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The BioVid Heat Pain Database

Data for the Advancement and Systematic Validation of an Automated Pain Recognition System

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***Abstract*—The objective measurement of subjective, multi-dimensionally experienced pain is still a problem that has yet to be adequately solved. Though verbal methods (i.e., pain scales, questionnaires) and visual analogue scales are commonly used for measuring clinical pain, they tend to lack in reliability or validity when applied to mentally impaired individuals. Expression of pain and/or its biopotential parameters could represent a solution. While such coding systems already exist, they are either very costly and time-consuming, or have been insufficiently evaluated with regards to the theory of mental tests. Building on the experiences made to date, we collected a database using visual and biopotential signals to advance an automated pain recognition system, to determine its theoretical testing quality, and to optimize its performance. For this purpose, participants were subjected to painful heat stimuli under controlled conditions.**

Keywords: pain; quantification; heat; biopotential; facial expression; pain computing

I. INTRODUCTION

Pain is a very individual sensation that is difficult to interpret without any communication from the patient. Especially, when the patient is not able to utter on his pain experience (for example neonates [1], somnolent patients, demented patients [2,3,4]), a method for objective measurement would be beneficial, we see analysis of facial expression and biopotentials as a basis for such a measurement system. Under certain circumstances, the correlation found between subjectively experienced pain and tissue lesions or other pathological changes is low; the pain may even be completely unrelated. Therefore, the somatic pathology does not allow for any conclusions about subjectively experienced pain [5,6]. Children, older individuals and patients suffering from dementia present different pain thresholds, as well as a varying pain tolerance relative to healthy adults [3,7,8,9].

One central problem is the fact that there is currently no easy method to measure pain directly. The examining physician must rely on the patient's qualitative description about the location, quality and intensity of the pain sensation. It is possible to quantify pain with the help of the visual analog scale (VAS) or the numeric rating scale (NRS). However, these methods only work when the patient is sufficiently alert and cooperative, which is not always possible in the medical field (e.g., post-surgery phases). Overall, the methods are either considered inadequate or still in development [8]. If the conditions do not allow for a sufficiently valid measurement of the pain, treating the pain may lead to cardiac stress in risk patients, under-perfusion of the operating field, or to the chronification of pain. For example, 30 - 70% of patients report moderate to severe pain after surgery [10].

In the field of automatic pain recognition, the studies of the team around Cohn and Lucey [11,12,13] appear to be noteworthy, in addition to other studies [14,15,16]. Many studies (especially using fMRI and EEG) that have tackled the relation between pain and its central nervous system/peripheral-physiological correlate may be found in pure research.

However, to the best of our knowledge, studies aiming at a practical application of findings in the field of automatic pain recognition are virtually non-existent. Also to the best of our knowledge, no multimodal studies have to date been performed in this research area.

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Hence, the motivation of the present study was to develop a multimodal (i.e., based on biopotentials and video) data set, in which pain would be induced in different levels. Additionally we elicit emotions with the dimensional and discrete paradigm. We call the data set Biopotential and Video (BioVid) Heat Pain Database. The database is planned to be released for reserach purposes.

The aim of the study is to select the features and feature patterns that contribute to the highest recognition rate for pain recognition, quantification and dissociation from emotion. To this end, a range of data fusion procedures would be tested [17,18,19].

The study has unique properties:

- Highly-controlled pain stimulation
- Multiple camera setup
- Recording of depth information via a *Kinect-Camera*
- Multimodal detection, i.e., simultaneous data collection on skin conductance level (SCL), electrocardiogram (ECG), electromyogram (EMG), and electroencephalography (EEG)

II. METHODOLOGY

A. Participants

A total of 90 subjects participated in the experiment, which had been recruited from the following age groups: (1) 18-35 (N = 30; split half man/women); (2) 36-50 (N = 30; split half man/women); (3) 51-65 (N = 30; split half man/women). The subjects received an expense allowance. The study was conducted according to the ethical guidelines of Helsinki (there was an ethics committee: 196/10-UBB/bal.

B. Measured Parameter

1. Biopotentials: A Nexus-32 amplifier (http://www.mind media.nl) was used for recording biopsychological data during the experiment. Biosignals and event data were recorded via the Biotrace software. The following parameters were included in the classification (see Fig. 1) [20].

a) SCL: To measure the skin conductance level, two electrodes of the sensor were positioned on the index finger and ring finger. Since the sweat glands are innervated exclusively sympathetically, i.e., without influence of the parasympathetic nervous system, the electrodermal activity is considered a good indicator of the ”inner” tension of a person. This aspect can be reproduced particularly impressively by the observation of a rapid increase in skin conductance within one to three seconds due to a simple stress stimulus (e.g., deep breathing, emotional excitement or mental activity).

b) ECG: We measured the average action potential of the heart on the skin using two electrodes, one on the upper right and one on the lower left of the body. Common features of the ECG signal are heart rate, interbeat interval, and heart rate variability (HRV). The heart rate reflects emotional activity. HRV refers to the oscillation of the interval between consecutive heartbeats. It has been used as an indication of mental effort and stress in adults [21].

c) EMG: Electrical muscle activity is also an indicator of general psychophysiological arousal, as increased muscle tone is associated with increasing activity of the sympathetic nervous system, while a decrease in somatomotor activity reflects a predominantly parasympathetic arousal. We used two channel EMGs for corrugator, zygomaticus and trapezius muscles. EMG responses over facial muscle regions like corrugator supercilii which draws the brow downward and medialward to form a frown and zygomaticus major which elevates the corner of the mouth superiorly and posteriorly are expected to be active during pain stimulation. The activity of the trapezius is a hint of a high stress level which is to be expected during pain stimulation.

d) EEG: We measured 21 EEG channels including two EOG (horizontal, vertical) channels. EEG was recorded from 19 sites according to the 10/20 system using an Easycap. Ag/AgCl electrodes were placed at FP1, FP2, AFz, F3, F5, F7, F6, Fz, C3, C5, Cz, FCz, P3, P5, Pz, O1, O2, T7 and T8. The linked mastoid (A1, A2) served as a reference.

2. Video signals: For video recording we used setup (see Fig. 1). This allowed the study participant to move his head freely, while ensuring that his face is fully visible even in case of large out of plane rotations. We employed three AVT Pike F145C cameras, one directly in front of the study participant and two at the side. The latter captured a frontal face in case the participant turned his head 45° to the left or right, respectively. The Pike cameras were triggered synchronously at a frame rate of 25 Hz and recorded at a resolution of 1388 x 1038 colored pixels. To synchronize the video streams and the biofeedback data, we recorded a frequency divided version of the camera trigger signal along with the biofeedback signals using the Nexus device. Afterwards we automatically analyzed the recording of this known trigger signal to compensate for the offset and drift between the biofeedback and the Pike video recordings. Additionally, a Kinect Sensor was utilized from above the frontal Pike camera to record depth maps (640 x 480 pixels, ca. 30 Hz), color images (1280 x 1024 pixels, ca. 10 Hz) and the associated timestamps provided by the Kinect. Although the depth map resolution is not very high, the Kinect is a valuable sensor for head pose estimation that also has shown potential for facial expression recognition [22]. The Kinect and Pike video streams were synchronized manually by finding a kind of clapperboard action in both streams. These were used to correct offset and drift assuming a constant clock drift rate. All videos were encoded using the HuffYUV codec during the recording and transcoded to H.264 afterwards. The depth map streams are encoded in a lossless format.

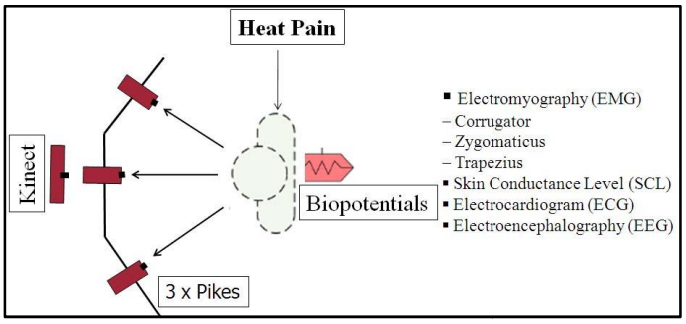

Figure 1. Experimental setting with heat stimulation and recording of biopotentials and video

C. Design of the experiment

For the pain elicitation we used a thermode (PATHWAY, http://www.medoc-web.com) at right arm (see Fig. 2). During whole experiment the participants sat in a chair, with his arms resting on the desk in front of him. With this kind of technology it is possible to elicit quantified pain under a high control condition without causing skin burns. The temperature of 50.5°C must not be exceeded.

Figure 2. Pain stimulation

All in all, we performed 6 sub-experiments.

1. Calibration of thresholds: At the beginning of the experiment we tested for every participant the pain (T_P) and tolerance thresholds (T_T).

Instruction pain threshold: *Please immediately press the stop button when a feeling of burn, sting, drill or draw appears in addition to the feeling of heat.*

Instruction tolerance threshold: *Please immediately press the stop button when you cannot accept the heat regarding the burn, sting, drill or draw any more.*

We use these thresholds as two pain levels and add two additional intermediate levels, thus obtaining four pain levels in total. The temperatures are equally distributed in the range between T_P and T_T (see Fig. 3). After the testing procedure, we calibrated the thermode software with the fourpain levels for the actual experiment.

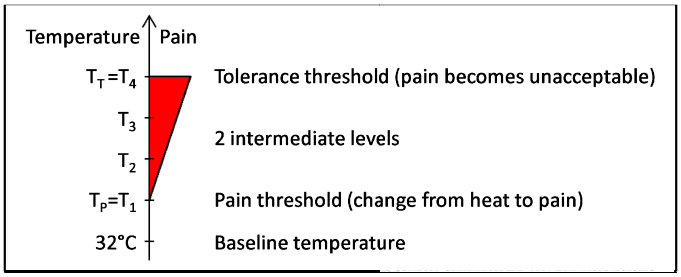

Figure 3. Elicited pain levels

2. Pain stimulation (I): For about 25 minutes, we randomly stimulated the participants with the four individual specific levels of pain (determined from the first experiment). Every level was stimulated 20 times, thus resulting in a total of 80 stimulations. Fig. 4 shows a temperature plot of a stimulus and the following pause. The maximum temperature of each pain level was hold for 4 s. The pauses between the stimuli were randomized between 8-12 s. The measurement was taken without facial EMG, in order for the electrodes on the face not to compromise mimicry recognition (video recording) and thus facilitate data fusion based on video recording and biopotentials.

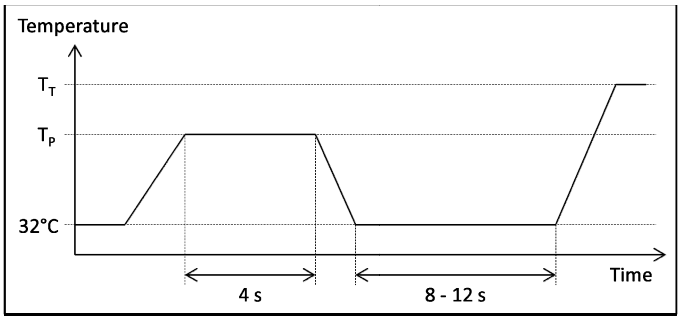

Figure 4. Heat stimulus and pause between stimuli

3. Posing basic emotion: The participants posed every basic emotion (happiness, sadness, anger, disgust, fear, pain) - with a case vignette - we measured the pose with 1 min.

4. Emotion elicitation with picture: We elicited an emotion via the International Affective Picture Systems (IAPS) based on the paradigm of the Valence/ Arousal/ Dominance space [23]. A total of 28 images were presented: 7 positive in valence/ low arousal, 7 negative in valence/ low arousal, 7 positive in valence/ high arousal, and 7 negative in valence/ high arousal.

5. Emotion elicitation with video clips: We elicited basic emotions (happiness, sadness, anger, disgust, fear) with videos clips [24]. Three clips were presented for each basic emotion. After every basic-emotion-presentation the participant selected the film with the strongest emotional content. Subsequently, a rating (1-9) was given for valence, arousal, joy, sadness, anger, disgust, and fear.

The emotion induction under point 4 and 5 is necessary in light of the fact that a classification of emotions and pain is to be tested.

6. Pain stimulation (II): The experiment (2) was repeated with facial EMG.

In Fig. 5 we describe the whole procedure of the experiment and the planned evaluation.

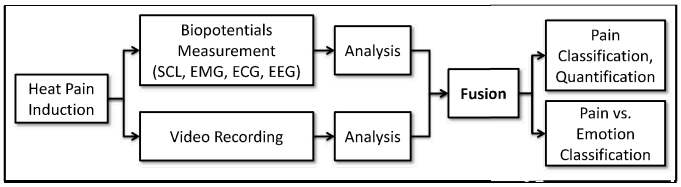

Figure 5. Procedure of the study

III. CONCLUSION/ PLANNED ANALYSIS

We have presented a newly collected multimodal data set to facilitate advances in robust recognition of pain and its intensity and in the dissociation of pain from emotion. Currently we are performing biopotential and video analyses, aiming at answering the following questions: (1) What kind of features and feature patterns are most relevant to the robust pain and pain vs. emotion recognition? (2) Which kind of multimodal data fusion has the most robust pain and pain vs. emotion recognition output?

All in all, we are advancing towards our vision of an automatic system for an objective measurement of pain which will facilitate pain monitoring, logging and support in a clinical environment. We think it is time to find a name for this kind of research. We call it "Pain Computing".

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