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Affective gaming in real-time emotion detection and music emotion recognition: Implementation approach with electroencephalogram

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Abstract: **Affective Gaming can be considered as the concept of detecting the real-time emotional state of a player during various stages in gameplay and then enhancing the user interactivity accordingly to the emotional state. Based on this conception, this paper presents the research phase of the development of an Affective Car Racing computer game. The designs were created based on the theory of "Affective Loop" in games. Affective Loop consists of Emotion Elicitation, Emotion Detection/Modelling and finally Emotion Expression by Game Engine. This paper considers the second and third subphases of this loop. Designs are done for these two phases based on technologies that are still not been utilized by many game developers when designing a game. Emotion Detection/Modelling phase is introduced with a technique of capturing Electroencephalography (EEG) signals for predicting the real-time emotion of the player while interacting with the game engine. Emotion Expression phase considers the concept of Music Emotion Recognition (MER), which is a novel concept for the Gaming Industry. The authors had trained SVM models for emotion modeling via EEG Signals that will be captured by the Emotiv Epoc 14 channel device. The authors had classified the Rock and Electronic genre of music via Multi-Label RAKEL classification (Precision score of 75%) to play music excerpts based on the effect of the gamer during gameplay.**

Keywords: *Affective gaming, Affective loop Concept, Emotion detection through electroencephalography, Music emotion recognition*

I. INTRODUCTION

The term "affect" in psychology is defined as a feeling or an emotion expressed for some event [1]. From a psychology perspective, computer games consist of higher amounts of "affect" because computer game environments are built to change according to user interactivity. The interactions occur when the game environment receives inputs from the player's side by executing actions via the game controller.

"Affective" gaming can be considered as detecting the real-time emotional state of a player during various stages in gameplay and then enhancing the user interactivity accordingly to the emotional state. Methods of widely accepted emotional change detections are done by monitoring the changes in facial expressions, gestures, body posture, speech, physiological responses such as EEG signals etc. during user interactivity within the game environment [2]. Examples of such games include arousal-driven play of non-player characters (NPCs) in Left 4 Dead 2 the combat skills of opposition NPCs in F.E.A.R., the emotional expression of avatars' in The Sims series, game characters' emotional expressions in Prom Week and Façade, Storybricks, the game narrative building influenced by player emotions etc. [3].

The basic principle of affective gaming lies within the communication between human to human, human to a computer and human to human through a computer. According to Sundstrom, the design of affective loops in computer games makes possible all mentioned forms of communication. The affective loop treats emotions as processes. The affective loop in gaming can be viewed as a closed loop with three sequential key phases.

1) the player reveals his feelings during interaction with a game mainly via bio-signals,

2) Biosignals of the player are detected by the game engine and interprets those signals into the emotion experienced,

3) based on that emotion recognition of the player, the game adjusts itself following the player's emotions.

This is an on-going cycle, affecting the player's both mind and body, making him respond through game actions and emotional reactions [4].

At stage 1 of the loop, the player expresses his emotions when he reacts to the game content. Game content is a collection of game mechanics, game environment and background music content. Game mechanics are the methods and rules specific for any game type that makes the game player interact with the game environment [5]. The game environment consists of visual settings such as graphics, background lighting levels, saturation levels etc. Background music content includes music clips played in the background [6].

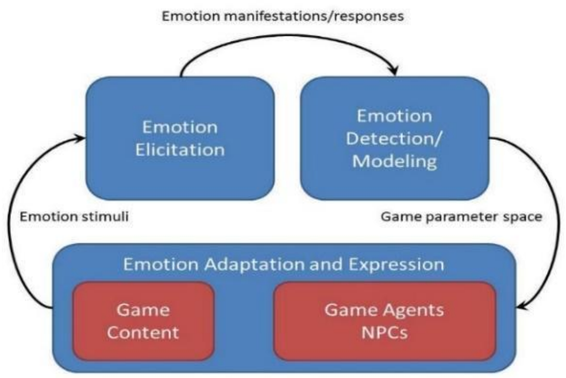

Fig. 1. Affective game loop [4]

This research paper is based on this Affective Loop. The researchers focus on introducing novel technologies to implement the above loop.

For the Emotion Elicitation phase, the authors focus on real-time capturing Electroencephalogram (EEG) signals and Modelling via Machine Learning approaches.

For the phase of "Emotion Adaptation and Expression," they focus on using background music content to express the desired emotion. Music will be played accordingly to the player's emotion detected via EEG Signals. Hence, music that will enhance the effect of the player will be played correspondingly. To identify music excerpts that enhance specific emotions, theories of Music Emotion Recognition (MER) were practiced by the authors.

This research paper aims to provide the general public the opportunities of the advancements of Research in Technology. At Present, products/services created from concepts of "Affective Loop", MER are at limited numbers and a survey was performed by the authors to observe the knowledge of these concepts among the general public. 18% in total of the participants have had only heard the names of the above ideas. Hence, this suggests that these concepts are yet to be established among the general public. The authors focus on making aware of these novel concepts in the day-to-day living of the general public.

The objective of this research is to develop an integrated software prototype for Computer games where the player's emotions are detected in real-time and the software relays back to the game engine with music excerpts to be played in the background in accordance to the emotions expressed by the player. The reason for this development is that the authors' outlook to establish the concepts described above in the general public. To the best of their knowledge, the effective approach is developing a computer game integrated with the above concepts because computer games are highly popular among the public at present.

II. SCOPE OF THE RESEARCH

The authors primarily designed this prototype to "Car Racing" Game Genre because it is the game genre that gamers prefer to listen to music when playing. The scope of the entire research was narrowed down under the selected game genre. Fig.2 shows the process of defining the scope in tiers.

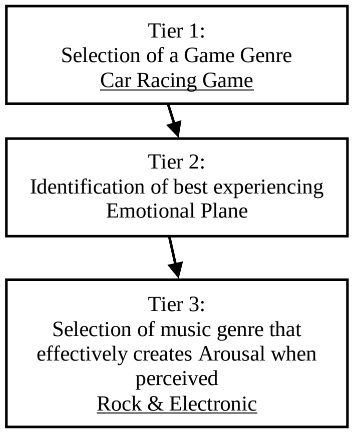

Fig. 2. Process of narrowing of the research scope

Tier 2 - During the Literature study, it was identified that Car Racing Games increase players' risk-taking inclinations, known as "The Racing Game Effect" [7]. The Players are in an aroused state of emotion during the entire gameplay. The authors were able to analyze the main 4 emotion labels based on the theory of "Racing-Game Effect" followed by a survey performed on Car racing computer game players as a proof of concept. They identified emotion labels as "joyful activation", "sadness", "tension" and "power". They plotted the intensity of the above emotion labels in a single-dimensional arousal plane.

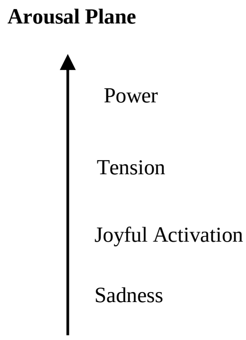

Fig. 3. Emotion taxonomy for this research

Tier 3 - With the survey, the authors inquired from the racing computer gamers' audience their preferred music genre during gameplay, 88% responded that they prefer "rock" and "electronic" music genres. Hence, the above genres were selected to perform MER concepts to identify the music excerpts that make gamers perceive the desired emotion labels, the authors had identified in Tier 2.

This paper henceforth discusses research findings and implementation separately of Emotion Detection/ Modelling via EEG Signals in Part A and Emotion Expression using background music content in Part B.

III. DESIGN

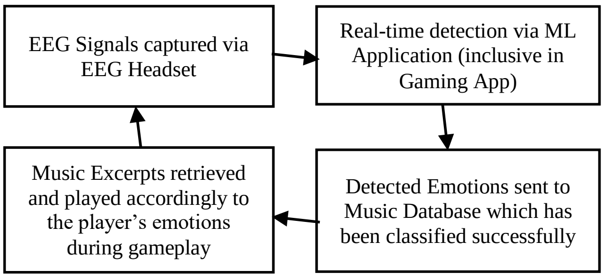

Fig. 4. Design workflow of an affective game during gameplay

IV. RESEARCH FINDINGS AND IMPLEMENTATION

A. An emotion detection/ Modeling phase

In this paper, the researchers are utilizing EEG signals as physiological responses to recognize human emotions according to the constructed emotion taxonomy. The reason behind this selection is that although detecting human emotions based on facial, behavioral, text and speech are widely accepted, analyzing facial expressions, text, speech, gestures or behaviors can be proven to be not very effective at times since these can be consciously altered. Due to this reason, the researchers have diverted their focus to studying emotions through physiological signals like electrocardiogram (ECG), electroencephalogram (EEG) [8], blood volume pressure (BVP), Heart-rate variability (HRV), temperature (TEM) etc. According to previous works, EEG signals have become more interesting for the researchers of this area since it comes directly from the human brain and therefore, the changes in EEG signals will directly reflect the changes in human emotional states. Design Methodology of this phase is as follows:

The classification model is developed using the Mahnob-HCI tagging database [9] (which contains classified emotions in terms of arousal based on EEG, ECG, respiration rate, temperature, GSR and eye-gaze.) In the context of this research, only the EEG signals are considered. The following diagram shows the design steps.

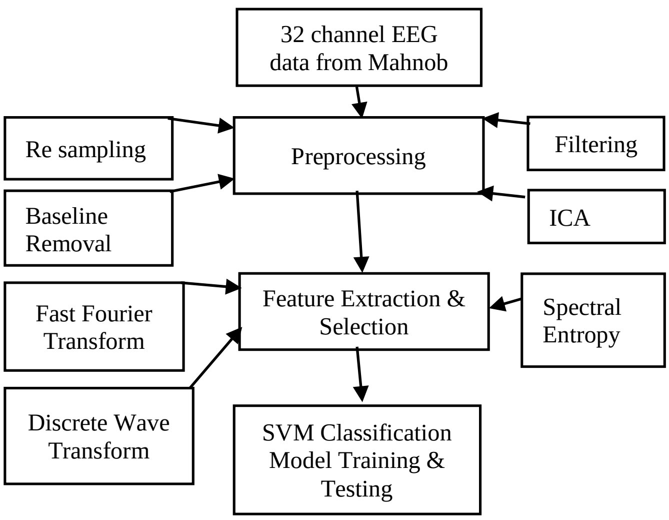

Fig. 5. Design methodology for emotion detection & modelling phase

The acquired EEG signals contain noise and artifacts. Therefore, the signals are first pre-processed.

The MATLAB EEGLAB Toolbox is used to pre-process the signals. The signals obtained from the Mahnob database are in the BDF (Bio-semi data file) format. These can be read and plotted through the EEGLAB Toolbox easily. The signal pre-processing involves the following steps.

- Resampling – The signals are resampled at 128Hz. (originally its 256 Hz)
- Filtering – A bandpass filter (2-40Hz) is used so that noise removal and artifact removal can be achieved at once.
- ICA (Independent component analysis will be performed.

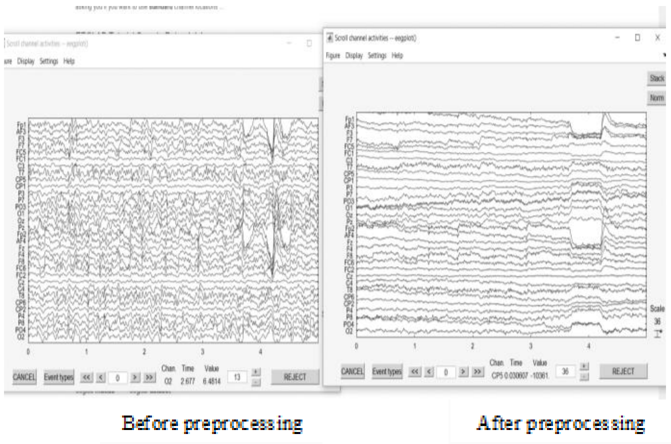

Fig. 6. Pre-processing

EEG feature extraction is quite a complex task which is also the reason why most researchers tend to turn away from BCI research. EEG signals are non-linear, nonstationary, and random in nature and therefore the feature extraction process becomes challenging. The features extracted in this research depend on statistical techniques, time-frequency based on Fast Fourier Transform (FFT), max-min features in temporal sequences, Shannon entropy, log-covariance etc.

The Hjorth parameters are extracted as well. These parameters characterize the EEG signals in terms of amplitude, timescale and complexity. The parameters are *activity*, *mobility* and *complexity*. They can be mathematically computed as shown.

$$h_1 = \sigma_x^2 \tag{1}$$

$$h_2 = \frac{\sigma_d}{\sigma_x} \tag{2}$$

$$h_3 = \frac{\sigma_{dd}}{\sigma_d} \bigg/ \frac{\sigma_d}{\sigma_x} = \sigma_{dd} / \sigma_x \tag{3}$$

Furthermore, the cross-correlation, peak frequency and the ratio of band power at a given time to baseline band power are considered. Around 2000 features are extracted originally, but before classification, several essential features must be selected. The *mrmr algorithm* is used for feature selection since it involves maximizing relevance and minimizing redundancy. This algorithm provides a ready to use implementation for MATLAB making it more convenient and therefore was used in this research.

After mapping the obtained features into the arousal scale, linear SVM (Support Vector Machine) classifier is used for classification. An SVM classifier is used since it can separate highly dimensional data. The Classification Learner extension for MATLAB can be used for this purpose.

The data is plotted as illustrated in Fig.7. Several models must be trained to achieve considerable accuracy. Currently, the authors are yet to evaluate accuracy metrics.

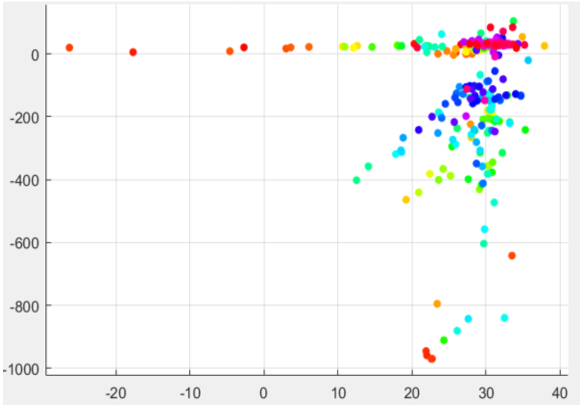

Fig. 7. EEG emotion plot

B. Emotion expression using background music content

At present, game mechanics are maximumly being utilized for the emotional awakening of the game player. The authors' observation of different brands of computer car racing games were that even though background music content is used, the background music is static throughout the gameplay. The background music content is not made to impact the player's emotional awakening.

It is in fact, a surprise that music content is not being used for emotion awakening when many music psychologists have proven that music does create an impact on human emotions [9],[10]. Keynote researcher Juslin had defined a research area where he finds relationships between music acoustic features and perceived music emotions. This area is known as Music Emotion Recognition (MER). MER is a cross-disciplinary field of auditory perception, psychology and music theory. With technology mixing in, MER is now a field consisting of signal processing and machine learning [11]. MER is yet to be utilized in the day-to-day lives of the general public. Until present, the only application developed for the use of the public with MER technology is a Music Player [12].

Reasons as to the question of game developers not utilizing music for emotional awakening may be due to the trend of allocating a low budget for background music content when compared with the budget allocated to that of graphics by game developers [13]. This trend may be due to MER is an expensive task. Emotions perceived from music is extremely subjective for humans. In fact, it is a timely and exasperating task to identify various emotions perceived and then match against the acoustic features of music to identify relationships between perceived emotions and music acoustic features.

The authors' goal is to develop a Rock and Electronic music excerpts containing a database where the excerpts have been labeled according to the emotion perceived based on the music genres' acoustic features. The emotion labels are in a tie with the emotions modelled in phase 2 of the Affective Loop. To achieve this goal, authors use the concepts of MER to identify the relationship among the acoustic features of the above genre and then designed a Machine Learning (ML) model to predict the emotion perceived in a certain music excerpt. The workflow of designing and developing the ML model is illustrated in Fig.8.

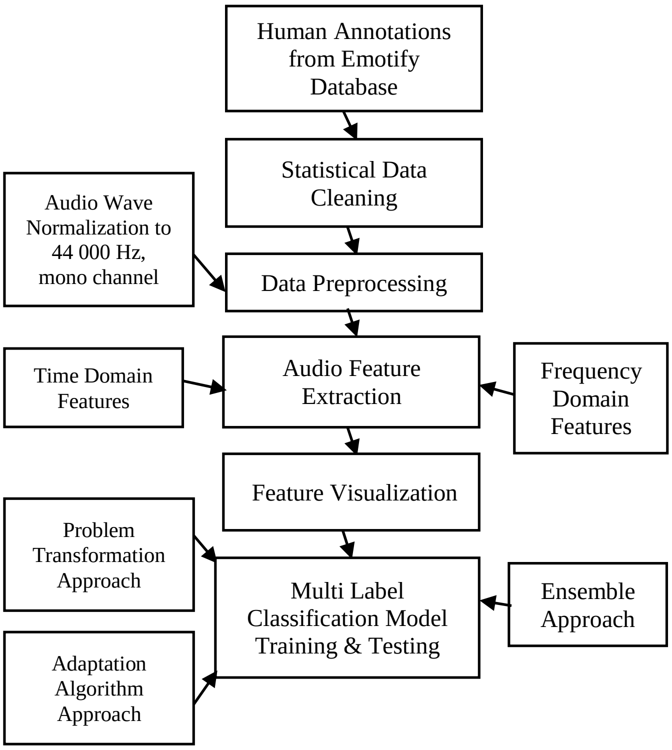

Fig. 8. Design methodology for music Emotion Recognition

'Emotify'[14] Data Set was selected for this methodology. This data set consists of music tracks of different genres including Rock and Electronic, where the excerpts are humanly annotated on perceived emotion. For each music excerpt, several human subjects rate their perceived emotion for the excerpt on a binary scape(either present or not) Emotify is the only a standard database recommended by the International Society of Music Information Retrieval (ISMIR) which consist of music annotations for the genre of Rock and Electronic.

Music annotations of the genre "Electronic" and "Rock" are cleaned for modeling. A music excerpt was labeled specifically by the amount of agreement among the annotations. This is calculated using the formula specified in (4).

$$P_i = \frac{1}{n(n-1)} \sum_{j=1}^{k} n_{ij}(n_{ij}s - 1) \tag{4}$$

Where n is the total number of ratings per subject. The subject is the emotion label and expressed as *i*. *i*=9. k is the number of categories, a category where the respective emotion label is selected or not. The categories are expressed as j. j is either 1(emotion selected) or 0(not selected). n_{ij} is the number of participants who assigned the i-th emotion to the j-th category [14]

After the data cleaning process, it was revealed that the excerpts are having more than one emotion label (the amount of agreement is the same for 2 or more emotion labels). Hence, it was concluded from here that the Multi-Label ML approach should be conducted.

A total number of All music excerpts were then pre-processed and normalized to 44 000Hz mono channel and 30-second duration.

Acoustic features of the music excerpts were extracted using MATLAB's MIRToolbox [15]. The acoustic features extracted were Root Mean Square (RMS) Energy, Entropy of Energy, Spectral Roll-off, Spectral Centroid, Tempo, Zero Crossing Rate & Spectral Flux. These features were selected based on the works of Tan et al. [16]. Tan had dedicatedly worked on researching to reveal acoustic features that enhance Arousal. These acoustic feature values were then used to train and test the Multi-Label ML model.

Algorithms from the 3 categories of Multi-Label classification were selected. The data set was split into 70:30 ratios of train and test data. The authors selected Binary Relevance (BR), Classifier Chain (CC) under problem transformation category, ML-kNN from Algorithm Adaptation category and RakEL as the Ensemble approach of multi Label classification [17]. BR and CC were selected as they are the fundamental levels in multi-label approaches. ML-kNN was selected as it has a higher performance and accuracy score than problem adaptation methods [17]. Finally, RAkEL was selected as it is the only ensemble approach in multi-label classification, to the best of authors' knowledge.

ML models of the above-described algorithms were trained (with a train test ratio of 70:30) with the acoustic feature values of the rock music genre. Python was selected as the programming language to train the models. The best algorithm that outputs the highest evaluation metrics were then selected. Accordingly, RAkEL produced the highest accuracy scores. Table I shows the obtained accuracy values for ML Models.

TABLE I. EVALUATION METRICS SCORES FOR MULTI-LABEL ALGORITHMS

Evaluation Metrics	BR	CC	ML -kNN	RAkEL
Jaccard score	0.28301	0.35849	0.35849	0.58980
Hamming Loss	0.31132	0.23112	0.23112	0.19811
Micro Precision	0.55096	0.70740	0.74071	0.75428
Macro Precision	0.41773	0.55280	0.55285	0.57739
Average Precision	0.50535	0.67260	0.66276	0.70276

V. CONCLUSION

In this paper, a Car Racing game is designed based on the concept of the Affective Loop. In fact, this Racing Game developed with concepts on Affective Artificial Intelligence, which will enhance user experience level as this directly connects with the player's emotions during gameplay. In other words, boost the Racing Game Effect. This affective Loop consists of real-time physiological signal elicitation of the player, emotion modeling based on the physiological signals and adjusting game parameters according to the player's real-time emotion.

The real-time physiological signal elicitation is performed using EEG Signals of the player. This work includes a study of modeling emotion using EEG signals and developing a Machine Learning framework to model emotion elicitation. Data from the Mahnob HCI Tagging database was used. The signal processing, feature extraction as well as classification was done using MATLAB toolboxes. The future work of this part of the research includes further extending to determine emotions not only with the emotional arousal domain but also the dominant emotion domain described in human psychology to achieve more accuracy.

The authors had focused on background audio music inside the game parameter space that will be deployed to change according to the player's real-time emotion. They have focused on developing music containing a database that has excerpts classified under emotion labels. To classify music excerpts into emotion labels, they have approached a scientific technology called MER. They have developed a Machine Learning model that can predict the perceived emotion of a musical excerpt. Emotify Dataset was used. Acoustic features were extracted using MATLAB toolboxes.

The future work of this part of the research includes further optimization of i) EEG signal analysis for the detection of above emotions and also to detect other emotional categories and ii) classification of music based on perceived emotions by further analyzing audio waves and extract high dominant features for emotion detection in Music.

ACKNOWLEDGMENT

International Society of Music Information Retrieval for recommending and supplying "Emotify" Human annotation dataset, "Mahnob HCI tagging" database supplied the dataset of EEG signal varies according to human emotion.

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