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Fizyolojik Sinyaller Kullanılarak Otizmli Çocuklarda Stres Tanıma
Stress Detection of Children With ASD Using Physiological Signals

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***Özetçe* —Bu çalışma otizmli çocuklar için fizyolojik sinyallere dayalı bir stres tespit yaklaşımını konu alır. Bu yaklaşımın otizmli çocuklar için sosyal ve yardımcı robotlar kullanılarak geliştirilen müdahale/terapi yöntemlerinde kullanılması hedeflenmektedir. EMBOA projesi kapsamında çeşitli ülkelerde otizmli çocuklardan bir robot etkileşim oyunu esnasında E4 akıllı bileklikle toplanan EDA (Elektrodermal Aktivite) ve BVP (Kan Hacmi Nabzı) sinyalleri analiz edilmiştir. EDA sinyalinden elde edilen tepe sayısı ve ortalama genlik değerleri önceki çalışmalarda sunulan alt sınır değerleri baz alınarak işlenmiş ve çocuklardaki stresin tespiti için kullanılmıştır. Ayrıca BVP sinyalinden elde edilen düşük frekans (LF) ve yüksek frekans (HF) değerleri kullanılarak tespit edilen stres değerleri ile de karşılaştırma yapılmıştır.**

Anahtar Kelimeler—fizyolojik sinyaller, çocuk-robot etkileşimi, otizm, stres.

***Abstract*—This paper proposes a physiological signal-based stress detection approach for children with autism spectrum disorder (ASD) to be used in social and assistive robot intervention. Electrodermal activity (EDA) and blood volume pulse (BVP) signals are collected with an E4 smart wristband from children with ASD in different countries. The peak count and signal amplitude features are derived from EDA signal and used in order to detect the stress of children based on the previously provided reference baselines. Furthermore, a comparison has been made with the stress values determined using low frequency (LF) and high frequency (HF) values extracted from BVP signal.**

Keywords—physiological signals, child-robot interaction, autism, stress.

I. INTRODUCTION

This study is a part of the EMBOA project that aims to combine affective computing technologies with the social robot intervention for children with Autism Spectrum Disorder (ASD). The emotional state, motivation, and stress of children with ASD are analyzed via different modalities during their interaction with the Kaspar robot. This study focuses on a stress detection system using the physiological signals combined with video recordings of children with ASD during robot-based intervention. A comprehensive review of stress detection approaches based on physiological data has been presented in [1]. Skin conductance (SC), skin temperature (ST), electrocardiogram (ECG), blood volume pulse (BVP), and Electroencephalogram (EEG), as well as speech, eye activity, and body posture/movements, have previously been used to detect stress [1], [2]. Stress detection in people with ASD has also been a hot research topic recently [3], [4].Heart rate variability (HRV) based stress markers in children with Asperger syndrome has previously been investigated that LF power increases and HF power decreases in stressed situations compared to the non-stress baseline [5]. Galvanic Skin Response (GSR) or Electrodermal activity (EDA) has also been used to detect stress levels by measuring skin conductance [6]. The instantaneous peak rate and amplitude of EDA signal has been shown to carry crucial information about stress levels and stress has been detected with an accuracy of 82.8% [7]. Moments of stress have been detected with 84% accuracy based on features extracted from the EDA signal combined with ST [8]. EDA has also been used to measure the emotional states of children [9]. The emotional state of a child has been identified with 68% mean global accuracy for Logistic Regression and Support Vector Machine and 63% for Decision Tree [9]. Furthermore, combination of EDA and heart rate (HR) has also been used to classify stress using various machine learning methods [10].

This study presents the preliminary results on the stress of children with ASD during the interaction studies with Kaspar. 29 children aged between 2-12 years old from 4 countries attended Kaspar robot-based intervention sessions, and their physiological, audio, gaze, and facial data were recorded. The study focuses exclusively on the physiological data. In this study, an Empatica E4 wristband is used to record the physiological signals of children with ASD during their interaction with Kaspar. The EDA and BVP signals are used for stress detection in the study. The previously provided reference baselines [5] for LF and HF features derived from BVP data for children with ASD are used to detect the stress of children. The peak count and signal amplitude features are derived from EDA data and used to detect the stress of children based on the previously provided reference baselines, presented in the literature [11]–[13]. The extracted features are also evaluated individually for each child based on their individual statistics computed from their overall session metrics.

II. EMBOA Project

This project aims to find a new approach to create an affective loop in robot-based intervention for children with ASD to improve the intervention gain regarding emotional intelligence building. In order to explore available technologies and practices serving this purpose, a set of interaction scenarios were implemented with the Kaspar robot.

Each interaction scenario was based on the principle of turn-taking, imitation, and role changing requiring basic language understanding and verbal skills about emotions, animals, and body parts. Kaspar used basic sentences with some behavioral cues to guide the children with positive, neutral, or negative feedback throughout the interaction. The therapist determined the interaction flow and adapted it with respect to the children's profile.

During the interaction studies, multi-modal interaction data were collected to evaluate and analyze the proposed intervention scheme. The collected data were composed of: (1) Physiological signals, captured by E4 wristband; (2) Eye gaze movements, duration, and fixation data, captured by Gazepoint Eye Tracker; (3) Audio recordings, captured by H4n Pro sound system; (4) Video recordings, captured by 2 video cameras, one placed above the robot's head to capture the facial expressions of children and the other placed on the right side of the robot to capture the whole interaction session; (5) Children's demographic profile and diagnostic history.

The interaction studies were conducted in 4 collaborating countries: Turkey, North Macedonia (MAAP), United Kingdom (UH), and Poland (GUT). A total of 29 children (25M, 4F) diagnosed with ASD participated in the studies. The age of children ranged from 2 to 12 years old, and the children had a moderate or high level of language understanding and verbal skills. The interaction study was conducted at least once with each child and repeated in multiple sessions based on the therapist's opinion (2 to 11 sessions). The ethical board approved the interaction studies of the Gdansk University of Technology (Poland). In addition, the parents of the children were informed about the experimental procedure, and they signed written consent.

III. Methodology

The Empatica E4 wearable device collected children's BVP, ST, and EDA during the interaction with Kaspar. BVP (64 Hz), EDA (4 Hz), and ST (4 Hz) are measured by photoplethysmogram, electrodermal activity, and infrared thermopile. The data collection procedure included feature extraction, usability analysis, and baseline comparison. HeartPy Python Heart Rate Analysis Toolkit extracted the time-domain features SDNN, PNN50, RMSSD, HR, and frequency domain characteristics LF and HF from raw BVP data. The reference ranges used to assess the signal's usability are taken from the literature [5], [14]–[18]. The features for all signals were rated according to their range.

Stress detection in children was based on the LF and HF values of the usable BVP signal, and peak count and average amplitude of EDA signal. The reference LF and HF values for children with ASD were previously provided in [5]. It had been demonstrated that LF power increased while HF power decreased in stressful settings. Thus, the previously reported mean values for LF (M= 2243 ms^2), and HF (M= 3127ms^2) have been used as a baseline for stress detection. If the calculated LF value was greater and HF was less than the reference, the child was labeled as stressed.

The raw EDA signal were processed via MIT EDA explorer tool [19] and cvxEDA library [20]. Peak counts, signal amplitudes, Area Under the Curve (AUC), skin conductance response (SCR) width, decay time, rise time features were extracted from the signal based on the default parameter provided by the toolkits (threshold: 0.02, offset: 1, rise time: 4, and decay time: 4). For the stress detection from the EDA signal, average peak counts (also known as "SCRs") and amplitude values were used. Previous studies indicated that the average number of peaks in the EDA signal is 1-3 per minute'for adults with typical development [13], but it increased to 20-25 peaks/minute in case of high arousal in the emotional state [12]. Due to lack of studies in the literature on the physiological statistics of children, especially children with autism, the average number of peaks computed for each children based on their overall sessions statistics were used as baseline in this study. On the other hand, the resting mean amplitude has been reported as 0.66±0.13 µS for children with ASD for the average amplitude baseline [11]. Therefore this value was used as the ASD baseline in this study.

The video recordings were also combined with physiological characteristics to corroborate the BVP and EDA findings. Open source toolkit OpenFace [21] was utilized to identify children's facial expressions and infer their emotional status throughout their engagement with Kaspar. OpenFacecomputed the affective state features and provided data on face action units (AUs), the modular components of emotional expressions. OpenFaceprovided the binary presence information for 18 AUs for each video frame. They were then analyzed and turned into emotional labels using FACS principles defined by [22] e.g. if both AU06 and AU12 was present in a frame, then it was labeled as "happy". And the frame was labeled as "neutral" if it lacked an emotional label. After the annotation procedure was complete, the number of occurrences of the emotional labels within a specified time interval was calculated and sorted to identify the dominating emotion. Due to their frequency, the number of neutral frames was eliminated from the analysis. Calculated affective labels were employed to determine children's emotional states during interactions.

IV. Experimental Results

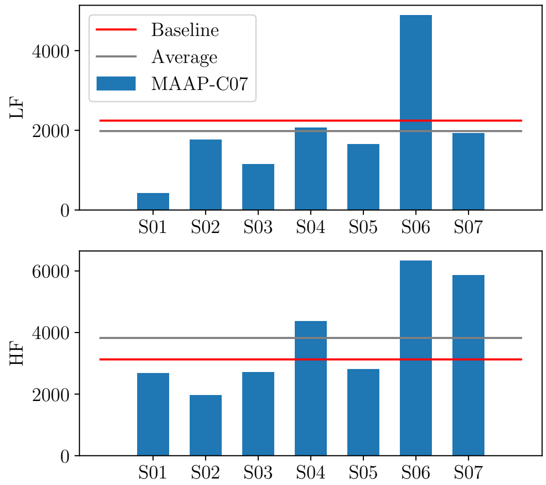
The usability analysis study was conducted for all the data collected within the project partnership, and the usable physiological signals labeled were pre-processed, and average levels of LF and HF extracted from the BVP signal, as well as the average peak count and amplitude extracted from EDA signal were computed for each child. Each interaction session was analyzed in detail in 2-3 minutes intervals and validated with emotional labels.

In this study, we present a case study for the physiological analysis performed for a 3-year-10-month-old boy, coded as MAAP-C07. MAAP-C07 had 7 sessions with Kaspar, the average LF and HF values, peak counts and average amplitude for all the sessions were presented in Fig 1a and 1b, respectively. The results showed while LF and HF values agreed that he was not stressed in his 4th and the last session with Kaspar based on the baseline and the overall average of his sessions. But the features extracted from EDA signal did not supported this hypothesis, even though the peak count were lower than the baseline, it was higher than his individual average, and the amplitude was also higher than the baseline and his average, indicating a high arousal in the signal.

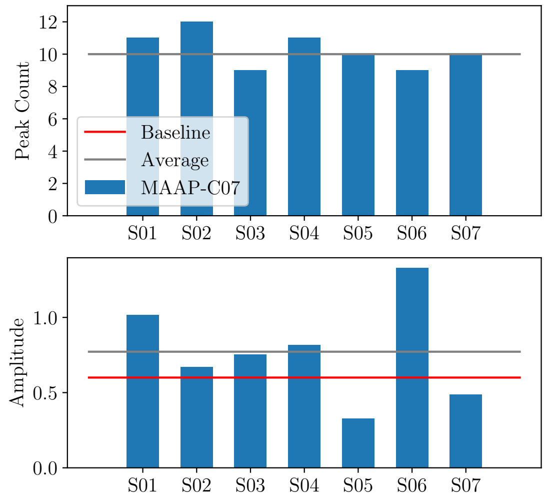
In order to examine the inconsistency between the features extracted from BVP and EDA signals, MAAP-C07's 4th session was analyzed based on the 2-minutes time intervals. The results are displayed in Fig 2a and 2b. When the results were evaluated based on the ASD baseline (drawn in red) provided in the literature, they showed that LF-HF values agreed with the amplitude values and they indicated stress for the 4-6 minutes intervals. However, when the results were assessed based on MAAP-C07's own average (drawn in gray), the results showed that LF and HF values agreed on the stress of the child for the first 6 minutes of the interaction. Combined with the peak count and average amplitude values for the intervals, the results indicated that all the features agreed on the stress of MAAP-C07 for the 2-4 mins intervals (shown with "**" on Fig 2a and 2b). The results were also validated with the dominant emotion labels extracted for the determined time intervals. The detailed session statistics with the interval lengths in minutes, average LF, HF, peak count and amplitude values for the corresponding intervals, and the dominant emotion computed by the number of occurrence in the given time interval were presented in TABLE I for the 4th session. The selected threshold values for the evaluation of the physiological signals were MAAP-C07's individual averages computed from his overall session statistics. Additionally, the dominant emotion for his entire sessions were found out as "sad". The results extracted from all the modalities point out that MAAP-C07 was stressed between the 2-4 minutes of his interaction based on his average session statistics.

V. Conclusion

This study proposes a stress detection approach for children with ASD based on physiological data. The study focuses exclusively on the physiological data collected from children using an Empatica E4 wristband during their interaction with the robot Kaspar in different countries as a part of EMBOA project. The features of BVP (LF and HF) and features of EDA (peak count and amplitude) signals of children are used for stress detection in the study. The previously provided reference baselines are used for LF and HF features derived from BVP, and peak count and signal amplitude features derived from EDA data to detect the stress of children.This study will be a step towards affective social robots for the assistance of children with ASD. As a future work, the other modalities such as gaze and audio will be integrated to the study.



(a) BVP features for all sessions

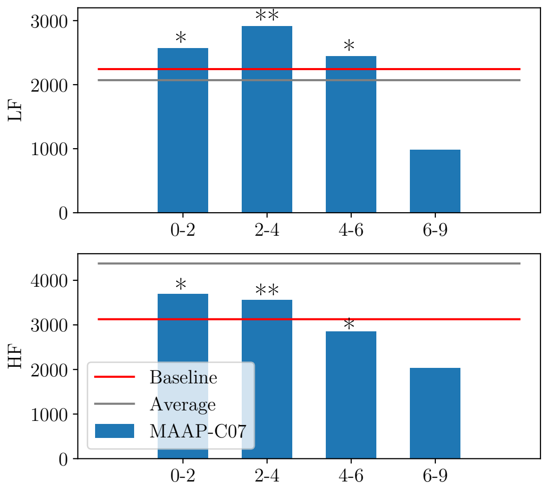


(b) EDA features for all sessions

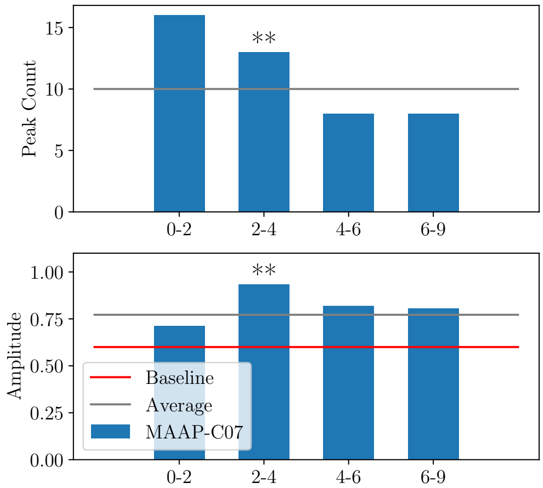
Fig 1: Session statistics for MAAP-C07

TABLE I: 4th Session Statistics for MAAP-C07

Interval	LF	HF	Peaks	Amp	Emotion
0-2*	2565.34	3691.96	16	0.7127	sad
2-4**	2912.78	3565.82	13	0.9349	sad
4-6*	2439.87	2852.65	8	0.8198	happy
6-9	980.68	2036.96	8	0.8049	happy
Baseline	2243.00	3127.00	25	0.6600	-
Threshold	1783.05	4062.36	10	0.7355	sad



(a) BVP features for the 4th session



(b) EDA features for the 4th session

Fig 2: 4th session statistics: (*) LF and HF agree on stress detection, (**) All features agree on stress detection

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