Emotion Measurement from Gaze in Playful Virtual Reality Interaction

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Abstract
Measuring human emotion from affective interaction is an important part of computing for mental health applications. Our work refers to non-obtrusive emotion measurement from eye tracking that gets increasingly ubiquitous, e.g., in Virtual Reality (VR) technology. We present a concept and first results of a feasibility study in which affectively weighted imagery of an image database is presented and integrated using discriminative observation, multi-object tracking and video-gaming. We measured attention preference for affective image classes and found relevant correlation with data extracted from a questionnaire on emotional states (MDBF) that would eventually substantiate basic valence classification from eye tracking data. The playful approach using the well-known concentration (pairs) game enables frequent repetition of the measurements in mental health care, therapeutic or pedagogical scenarios.

Author Keywords
Human emotion measurement; gaze analysis; virtual reality; affective imagery; videogame.

ACM Classification Keywords
H.1.2 User/Machine Systems - Human information processing.

Figure 1. Measurement of emotion using VR technology with built-in eye tracking and analysis of gaze behavior towards selected stimuli of an affective image database [9]. Participants manually select image pairs in a concentration game while gaze (red point on operator display) is tracked.

Introduction

Technologies for the measurement of human emotion play an important part in the impact of affective computing in human computer interaction [1,2]. Computing methods for emotion recognition have emerged from the analysis of a variety of multimodal sensors [3], such as, psychophysiological [4], EEG [5], electromyography [6], audio [7] and camera based facial behavior information [8,27].

The presented work refers to emotion measurement exclusively from eye tracking data in Virtual Reality (VR) technology. Eye tracking is a non-invasive technology that gets increasingly ubiquitous. The advantage of VR is the high degree of immersion of users towards artificially created stimuli. Methods involving affective feedback are first designed in VR technology and can be transferred onto other devices, such as, tablet PCs, smart-TV, and smartphone devices.

We propose a concept and first results of a feasibility study in which affectively weighted imagery of the GAPED database [9] is presented and integrated using discriminative observation, multi-object tracking and video-gaming. We measured attention preference for affective image classes and found relevant correlation with data of the MDBF questionnaire [10] on emotional states that would eventually substantiate basic valence classification only from eye tracking data. A playful approach using the well-known concentration (pairs) game enables frequent repetition of the measurements in mental health care [11] or pedagogical scenarios.

Related Work

Emotion plays a central role in the parametrization of human behavior, such as, in the interplay between emotion and cognitive control via the dual competition framework [12]. Emotion and motivation have an amplifying or inhibiting effect on the performance of human behavior, in particular, in attention driven tasks, and in this sense are intrinsically linked to eye movement analysis.

The capacity to regulate emotion is an important cognitive function for human adaptation, and the regulatory efforts largely determine the impact that some negative emotions will have on our mental health and physical well-being [13]. Mental health technologies have recently increasingly emerged from innovations in novel affordances in human-computer interaction [34] as well as in the measurement

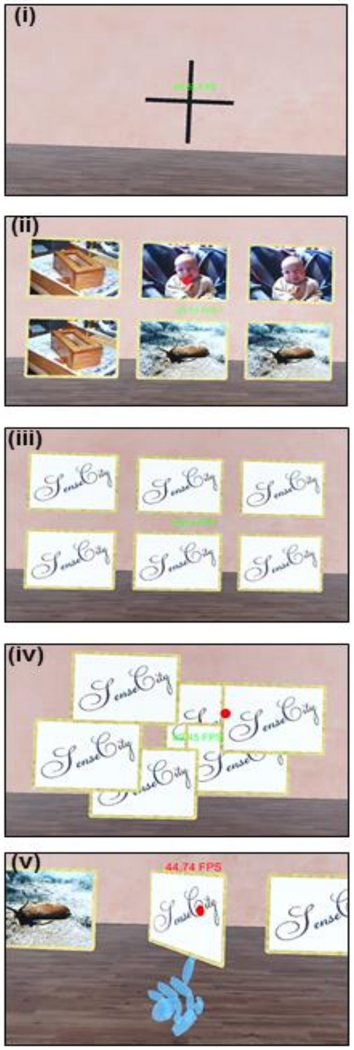

Figure 2. Playful emotion measurement stages: (i) initializing attention, (ii) eye tracking measurement phase with affective imagery, (iii) flipping cards, (iv) position change, (v) pairs game.

technologies [14]. Virtual reality has been widely applied in the assessment, understanding, and treatment of mental health disorders [15]. However, although neurological disorders can be diagnosed using eye movement analysis [16] - such as, for Alzheimer [17] and ADHS [18] – Virtual Reality and eye tracking has not been integrated for mental health at large.

The experimental link between eye tracking and emotion measurement has recently been discovered in the frame of neuropsychological research and affective image databases. [19] demonstrated that affective disorders can be precisely measured in eye tracking studies. In particular, participants with depression showed reduced orientation towards and focus on positive stimuli while having longer focus duration on stimuli with dysphoric content [20]. Research on persons without affective disorders but with sensitive emotional regulation in pre- or post-clinical state are also demonstrating differences in attention based processing of emotional stimuli. These investigations resulted in differences in pupil diameter behavior [21], visual search [28], and selection of positive and negative facial emotions [22].

The objective of the presented emotion measurement technology is to estimate the emotional state determined by a standardized questionnaire of emotion psychology [30]. Positive and negative affect are usually measured with the PANAS-X [23] to measure momentary emotional state. However, other dimensions, such as, arousal, are not analyzed. Therefore, this work refers to the MDBF questionnaire on emotional states [10] that is capable to determine affective dimensions of valence and arousal.

Serious games for mental health are seen as the groundwork for assistive technology to maintain and improve mental health [17]. Emotion plays a major role in the frame of process- or outcome-focused motivation [24] which is an essential parameter in healthcare oriented training processes. Emotion-oriented care can be more effective than standard care with regard to positive emotion in nursing homes residents with mild to moderate dementia [25]. Playful and personally unaware emotion measurement are preferred to subjective emotion statements, such as, in Pick-a-Mood [31] or SAM [32] since we assume higher potential for credible repetitions. The presented work therefore attains to start to bridge a gap to make everyday emotion sensing in mental health care possible, in a framework of playful diagnostics.

Playful Diagnostics with Affective Images

The emotion measurement technology is implemented using the well-known concentration (pairs) game. The objective of a game is to offer the opportunity to users to enjoy the game and in this sense gain emotional data more frequently for investigation.

Pairs game for emotion measurement

The game consists of the following stages (Figure 2):

i. Initialization by forcing a referenced focus of attention in the center of the display using a cross-hair symbol (3 seconds).
ii. Presentation of 3 pairs of different affective images of GAPED database [9] (10 seconds). The user should memorize positions of images since these will be moving in a later stage of the game.
iii. Flipping of the images and the backside of cards with unified appearance is shown. The user has to memorize by heart the position of the images.
iv. Synchronous motion of the cards to other positions that were randomly selected, via 3 separated motions, each with a duration of 3

Figure 3: Hand gesture (Leap Motion) for the selection of affectively weighted image 'cards'.

Figure 4: For the VR study a HTC Vive head-mounted device with built-in eye tracking from Tobii and Leap Motion sensor was used.

Figure 5: Hand gesture for interaction, such as, for progressing in the calibration procedure.

seconds. The user has to track the positions of memorized images along several motion stages.

v. Interactive selection of image pairs using an intuitive interaction tool, i.e., the user's own hands. By finger-tipping on the cards in virtual Space (Figure 5), cards are flipping back and the image is displayed. If the pair of flipped images does not match the user needs more attempts to flip the complete card set back. The user in this way can perform several errors.

Affective image database

There is one pair of each category, i.e., of (a) positively, (b), neutrally and (c) negatively weighted images, presented at the same time. The user should now memorize the positions of the images since these will be moving in a later stage of the game. The images that are triggering the emotion of users are selected out of the GAPED pool of 130 positive, 111 neutral and 126 (humans) as well as 131 (animals) negative images. There is no consideration about the individual weighting of the imagery. It is important to determine that *positions within the sextet are randomized so that no stimulus class is preferred by position*. In particular, over a sufficiently extended sequence of games, *stimuli are globally assumed to be uniformly distributed in value and position and sum up to zero triggering of specific emotions*. Therefore, only the *specific reaction of users* would enable to determine the specific emotion state during eye tracking.

Additional diagnostics

There are only emotion measurements during the (second) game stage with the presentation of images. The position changes are following a multiple object tracking test [26] paradigm that in addition tests the executive function of control of attention in space.

Experimental results

Technical specifications

Eye tracking was performed with a Tobii Pro VR with HTC Vive (display resolution 2160x1200, display refresh rate 90 Hz; Figure 4) headset mounted display (HMD) including a seamless eye tracking integration. The gaze data output frequency (binocular) is 120 Hz with estimated accuracy of 0.5 degrees. A 5-point calibration procedure was performed before the studies. A Leap Motion[1] sensor was used to track hand movements via 180x180 degrees (Figure 5).

Descriptive statistics

8 individuals (3 female, 5 male), age M=32.0 ± 8.8 years, participated in the study being naïve to the task. After insight and signature in the information consent they entered a sequence of approximately 25 rounds, each of 10 seconds observation time, on pairs with affective imagery. 22500 point-of-regards were stored with gaze time on areas of interest categories P (positive image), Z (neutral image) and N (negative image). None of the individuals reported motion sickness or any other degradation of well-being. After the VR session, the MDBF questionnaire was filled.

Inferential statistics

Table 1 depicts the individual results from the MDBF questionnaire [10] with resulting valence GS and arousal RU, mean observation times per task round and results from a feature function F(P, Z, N) = (P+N)/Z. Valence data in relation to data from feature function F(P, Z, N) provides a Pearson correlation coefficient r=0.449. Linear discrimination $\tau()$ with respect to a threshold on F() provides high accuracy in the valence classifier compared to the ground truth T(GS) with

[1] https://www.leapmotion.com

	GS	RU	P	Z	N	F	S	T()	τ()
TP1	35	38	2.49	2.08	1.20	1,78	3.83	1	1
TP2	33	32	2.23	2.18	0.83	1,40	3.73	0	0
TP3	35	33	2.83	2.13	1.08	1,84	3.42	1	1
TP4	37	38	2.10	2.45	1.88	1,63	3.50	1	1
TP5	24	27	2.62	2.81	1.50	1,47	3.89	0	0
TP6	40	37	3.08	2.63	1.47	1,73	4.19	1	1
TP7	34	35	2.52	2.90	1.19	1,28	3.35	0	0
TP8	33	27	2.12	2.37	1.43	1,50	3.38	0	0
M	33.9±4.3	33.4±4.2	2.5±0.3	2.4±0.3	1.3±0.3	1,58±0,18	3.7±0.3		

Table 1: Experimental results of the emotion measurements, analysis and classification. Emotional states of test persons TPi were estimated from MDBF questionnaires [10] with valence GS and arousal RU (MDBF long form). Eye tracking data in VR resulted in AOI mean gazing time for positive (P), neutral (Z) and negative (N) affective imagery (GAPED database [9]). A feature function F(P, Z, N) provides a Pearson correlation coefficient r=0.449. Emotion classification τ(F()) provides 100% prediction accuracy for positive/negative valence T(). Score S refers to the average number of trials to solve the pairs task.

T(GS) = 1 if GS>mean(GS) and 0 otherwise, and τ(F) = 1 if F>mean(F), 0 otherwise. It is noted that valence (GS) and game performance (S) did not correlate (r=-0.021) so that we conclude that *emotion measurements were not impacted by emotions from game play*. Limitations of the experiment are small number of cases, lack of consideration of gender bias [33], and lack of comparison with MDBF scores before playing.

Conclusions and future work

The presented early work on emotion measurement using VR technology and affective imagery provided first indication for successful estimation and the potential for emotion classification. This would provide a relevant tool for emotion measurements that are non-invasive, playful and therefore enabled more frequently as required for motivation analysis in mental health care [29]. Future work will focus on using larger populations to specify the accuracy of the measurement, studies to determine the required frequency for robust analysis, and profound eye movement analysis on (dis-)engagement behavior on affective stimuli.

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