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Towards Emotionally-Adaptive Virtual Reality for Mental Health Applications

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***Abstract*—Here we introduce the design and preliminary validation of a general-purpose architecture for affective-driven procedural content generation in Virtual Reality (VR) applications in mental health and wellbeing. The architecture supports seven commercial physiological sensing technologies and can be deployed in immersive and non-immersive VR systems. To demonstrate the concept, we developed the "The Emotional Labyrinth", a non-linear scenario in which navigation in a procedurally-generated 3D maze is entirely decided by the user, and whose features are dynamically adapted according to a set of emotional states. During navigation, affective states are dynamically represented through pictures, music, and animated visual metaphors chosen to represent and induce affective states. The underlying hypothesis is that exposing users to multimodal representations of their affective states can create a feedback loop that supports emotional self-awareness and fosters more effective emotional regulation strategies. We carried out a first study to (i) assess the effectiveness of the selected metaphors in inducing target emotions, and (ii) identify relevant psycho-physiological markers of the emotional experience generated by the labyrinth. Results show that the Emotional Labyrinth is overall a pleasant experience in which the proposed procedural content generation can induce distinctive psycho-physiological patterns, generally coherent with the meaning of the metaphors used in the labyrinth design. Further, collected psycho-physiological responses such as electrocardiography, respiration, electrodermal activity, and electromyography are used to generate computational models of users' reported experience. These models enable the future implementation of the closed loop mechanism to adapt the Labyrinth procedurally to the users' affective state.**

***Index Terms*—Emotion regulation, physiological computing, physiology-driven VR, procedural content generation.**

I. Introduction

During the last two decades, Virtual Reality (VR) has been extensively applied to the treatment of mental health disorders [1], [2]. For instance, VR has been used in the treatment of anxiety disorders [3], [4], addictions [5], [6], and eating disorders [7]–[9], with very promising results. However, current VR-based treatments are mostly based on the use of pre-defined scenarios that are "fixed" for all patients, thus providing limited possibilities for personalizing treatment [10], [11]. In some cases, VR is combined with biofeedback strategies to inform the patient on his/her internal state. For instance, many virtual biofeedback approaches for mental health have in common the training of emotion regulation [12]–[18], as this is an essential feature in the treatment of several psychological conditions [19]. As an example, anxiety disorders and depression share impairments in emotion regulation. Namely, patients show a limited ability in suppressing negative emotions and/or re-evaluating emotional stimuli (reappraisal) to modify affective reactions [20]. Dysfunction in emotion regulation is also common in maladaptive and risky behaviors such as those related to eating (e.g., binge and fasting), as well as sexual disorders and substance abuse [21]–[23].

In the biofeedback approach, the patient is presented with information about changes in his/her physiological activity, i.e., in the form of virtual objects that dynamically change their shape typically according to variations in heart rate. The goal of this technique is to help patients gaining greater awareness about their bodily reactions and learn how to modify them voluntarily. In fact, changes in physiological signals such as heart rate, respiration, blood pressure, electromyogram, electroencephalogram, and electrodermal response have been related to specific emotional states [24]–[26]. For example, decreases in heart rate variability have been associated with fear, joy, and sadness [25], and higher skin conductance with negative anticipation and stress [27]. Hence, real-time analysis of physiological signals could be used to infer the emotional states experienced during VR interaction and to adapt the elements of the virtual scene in accordance [28]–[31]. In some applications, the biofeedback component has been combined with gaming features to enhance the patient's motivation in performing the task [14], [15], [17].

The body of research on VR and game-based applications for

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mental health using physiologically driven biofeedback is large and growing, although its impact is still limited [32]–[36]. VR-based biofeedback has been applied to the treatment, management or prevention of stress-related disorders with a large focus on Post-Traumatic Stress Disorder (PTSD) [29], [32], [37]–[41]. For example, Bouchard et al. studied the impact on stress management in soldiers of a video game with visual and auditory biofeedback based on heart rate and skin response, in a controlled study with 41 participants [37]. Stress was measured through salivary cortisol and heart rate, and the results showed more effective stress reduction in the video game condition when compared to standard training. A different system uses a game (StartleMart) that combines exposure therapy, stress inoculation training, and the measure of skin conductance and blood volume pulse to personalize PTSD treatment [41]. A study with 13 veteran soldiers that used this system showed that the physiological responses to the game were correlated with the severity of the diagnosis, showing the potential of this tool for personalized treatment [42].

Anxiety treatment and prevention has also been widely addressed using VR-based biofeedback [12], [13], [43]–[45]. For example, a phase-2 controlled clinical trial with 25 patients with general anxiety disorder, showed some evidence that VR combined with biofeedback could potentially be more effective than VR without biofeedback in reducing anxiety as measured by physiological and self-assessment measures of anxiety [44]. In a study on anxiety prevention, Scholten et al. studied the impact on anxiety reduction in adolescents of a 3D biofeedback game that captures heart rate through a sensor attached to the player's fingers [12]. Seventy adolescents used this game for three weeks, and the results were compared to a control condition where a standard PC game was used. Although overall there were no significant differences between groups on anxiety levels at post-test, adolescents that used the biofeedback game showed a steeper decrease in personalized anxiety symptoms. An interesting approach is the one proposed in Nevermind [14], a horror-themed biofeedback game. Heart rate variability is measured, and higher levels of stress make the game more difficult and more disturbing. The goal is to have users improving their emotion regulation skills to better deal with stressful situations.

To a lesser extent, there is also work on physiology-driven adaptive approaches for eating disorders [15], [46]. addictions [16], and depression [43], [47]. For example, Claes and co-authors used a video game (PlayMancer) that uses physiological sensing (heart rate, respiration, blood flow) and facial recognition to modify game elements and difficulty levels, in a study with patients with eating disorders [15]. The results showed that the participants that used the game displayed less facial expression of anger during the interaction. The same game was used in a 16-weeks intervention that combined cognitive behavioral therapy with the game in gambling disorder, with significant changes in impulsivity and anger expression [16].

However, despite the extended use of physiological data for VR-based biofeedback, the detection of even basic emotions in VR is still a major challenge. Algorithms are not reliable and generalizable because of the high variability and overlap of physiological patterns, and the multimodality of emotional experiences [48]–[50]. Some classification algorithms are addressing this limitation by combining different physiological responses to infer emotional states [25], [51], [52]. Nevertheless, further work is needed to identify robust correlates of affective states that can be used in a variety of contexts. Because of these limitations, up to now, the use of physiological data in VR has been mostly limited to biofeedback applications, typically consisting of very basic biofeedback scenarios, using simple feedback cues or task adaptations. What if we had a technology able to dynamically generate the virtual environment according to the affective states experienced by the patient? We argue that this scenario could benefit different mental conditions, with emphasis on those disorders in which distortions in emotion regulation plays a central role. We propose to advance state of the art in VR-based biofeedback applications using Procedural Content Generation (PCG), where the content of the virtual environment is created algorithmically [53], [54]. To our knowledge, currently there are no frameworks for designing and implementing emotionally-adaptive VR experiences relying on physiology-driven PCG [55], and the few existing approaches are designed for physical rehabilitation, but without biofeedback [56], [57] or without PCG [58]. To address this gap, here we propose a novel framework that through PCG, contents of the virtual environment are generated and adapted at runtime according to the users' affective states, which are detected via the analysis and classification of physiological signals collected through wearable biosensors. This framework faces two major challenges: (1) the design and implementation of procedural virtual content generation techniques with a valid emotional charge, and (2) the adaptation of the virtual environment in real-time to the users estimated affective state through psycho-physiological variables.

In this paper, we present a framework that addresses the above challenges. Its current implementation supports seven different physiological sensory technologies and can be deployed in standard PCs or immersive VR systems such as Head Mounted Displays or CAVEs. Next, we present the Emotional Labyrinth, a first prototype developed using the framework. We also describe the results of a study to validate the system's ability to elicit four emotional states (anger, joy, sadness, and fear) in healthy participants through the procedural generation of emotionally-controlled audiovisual stimuli. Finally, models of subjective experience are presented from cardiorespiratory, electromyography and electrodermal signals. These models are used to identify psycho-physiological correlates of users' experience that can enable in the future the emotionally-driven adaptation of the procedural virtual environment.

II. Framework

The proposed framework for an affective-driven PCG in VR consists of three modules (Real-time Affective State Estimation, Event Trigger Computation, and Virtual Procedural Scenario) in a closed loop (Fig. 1). The *Real-time Affective State*

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Estimation module encompasses the acquisition of physiological signals (e.g., heart rate) from sensors and their processing for classification of the affective state. The *Event Trigger Computation* module uses the affective state estimation to define a set of rules (triggers) that establish the timings and parameters of when and how the VR content should be modified. The *Virtual Procedural Scenario* module responds to the triggers and modifies the virtual environment with a wide variety of content generated procedurally. Hence, the content is different for each user and each execution of the application. Finally, the biofeedback loop is enabled by presenting the resulting VR content according to the user's affective state. Thus, the biofeedback loop can in its turn influence the state of the user, revealed by the physiological variables that are being monitored, resulting in a new cycle with new changes to the environment. Through this approach, the experience unfolds dynamically by the interaction of the user with the environment through the interpretation of physiological signals, and not by predefined programmed scenarios and conditions.

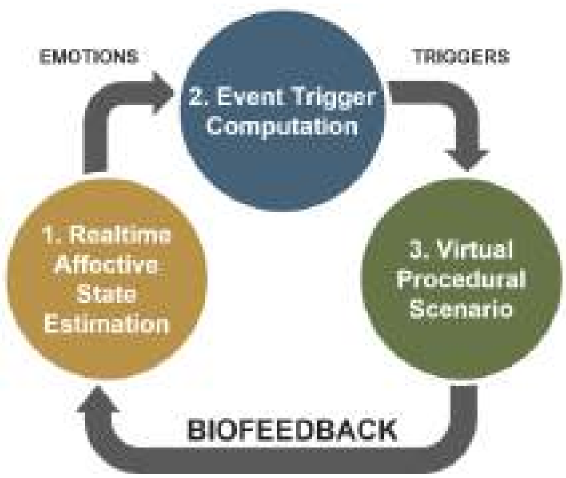

Fig. 1. Our conceptual framework for the emotionally-adaptive VR architecture.

A. Architecture

The architecture has been designed as a generic framework to support an unlimited number of procedural virtual scenarios. It has been developed in C# using Unity3D (Unity Technologies, San Francisco, USA). This tool provides the necessary functionality to build an integrated solution that comprises real-time signal acquisition, a decision-making system, and the procedural generation and modification of VR content to implement applications with the proposed architecture (Fig. 2). The renderer module was developed with the VRTK library, that implements body physics, locomotion, 2D and 3D controls and enables interacting with the Unity 3D UI elements through pointers or touch. It natively supports seven different physiological sensor systems and both immersive and non-immersive VR technologies. It supports HTC Vive (HTC, New Taipei City, Taiwan) and a custom-made CAVE, with support to be executed as a traditional desktop application.

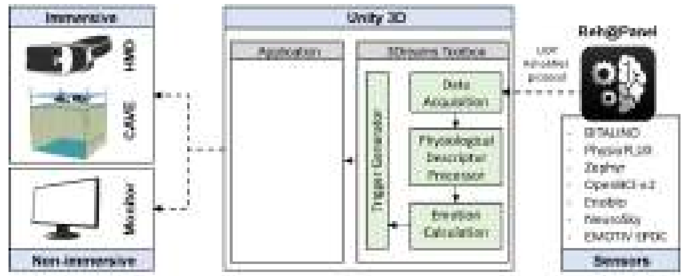

Fig. 2. The software architecture is implemented in Unity, uses the Reh@Panel software toolkit for physiological sensing, and can be displayed in both immersive and non-immersive VR.

1) *Real-time Affective State Estimation*

The primary goal of this module is to infer the affective state from physiological signals that are being measured from the user. This module is implemented using the Reh@Panel software toolkit, a tool designed to facilitate the interfacing of sensors in VR applications *[59]*. Signals that can be measured include among others heart rate, electrodermal activity, or breathing rate. This toolkit supports multiple commercial physiological sensors (BITALINO, BioSignalsPLUX, Zephyr, OpenBCI, Enobio, NeuroSky, EMOTIV EPOC). Sensor data are sent to the module over the UDP protocol. Connection through this protocol allows easy scalability of the supported hardware; new devices can be easily incorporated with low programming effort. Emotion classification algorithms should be implemented in this module to infer the affective state from the acquired physiological signals. The output of this module is structured information that provides labels for the affective states (for example, joy), their intensity and range of values. It is important to highlight that this module does not consider any specific algorithm. The labels and their intensities will depend on the particular implementation used for each application.

2) *Event Trigger Computation Module*

The objective of this module is to enable the construction of the rules that should trigger modifications of the virtual environment in response to the output of *the Realtime Affective State Estimation* module (i.e., detected affective state and its intensity). Changes in the virtual environment are event-driven and always occur in response to a trigger. Specifically, triggers are responsible for generating, modifying, or deleting content in the current virtual scene. Triggers and their behavior are defined at the implementation level and executed during application runtime while interacting with the virtual scenario.

There are two types of triggers, collision-based, and time-based. The moment they are triggered defines the exact moment in which the *Realtime Affective State Estimation* module should process a new output to generate changes in the scenario. In the case of collision-based triggers, the recalculation of the scene is done only when there is physical contact between two objects in the virtual scene; for example, when the user reaches a certain point inside the world map. On the other hand, time-based triggers are used to update the scenario periodically at a specific time or intervals regardless of the events occurring in the scene. The use of triggers allows us to efficiently implement multiple scenario adaptations simultaneously running at different update frequencies or driven by discrete events resulting from the interactions in VR. Hence, the triggers allow defining and controlling the occurrence of VR changes in a systematic way. When raised, a trigger sends a package that contains the information concerning the specific trigger. Since there can be multiple triggers coexisting at the same time, this information allows a listener to identify and filter which trigger was activated and act accordingly.

A trigger does not only signal a time or collision event, but it also carries the responsibility to perform a computation when it is triggered. This computation can be rule-based or algorithmic and determines if a specific condition is met. For instance, suppose that the intensity of four emotions is being calculated by the *Affective State Estimation* module, there could be a time-based trigger every five seconds that applies a simple rule to compare the current emotion intensities and pick the highest intensity one. This trigger would raise events periodically sending packets with the detected emotion and a value with its intensity. A listener would then receive the trigger and implement the corresponding changes in the VR scenario.

3) Virtual Procedural Scenario

This module is responsible for the graphical content of the application. It is procedural because it is accountable for the generation of entities inside the scenario that are controlled algorithmically. This approach allows creating very different VR experiences from the same construction patterns using pseudorandom generators *[60]*. This module addresses the responses of the events that are raised in the *Event Trigger Computation* module. When a new trigger is activated, it reaches all the elements that are listening to that specific event, that act as observers. Any element inside the scene can be an observer of one or multiple triggers. When a trigger is raised, the observers that are registered to that event will execute a specific behavior that implies generation, change or deletion of its properties in a procedural manner. Hence, the intensities of affective states are transferred to the scene via triggers to change the environment.

III. Application: The Emotional Labyrinth

The Emotional Labyrinth is the first application that we developed to demonstrate the potential of the previously-described architectural framework. It consists of a procedurally-generated 3D maze whose shape and features are dynamically adapted to the emotional states of the user. The user explores the maze while visual and auditory features are procedurally generated according to four emotional states (Anger, Fear, Joy, Sadness) and changes in cardiorespiratory, electrodermal and electromyographic signals are being recorded. These four emotions were selected as they have been extensively operationalized and studied in numerous psychological experiments [61], [62], and have long been considered necessary for the regulation and basic cognitive mechanisms [63] and their regulation has been related to basic mental disorders [19]. The goal of the application is to expose the participant to procedurally generated audio-visual VR content to induce specific user's emotional states, which in turn trigger the generation of new emotional stimuli, in a closed-loop approach. The underlying hypothesis is that by visualizing their affective states, users can develop new strategies to recognize and regulate their emotional states.

A. Mechanics

At the beginning of the experience, the user is placed at the starting point of one procedurally generated labyrinth. The goal is to move through the maze until an exit point is reached. During the exploration, the labyrinth generates audio-visual stimuli specifically tailored to affect the emotional state of the user. These stimuli include images, music and procedural changes to the environment such as fire (anger), blooming flowers (joy), rain (sadness), and obscurity (fear). The experience finishes when the user reaches the exit point of the labyrinth. The main concept behind the stimuli is that, to train self-regulation, these should be able to trigger controlled changes in the affective state of its users. The application can be run either in the "adaptive" mode or the "non-adaptive" mode. In the non-adaptive modality, the complexity of the labyrinth is determined by the experimenter, as well as the presence and type of affective audio-visual stimuli. In the adaptive modality, the generated stimuli are directly determined by the measured affective state of the user and are used also to represent this state. Hence, the adaptive version of the Labyrinth requires the user to drive changes in the virtual environment through an effort of self-regulation of his/her own affective state.

B. Virtual Procedural Scenario

In the Emotional Labyrinth, both the maze and visual and auditory stimuli are constructed and modified procedurally.

1) Procedural Labyrinth Generation

The maze is the largest element of the virtual environment. It is the structure the user navigates, and it hosts all the objects in the scenario. In the literature, different algorithms from graph theory have been proposed for the procedural generation of mazes including recursive backtracker, Kruskal's and Prism's algorithms and recursive division and binary trees [64]. We decided to implement an algorithm called depth-first search which is based on the recursive backtracking method [65]. This algorithm provides a high construction variability and a fast generation time, essential features for real-time systems like the Emotional Labyrinth. The original algorithm uses the number of columns and rows as input parameters to generate the 2D labyrinth; we extended the algorithm to include additional features such as the height of the walls and width of the passages. These parameters define the shape and difficulty of the maze. Because of the pseudo-randomness applied to each step of the construction procedure, even when the same parameters are used, the resulting labyrinth will always be different. This prevents a learning effect and ensures high levels of replayability, a requirement for a system like this designed to be used repeatedly by the same user. The maze is built using prefabricated objects: one wall and one floor tile, which are combined algorithmically to generate long, short, narrow, wide, tall, or small labyrinths, always preserving the appearance of continuity between the building objects (Fig. 3).

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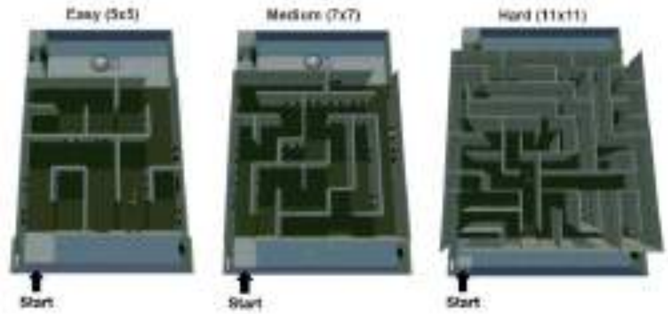

Fig. 3. Top-view of the mazes created at runtime using the depth-first search algorithm for different complexities.

2) Procedural audio-visual stimuli and affective metaphors

The audio-visual elements in the Emotional Labyrinth were designed with carefully chosen stimuli to represent and induce emotional states. Three types of stimuli are used: pictures, background music, and visual metaphors of emotions:

a) Pictures: Pictures are displayed as framed paintings hanging from the walls of the labyrinth. These change dynamically according to the emotion intended. Pictures were selected from the International Affective Picture System database (IAPS), that consists of a vast repository of images that have been rated for valence and arousal [61]; these images have been evaluated as able to elicit the target emotions. These stimuli have been extensively studied and validated using a similar protocol as used in this experiment, and have also been used with clinical populations such as bipolar disorder [66], anorexia [67] or borderline personality disorder [68]. A total of 54 pictures were selected for their capacity to elicit anger (10), fear (15), joy (15), and sadness (14) following the classification proposed by [58]. Paintings are positioned on the walls procedurally after the labyrinth is created (Fig. 4). Thus, the location of the frames on each execution is different.

(b) Background Music: Soundtracks were selected from the International Affective Digital Sounds (IADS) database [62], which includes validated labeled emotionally-evocative sound stimuli. We selected 51 sound stimuli related to anger (11), fear (10), joy (20), and sadness (10). Every time a trigger is raised, one track from the list of the corresponding emotion is randomly chosen.

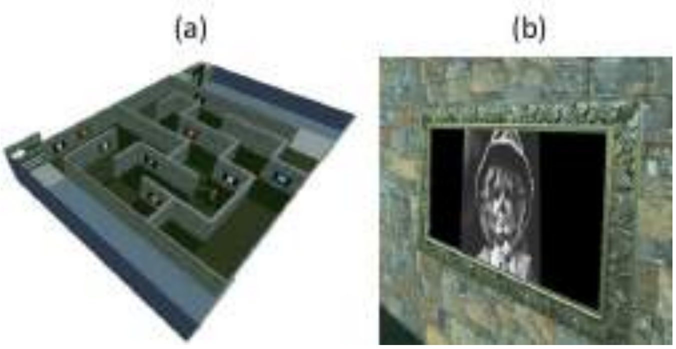

Fig. 4. Emotionally-evocative pictures on the walls of the labyrinth (a) presented as framed paintings (b). For illustration purposes, IAPS images have been substituted by visually similar ones with a Creative Commons license.

(c) Visual Metaphors of Emotions: The visual metaphors used to convey the representation of the user's emotions are derived from metaphors used in verbal language. A study by Verspoor [69] served as a reference to identify metaphors that represent each emotion. Based on this preliminary work, we defined a visual metaphor for each emotion: fire represents anger, flowers represent joy, rain represents sadness, and nightfall represents fear (Fig. 5). Anger generates a fire wall with fire audio effects around the user, with adjustable intensity. Joy is represented by flowers blooming in the ground around the user; the intensity of the emotion controls the radius of generation and the flowers density. Sadness is represented by the appearance of clouds and rain in the sky. Here, the emotion intensity modulates the sound effects, cloud density and rain force. Finally, fear is represented as nightfall, and the intensity of the emotion controls the brightness of the sky from a sunny day to complete darkness.

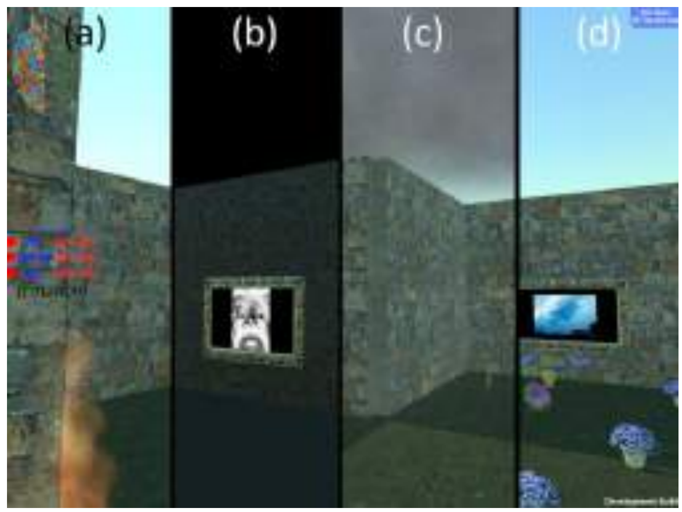

Fig. 5. View of the Labyrinth where each segment of the image displays the different visual metaphors for the same point of view: (a) fire for anger, (b) nightfall for fear, (c) rain for sadness, and (d) flowers for joy. Pictures of the IAPS database have been omitted in this example.

IV. STUDY

Although the architecture and implementation of the labyrinth are prepared to both infer the affective state and generate procedural audio-visual stimuli simultaneously in a closed biofeedback loop, it is not possible to validate both the effectiveness of audio-visual virtual PCG and the effect of the biofeedback loop in the same experiment. Hence, a preliminary study was carried out using the Emotional Labyrinth to (i) assess the effectiveness of selected metaphors in inducing target emotions, and (ii) identify relevant psycho-physiological markers of the emotional experience generated by the labyrinth. Consequently, this study does not consider the biofeedback component as this component will be added after validating the labyrinth PCG and identifying the candidate physiological markers to use in a closed loop. For this reason, participants were exposed to four different versions of the labyrinth, each displaying the content related to a specific emotional metaphor (*Anger*, *Fear*, *Joy*, and *Sadness*), and a neutral one as a baseline (that is, the empty labyrinth without any emotional stimulation), in a within-subject design. For that, we assessed the felt

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emotions (i.e., the emotions subjectively reported) together with the user's physiological data.

To sum up, the objectives of the study were:

- Analyze whether the four emotional versions of the labyrinth would elicit the four target emotions (i.e., participants would report of having subjectively-felt the target emotion to a stronger extent than the other for any version of the labyrinth);
- Assess whether physiological signals could distinctively predict each emotional state (i.e., specific patterns of physiological activations would predict any subjectively-felt emotion).

A. Participants

A sample of 20 participants (11 males) participated in the study. The average age was M=28.15 ± 4.15, with an age range of 22-41 years. All participants provided written informed consent before participation. The study was approved by the ethics review board of the Madeira Interactive Technologies Institute, MITI-HCI-2018-1.

B. Hardware Setup

The Emotional Labyrinth was run on a computer with Windows 10, an Intel processor I7-6700 3.4GHZ, with 8GB of RAM, and a Radeon R9 390 8GB graphics card. The computer was connected to a Samsung television 55" in full HD resolution placed in front of a seat; the same computer was connected to an EX2 USB arcade game controller for Xbox360 to enable the navigation within the virtual environment.

A BioSignalsPLUX, a wearable body sensing platform (Plux Wireless Biosignals, Lisbon, Portugal), was placed on the left forearm and was used to acquire electrophysiological data. It was connected via Bluetooth to a second computer that received raw sensor data acquired at 1000 Hz. Data was fed into a custom standalone application (Bioplux client, https://neurorehabilitation.m-iti.org/tools/) that retrieved and parsed the data and converted it into a UDP datagram and sent to the Emotional Labyrinth. A surface-mounted triode dry electrode with standard 2 cm spacing of silver chloride electrodes placed on the V2 pre-cordial derivation was used to record Electrocardiography (ECG). Three bipolar sensors were used to record Electromyography (EMG) from the corrugator supercilii, zygomatic major muscles and maxillary as reference. A piezoelectric sensor with an adjustable chest strap was used to measure Respiration frequency and amplitude. Electrodermal Activity (EDA) was measured from the palm.

C. Procedure

Participants were welcomed in a quiet room. Three researchers were present. At first, the participant was invited to read a description of the procedure and sign the informed consent. Then, the physiological sensors were attached to the participant's body. EDA sensors were always attached to the hand not used to operate the navigation controller. Physiological sensors were controlled by Researcher 1 by using the *OpenSignals* software (http://bitalino.com/en/software). Sensors were tested by asking participants to make voluntary facial expressions. If a good signal was received and sensors were stable on the participant's skin, the study would commence. Researcher 3 explained the experiment. Each participant explored the Emotional Labyrinth 5 times in total, each one lasting about two minutes. Between explorations, participants filled in brief questionnaires. The order of the conditions always started with *Neutral*; the participant explored the empty labyrinth (no animations) for two minutes. Subsequently, the participant explored each of the procedural emotional metaphors of the environment (*Fear, Joy, Sadness, Anger*) in a randomized order. During the VR experience, information regarding the physiological signals, emotions, and events in the labyrinth was recorded as plain text documents for further analysis. Self-report measures (VAS and SAM) were filled in by participants immediately after each exposure to the labyrinth.

D. Measures

Demographic information of participants including gender and age were collected. Self-report measures included a brief self-report for emotional experience. Visual Analogue Scales (VAS) were used for quantifying the intensity of specific emotions on 9-point Likert scales (namely *Fear, Joy, Sadness, Anger*); the Self-Assessment Manikin (SAM) [70] was used to quantify properties of the felt overall mood (arousal, pleasantness, dominance). Specifically, VAS items were phrased as such: "Please, select a number to say how much do you feel the corresponding emotion RIGHT NOW" (with the four emotions following with the Likert scales), while the SAM item was phrased as such: "Please, using the following images as a reference, select the numbers to rate your current emotion", with the SAM Likert-images following.

E. Data analysis

Physiological data were filtered and analyzed using the PhysioLab toolbox, a multivariate physiological software tool [71]. In total, 16 features were extracted from the BiosignalPLUX sensor data. ECG waveform was analyzed, and detection of the R-peaks was carried out. From it, Heart Rate (HR) and SDNN (standard deviation of normal RR intervals) were computed. EDA signals were filtered with an 8th order low-pass filter with a cut-off frequency of 15 Hz. From EDA, Galvanic Skin Responses (GSR) – noticeable episodes of sudden increases of skin conductance caused by arousal – and Skin Conductance Level (SCL) were extracted. EMG signals were detrended, full-wave rectified, low-pass filtered, and the Root-Mean-Square (RMS) and the Mean Frequency (MNF) and Median Frequency (MDF) of the power spectrum were extracted. Questionnaire data were collected electronically using the Qualtrics platform (Qualtrics, Provo, Utah and Seattle, Washington, USA). All data were stored in CSV files and processed for statistical analysis using Matlab R2017a (Mathworks, Natick, USA).

The One-sample Kolmogorov-Smirnov test was used to assess normality. Since most data revealed non-normal, effects across conditions were assessed with the non-parametric Friedman test, and pairwise comparisons with the Wilcoxon signed rank test. All physiological features were normalized in the mean and standard deviation before performing a linear

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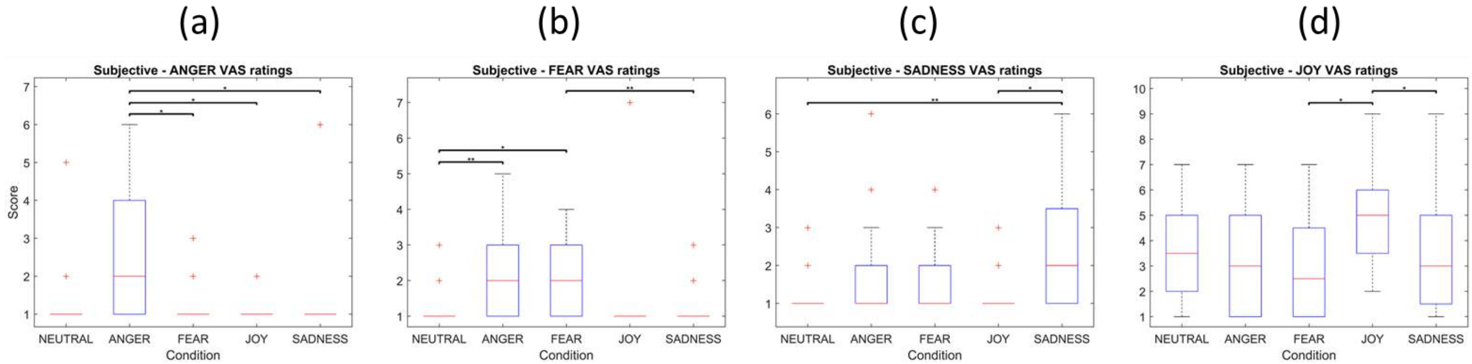

Fig. 6. Boxplots representing the subjective ratings for the four emotional states (a=anger, b=fear, c=sadness, d=joy), that is, median values of how much the participants felt the corresponding emotion (y-axis represents the scores on the VAS-scales). Inside each boxplot, on the x-axis the five conditions of the study are reported, i.e., the four emotional metaphors participants have been exposed to and the neutral condition. * indicates p<0.05 and ** p<0.01

regression modeling. We used a stepwise regression approach for selecting the predictive variables of our linear regression models by an automatic backward elimination procedure. This procedure starts considering all candidate variables, and iteratively deletes the variables whose loss gives the most statistically insignificant deterioration of the model fit. The process is repeated until no further variables can be deleted without a statistically significant loss of fit.

Data sets of four participants were incomplete due to high noise, non-removable artifacts or data corruption.

V. Results

A. Visual Analogue Scales

The four procedural audio-visual metaphors *Anger, Fear, Joy, and Sadness* plus a *Neutral* version of the emotional labyrinth were contrasted against the participants' subjective responses to those exact emotions (Fig. 6). The Friedman test revealed a significant condition effect for the subjective ratings of anger ($\chi^2(4)$= 25.53, p<0.001), fear ($\chi^2(4)$= 32.12, p<0.001), sadness ($\chi^2(4)$= 25.84, p<0.001) and joy ($\chi^2(4)$= 17.39, p=0.002), and all procedural metaphors always elicited the highest responses of the targeted emotion. The most robust specificity in subjective responses was induced by the *Anger* metaphor, with the anger rating (Mdn=2, IQR=3) being significantly higher for this condition than for *Fear* (Z=2.83, rank=55, p<0.05, r=0.46), *Joy* (Z=-2.83, rank=0, p<0.05, r=0.45) and *Sadness* (Z=2.34, rank=59, p<0.05, r=0.37).

The subjective rating of fear revealed that both *Anger* and *Fear* metaphors induced higher fear responses (Mdn=2, IQR=2) than the other conditions (Mdn=1, IQR=0). However, the *Fear* condition revealed statistically significant differences with both *Neutral* (Z=-2.85, rank=0, p<0.05, r=0.45) and *Sadness* (Z=-2.99, rank=0, p<0.01, r=0.47), while the *Anger* condition only with *Neutral* (Z=-3.13, rank=0, p<0.01, r=0.51). The *Sadness* condition elicited higher ratings of sadness (Mdn=2, IQR=2.5) than *Joy* (Mdn=1, IQR=0; Z=-2.99, rank=3, p<0.05, r=0.47) and *Neutral* (Mdn=1, IQR=0; Z=-3.21, rank=0, p<0.01, r=0.51). Finally, all conditions elicited some degree of joy (*Neutral* Mdn=3.5, IQR=3; *Anger* Mdn=3, IQR=4; *Fear* Mdn=2.5, IQR=3.5; *Joy* Mdn=5, IQR=2.5; *Sadness* Mdn= 3, IQR=3.5), being the *Joy* metaphor the one that elicited the most. Joy ratings were higher in the *Joy* condition when compared to *Fear* (Z=-2.87, rank=13, p<0.05, r=0.45) and *Sadness* (Z=-3.18, rank=11, p<0.05, r=0.50) conditions.

B. Self-Assessment Manikin

The Self-Assessment Manikin was used to assess participants' pleasure, dominance and arousal responses to the different procedural emotional metaphors. The SAM-Pleasure ratings indicated that the emotional labyrinth, overall, was a pleasant experience, achieving the highest reported subjective ratings (*Neutral* Mdn=6, IQR=2.5; *Anger* Mdn=4, IQR=3.3; *Fear* Mdn=4.5, IQR=4.5; *Joy* Mdn=6.5, IQR=2; *Sadness* Mdn= 3, IQR=3.5). In this dimension there was a clear condition effect ($\chi^2(4)$=53.13, p<0.001), being all negatively balanced conditions significantly lower rated than the neutral condition [*Anger* (Z=3.39, rank=133, p<0.01, r=0.55), *Fear* (Z=3.14, rank=127, p<0.05, r=0.50) and *Sadness* (Z=3.67, rank=185, p<0.01, r=0.59)] and *Joy* significantly higher rated than *Sadness* (Z=3.28, rank=145, p<0.05, r=0.58) and *Anger* (Z=2.82, rank=150, p<0.05, r=0.46). SAM-Arousal ratings revealed a strong condition effect ($\chi^2(4)$=48.15, p<0.001), with a single pairwise difference in the *Anger* (Mdn=4.5, IQR=2) being it higher than for *Neutral* (Mdn=3, IQR=1; Z=-3.27, rank=3, p<0.01, r=0.53). Finally, the SAM-Dominance ratings revealed a condition effect ($\chi^2(4)$=66.59, p<0.001), but no pairwise differences were found, being the responses to all conditions between 2-3 (*Neutral* Mdn=2.5, IQR=2.5; *Anger* Mdn=3, IQR=3; *Fear* Mdn=3, IQR=3; *Joy* Mdn=3, IQR=3.5; *Sadness* Mdn= 2, IQR=2.5).

C. Subjective responses modeling from physiological data

To understand how psycho-physiological responses relate to the procedurally generated virtual experiences, we used the extracted physiological features including Respiration, ECG, EDA and EMG as predictors of the reported subjective ratings. Stepwise linear regression models were used to identify which features contributed significantly, and to what extent, to the reported experience (Table 1). Significant models were found for all subjective metrics, except for *Sadness*. The models for the underlying emotions targeted with the metaphors are those that have the contribution of fewer physiological features. *Anger* is modelled with contributions from reduced HR, increased SCL, and Corrugator activity. *Joy* is modeled through respiration features. *Fear* considers reduced HR, higher levels of SCL, increased Corrugator RMS and reduced spectral contributions from both Corrugator and Zygomatic activity. Consistent with the *Joy* rating, SAM-Pleasure has positive contributions from frequency and amplitude respiration variables and low levels of Corrugator RMS. SAM-Arousal includes the same variables as SAM-Pleasure, but with a stronger contribution of respiration amplitude, plus contributions from low HR variability and GSR components, and opposing contributions from Corrugator and Zygomatic EMG features. Finally, SAM-Dominance considers includes higher respiration amplitude, higher HR values, less GSR and differential contributions from Corrugator and Zygomatic activity. All models reported large effect sizes, except a moderate to high effect size for SAM-Pleasure.

VI. Discussion

Here we presented a general-purpose framework that integrates seven commercial physiological sensing systems and supports immersive and non-immersive VR systems. Our architecture enables building procedural adaptive virtual environments and makes it more accessible to the research community and easier to implement. The Emotional Labyrinth is the first step in the study of how to effectively create procedural virtual content scenarios in closed loop with psycho-physiological models of users' affective state. As opposed to previous research, our study does not consist of a linear presentation of stimuli, but it is an open loop experiment in which navigation within the labyrinth is fully decided by the user. That implies that elements such as the timing of events, the order of stimulus, the amount of stimulation or their length, are not controlled. Hence, in this respect it is closer to a real-world scenario. That means that findings from previous electro-psychophysiological research of emotions studied in those controlled settings do not necessarily generalize to the proposed Emotional Labyrinth scenario. It is for this reason that new models for affective state detection need to be developed.

Although preliminary, the results of this study show that the Emotional Labyrinth is overall a pleasant experience, but that the different versions of the labyrinth are able to induce to some extent distinctive patterns of emotional responses, and that these patterns are coherent with the emotional metaphors used in the labyrinth design. For example, considering subjective responses on categorical emotions, each version of the labyrinth elicits in average the expected emotion more than the others. The only exception is the *Anger* metaphor, which elicits both fear and anger in similar median amounts. This indicates that the emotional metaphors can be improved in future versions, but also that users could reasonably experience multiple emotions at the same time or meta-emotional activations (e.g., being angry because of getting the fire metaphor but also being scared by surrounding fire at the same time). Also, the responses to the Self-Assessment Manikin are consistent with the procedural virtual emotional metaphors. For example, the responses to negative emotional metaphors (those of *Fear*, *Anger*, and *Sadness*) were rated systematically less pleasant than in response to neutral and the positive emotional metaphor (*Joy*).

Next, we assessed whether the collected physiological data could act as predictors for the subjectively experienced emotions. With this, we do not implicitly-affirm that the

TABLE I
STEPWISE LINEAR REGRESSION MODELS USING PHYSIOLOGICAL RESPONSES AS PREDICTORS OF SUBJECTIVE EXPERIENCE. VALUES CORRESPOND TO THE CORRESPONDING WEIGHTS IN THE MODEL. ONLY FEATURES WITH STATISTICALLY SIGNIFICANT CONTRIBUTIONS ARE REPORTED. RMSE, P-VALUES AND EFFECT SIZES ARE INDICATED.[1]

		VAS-Anger	VAS-Fear	VAS-Joy	VAS-Sadness	SAM-Pleasure	SAM-Arousal	SAM-Dominance
Intercept		-0.4192	5.1022	-10.0056	-	-12.7879	-25.1044	-22.8178
Respiration	rate	-	-	0.8351	-	1.0966	0.7748	-
	amplitude	-	-	0.5487	-	0.4437	0.9858	0.8600
ECG	HR	-0.3651	-0.2311	-	-	-	-	0.6401
	SDNN	-	-	-	-	-	-0.5565	-
EDA	# GSR	-	-	-	-	-	-0.5629	-0.4799
	Max. Vel. SCL	-	-	-	-	-	-	-
	Max. SCL	0.2717	0.2350	-	-	-	-	-
EMG Corrugator	RMS	0.2726	0.3667	-	-	-0.5343	-1.4177	-0.4183
	Mean freq.	-	-	-	-	-	-	-
	Median freq.	-	-0.2237	-	-	0.6880	8.2481	2.4396
EMG Zygomatic	RMS	-	-	-	-	-	1.9346	-
	Mean freq.	-	-0.2785	-	-	-	0.8735	0.9578
	Median freq.	-	-	-	-	-	-8.5941	-2.1000
p-value		**0.0184**	**0.0363**	**0.0003**	-	**0.0023**	**0.0004**	**0.0018**
RMSE		0.8783	0.7928	1.6640	-	1.8490	1.2814	1.5124
Cohen's f^2		0.7835	1.0238	0.6253	-	0.3098	0.8592	0.3958

[1] VAS indicates the Visual Analogue Scale ratings; SAM indicates the Self-Assessment Manikin ratings; EMG stands for electromyography; ECG for electrocardiography; and EDA for electrodermal activity.

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subjective experience of emotion is determined by physiology, which is a topic of debate [72]. On the contrary, one could also consider that emotions are episodic and contextual, while beliefs about emotions (also emotional recall after the emotion has been experienced) are semantic, conceptual and contextualized [73]. In the present study, physiological indexes are tested as predictors of self-report data in order to assess coherence among them [74] and to perform a preliminary evaluation whether, by using the procedural emotional metaphors-based versions of the labyrinth, it is possible to induce changes related to users' emotional states. Our results show some consistency between physiological responses to the procedural emotional stimuli embedded in the virtual scenarios and the subjective reporting of emotions. Specifically, more consistent results appear regarding the Self-Assessment Manikin (which assesses general mood features), but also specific markers seem to facilitate consistency (e.g., changes in respiration rate and amplitude for *Joy*; changes in EMG corrugator for *Fear*; increased SCL for *Fear* and *Anger*). However, not all self-reported data could be modeled with the proposed physiological indexes. This study confirms a limited specificity of physiological indices for emotion state estimations. Multiple factors can contribute to it, from the reduced sample size to the specifics of the sample studied. Although the sample was a reasonably uniform sample of healthy young university students and employees with no known psychiatric disorders, several factors were not controlled for. Differences in the body mass index, health habits, ongoing treatments or medication, can have modulated their responses to the Emotional Labyrinth.

When comparing our data to previous work, we find consistency in decreases in heart rate variability with arousal [25], as well as higher skin conductance with negative anticipation in Anger and Fear [27]. However, our models also show substantial differences from previous studies, such as those in [24]–[26]. The reasons can be manifold. First, our study is based on generative interactive experiences as opposed to recall of autobiographical experiences or the use of video stimuli. As such, the nature of the experience is very different. In our case, participants had a different configuration of stimuli depending on how the labyrinth was explored, as the labyrinth's shape and content changed at each presentation. Also, our models report on the relationship between the subjective ratings and psycho-physiological responses, considering the extent of meta-emotional activations during the labyrinth explorations, and not only binary contrasts among emotions.

VII. Conclusions

Here we presented a framework to develop rich procedural experiences for immersive VR through the generation of visual and auditory content in response to the affective state of the user. The Emotional Labyrinth is the first application that we developed in this architectural framework. It consists of a procedurally generated 3D maze whose visual and auditory features are generated according to four emotional metaphors (*Anger*, *Fear*, *Joy*, *Sadness*). The first step in the validation of this framework was to test the selected set of procedurally generated audio-visual VR metaphors regarding their ability to affect the user's emotional states.

Further, models are proposed that quantify the relationship between physiological responses and subjective ratings of emotions in this PCG approach. The statistical analysis of both impacts in subjective responses and the derived models reported moderate and large effect sizes.

However, we identified some limitations in this work. Although all the proposed emotional metaphors do successfully induce the targeted emotion, their specificity is limited. That is, the difference between the targeted emotion and the rest is only between 1- 2.5 points in the VAS assessment. That can indicate that in future experiments, the intensity and frequency of the PCG for the metaphors may need to be increased. Also, the metaphor used for anger has been found to induce some fear as well. Hence, this metaphor should be revised and improved in its specificity. Finally, although successful psycho-physiological models of user experience have been identified for most VAS ratings, that was not the case for sadness. These models are critical to implement the closed loop mechanism to adapt the Labyrinth procedurally to the users' affective state. Hence, in future work we may consider additional measurement techniques and tools, or a scenario that does not require the detection of sadness. This is fundamental given that the final goal of this application is to be used in a clinical context.

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