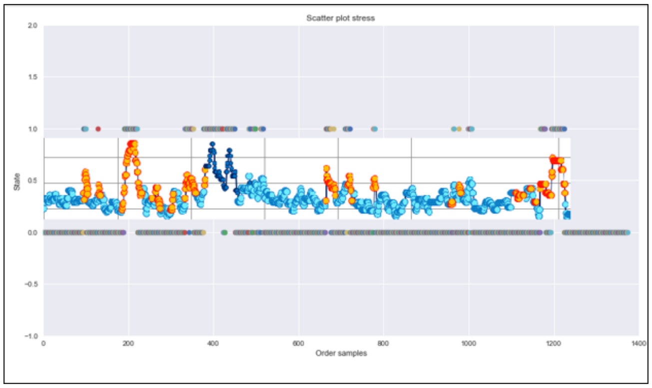


Fig. 11. Test of the algorithm on a heart rate recording of a client from Severinus. Light blue: calm state. Orange/red: stress moments. Dark blue: moving moments. The grey dots are the prediction of the algorithm.

Fig. 12. Test of the algorithm on another heart rate recording of a client from Severinus. Light blue: calm state. Orange/red: stress moments. Dark blue: moving moments. The grey dots are the prediction of the algorithm.

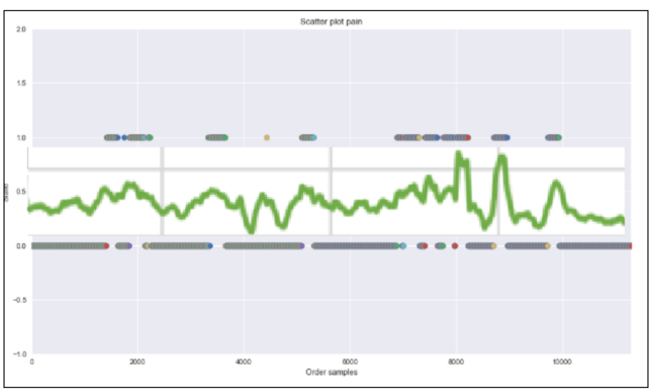


Fig. 13. Test of the algorithm on a third heart rate recording of a client from Severinus.

VI. CONCLUSION

This paper presents an approach for stress recognition based on skin conductance and heart rate body signals. Physiological data were acquired on 13 participants exposed to video content that contained a clear stimulus creating fear. The study shows a distinct correlation between the heart rate and electrodermal activity responses of the participants. The stimulus provokes an increase of skin conductance and heart rate, the delay and scope depending of the participant. In addition, the stress index turns out to model the stress state of the participants. This data set was then used to train a deep learning algorithm that can predict stress moments in heart rate signals. The results turned out to be quite accurate compared to a psychologist analysis.

Based on a combination of electrodermal activity and heart rate, this study is a substantial step towards accurate emotion sensing from physiological signals. Future work will focus on increasing the accuracy of emotion sensing by improving the deep learning models, and by adding other physiological responses, the addition of face and voice recognition.

APPENDIX

The participants have been shown a 8:44 minutes video on the topic ”cars”. The video is divided into 9 parts. It aims at having a baseline so that the stimulus (see fig.14) creates a clear difference in the physiological signals.

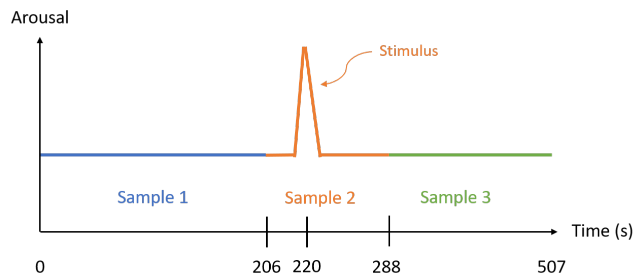


Fig. 14. Sketch of the video. The peak represents the stimulus (screamer) creating surprise and fear. Samples 1 and 3 are relaxing moments taken as reference baseline.

For further analysis, the whole video is divided into three samples as follows.

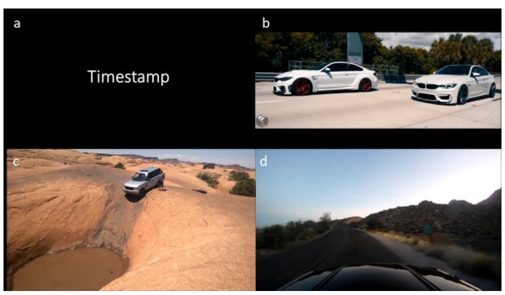


Fig. 15. Sample 1 from the video. a) Time stamp to synchronize every participant. b) First relaxing sequence. c) Neutral sequence. d) Second relaxing sequence.

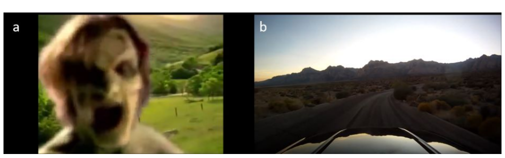


Fig. 16. Sample 2 from the video. a) Screamer at the end of the sequence: stimulus. b) Third relaxing sequence.

Fig.15 is the first sample. The first image ”Timestamp” is used to synchronize the participants. A time stamp is then visible in the data set. Video b) represents a video showing cars. That is a relaxing moment. Video c) is a neutral video, during which a car crosses a hole full of water in a steep incline. Video d) is a relaxing video showing a car driving.

Fig.16 is the second sample. Video a) is the screamer. A car is driving up an hill when suddenly a man appears and screams. Video b) is again a relaxing moment. This sequence is supposed to cause stress.

Finally, Fig.17 is the third sample, acting as a baseline as the first sample. Video a) is again a neutral video in which a 4x4 climbs a huge step. Video b) is a relaxing moment, and video c) is a neutral/fun video to conclude the sequence.

Fig. 17. Sample 3 from the video. a) Second neutral sequence. b) Fourth relaxing sequence. c) Neutral/fun sequence.

All of these videos are in free access on *Youtube*.

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[5] https://www.severinus.nl/