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Analysis of EDA and Heart Rate Signals for Emotional Stimuli Responses

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Abstract: Emotion intelligence is a popular research topic that stems to bridge the gap between human-machine interaction. The use of such systems varies, however, the goal remains the same, to develop a robust and accurate model for detecting and identifying emotions. Physiological signals, such as electro-dermal activity (EDA) and heart rate (HR), when coupled with facial expression analyses can bolster the efficacy of the recognition system. To this end, the aim of this study is to analyse EDA and HR signals to identify reactions to emotional stimuli. The data used in this work was collected from different subjects taking part in a separate study on emotion induction methods. The obtained physiological signals were processed to identify the stimulus trigger instances and detect trends between the different administered emotional stimuli. The results showed that the EDA signal was able to pinpoint the emotional trigger with a root mean squared error (RMSE) of 0.9871. The HR signal showed inconsistencies, however, a clear trend was observed between the emotion reaction and relaxation phase. This preliminary study assessment highlights the possibility of implementing data fusion in emotion recognition systems.

Keywords: Electro dermal activity (EDA), Emotion recognition, Heart rate (HR), Signal processing.

1 Introduction

The integration of artificially intelligent (AI) systems in day to day activities has gone mainstream. The computational power of machine learning systems, thanks in part to advancements in technology, make AI a cornerstone for industries and domains of the future. The incorporation of AI holds a lot of potential in the field of medicine, ranging from patient diagnosis, to monitoring and treatment [1].

Emotion intelligence is considered an application of AI in medicine, when used as a component in a closed-loop system [2] designed to aid in the therapeutic treatment of people. These systems could be used for people with autism spectrum disorder (ASD), which are defined as neuro-developmental conditions which affect the individuals' social skills by impairing their interaction, communication, behaviours, and interests [1], [3], [4]. It is estimated that ASD affects 1 out of 59 people [5] which constitutes around 1~2% of the general population [4].

In order to achieve an efficient emotion recognition model, markers that identify emotions need to be analysed. These include facial components, speech pattern and physiological signals. Separately, each marker has the ability of providing an efficient emotion classification. Collectively however, it creates the potential for a more robust classification. To this end, this study investigates the responses of physiological signals to emotional stimuli. The physiological signals are perceived to constitute 10% of the emotion recognition process [6].

The two physiological signals of electro-dermal activity (EDA) and heart rate (HR) were used for the analysis. The data was collected as part of a separate study on emotion induction methods [7]. The signals were analysed for emotional stimulus trigger point detection and assessed for a trend in emotional responses. Different signal processing methods were adopted in order to smooth out, patch and detect features of interest. The root mean squared error (RMSE) was used for the evaluation process. The aim of this preliminary study is to analyse EDA and HR signals in identifying reactions to emotional stimuli.

Similar studies [8]–[10] have shown the impact of using EDA and HR signals on emotion recognition. In [8] different techniques and features were assessed for the use of EDA signals in emotion recognition yielding higher accuracy and possible real-time application. In [9] a neural network model was developed for emotion classification using EDA signals

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achieving an accuracy of 82% for subject independent analyses. In [11] the use of HR signals from a wearable device was evaluated for emotion recognition with promising outcomes. The fusion of different signals for a more robust classification model was studied in [12]–[14] yielding more robust and better performance models. This indicates that such data fusion methods are beneficial to recognition systems.

2 Methods

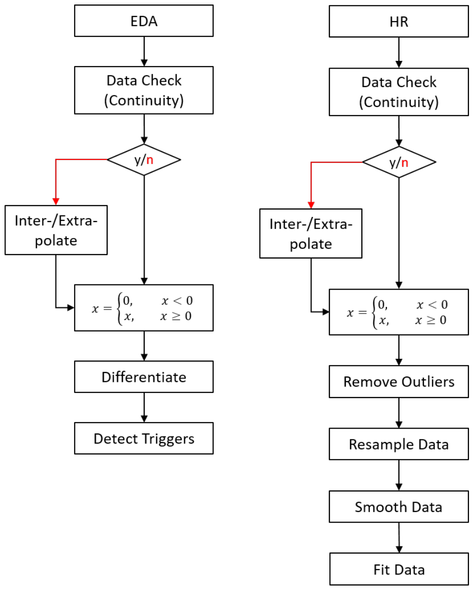

Figure 1: Flow chart of the algorithm workflow for EDA and HR analysis.

2.1 System Methodology

The data was first pre-processed in order to address data collection disturbances such as a break in the continuous signal or invalid measurements. Afterwards the EDA signals were processed to detect each of the emotional stimulus trigger marks. The HR signals were processed to find a pattern within the data.

The RMSE measure was used to analyse the performance of the stimulus trigger detections. The system flowchart is depicted in figure 1.

2.2 Signal Pre-processing

In order to highlight and address inconsistencies in the data, signal pre-processing was conducted. The data was first checked for missing information, i.e. not a number (nan) errors, in the complete time frame of each of the EDA and HR signals for each subject. If a break in the continuous signal was detected a data filling operation was implemented. The method was based on piecewise cubic spline interpolation.

After filling the missing data, a threshold value was set such that any value below 0 will be set to 0. This was done in order to counteract false measurements form the sensor. Figure 2 displays a sample from the EDA signal before and after the pre-processing.

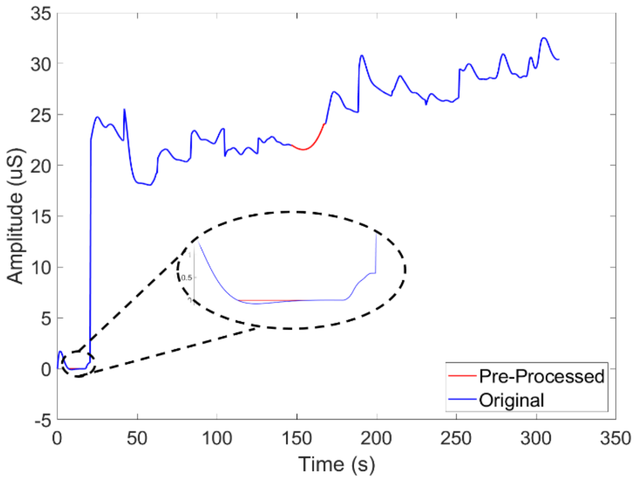

Figure 2: EDA sample signal before and after pre-processing. The blue line indicates the original signal, the red lines refer to the pre-processed signal.

2.3 EDA and HR Signal Processing

In order to detect the emotional trigger time stamps from EDA and analyse a trend in HR data, signal processing was performed. A second order derivative was performed on the pre-processed EDA data in order to locate the deflection points of the signal. After-which the peaks from the derived signal were extracted.

The pre-processed HR signal was passed through an outlier detector, where values with more than three standard deviations from the mean were removed from the sequence. The achieved output was then resampled to fit the sampling rate of the EDA data. This was achieved by fitting the data with a shape-preserving piecewise cubic Hermite (PCHIP) interpolation method. The goodness of fit of the model were assessed using r^2 and sum squared error (SSE). Afterwards the signal was smoothed using a moving mean with a window length of 30 seconds to reduce noise. The data was then normalised using a centered mean, with a mean value calculated from the baseline HR collected at the beginning of each experiment. Afterwards the normalised data was fitted based on the sum of sines method with a degree of seven. This was performed to compare the patterns in the data between the different subjects and emotions.

2.4 Dataset Description

The data was collected, as part of a separate study on emotion induction methods, in a controlled lab environment. A total of 24 subjects (10 male, 14 female) took part in the experiment. As part of the experiment, the participants were subjected to images that were intended to induce specific emotional responses. The physiological data of EDA and HR were recorded using the sensors of “EdaMove4” and “EcgMove4” (Movisens GmbH, Karlsruhe, Germany) along with visual recordings of the face from a high resolution camera. The videos were captured at a rate of 60 Hz, physiological signals of EDA at 34 Hz and HR at 1 Hz. For a more detailed description of the experiment refer to the following publication of *Schmid et al.* [7].

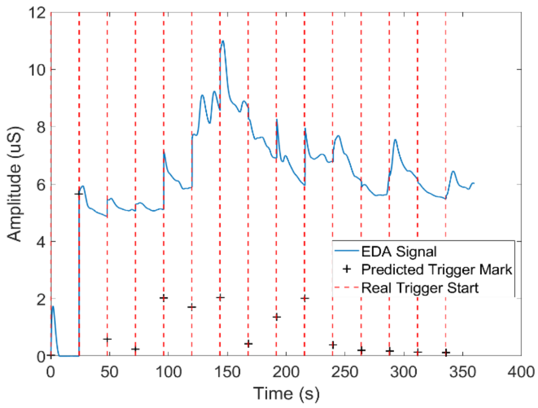

Figure 3: EDA sample signal with emotional stimuli trigger marks. The blue line indicates the original signal, the red dashed lines the real stimulus start, black + signs the predicted trigger instances.

3 Results

In figure 3 a sample of the EDA processing outcome is represented. The predicted trigger marks were in-lined with the real trigger start time stamps, achieving an RMSE value of 0.9871 for all subjects.

Figure 4 represents a sample of the fitted data of the HR signal. The resampled original signal depicted in grey is smoothed and the output is represented by the red curve. The resampling of the HR signal yielded a mean r^2 value of 1 and mean SSE of 0 indicating a perfect fit with no loss of information. The mean r^2 value of the smoothed curve against the resampled signal, i.e. original signal, for all subjects was 0.187 ± 0.162. The blue curve in figure 4 represents the fitted HR signal with an RMSE and r^2 value between the smoothed and fitted curves of 0.538 ± 0.177 and 0.949 ± 0.029 respectively.

The mean of the normalized fitted HR signals for all subjects for each emotion is depicted in figure 5. The red dashed line represents the start of the rest stage.

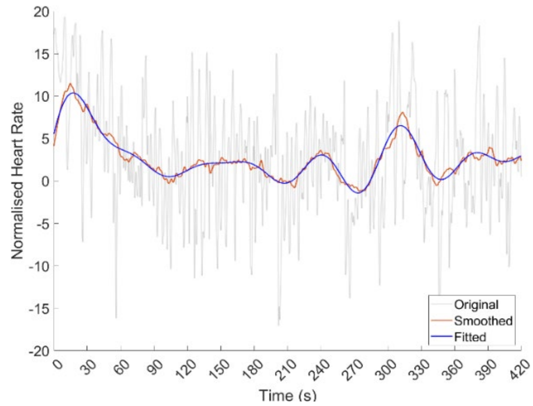

Figure 4: Fitted HR sample signal. The grey line indicates the original signal, the red line refers to the smoothed signal, the blue line represents the fitted signal.

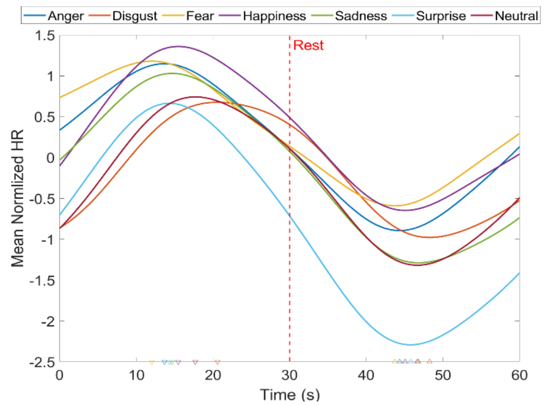

Figure 5: Mean HR signal for each emotion including rest stage for all subjects. The dashed red line represents the start of the rest stage.

4 Discussions

As observed from figure 3, the EDA data processing was able to achieve a robust emotional stimulus detection. The time stamps extracted from the peaks represents a change in the data which is directly related to a change in the experiment. This change is linked to the start of an emotional stimuli as well as the beginning of the resting stage which supersedes it. The EDA has the potential to be used as trigger marks for consequent physiological data analysis for emotion recognition. Using EDA as a stand-alone signal for emotion detection yielded no conclusive evidence, at the time of writing this article, as the data showed no discernible pattern between the different subjects for each emotion.

The results from the analysis of the HR data showed inconsistencies in the pattern of emotional stimuli response. The original signal showed a lot of noise and its smoothing yielded a low goodness of fit of 0.187 indicating it does not represent the data well. However, when analysing the profile of the smoothed signal, it was observed that it was mimicking that of the original signal. Although the HR data could not be effectively used for emotion detection analysis, given the high fluctuation between subjects and inconsistencies in the emotional response, a pattern was able to be derived from the information.

The analysis of figure 5 shows that the peak of the emotional stimulus response is being detected at the middle of the experiment. The effect of the stimuli response is seen trailing in to the resting stage. This suggest that administering a longer resting stage is desirable in order to give the subjects the opportunity to feel comfortable again as they could be experiencing anxiousness and stress relating to the upcoming stimulus. Some limitations are considered in this study, i.e. the size of the database.

5 Conclusion

In this study the analysis of EDA and HR signals to identify reactions to emotional stimuli was assessed. The outcomes revealed, that the EDA data can be used for the emotional stimulus time stamp detection with a RMSE of 0.9871. The HR data showed some anomalies, however, a trend could be extracted from the signals revealing the presence of the emotional response in the resting stages of the experiment. This preliminary study assessment highlights the possibility of implementing data fusion in emotion recognition systems. Further research is required to achieve a discernible pattern for emotion classification.

Author Statement

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