Emotional Synchrony and Generative Art in Interactive Multisensory Environments

ANONYMOUS AUTHOR(S)

Human beings hold the unique ability of spontaneous sharing and coordination of emotions with others, a concept known as "emotional synchrony". We know that emotional synchrony is an essential part of the way we bond with others, increases the feeling of closeness, and is related to positive aspects of the relationship and social abilities. Our research explores emotional synchrony in multi-user experiences that take place in interactive multisensory environments. We use AI techniques for different purposes: i) to recognize children's emotional synchrony at run-time, using a Machine Learning algorithm to identify individual's emotional states from the raw data generated by biosensors worn by the user; ii) to generate an evolving graph of the shared emotions that are dynamically anchored to the users' positions inside the space and are used to visualize dynamically artistic shapes created by means of AI-based generative art techniques. This paper describes the design and technology underlying our research and presents a scenario of use.

CCS Concepts: • **Human-centered computing** → *Collaborative content creation*; *Interactive systems and tools*; • **Computing methodologies** → **Bio-inspired approaches**; **Machine learning algorithms**; **Artificial intelligence**.

Additional Key Words and Phrases: Emotion Synchrony, Multisensory Environment, Machine Learning, Emotion Recognition, Generative Art, Wearable Biosensors

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1 INTRODUCTION

Human connections play a fundamental role in our life: as Wheatley et al. [22] summarize, in our ability to connect lies the difference between "surviving and thriving" in a social world. The benefits of these connections are indeed well known: they facilitate feelings of closeness while strengthening social bonds and enable social learning over the long term [23]. Today more than ever, we need new experiences that enable us to resonate with others deeply. Despite the indisputable benefit of achieving emotional connections, previous research has highlighted the complexity in inducing them. A possible solution, as shown by Lankens and Stel[7] is to stimulate behavioral synchronicities, which in turn should activate emotional ones. However, as Semin[19] outlines, connected minds do not necessarily require connected bodies, as the synchrony is indeed manifested but not exclusively reducible to behavioral synchrony (e.g., listening to the same music or attending the same sport event). Building on this understanding, our intuition has been to exploit the potential of interactive MultiSensory Environments (MSE), which are able to foster social initiation between people [11], stimulate, and share emotional experience between users [18], with the vision of designing new experiences of profound human connection. Since the first studies on the creation of emotion machines [13], significant improvements have been made in this field. Developments in machine learning, physiological signal processing, and wearable devices have made it possible to study emotions even out of controlled settings [1, 5], such as research labs. Achieved results are promising, yet many challenges and problems have still to be solved to enable reliable emotional monitoring in the wild [16]. In such context, interactive MSE represent the perfect background to investigate these emotional dimensions pushing the users to deal with the presence, facial expressions, and gestures.

Our research explores emotional synchrony in multi-user experiences that take place in interactive MSEs. We relies on run-time applications of artificial intelligence in two ways. Initially, we used a Machine Learning approach to classify a stream of raw data, obtained from biosensors worn by children in the MSE, into emotions. Secondly, by dynamically clustering the emotion data and by continuously referring to each children's position, a Generative Art engine modifies the digital content shown by the MSE to let the users visualize their emotional synchronies.

2 STATE OF ART

2.1 Multi-Sensory Environments

An MSE is a room-size space equipped with physical materials and devices that provides gentle stimulation of multiple senses. MSEs are in general designed for persons with Intellectual Disabilities (elderly or children) to relax, to promote agency [12], and to improve inclusion and socialization for groups of children with and without disabilities [2, 3]. Few interactive MSEs were designed to adapt their behavior according to the user's emotional state. In MEDATE [12] the response of the system to a specific interaction is reduced in intensity according to the number of consequent repetitions of the task, as a measure of stereotypical behaviors of autistic children. In the Magic K-Room, the authors had started exploring the use of "low-cost" commercial EEG headsets to adapt the color of the environment and the music volume of the room [4]. However, emotional recognition has not yet been used as the primary interaction paradigm.

2.2 Smart Band for Emotion Recognition

Smart bands are widely used nowadays to monitor user health, physical activity, and sleep quality, to mention a few. They can accurately monitor physiological parameters (e.g., Heart Rate (HR), Electrodermal Activity (EDA), Blood Volume Pulse (BVP)), which provides insights about the emotional states of the humans [6, 9, 15, 20]. In state of the art, physiological signals have been used to detect complete or partial emotional statesFor example, Lidberg et al.[8] proved that sympathetic bursts affect the amplitude of the EDA: when the sympathetic branch of the autonomic nervous system is aroused, sweat gland activity increases, resulting in an escalation in skin conductance. However, the most sophisticated analysis considers and merges multiple signals. Villon et al.[21] combine both EDA and HR to estimate both the valence and arousal levels. There is no single unique signal to determine emotions, and sensor fusion seems to be the general approach to coping with single signal uncertainty.

3 EXPERIENCE DESIGN

Our aim is to exploit emotions naturally arising thanks to multi-sensory stimulation and use it to generate visual outputs that simultaneously represent the emotional connections among the children who are sharing the experience and create new content for the experience itself. There are several evidences that MSEs have the potential to provoke different emotions by combining their stimuli [18]. We divided the experience into three "conceptual" steps:

- Eliciting emotions: the MSE, with its ability to provide visual, sound, and olfactory stimuli, represents the perfect tool to engage children emotionally [2, 18].

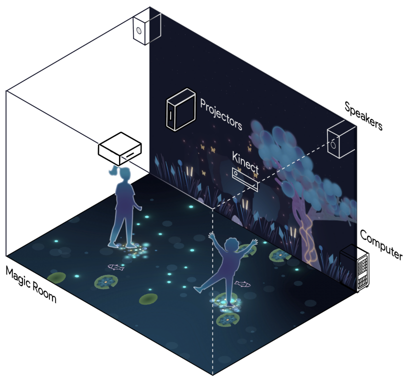

Fig. 1. 3D render of frontal and floor projections of the contents designed for the MSE

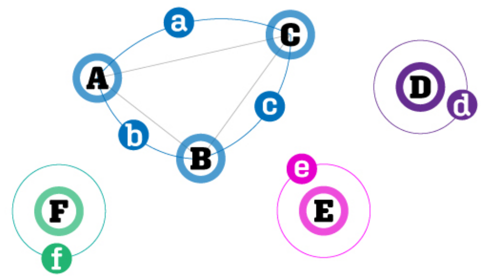

Fig. 2. Schematic representation of users and avatars in the MSE from zenith point of view

- Measuring connections: the measurement of physiological signals related to the functioning of the autonomic nervous system and their subsequent processing is our gateway to emotional synchronicities. We will first apply emotion recognition algorithms to infer the emotional state of each user in the room and then look for a correlation between emotions experienced as the activity unfolds.
- Rendering connections: integrating motion sensors and projectors enables us to render emotional connections within the room in space. In particular, the motion sensor allows us to know the children's position, while the projectors allow us to connect those experiencing the same emotional state.

3.1 User Experience scenario

Considering that the activity was designed for small groups of children (4-6), a fairytale-like setting was chosen to build the visual outputs. We have created an enchanted pond environment with glowing elements in a cold-dark tones background to recall a magical atmosphere (Fig 1). The magical pond is inhabited by different fishes, which are the children's avatars. They change their behavior accordingly both to the emotion sensed by the biosensor and to the movement tracked by the motion sensor in the space of each user. From the user experience point of view, the children will live the following macro moments: exploration, interaction, and connection.

(1) Exploration: In the introductory phase, a gradual enrichment of visuals and sound elements that characterize the pond (Fig. 1) recreate a magical environment. To expand the emotional impact, smells are used.
(2) Interaction: Once the magical environment has been set, the users can explore it freely. The biosensor collects biometric data and decodes the emotions aroused by the experience. Those emotions are used as triggers to animate the "living" visual elements on the floor projection. Every avatar follows one user throughout the space and moves around him/her. During the interaction phase, the user is led to embrace the environment and be emotionally aroused by being exposed to various visual and auditory stimuli.
(3) Connection: The fishes avatar make evident the emotional connection among children: when the users share the same emotion and approach (<1.5m), the movements of fishes in the pond change, visualizing a sort of choreography enclosing all the synchronized children. This choreography is meant to explicit the existence of emotional synchrony, even if not explicitly reveal their emotional state.

4 WEARABLE-BASED EMOTION RECOGNITION

4.1 Emotion recognition algorithm

Physiological signals are collected through wearable devices. In particular, the wearable adopted is the Empatica E4, which was identified as the most suitable device to be used in emotion-related studies [16]. The mapping from physiological signals to emotions is achieved by employing a machine learning algorithm. The model has been trained on the Wearable Stress and Affect Detection Dataset (WESAD)[17], the only publicly available dataset containing signals recorded by Empatica E4. The development of the machine learning algorithm was inspired by the work of [17], which addressed the same task of training a multi-class classification model on WESAD with a 75% precision in the classification. However, their algorithm was not designed to operate in real-time. Hence we changed the original pipeline able to classify emotions in real-time. Firstly, we removed the features most sensible to the movements (e.g., HRV [10], acceleration, and rotation). To increase the responsiveness of the algorithm, we segmented the signals prior pre-processing step in 60-seconds long windows. Each window overlaps with the previous of 30 seconds. The window dimension has been chosen as the best compromise between the prediction time, the sample rate of sensors, and the prediction's quality. Signals have been filtered. EDA signal was decomposed into phasic and tonic components, using SparsEDA[14]. The training was performed with the Random Forest approach and validated with leave-one-out cross-validation. Our result has an accuracy of 77.9% in identifying emotions.

5 GENERATIVE VISUAL CONTENT CREATION

The visual content generator is based on two elements: environmental content and generative visual content. The first is responsible for rendering invariant elements in the activity (e.g., the pond, the trees), and that can stimulate emotions. The core of our application is the generative visual content. The engine creates a dynamic graph representation, where each state represents a child, with its current emotional state and physical position in the room. Arcs are dynamically placed between two nodes presenting the same emotional state and euclidean distance between positions lower than 1.5 meters. In this way, relevant clusters of children are defined. Then, our dynamic content generator creates a geometric shape connecting all children in the cluster. Lines are then distorted randomly to have smoother corners. Such route is then followed by children's avatars, each with a random distortion applied to give uniqueness. Fig. 2 provide an example where children A, B, and C form a cluster (grey lines), while children D, E, and F each form their single-user cluster. Avatars a, b, c, d, e, and f move along the colored lines. Clusters are recomputed every 250 milliseconds to be connected with the motion tracking and maintain the emotional state until the ML algorithm re-evaluates it (once per second). The result is a visual environment that reacts to the users' movements and does it empathetically, to let users be aware of sharing the same emotions.

6 CONCLUSIONS AND FUTURE WORK

This paper presents the initial step in exploring and exploiting human emotional connections in MSEs. Despite their potential in stimulating emotions, MSE research has not yet fully explored the use of emotions as an interaction mode. To address this topic, we propose modifying the state-of-the-art machine-learning algorithm to recognize emotions using non-invasive biosensors data (e.g., BVP, EDA, and temperature). The recognized emotions are associated with the location of each user. This information generates a graph of emotional synchronies, which an generative artistic AI uses as an input method. The system we proposed uses AI approaches both to recognize the children's emotion and generate a visualization of the user's emotional synchronies at runtime.

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