Experience Modeling for Candy Crush Game Player using Physiological Data by means of Homogeneous Transfer Learning

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Abstract— **Game Player Experience modeling refers to the descriptions of the players during the game play. It is based on the cognitive and affective physiological measurements collected from the sensors mounted on the player's body or in the player's surroundings. In this paper, the player's experience modeling is studied on the board puzzle game "Candy Crush Saga" by means of transfer learning concept. The physiological data of 16 channels is collected using three peripheral devices; The Emotiv Epoc, Zypher BioHarness and IOM Grapher Device. Out of 40 channels DEAP dataset, the selected 16 channels DEAP dataset is used to train the LSTM-DNN model and then the Network is tested using the player's Candy Crush collected data by means of homogeneous transfer learning concept. Several experiments are conducted to find out the performance of the proposed model and proposed idea. The result concludes that performance of the LSTM-DNN model is still efficient even by using the concept of homogeneous transfer learning.**

Keywords—Game Player Modeling; Experience Modeling; Candy Crush; Physiological data Analysis; LSTM, DNN; Transfer Learning

I. Introduction

Experience modeling refers to the association of the human player during the gameplay [1]. Player experience defines the individual and personal experience of the player while he/she is playing the game. It describes the interaction of the distinct people with particular game states investigated during or after the gameplay. It is analyzed using the physiological response of the players. These physiological responses are collected from the sensor attaching with the player's body or its surroundings [2, 3].

Player's experience modeling is generally considered as learning the subjective nature of the game player during the game [4]. This learning is dependent on the investigation of the player's physiological data to estimate the player's experience. The purpose of this learning is to understand the situations within the game which really affect the player's cognitive focus. It helps to analyze the influence of the games to the users and can be used to generalize the contents of the game based on the analysis. Furthermore, it can then be used for content generations, content customization and game customization. Player's experience may be inferred by analyzing the interaction pattern during the game play and the emotions associated to the game.

In this paper, experience Modeling is mapped to the data collected during the game-play interaction of the player and the player's affective states. The systematic computational analysis of the player's physiological data to detect, predict and estimate the experience of the game player is called the player analytics. For such experiments, input to the model includes an affective stimulus, emotional responses and the nervous system activities. The outputs of the model could be the emotional states, personality traits, annotations, rankings, and so on. These outputs are based on the objectives of the experiments used for the experience modeling. For the emotions, the valence-arousal scale by Russell and the Plutchik's emotion wheel are the most popular method [5, 6]. However, Big-Five Model and PERSONAGE are used for physiological factor classifications and speech psycholinguistic nations respectively [7].

II. Literature Review

Video games provide a dynamic media for gamers to interact with artificial environment. This advanced potential of digital games provides highly engaging manifestations, incorporating game players to express complex cognitive, affective and behavioral responses. For any particular video game, each individual (or a group of individual) has a unique way of behaving and experiencing different possible situations and scenarios in the game [8].

Evolutionary algorithms are latest approaches for learning player behavior and experience. For instance, genetic algorithm learning gamer's strategies and reinforcement learning separate expertise level [9]. The goal based actions in a sequence provide sufficient explanatory values[10]. Markov Logic Network has been adapted to develop a successful goal recognition framework for players [11].

Another Input-Output Hidden Markov Model method is proposed in [12] to predict player goals in action games. A goal recognition framework based on stacked de-noising auto-encoders using deep learning algorithm, trained through game player interaction, without feature engineering. It has shown superior performance over Markov Logic networks and many other algorithms by skipping labor-intensive and hand-crafted features extraction tasks.

Deep neural network approach is adapted in [13] where researchers asked players to play procedurally generated levels of Super Mario and collected data of more than hundred players.

The level generation is based parameters of amount of enemies and distribution of gaps between them. The players were requested to express their feelings about each played level. The annotation is based on fun, frustration and challenge. Besides this, LSTMs (Long Short-Term Memory) are an advanced variant of Recurrent Neural Networks (RNN). They are designed to sequentially label the temporal data. They have shown great performance in predicting the labeling tasks over the standard RNN. This is due to their longer-term memory leverage over the simple RNN and their effective addressing with the vanishing gradient problem [14].

The proposed game player modeling framework is based on LSTM-DNN with concept of transfer learning of knowledge obtained in one domain and used for prediction on another domain. The experience of game players for playing video games is predicted by training LSTM-DNN model with experience data of subjects while watching video games. The detailed explanation can be found in the following section.

III. Concept of Transfer Learning

Transfer learning focuses on gaining the knowledge while solving one problem and use the same knowledge to solve the different but related problem. Traditional machine learning algorithms have been working very accurate when they trained and tested on one data distribution. However, there may be situations where the training and testing data have different data distributions. For example, training a model with categories of book A and testing it on book B with different categories [15], cognitive learning on different Atari Games[16], and constraint-based generalization [17, 18]. Instead of different data distributions, there can be situations where the features of one dataset are different to features of another data set. Or, labels that have been used during the training are different at testing or no labels as in un-supervised learning [19,20]. Such problems can be solved using transfer learning methods with the fact that the performance of these methods will be degraded.

The concept of transfer learning arises when the knowledge of one domain is adjusted to use it to another domain. The challenge is to consider the beneficial knowledge between two different domains. However, when the target of the prediction model is similar in both domains, the solution to the problem becomes very easy. One such scenario is considered in this paper known as homogeneous transfer learning. The data of one domain is used to train the model and the data of another domain is used to test the model [21]. The physiological responses of the subjects are used as a training set while the subjects are watching the music video clips. The same physiological responses of the subjects are used to test the model while the subjects are playing the video game. The two domains (watching the music video clips and playing video games) have different impact on the physiological responses of the subjects. However, both represent the experience of the subjects in terms of emotions.

IV. Comparative Analysis of Physiological Response for Video Clips vs. Video Games

Emotions are defined as the physco-physiological fluctuations prompted by several external and internal stimuli such as an object, situation or a contextual environment. Specifically, in terms of music videos, the physiological responses of humans (subjects) are affected by the scenes, situations, and the context in the video clips. The subjects can express their emotions after watching the videos. They may also express the attractions and distractions during the video clips. Along with these, the liking/disliking and dominance of the video clips are also recognizable.

The video games provide the same media as that of video clips except that the player controls an avatar in the game and perform several actions to achieve the target. This is somewhat similar to watching the video clip with an addition of performing physical activity during playing the game. Along with some emotions elicited by watching the video game screen, the players are more concerned for playing the video game and trying to achieve the target. Their physiological response of the players is not only due to watching the video game, but also based on the intention of the players with the fear to Win/Loose the game, and to perform in the game to achieve the targets.
The physiological responses of the audience (while watching the video clips (This data is available online known as DEAP data explained later) and the players (while playing the video games (collected while players playing Candy Crush game) can be considered as a dataset of two different domains. Since we have no intention at this time towards the context of the video clips and video games we can say that the Video Clips and Video Games have the same physiological stimuli except that the player also focuses on thinking and playing the game.

Table 1: Physiological and Peripheral Devices and sensors

Device Name	Sensors	Data Collected
Emotiv EPOC+	Electroencephalography	14 Channels
IOM Divine	Galvanic Skin Response	1 Channel
Zephyr Bio-Harness	Respiration	1 Channel

V. DEAP Dataset

The DEAP Dataset [7] is a publically opened multi-model database. There are 32 channel EEG physiological signals and 8 peripheral physiological signals. The data of 32 subjects were recorded while each subject was watching the one-minute lengthy music video clip. Every subject responded to 40 watched videos by expressing their emotions in the form of Valence, Arousal, Dominance and Liking of the videos.

In order to use the DEAP dataset for the experimental evaluation of the model as well as the proposed method, some preprocessing is done on the DEAP dataset.

a. First of all, the binary classification methodology for the labels is preferred. This is done by thresholding the stimuli assessments into half of the defined scale. The value ranges from 1 to the middle of the scale of the Arousal, Valence, Dominance, and Liking (i.e. 4.5) are marked as zero and remaining high range values are marked as one using the binary classification.
b. A total of 63 seconds data was pre-processed for every channel with a sampling rate of 128 samples per second.
c. This classification mapped the assessments into four conditions. Low Arousal (LA), High Arousal (HA), Low Valence (LV), High Valence (HV).

d. The binary labels are generated per each subject and each video watched by the subjects. The four affect elicitation conditions are LALV, LAHV, HALV, and HAHV in the Valence-Arousal plane.
e. Among the 32 physiological sensors data, the only 14 sensors data were extracted from the DEAP dataset. The chosen channels are same as that of the Emotiv Epoc Headset used in the experiments to collect the data of the game players (will be explained in next section).

Figure 1 Screenshot of computer screen, a player is playing Candy Crush on the right, while the EEG signal are shown on the left

VI. CANDY CRUSH SAGA

Candy Crush Saga[1] is the most popular social game played on the mobile as well on the desktop computers. It is a puzzle match-3 game in which players matches the candies in combinations of three or more to win the points and overcome the obstacles or the rounds. Upon the combination of the three candies, the combination is vanished from the board and some unknown pattern of candies fall down from the top filling the board with new pattern of candies. There are more than 6500 levels each of which offer a different puzzle challenge[2].

Each level in the Candy crush has a target defined. These are high dimensional targets and ranges from easy to the hardest. For each level, there are a limited number of moves that a player can take to complete the target or finish the level. Not only moves, in some levels of the Candy Crush, a limited time of 90 seconds, 120 seconds or up to 180 seconds are given to the player to complete the level or achieve the target.

VII. EXPERIMENT SETUP FOR CANDY CRUSH DATA COLLECTION

The novel experiment was performed in the Laboratory environment. Fifteen participants (only males) with aged between 21 and 34 (Mean age 27.53), took part in the experiment. Before recording the data for the game players, each participant filled a demographic form including the name, age, skill level, number of game level played, and also a questionnaire about their physical health and mental situations. Next, they are guided about the experiment, task and restrictions while recording the data. Since the game play require physical movements (a hand to control the mouse in this case), it was requested to the participants to keep the movement as less as possible. As a demonstration, the researcher itself mounted the devices and showed to the participants and warns them about the maximum necessary movements they are allowed in order to collect the accurate data. The Arousal Valence scales are explained to the subjects and it was made sure that they understood it as they have to express their emotions using those scales. The experiment was then started when everything was ready. A total of 16 channels data is collected from three different sensors as shown in table 1. After the experiments, each participant expresses its emotional states on a questionnaire using Valance, arousal, dominance and liking/disliking. These are the ground truth collected by every participant as per their experience.

Inputs: Input Layer	Input	None, 8064
	Output	None, 8064
Embedding_1: Embedding	Input	None, 8064
	Output	None, 8064,64
LSTM_1: LSTM	Input	None, 8064,64
	Output	None, 64
FC1: Dense	Input	None, 64
	Output	None, 256
Activation_1: Activation	Input	None, 256
	Output	None, 256
Dropout_1: Dropout	Input	None, 256
	Output	None, 256
Out_Layer: Dense	Input	None, 256
	Output	None, 4
Activation_2: Activation	Input	None, 4
	Output	None, 4

Figure 2 LSTM-DNN with Input layer, embedding layer, LSTM layer, Dense and Activation layers (from top to bottom)

The EEG physiological signals were recorded using Emotiv EPOC+[3] (Model: Emotiv Premium). The Emotiv EPOC is a pre-make head worn device with fixed 14 electrodes mounted on a wireless headset. These 14 electrodes are fixed with the headset device following the international 10-20 system.

The Galvanic Skin Response (Skin Conductance) of the subjects was recorded using The Wild Divine Grapher device. The Wild Divine Grapher is a biofeedback system consisting of three sensors worn over the three middle fingers of a hand connects to the three fingers. The respiration data of the subjects is recorded using the Zephyr BioHarness™ 3 belt. It is an advanced physiological monitoring wearable device worn around the chest.

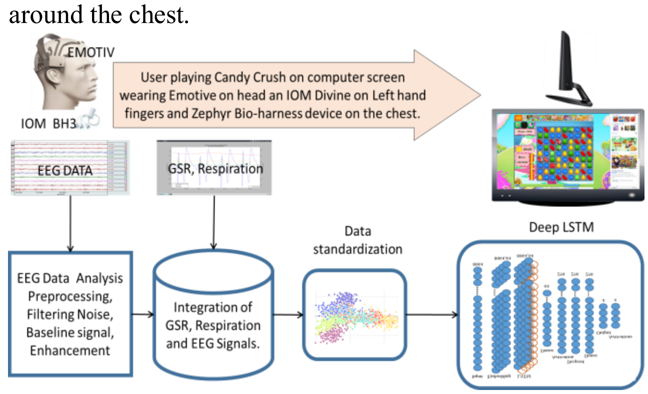

Figure 3 Framework of the Proposed Model

[1] https://king.com/game/candycrush
[2] http://candycrush.wikia.com/wiki/List_of_Levels
[3] https://www.emotiv.com/

Several pre-processing steps were taken in order to make the data useable for the experiments. The raw data of 14 channels is first down sampled to 128 samples per second, common averaged referenced and filtered with 2 Hz cut-off frequency. In order to maintain the resemblance of the Candy Crush Data with the DEAP Data, 63 seconds of data was finally extracted for each channel. Along with the EEG data, the GSR and Respiration channel data is also pre-processed. Table 1 shows the data collected for the players playing the Candy Crush game.

The Candy Crush Saga game is played using the trusted Microsoft app store on Windows 10 pro (64-Bit) operating system with Processor Intel® Core™ i7-4790 CPU @3.60Ghz (8 CPUs), RAM 32 Gigabyte and LG ULTRAWIDE (HDMI) MONITOR. The subjects used their one hand to play the game using the mouse while the other hand was kept still due to the IOM sensors attached with it. On one side of the monitor was the display of the Candy Crush Saga game while on the other side was the 14 Channel EEG signals recordings using the Emotiv Control Panel as shown in the figure 1.

VIII. Proposed Methodology

In this paper, LSTM Deep Neural Network (LSTM-DNN) is used to predict the experience of the players. Multi-layer Neural network is used with an embedding layer, LSTM layer, and two dense and activation layers as shown in figure 2.

The framework of the proposed method is shown in figure 3. The physiological signals are collected, pre-processed and given to the LSTM-DNN to predict the experience of the game players in terms of valence, arousal, dominance and liking of the players

Table 2 The Types of Experiments conducted for LSTM-DNN (DEAP-D: DEAP Dataset, Candy-D: Candy Crush Dataset)

No.	Training	Testing	Name
1	DEAP-D (40)	DEAP-D (40)	LSTM analysis on complete DEAP dataset
2	DEAP-D (16)	DEAP-D (16)	LSTM analysis on partial DEAP dataset
3	DEAP-D (16)	CCD (16)	LSTM based transfer learning with partial DEAP dataset
4	CCD (16)	CCD (16)	LSTM analysis on Candy Crush dataset
5	CCD (16)	DEAP-D (16)	LSTM based transfer learning with Candy Crush dataset

IX. Experimental Results

After collecting the game players' data and pre-processing it to minimize the difference of the DEAP data with the collected data (in terms of sampling rate, dimensions, labels, and format) the data is given to the LSTM-DNN as an input. Considering the variance and performance statistics, the data is split into 75:25 ratios to the training and testing. Several experiments have been conducted in order to test the performance of the LSTM-DNN model as well as to validate the homogeneous transfer learning approach to get considerable results. Table 2 shows number of experiments to evaluate the model as well as to measure the performance of the homogeneous transfer learning.

Figure 4 shows the accuracies of the experiments mentioned in table 2. The performance of LSTM-DNN is measured in table 3. The accuracy is dependent on the training and testing data used for the experiments. The most interesting experiment is number 3 which is totally homogeneous transfer learning approach and it shows considerable results. Although the accuracy of the other experiment was expected to be more, still it meets the state-of the art machine learning algorithms and the results are comparable to others.

Table 3: Performance measure of LSTM-DNN using different experimental settings (DEAP-D (): DEAP Data (channel), Candy-D: Candy Crush Data)

No.	Training	Testing	Accuracy
1	DEAP-D (40)	DEAP-D (40)	71.25
2	DEAP-D (16)	DEAP-D (16)	64.86
3	DEAP-D (16)	Candy-D (16)	62.50
4	Candy-D (16)	Candy-D (16)	59.17
5	Candy-D (16)	DEAP-D (16)	42.18

It is interesting that the results of the second experiment are approaching to the first experiment even though one third of the channels are used for the experiment. The accuracy fall is just 6%.

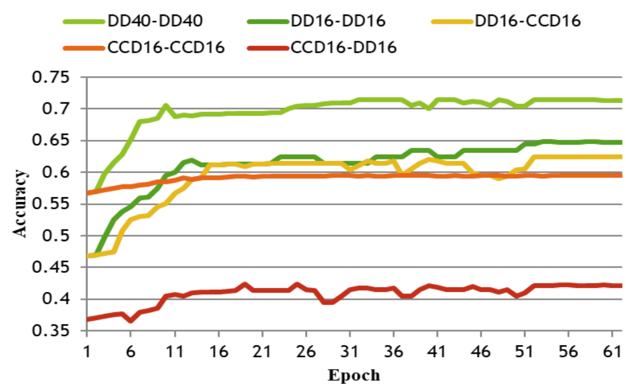

Figure 4 Performance of Different Experiments in terms of Accuracy (DD: DEAP Data, CCD: Candy Crush Data)

The proposed model is compared with state-of-the-art Support Vector Machine and Decision Tree algorithms. All five experiments are repeated with SVM and Decision Tree. The recall, precision and F-measure is computed for these techniques and is compared with proposed LSTM. The results show that proposed model outperforms in every experiment. The table shows Accuracy and F-measure for proposed Model, SVM and Decision Tree.

Table 4IX The comparison of performance of LSTM-DNN with SVM and Decision Tree under different experimental settings

No.	Experiments	SVM	Decision Tree	LSTM-DNN
	Training-Testing	Accuracy	Accuracy	Accuracy
1	DEAP-D (40)-DEAP-D (40)	0.41	35.00	0.712
2	DEAP-D (16)-DEAP-D (16)	0.39	0.36	0.648
3	DEAP-D (16)-Candy-D (16)	0.33	0.32	0.625
4	Candy-D (16)-Candy-D (16)	0.36	0.37	0.60
5	Candy-D (16)-DEAP-D (16)	0.28	0.32	0.421

X. Conclusions and Future Work

Game player experience modeling is the study of the description of the players while playing the game. The physiological signals of the players are analyzed to investigate the impact of the games over the emotional states of the gamers. This is an ongoing research work and it requires more time and experiments to reach its final conclusions. However, it can be seen that the emotions of the players can be predicted with the physiological signals of the game players. Furthermore, not only the experience, the vision of the research is to predict the in-game behavior of the gamers using the game-analytics as well as the contents customization based on the emotional states of the players. In future, we will further hypothesize that games that explore their players based on the principles of active learning will turn out to select game configurations that are interesting to the player that is being explored.

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