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Affect Adaptation for Virtual Reality: A Review of Efforts in Affective Computing

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Abstract—As experiences continue to advance, recognizing, understanding, and responding to affective states is anticipated to become more important. Emotion-aware systems have significant implications for human-computer interaction. By responding to emotional feedback, experiences can become more personalized and improve usability. Virtual reality (VR) allows users to interact with a fictional world capable of evoking various emotions. Combining VR and affect adaptation is likely to assist user outcomes, for example, for learning or psychological benefits. There is a current lack of real-time solutions developed for affect adaptation, which refers to the system controlling the experience based on emotional feedback inference. This paper suggests a framework that uses deep Q-learning with offline training to identify and respond to emotion-related data, and it outlines future research directions. The aim is to summarize and discuss the challenges in affective computing to establish how affect adaptation can be applied to improve applications in VR.

Index Terms—Affective Computing, Virtual Reality, Affect Adaptation, Emotion Recognition, Human-Computer Interaction

I. INTRODUCTION

A. Affect Adaptation

Affect adaptation is the adaptation of game material to emotional or affective data from the player [1]. The approach involves applying emotion theory in designing experiences, and most often uses the classification of emotions to decide how the experience should change. Emotion is central to human-computer interaction, and there are many ways in which it is relevant to the use of technology [2]. The work of Croissant, Schofield, and McCall introduces a framework for affective interactivity [3]. This involves key steps for integrating emotional input, including identifying modalities (relevant input data), examining the relationship between users and measures, and operationalizing the measures. The second part of an adaptation framework is the design of emotion output, notably the stimuli for a target emotion. For the present work, the focus remains on integrating emotional input in

adaptation applications, with the main aim of improving user experience by emotionally connecting with the user.

B. Ethical Justification

As discussed in the work of Picard [4], emotions are personal and private and provide information regarding the most intimate motivations. There are outweighing benefits that can offer new possibilities regarding the use of technology with emotions. This point is particularly relevant to health care, including exposure therapy, mindfulness applications, incorporated into another field referred to as ‘positive computing’. Calvo and Peters [5] explain that positive computing encompasses interventions that focus on enhancing eight prosocial positive emotions: love, gratitude, hope, joy, forgiveness, compassion, faith, and awe. Moreover, Picard argues that humans routinely detect, recognize, and respond to emotions or manipulate them in ways that many individuals would consider highly ethical and desirable [4]. In a similar way that pioneers have successfully attempted to emulate traditional intelligence in digital systems, there is a reason to also focus on emotional intelligence to enhance applications. However, as Picard discusses, not all systems require emotional intelligence to achieve their purpose [6].

C. Section Overview

As a work-in-progress, this contribution outlines the current focus and offers insights into future research directions. In section II, we offer background to the field and introduce the importance of the affective loop. In section III, the most relevant examples are critically reviewed, including the challenges originally presented near the field’s conception. In section IV, we discuss the devised approach to a framework that adapts content to emotion data. Finally, section V concludes the main findings from the review and how this informed the approach to the affect adaptation framework.

II. BACKGROUND

A. Affective Computing

Affective computing involves the act of studying how human emotions are perceived and expressed, which in turn, informs the design of emotion-intelligent agents for improved communication with users. The field is explained by Picard [6] as computing that relates to, arises from, or influences emotion. Human physiology reaction relevant to emotions originates from the Autonomic Nervous System (ANS) and cannot be triggered or influenced by conscious or intentional control [7], [8]. This advantage is not present with other emotion recognition input data, including facial expressions and speech. The three major approaches have been defined by [9] for emotion recognition, including 1) analyzing facial expressions and speech, 2) peripheral physiological signals, and 3) brain signals recorded from the central nervous system.

B. Affective Loop

A core concept of affect adaptation is the affective loop. The affective loop describes the functioning of affect adaptation. The affective loop is a continuous cycle that involves

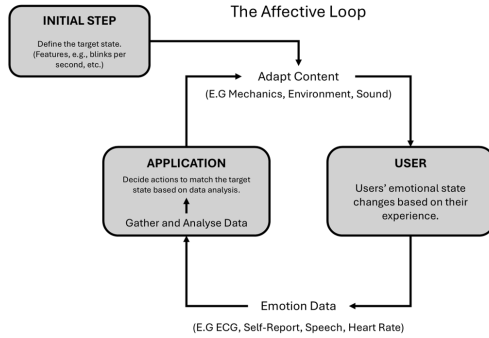


Fig. 1. A visualization of the affective loop, using an agent to select actions based on chosen emotion data features. E.g., blink rate or heart rate variability.

the application adapting content based on emotional input. The application influences the player's experience, and by detecting the emotional state, content is changed, replaced, or created to provide stimuli that match a target emotion or feeling. Lara-Alvarez, Mitre-Hernandez and Pérez-Espinosa [10] implement a serious game for teaching mathematics. The findings illustrate that certain emotions enable learning while others can negatively impact attention and focus. The work references the affective loop, giving a high-level overview of the process for affect adaptation, as similarly referenced by Yannakakis and Togelius in [11]. Using emotion data-related features to determine the intensity and content of the experience, the framework applies to applications that aim to increase emotion awareness and well-being improvements, as indicated by a similar study [12]. However, determining an affective loop implementation remains highly complex due to expression variability in users.

III. CRITICAL REVIEW

A. Review Methodology

Using a scoping review, this work summarizes the key developments of applied affective computing and identifies challenges for future discussions. Due to the nature of an emerging technology area in terms of commercialization and broader research, a scoping review is justified for identifying knowledge gaps, clarifying concepts, and informing future research. The question guiding this review is: What primary challenges must be overcome to enable the adoption of affect adaptation and similar techniques for virtual reality? The review established foundational sources, including the early work of Picard [6], the book *Applied Affective Computing* [13], and the VREED study [14]. A systematic search strategy was employed across multiple academic databases, including IEEE Xplore, ACM Digital Library and Google Scholar. The most relevant keywords included affective computing, emotion recognition, affect adaptation, machine learning, and virtual reality, and were used to identify relevant literature from 1995 to 2025. The initial search yielded approximately 38 results. These sources were screened by title and abstract to confirm relevance. Subsequently, a thematic analysis was conducted on the identified literature to synthesize the key developments, common methodologies, and recurring challenges within the field. We used the recent publication 'Applied Affective Computing' [13] to verify current state of the art, and to compare methodologies and practices with previous and current works.

See Table 1 for a sample of relevant sources found in the review. Modalities and features differ depending on the goals and rationale of each study, and there is limited consensus in the literature on best practices and methods.

B. Challenges

Picard explains the variability of emotions using [15] weather metaphor for how emotions are defined and experienced, [4]. Kagan describes the term 'emotion' as follows: The term 'emotion' relates to external incentives, thoughts, and changes in internal feelings, as weather is for the changing relations among wind velocity, humidity, temperature, barometric pressure, and form of precipitation. Using physiological measures to detect the affective states of individuals has been favored due to the unbiased representation of the autonomic nervous system. [16]. The authors also highlight that physiological signals are highly complex and sensitive to movement artifacts, and so the development of sensors, data acquisition, and classification needs to be advanced further.

C. Comprehensive Analysis

The work of Zhang, Fort, and Giménez Mateu [17] focused on using facial expression to recognize and interpret a user's affective state. To achieve this functionality, the authors have used MobileNet V2, suitable for running on resource-constrained devices, such as VR headsets. The authors' [10] game involves a player and a speaking scene. In the speaking scene, the user's voice is obtained via a prompt to speak, and the audio captured is then analyzed to determine the

TABLE I
A SAMPLE OF REVIEWED STUDIES THAT AIMED TO INVESTIGATE CLASSIFYING OR ADAPTING AN APPLICATION TO EMOTIONS.

Study	Modalities	Context
[14]	Eye-Tracking, Galvanic Skin Response (GSR), Electrocardiography (ECG)	Emotion recognition in virtual reality. Using the Support Vector Machine (SVM) algorithm to classify participant states according to the four quadrants of the circumplex model of affect.
[10]	Speech Analysis	Emotional states in educational games. Educational mathematics games controlling the level and aesthetic content according to player performance and emotional state.
[17]	Facial Expression	Facial emotion recognition in virtual reality. Utilized MobileNet V2 to observe several emotions, including neutral, happiness, sadness, and surprise.
[19]	Galvanic Skin Response (GSR)	Adapt the player's/enemy's abilities and the environment according to galvanic skin response and GSR. The work suggests that adapting games based on user affective state can increase excitement and potentially automate balancing the game difficulty.
[12]	Electrocardiography (ECG), Respiration, Electrodermal Activity (EDA), Electromyography (EMG)	Affect-driven procedural content generation in virtual reality for well-being improvement. Visual and auditory content are generated based on four emotional states (anger, fear, joy, and sadness).
[20]	Facial Expression, Speech Analysis	Analysis to enable computers to understand and respond to emotion. An in-depth review of using facial expression and speech to infer emotions.
[21]	Facial Expression, Speech Analysis	Introduces an artificial neural network (ANNA) developed for classification of emotional states. Focuses on applying emotion theory, measuring emotions, and exploring the potential for emotion-aware systems.

emotional state of the player. The authors [18] review the applications of eye-tracking for emotion recognition. Eye-tracking is the process of measuring where and when the user's eyes are focused, the point of gaze, and the size of the pupil. From the authors' survey, there is no clear indication of which eye features or combinations perform best. The exciting aspect of affect adaptation in virtual reality is that commercial hardware is beginning to involve more sensors, particularly those for eye and facial features. Speech analysis has also been demonstrated as a viable solution for supplying emotion-related input. The main caveat of speech and facial expressions is that several conscious factors can influence these measures [16].

D. Affect-Adaptive Applications

The work of [22] introduces an affect adaptive serious game 'Hiramon' that teaches the Japanese syllabary hiragana. To determine emotional arousal, the user's interaction with a graphics tablet was measured. The analysis included using machine learning classifiers, including random forest (RF) and support vector machine (SVM). The features extracted are in part due to the user's hand gestures. Using a combination of self-reports, in-game performance, and input parameters, emotions were continuously predicted, allowing for the rule base to be dynamically changed to be personalized for the individual. One criticism of the author's work is that they do not outline adaptation at length, but it can be assumed that the game adapts to difficulty based on user emotional feedback. Moreover, the authors point out that the work does not show how the approach of emotion-based adaptivity impacts players.

There are various components of games that can be adapted via affect feedback, including characters/NPCs, the environment, or difficulty. The authors [19] created a custom zombie level that was adapted by determining the user's emotion

based on Galvanic Skin Response (GSR). The work details how each component was adapted, including varying player speed and rate of weapon fire, adapting the density of fog in the environment to obscure the player's vision, changing environment health pack rates, and altering the speed and rate of enemies. As well as Galvanic Skin Response (GSR), the experience was adapted based on performance (player deaths and eliminations) and experience (mean GSR and self-reports of competence and enjoyment). This example shows that physiological signals do not have to be the primary and singular source to infer emotions. The authors suggest refraining from adapting to the challenge of obstacles/enemies, as a key finding of this research is that adapting these elements based on affective feedback can impede the player's feeling of competence. Instead, it is recommended to focus on adapting player mechanics and the environment.

IV. DISCUSSION

A. Approach to Affect Adaptation

The case for using virtual reality as a testing ground for future affect adaptation applications is promising. The presence as a 'gateway' theory suggests that more intense emotion can occur when the user is immersed in their surroundings and situation [23]. Evidence indicates that virtual reality introduces presence for the user [24]. The authors argue that presence can be enhanced when users create their own narratives about events.

To develop a framework that can understand and therefore adapt accordingly to emotion data, understanding emotions and how certain stimuli can impact a user's feelings is a significant component. The most common approach to understanding emotion is the evolutionary theory, that humans developed emotions for survival [23]. Another popular conjecture is the use of universal emotions that coexist across cultures and

Research Roadmap

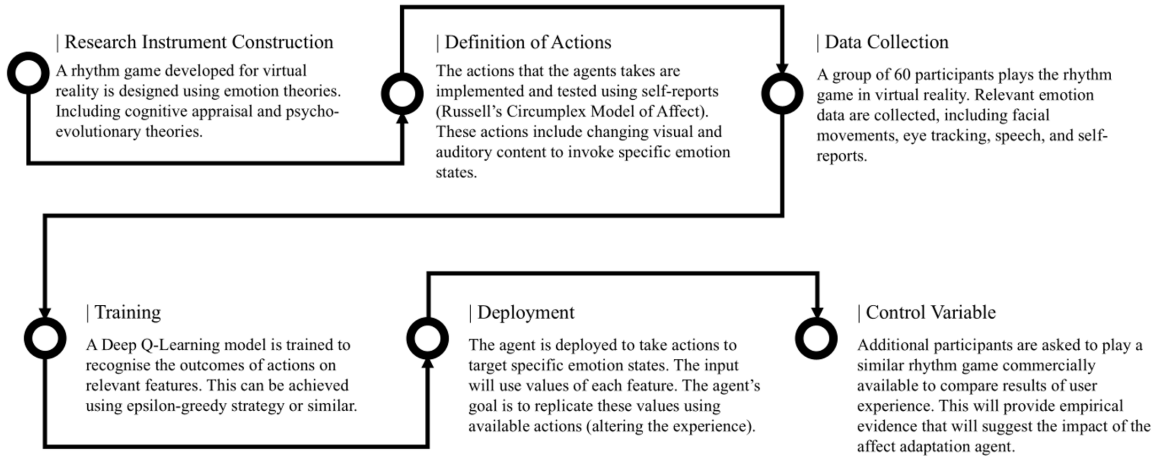


Fig. 2. A roadmap of each phase for developing the future research and agent. For training, with each participant, it is expected that the agent will take a set number of actions to benefit accuracy. An action refers to altering the experience through visual, audio or game mechanic means.

geography [24]. These theories should have an impact on how content is modeled and generated for the user, as developing content from a stimulus approach will afford better emotional data feedback.

B. Proposed Methods

Affect adaptation frameworks should be heavily inspired by the affective loop introduced by [25]. Researchers should choose methods that benefit validation and replication efforts. It should be the aim to use specific and identifiable sensor equipment. Sensors should be unidentifiable and non-intrusive to avoid impacting immersion. Self-reports will be used to design content that elicits a variety of states as a first step. The main measurement for state validation has been Russell's Circumplex Model of Affect [27]. Most distinguish emotion recognition as a dependency for affect adaptation, as seen in this example [21]. As established, emotion does not follow strict rules. Users may react differently to stimuli based on several uncontrollable factors such as background or lived experience. Classifying emotion is also difficult, as states vary in situations and backgrounds, thus, theories such as Ekman's basic emotions exist, [26]. In the proposed method, the agent is rewarded for selecting actions that result in target features, such as number of eye fixations or facial expression within a given time frame. A reward feedback includes taking actions according to a strategy (such as epsilon greedy). The objective, informed from the review, is to implement a framework that can offer new potential in various domains, as suggested in [13], including healthcare, education, and entertainment. It is not yet clear how systems should be integrated into these areas, both for performance, user experience, and from an ethical perspective.

C. Suggested Methodology

The suggested methodology involves testing a developed affect-adaptive game using a proposed framework against a similar but non-affect-adaptive game. The inquiry will follow how participants respond to both scenarios and aim to determine the efficacy of the implemented content recommendation systems. To achieve this feat, the following observations are relevant:

- Qualitative user self-reports on overall satisfaction, immersion, emotional feeling, and experience from both scenarios.
- Application response to defined input measures (facial movements, eye-tracking, and speech synthesis).
- Difference in levels of engagement and boredom between the affect-adaptive game with the non-affect-adaptive game.

The proposed study involves an agent trained using the Deep Q-Learning (DQN) algorithm. The goal of the agent is to select appropriate actions that guide the player toward a desired emotional state. Each action modifies specific aspects of the game content such as audio, visuals, or gameplay mechanics to elicit emotional responses. These changes could include genre of music, a type of background or different interactions for increasing score. The agent receives a reward when its selected actions produce emotion-related features that match the target state. Training data will be collected from participants playing a rhythm game in virtual reality. The agent is trained offline and learns the actions that will likely result in target features.

- Sensors must be commercially available or 'off-the-shelf' to aid in efforts to enable replication for validation and further experimentation.
- Movement anomalies or artefacts must not interfere with adaptation processes.

TABLE II
CONSIDERED DATA COLLECTION METHODS FOR MEASURING EMOTIONS, SCREENING PARTICIPANTS AND THE IMPACT OF ADAPTED CONTENT ON THE USER'S FEELING AND EXPERIENCE.

Reference	Data Collection Method	Description
[29]	PHQ-9 Questionnaire	Ensures participants do not possess depressive symptoms that may cause result bias.
[30]	Motion Sickness Susceptibility Questionnaire (MSSQ)	Screening questionnaire to avoid participants that suffer from motion sickness in the study due to VR environment.
[31]	User Experience Questionnaire (UEQ)	Measures attractiveness, perspicuity, efficiency, dependability, stimulation and novelty.
[32]	Cognitive Load Scale (CLS)	Important to establish if the affect-adaptive application is more chaotic compared with the non-adaptive games. This could be caused by the agent selecting actions that inhibit more reactions to satisfy the reward function.
[33]	Computer System Usability Questionnaire (CSUQ)	Measures usability and the impact the agent has on understanding through adaptation of game mechanics.
[34]	IGroup Presence Questionnaire (IPQ)	Establishes the scale of presence and immersion for each application. More presence in the affect-adaptive application will likely indicate better immersion due to the targeting of emotion states.
[35]	Unified UX in IVE questionnaire (IVEQ)	Used to specifically measure user experience in virtual environments. Measures presence, immersion, usability, emotional response, cognitive load and embodiment.
[36]	Self-Assessment Manikin (SAM)	Pictogram survey measuring valence (positivity of emotions), arousal (strength of emotions) and dominance (the rate of control the user feels over the emotion). (Data Acquisition Stage)
[37]	Positive and Negative Affect Schedule (PANAS)	Measures positive and negative mood post-exposure to the VR experience. The aim is to determine the impact of adaptation on the user's enjoyment of the experience. (Deployment Stage)

- Measurement equipment should be non-intrusive and not impact usability.

The hypothesis is that with the ability to target and evoke specific emotions, the user experience will be improved, resulting in higher ratings of immersion, satisfaction, and personalization [28].

D. Data Collection Methods

For the training of the agent to take optimal actions that result in targeting emotional states, the following measurements have been identified.

- Speech
- Facial Movements
- Eye-Tracking
- Self Reports

To ensure that the agent is unbiased to deficiencies in emotion regulation or motion sickness, participants will need to be screened.

E. User Experience Measures

The findings of this research will involve assessing the differences in satisfaction, immersion and usability between the three applications.

- Designed VR Rhythm Game (Non-Adaptive).
- Designed VR Rhythm Game (Affect-Adaptive).
- Commercially available VR Rhythm Game (Non-Adaptive).

Moreover, relevant questionnaires have been included to measure emotions during the data acquisition stage and the deployment stage. The deployment stage will also measure the difference in emotional feeling and stimuli to make comparisons that could indicate if one application results in more emotional activity than another.

V. CONCLUSION

A. Problems of Affect Adaptation

Three problems with current adaptation methods have been identified from the literature review.

- Systems rely on emotion recognition as a dependency for affect adaptation [22], [38].
- Current methods, sensors, and setups negatively impact an application's usability and are unsuitable for widespread adoption [22], [39].
- The impact of affect adaptation is unclear, and although many studies argue that the approach enhances user experience, results are limited [1], [40].

B. Contributions

This work identifies three key challenges concerning future efforts for affect adaptation. Virtual reality is the most applicable scenario for testing affect adaptation systems. The proposed methodology is a novel approach to affect adaptation as it does not use emotion recognition as a prerequisite for performing adaptation. The qualitative data tools that are recommended are helpful for practitioners to establish the impact of affect adaptation on user experience, particularly in virtual reality. Reinforcement learning can ease the adoption of affect adaptation in applications more broadly.

C. Future Work

Upcoming work will focus on developing a reinforcement learning approach for affect adaptation using identified measures in virtual reality, and prioritizing user-centered design and limited sensor intrusiveness to further applicability and usability. Future research should endeavor to experiment with new methodologies for adapting experiences to emotion, as there is inadequate evidence concerning the usefulness of affect adaptation in current literary works.

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