Using psychophysiological measures for fun factor modeling in electronic entertainment

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Introduction

Electronic entertainment (EE), especially video-games is undergoing an extensive growth in the past decade. In USA alone (biggest video-game market) the sales went from $7.3 billion in 2006 to $23.5 billion spend on game industry in 2015.

Companies creating EE content are gathering as much data about their customers as possible.
Considering that most of the EE content is consumed on-line, the data are fairly easy to collect.
Yet the self-reporting methods are still being used for assessing user-experience in movies or video-games.

In our dissertation, we will present a model of **fun factor** in EE based on correlations between self-reported experience of the subjects and **psychophysiological measurements**.
This poster presents the apparatus which will be used together with different psychophysiological measures and methods for creating the model.

Psychophysiological Measurements

- Respiratory activity (RA)
- Electroencephalography (EEG)
- Heart rate (HR)
- Electrodermal activity (EDA)
- Self-report (questionnaires and interviews)

Fig. 1 – Psychophysiological measurements used in our research

Methods

Even though time-series data analysis has mostly been done for prediction purposes in the past (weather forecasting, nature language processing), we have selected several methods to help us find patterns in existing data, similar to sequential analysis.

Random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees.

The **Hidden Markov Model** (HMM) is a powerful statistical tool for modeling generative sequences that can be characterized by an underlying process generating an observable sequence.

Long short-term memory network (LSTM) is well-suited to learn from experience to classify, process and predict time series when there are very long time lags of unknown size between important events.

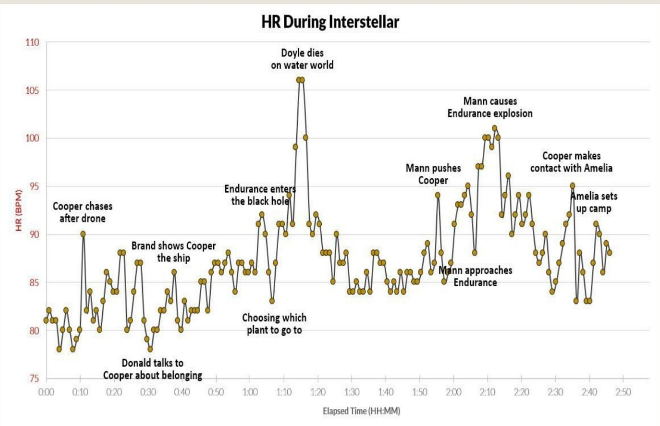

Fig. 2 – Heart rate of subject during the movie Interstellar

Fig. 3 – Screenshot of the subject playing Dota 2 during initial experiments

Apparatus

In the initial experiments (See Fig. 3), we gathered HR data of the single subject using Fitbit Surge HR sensor, an android Fitbit application and a simple python script for collecting data.

For future research, we plan to use Bioharness[2] or Hexoskin[3] sensor for measuring HR and RA.
For measuring GSR preferably wrist-worn sensor will be used, such as E4 wristband by Empatica[4] or edaMove by Movisens[5].
Finally, we will use Emotiv Epoc+[6] sensor for gathering EEG data.

For integrating data streams from multiple sensors, we plan to use initially MuLES[7] software for neurosignals and VivoSense[8] for HR and RA analysis.
One of our technological goals is also to create data analysis software able to process datasets from multiple different sensors.

Initial experiments

Initial experiments provided some findings proving the potential of the research. Subject was playing 18 games of Dota 2[1] (Fig 4).

Several findings have been discovered in these experiments:

1. Subject psychophysiological state prior to the experiment affect the average HR significantly (Fig. 5). Therefore we decided to ignore absolute values of HR, RA and EDA measurements and use only the deviations from the average values.
2. Several easy-to-observe patterns were detected:
   -HR drops rapidly while waiting for respawn
   -HR raises during massfights (big fighting encounters of multiple players)
   -last (game-deciding) massfight showed the highest HR values in 100% of games
3. No correlation between communication-related frustration (arguments with teammates, abusive chatting from opponents, etc.) and HR was detected yet.

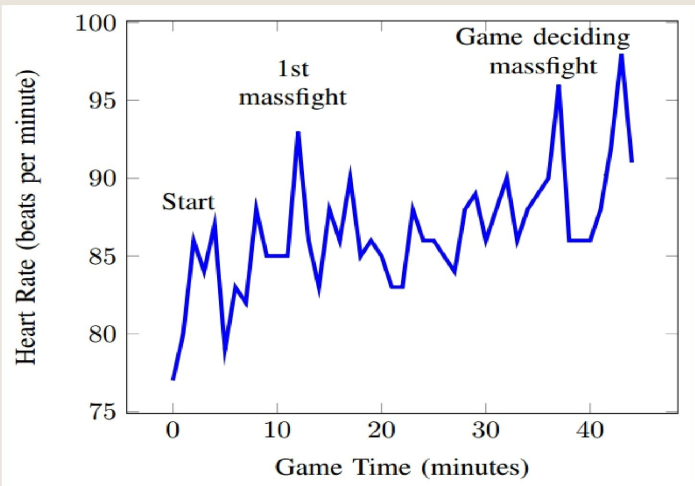

Fig. 4 – Typical game of Dota 2 in initial experiments.

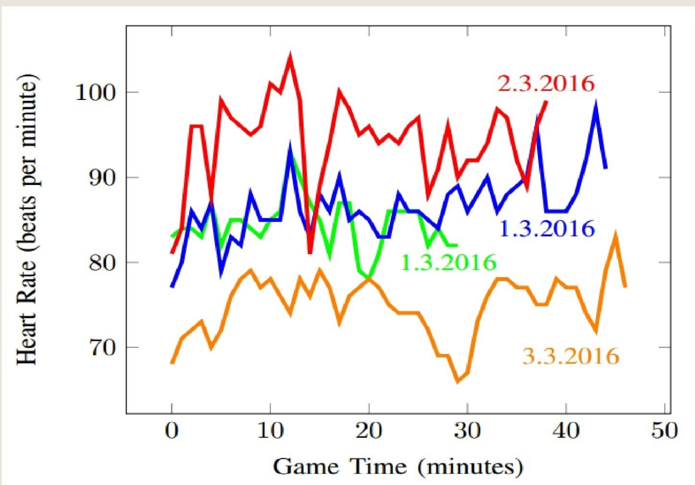

Fig. 5 – 4 games of Dota 2 played in 3 different sessions

Hypotheses and Conclusion

Scientific hypotheses:

- create a model of "fun factor" in EE based on correlation between user experience and psychophysiological measures
- find a correlations between psychophysiological data (how do HR changes affect RA and EDA?)
- compare the performance of different methods for modeling the "fun factor"

Technical hypotheses:

- acquire multiple sets of psychophysiological data using commercially available sensors
- synchronize and analyze the data of acquired dataset to find business-relevant patterns

This paper serves as a dissertation proposal. However, only a few initial experiments have already provided some significant findings.
Also, discussions with several video-game development companies have proven that this research has significant business potential.

Footnotes

1. www.dota2.com
2. www.zephyranywhere.com
3. www.hexoskin.com
4. www.empatica.com
5. www.movisens.com
6. www.emotiv.com
7. musaelab.ca
8. www.vivosense.com

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