An Introduction to a Neurofeedback-based Self-Rewarding Framework on Mobile Devices using Modern HCIs

Luca Szegletes, Bertalan Forstner

***Abstract*—**In this paper, our aim is to introduce a new approach in developing computer assisted educational games for children of different age groups. Brain-Computer Interfaces are applied in our experiments to acquire the maximal learning ability. Recent times, tablets are rapidly gaining popularity in education and smart phones are regularly used by children and by adolescents; therefore our primary research focuses on these mobile devices. Over the past decades, reinforcement learning - a learning algorithm well-known from machine learning - was applied in cognitive neuroscience; however, here the neurotransmitter dopamine is responsible for the rewarding signal. In our study, based on reinforcement learning we show how manipulating reward by a feedback from BCI through educational games can lead to a better learning ability in general. Therefore a neurofeedback self-rewarding learning framework is provided for game developers to create adaptive educational games on mobile devices.

***Keywords*—**adaptive games, EEG, neurofeedback, biofeedback, educational games, reinforcement learning, affective games, adaptive games, self-rewarding.

I. Introduction

THE purpose of our paper is to investigate measurement methods and construct an effective framework to develop adaptive 'serious' games.

Developing 'serious' games for children from different age groups offers a new approach in education to increase learning ability.

Educational games are designed to support children in achieving better performance in learning processes. The main goal of these games is to improve learning outcomes of players for certain tasks defined by instructors, teachers and psychologists.

On the other hand, tablets are gaining popularity in the educational system, and schools are open to innovative approaches.

Applying Brain Computer Interfaces (BCIs) beyond medication is a widely studied subject among researchers. It is a question, how we can implement applications in other fields [1].

The theory behind our research is based on reinforcement learning. Reinforcement learning originates from behavioral science and it is a well-known learning algorithm established in machine learning [2]. Over the past decades, reinforcement learning algorithm was adapted to cognitive and computational neuroscience as well.

The fundamental purpose of the theory is to explain how reward-seeking behavior affects the decision-making process of an agent. In a certain environment there are different actions to choose from. The primary goal of an agent is to achieve reward from this environment.

The agent attempts to interact with the environment to receive reward. Therefore, the agent takes an action according to the anticipated reward gained through this concrete action. Therefore an action is taken to receive this particular reward.

However, before learning, this anticipated reward differs from the actual one, and this error indicates learning progression as a result, because correction of the expected reward follows according to the previous difference [3] [4] [5] [6].

In addition, in cognitive neuroscience neurotransmitters are responsible for the error between the expected and the acquired reward [7] [8]. If the acquired reward is greater than the anticipated one, it accuses rising in dopamine level, and this produces a sensation of happiness.

Playing video games has similar effects [9]. Recent studies investigated physical explanation behind the affection of computer games [10].

By playing video games same progress happens in the background as in learning. Throughout playing computer games, the agent experiences similar joy and reward sensation as in learning.

In our study, based on reinforcement learning we show how manipulating reward through educational games by a feedback from our measurement framework can lead to better learning ability in general.

The aim of our study is to construct a framework, which supports educational game development and increases their performance by manipulating the reward adaptively according to measurements collected by the framework.

A neurofeedback self-rewarding learning framework is

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provided for game developers to create adaptive educational games on mobile devices.

II. Related Work

Over the past decades, neurofeedback games represent a very interesting class of games and examination of the influence of computer games is a widespread subject among researchers.

However, in recent time, studies started to observe new conceptions. In previous studies were shown how action games can improve attention skills [11].

In the past few years, the idea of using a BCI beyond medical applications spread among researchers [12]. Previous papers mentioned the concept of optimizing human learning and the performance of learning ability and improving the gaming experience in the future [13] [14] [15] [16] [17]. Despite that, they did not introduce a detailed method how to implement and develop that in practice. However, studies proposed challenges unique to BCI applications. For example the presence of artifacts and the bad signal-noise-ratio in EEG was mentioned as a serious problem to be solved in the future. Noise reduction with controlling the environment is commonly used in medical applications, however, when it comes to gaming, we cannot guarantee the same precise environment [18].

Our paper proposes an applied framework, a software tool and a software library to attach games (especially educational ones) easily to the self-rewarding framework. Our sustained feedback-based framework enables games to exploit the advantages of modern human-mobile interfaces and improve the performance of the game by the theory of reward manipulation.

The concept of the framework proposes other questions as well according to the measurement methods. Our research attempts to examine diverse approaches related to the topic.

Furthermore, previous studies introduced different biofeedback methods. Their goal was to control emotional state of a subject by monitoring heart rate, blood flow or biological alternations [19]. Our study tries to summarize a number of different approaches and presents a new approach by introducing a neurofeedback to the framework.

In recent times, mobile devices acquire more and more attention by game developers for economic reasons and therefore mobile devices has become their main platform. Personal computers are no longer monopolistic in developing computer games, and mobile games outperform desktop computer games in terms of usage frequency of causal games [20] Our research focuses on these devices as well.

In the past years, several mobile platforms were introduced to economy and society. In the first steps the prototype version of the framework is implemented on Android platform, because necessary software components are easy to access.

III. Use Case

In a typical scenario subjects are playing with their tablet. During a gameplay, different devices are measuring brain activity and changes in emotional state (for example from boredom to motivation). Measurement units are processing simultaneously.

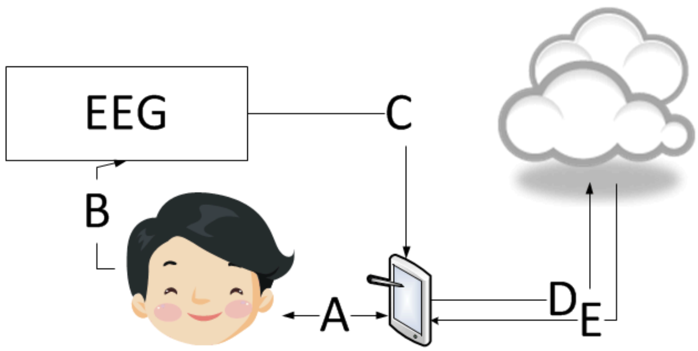

Fig. 1 **Experiment procedure.** In the experiment subjects are playing with mobile devices (A). While playing, EEG measurement follows (B). EEG signals are read by the mobile device (C). Background processes are collecting various data during the gameplay. Every data and signal are sent to the evaluation unit (D). These data are evaluated by cloud computing. Finally, after the calculation ended result is sent back to the game on the mobile device (E).

The aim of 'serious' games is to achieve better performance in the development of learning skills. Subjects are solving tasks developed by specialists: psychologists and teachers.

After every game section, subjects are receiving reward according to the goodness of the previously solved task.

However, this received reward is manipulated through the framework according to brain activity and emotional state. Furthermore, not only the reward is altered by the framework; the difficulty of the next level is also modified according to the previous game section.

Lastly, while subjects are playing with educational games, an instructor is present to check their development.

The supervisor is also using a tablet, and he/she can monitor the whole learning process, including real time game streaming, output signals of the framework.

Moreover, this supervisor unit enables the supervisor to replay the games anytime.

IV. Theoretical Background

Our research is based on reinforcement learning. To interpret the entire system one must know how rewarding signal is generated.

In reinforcement learning an agent takes an action in the environment to obtain reward. Decision-making depends on the prediction of positive outcome. Researchers have shown that dopamine activity is increased in anticipation of reward [21]. Therefore the positive outcome is not independent of the expectation of the subject.

We manipulate the reward in the game; therefore there is a difference between the expected reward of the subject and the acquired reward. If subjects receive less reward than the expected, the dopamine level drops, and this generates disappointment, and if the difference becomes positive, dopamine level rises.

To keep responsiveness we have to choose our rewarding system carefully. The controlling framework in our research gives suggestions to obtain the maximal available attention by providing the reward.

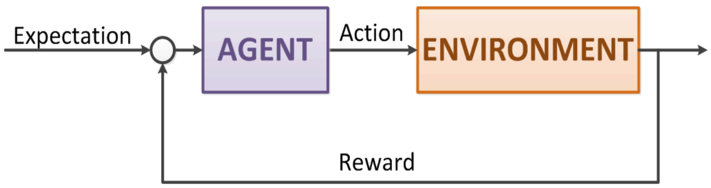

Fig. 2. **Schematic of the role of rewards**. In reinforcement learning, reward is the main reason behind motivation of a certain actions. The agent acts in the environment, and reward plays a crucial part in the learning process, because the global feedback from the environment appears in the form of a reward.

V. Rewarding System

The output of the control unit is attached to the educational game. Here, subjects obtain reward after every section of games.

The framework suggests a new reward according to the difference between the previous reward and the anticipation of the reward evaluated by the framework. After every gameplay the game asks the control unit about the next reward in the following section.

There are three different output presented in our framework: the difficulty, the value of the reward and the type of the reward. Though manipulating these outputs we can control attention and learning performance.

A. *Difficulty*

Difficulty defines the complexity of the game. For example, there are different game levels or sections with different difficulties; every game has easier and more complex parts as learning procedure occurs during games. The framework calculates the difficulty of the next game level by examining psychological and mental processes.

The framework determines the necessary level of difficulty in a percentage, and the game converts this value according to the concept of the game.

B. *Value of the Reward*

The value of the reward realizes the actual quantity of the reward (e. g. acquiring 100 or 300 points after a game level). By operating with the magnitude of the reward, we can catch and held attention and manipulate dopamine level.

The framework always gives a recommendation according to the next reward. Reward is escalating on an equidistant integer interval. The game developer has to define this scale (an interval between a minimum and a maximum value representing the reward).

C. *Type of the Reward*

One goal of instructors in education is to motivate children during teaching. But motivation can vary among different age groups and gender groups. For example, a 5-year-old girl is

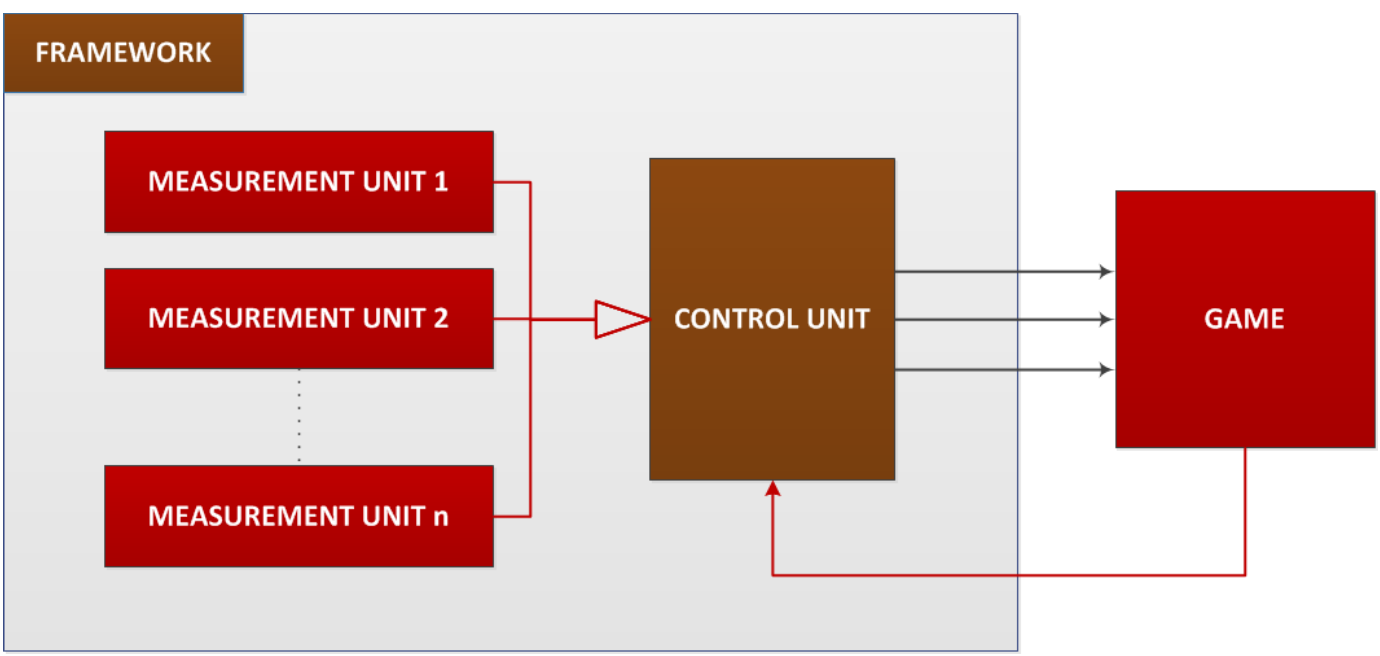

Fig. 3 **Schematic of the framework and its unit.** The framework contains two different parts: the measurement units and the control unit. The role of measurement units is to attach devices to the framework, configure these devices and preprocess raw measurement data for the control unit. The control unit is supposed to produce the rewards from the preprocessed data.

more interested in getting a "little flower or a puppy" as a reward, than getting a "car".

This is the reason why we defined the reward type in our rewarding system.

In purpose of deciding the type of the next reward in a gameplay an initialization process is included before the actual game session. While initialization the game has to register its reward types in the framework

VI. Framework

The main purpose of our study is to establish a self-rewarding measurement framework.

The framework is responsible for the rewarding signals. Games elaborate these inputs and the next game level is changed adaptively according to the generated rewards.

The framework provides the three type of reward introduced in the previous section: the difficulty of the next level, the type of the reward and the value of the reward.

The framework is constructed from two main units: the measurement unit and the control unit showed in figure 3.

The role of measurement units is to attach devices to the framework, configure these devices and preprocess raw measurement data for the control unit. Specific measurement preferences are hidden from the control unit. The measurement unit is responsible for the whole management of the different kind of measurements.

The control unit is supposed to produce the rewards from the preprocessed data. The control unit contains data analysis and machine learning algorithms for classification and regression processes.

VII. Measurement Units

Measurement units can contain different parts depending on which device is used in the actual measurement.

By designing the framework the primary aspect was to separate the implementation of low level software components from high level events.

A. EEG

In our study, to measure brain activity, we use a non-invasive technique used widespread in research area: electroencephalography.

EEG records the electrical activity of the brain along the scalp of the subject. Numerous and different EEG techniques are used in clinical and proved in experimental use.

The brain activity is measured with a device attached directly to the scalp of the subject. Measurements are processed while children are playing video games.

Measurement with EEG contains separable processes shown in figure 4. First, a preprocessor unit is introduced, this includes reading real time raw measurement data and high pass filtering and re-reference signals coming from the channels.

For the real measurements we gather data from the EEG devices (Emotiv EPOC EEG [21]). EPOC EEG has been chosen as our EEG device at the moment. The system has 14 channels and 2 reference channels.

We had to take numerous conditions into consideration in the selection process. A brief introduction is given in section IX.

In the experiment subjects are moving freely around, because they are playing with the mobile device. The device had to be wireless, portable and light because of the manners of these experiments. Our research focuses on children aged between 6 and 16, therefore the main aspect in selecting the right device needs to have a friendly appearance.

Secondly, we have to implement a driver to enable data collection from the EEG device on mobile devices. And therefore an interface has to be defined. Recent studies were published regarding to this subject, whereas reading process were handled by smart phones [22].

In our experiment, it is crucial for the algorithms to run fast – or real-time- and on the actual mobile device, because the adaptation has to be real time, automatic and cost-effective. The EEG reader is directly connected to the mobile device, it reads and sends the signals for analysis to the preprocessing unit.

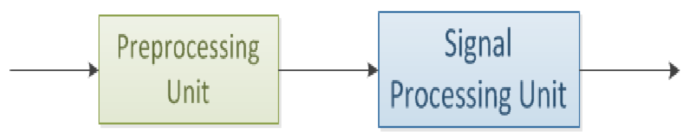

Fig. 4. **The parts of EEG measurement unit.** The preprocessing unit gets the raw measurement data and preprocess it. The signal processing unit is responsible for the actual evaluation of the preprocessed data.

Preprocessing Unit

The preprocessing unit contains simple, general procedures, like re-referencing the signals and applying a high pass filter with 0.16 Hz cutting frequency.

Signal Processing Unit

The signal processing unit is responsible for the evaluation. In this unit fastICA algorithm is applied to separate signals. Different transformations are used also in this unit (like Continues and Discrete Wavelet Transformation and Fast Fourier Transformation to define dominant frequencies [23] [24].)

There are several different techniques to analyze EEG signals [25]. By typical experiments in clinical use, amplitudes of signals are approximately 50-200V. Experiments measure event related potentials (so-called ERP) in the area of brain-computer interfaces (BCI). Here, an external stimulus appears and therefore neurons are activated, and the response is measured according to the stimulus. Event related potential is recorded about 300 ms following the event. These signals are on the order of microvolts; this is typically beneath the noise level. Therefore an averaging procedure is included. Methods to obtain these event related potential were introduced in previous papers [26]. Another technique is to analyze the power spectral density (PSD) of EEG signals [27]. Recent studied introduced HHT (Huang-Hilbert Transformation) as a new approach to analyze EEG signals in general [28].

B. Acquiring data through the mobile device

In a different, independent process from the previous procedure, incoming data from the mobile devices should be analyzed as well as the analogue signals earlier. Subjects are playing with their smartphones or tablets in the experiment.

While they are dealing with tiny tasks acquired from the game, they achieve results. They reach certain, different points every time, by every game section.

It is also important to monitor, how long we can maintain attention, because attention is the most important factor in developing learning skills.

Therefore, we should know exactly when attention drops and the subject loses interest. One option is to screen how response time of subjects is changing, they are immediately done or the decision process takes longer time.

If decision is not automatic or fast, then we should check what happened in the background. An important aspect of mobile devices is their limited capacity in resources. For an efficient solution, cloud computing is used to evaluate these algorithms.

C. Biological signals

Observation can be extended to the emotional level of the subject by measuring heart rate, skin conductance level or blood flow [29].

These recordings are not stored on the mobile device, but immediately are sent to the evaluation unit, where analysis algorithms are running.

D. Monitoring facial expression

The recent times, smartphones and tablets are equipped with built-in front-facing cameras, by using them the subject's facial expressions and eye-movements can be recorded for example, to monitor reflected emotions while answering a question or solving tasks of the gameplay.

We should detect these facial changes before, during and after the decision.

E. Supervisor

The main purpose of the framework is to support educational games. Children are playing with these games in a classroom. The supervisor is present during these sessions, and the supervisor is able to modify the result of measures.

The supervisor also has a tablet, and a specific application is running on it. It enables the supervisor to monitor the whole game session real time including game plays and outputs of the framework.

Furthermore, the framework enables the supervisor to modify game sessions, for example the supervisor can force the framework to repeat the previous game session in the gameplay.

VIII. The Control Unit

The measurement units are attached to the control unit. The control unit is responsible for producing the rewarding signal for the educational game.

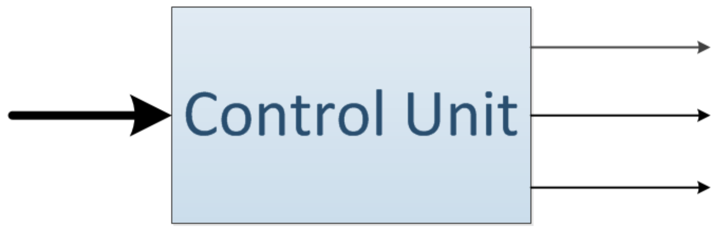

Fig. 5**. Schematic of the control unit.** The inputs of the control unit are processed measured data. The control unit produces the thee rewarding signals. The outputs of the control unit are the value of the reward, the type of the reward and difficulty**.**

There are more methods to measure attention and emotional state, the significance of these methods can diverse for every child. Therefore the control unit first has to learn how single measurement units influence the outputs. Different machine learning algorithms as classification and regression algorithms will be used to acquire the maximal performance in providing the optimal reward according the improvement of learning ability. In previous studies, pattern recognition algorithms were applied to mouse control [30].

Learning policy still is not decided but considered, so that part of the research is for further discussion.

IX. Brief Introduction of The Selected Device

As it was introduced in the previous section, the well-known Emotive headset was chosen as the primary EEG device of our system. In this section we provide a brief introduction of the device related to the framework. The research required special features of the experiments, these circumstances indicated exceptional conditions.

The Emotiv headset was used before in previous studies, where it enabled to control mobile phones for human-mobile interaction with brain signals [31]. Researchers implemented a brain-controlled address book dialing app, which works similarly to the p300-speller.

A. Emotiv Headset

The wireless EEG is the greatest advantage of the Emotiv system, because subjects are playing with their mobile device during an experiment. The environment of the experiment has to be as comfortable and user friendly as possible. Nevertheless, game experience can cause moving and fidgeting.

The Emotiv System has 14 electrodes and 2 reference channels: AF3, AF4, F3, F4, F7, F8, FC5, FC6, P3 (CMS), P4 (DRL), P7, P8, T7, T8, O1, O2. Furthermore, the Emotiv EEG possesses two-axis gyro for measuring.

The sampling rate is around 128 Hz.

At the moment, there is no available EEG driver for Android platform, but further work is in progress focusing on this issue.

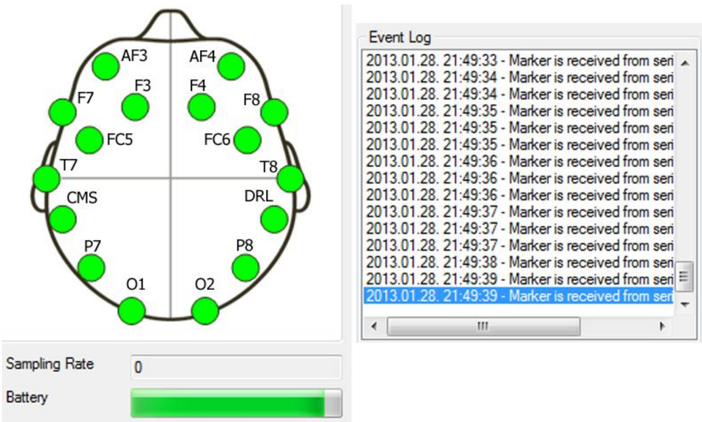

Fig. 6 **Channel locations of Emotiv Headset and Marked Events.** The channels are shown in the schematic. The incoming markers can be inquired manually or from the serial port.

B. Facial Expression

The ability of computers to recognize human emotional states given physiological signals is gaining in popularity. Emotional information is encoded by facial expression and body language. Facial expressions, gestures can be measured using the Affective Suite of the Emotiv system.

EEG sensors are working with signals linked to facial muscles, rather than by reading and detecting brainwaves. This gives a faster detection, than reading brain activity.

According to the description given by the company individual eyelid and eyebrow positions, eye position in the horizontal plane can be measured. Furthermore the following expressions are available and can be currently detected in the system: smiling, laughing, clenching, and smirking.

X. Estimation of the Error Between the Expected and Acquired Reward

The estimation of the difference between the expected and the actual reward can be approximated by feedback related negativity (FRN) in the frontal lobe and theta activity [32]. Previous papers studied the importance of feedback related negativity and its connection to the reward experience in the brain [33]. FRN delivers a method to study reward expectation, valuation and decision making processes.

It was presented earlier, that the Emotiv device is able to measure P300 activity [34].

Our future plan is to create algorithms to measure effectively single-trial ERP signals optimized on the Emotiv System. The Emotiv system has a slightly worse performance in detecting evoked potentials than EEG devices in the biomedical use according to the application of the P300 speller [35]. Therefore, applying noise reduction and signal processing algorithms are crucial.

In the last steps, the control unit will process this error of reward sensation, and it will generate the next reward according the importance and stability of this processed measurement acquired by the EEG.

XI. Interface Between the Game and the Framework

In the previous parts, hardware and software methods were introduced to construct brain-computer interfaces, in this section, the interface between the game and the framework is introduced; this special interface provides the connection between any educational game and the framework.

While subject participates in the experiments, examination processes calculate and evaluate alterations of brain activity and attention according to the game. The framework provides the optimal reward (difficulty, the value of the reward, the type of the reward) acquired from these evaluations through the interface.

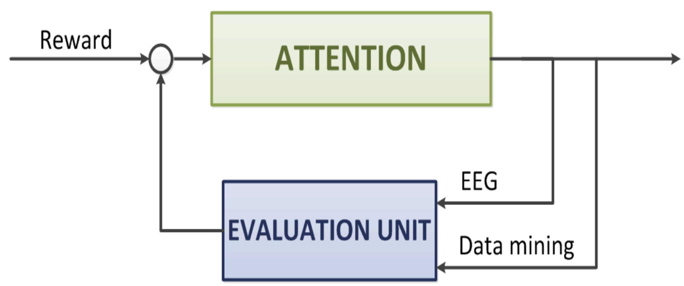

Fig. 7**. Schematic of rewarding framework.** The game produces a reward, the attention is measured by methods introduced before and correction is calculated by the evaluation unit from the obtained data. As a result, the reward will be altered according to the framework

Furthermore, every game contains game events. Game events are events, changes in the game, when the subject interacts with the game, solves a section, a game event is created to describe the modification caused by in the game. For example a game event is when reward was provided to the subject.

These game events have different priority according to the importance of their influence. A scheduler component is responsible for processing these game events.

Game events can trigger measurement units, configure the framework and mark special time intervals. The game is required to define game events, their parameters and priority.

Another requirement for the game appears in the initialization state. The type of rewards can differ in every game according to game events. The game has to select its clusters of reward types. These clusters and reward types have to be registered to the framework during the initialization process; therefore the control unit can decide later the next type of the reward.

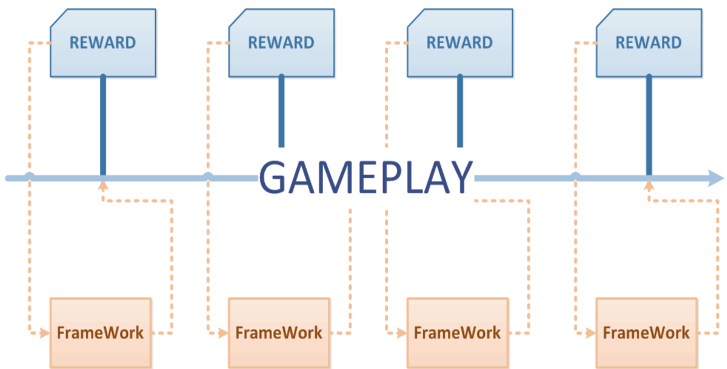

Fig. 8. **Continuous rewarding system.** During the play the actual rewards are sent to the evaluation unit. The framework defines the characteristics of the next game level. The framework determines the necessary level of difficulty in a percentage. As last step, the game receives this percentage. The game adaptively includes modifications in the play according to the percentage received from the evaluation unit.

XII. Discussion

The self-rewarding framework enables children to acquire better performance in learning and solving special tasks through controlling their attention level. The principal purpose of this framework is to help children in improving learning ability. Our framework enables attention controlled games, therefore mobile device assisted learning.

The central task of educational games is to maintain attention, concentration and motivation, this is not a simple task, and a large percentage of games never achieve success, because they cannot grasp attention. With that, a new approach was formed to apply reinforcement learning into a slightly different areas, into computer games. The environment is the game, the user takes an action and the framework produces the next reward.

The interface and the principle components of the framework were designed and the EEG device was chosen according to the circumstances of the research. The next step is to design and to establish measurement units and to attach them to the control unit. Finally, after the results are obtained by techniques from cognitive neuroscience and cognitive psychology, model has to be created to prove mathematically precisely the results.

XIII. Conclusion

In principle, to measure and control learning ability, we designed a framework. The framework has two principle parts: measurement units and a control unit.

The theory of our framework roots in the fact that small learning processes are behind the joy caused by computer games.

For numerous reasons, we chose mobile devices (especially tablets) as our primary development platform.

We defined different measurement methods for evaluation: EEG (the appropriate device was selected), heart rate, response time and a supervisor interface. An interface is designed between computer games and the framework.

The aim of the framework is to increase performance of learning ability by invent and develop adaptive 'serious' games for different age groups, nonetheless, the framework provides a testing environment for game developers.

The experiment focuses on school-aged children from different grades.

Children with learning disability (dyslexia, dysgraphia and dyscalculia) are also examined in the research.

Acknowledgment

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