Modeling Children's Entertainment in the Playware Playground

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***Abstract*— This paper introduces quantitative measurements/metrics of qualitative entertainment features within interactive playgrounds inspired by computer games and proposes artificial intelligence (AI) techniques for optimizing entertainment in such interactive systems. For this purpose the innovative Playware playground is presented and a quantitative approach to entertainment modeling based on psychological studies in the field of computer games is introduced. Evolving artificial neural networks (ANNs) are used to model player satisfaction (interest) in real-time and investigate quantitatively how the qualitative factors of *challenge* and *curiosity* contribute to human entertainment according to player reaction time with the game. The limitations of the methodology and the extensibility of the proposed approach to other genres of digital entertainment are discussed.**

Keywords: Entertainment modeling, intelligent interactive playgrounds, neuro-evolution.

I. Introduction

Cognitive modeling within human-computer interactive systems is a prominent area of research. Computer games, as examples of such systems, provide an ideal environment for research in AI, because they are based on simulations of highly complex and dynamic multi-agent worlds [1], [2], [3], and cognitive modeling since they embed rich forms of interactivity between humans and non-player characters (NPCs). Being able to model the level of user (gamer) engagement or satisfaction in real-time can provide insights to the appropriate AI methodology for enhancing the quality of playing experience [4] and furthermore be used to adjust digital entertainment environments according to individual user preferences.

Features of computer games that keep children (among others) engaged more than other digital media include their high degree of interactivity and the freedom for the child to develop and play a role within a fantasy world which is created during play [5]. On the other hand, traditional playgrounds offer the advantage of physical play, which furthermore improves the child's health condition, augment children's ability to engage in social and fantasy play [6], [7] and provide the freedom for children to generate their own rules on their own developed games. The 'Playware' [8] intelligent interactive physical playground attempts to combine the aforementioned features of both worlds: computer games and traditional playgrounds. This innovative platform will be described comprehensively and experiments with children on developed Playware games will be introduced in this paper.

Motivated by the lack of quantitative cognitive models of entertainment, an endeavor on capturing player satisfaction during gameplay (i.e. entertainment modeling) and providing quantitative measurements of entertainment in real-time is introduced in the work presented here. This is achieved by following the theoretical principles of Malone's intrinsic qualitative factors for engaging gameplay [5], namely *challenge* (i.e. *'provide a goal whose attainment is uncertain'*), *curiosity* (i.e. *'what will happen next in the game?'*) and *fantasy* (i.e. *'show or evoke images of physical objects or social situations not actually present'*) and driven by the basic concepts of the theory of *flow* (*'flow is the mental state in which players are so involved in the game that nothing else matters'*) [9]. Quantitative measures for challenge and curiosity are inspired by previous work on entertainment metrics [10] and extracted from corresponding game features that emerge through the opponent behavior. A mapping between the aforementioned factors and humans notion of entertainment is derived using a game developed on the Playware playground as a test-bed. Personalization is added to the model through the player's reaction (response) time with the game environment.

A feedforward ANN is trained through artificial evolution on gameplay experimental data to approximate the function between the examined entertainment factors and player satisfaction with and without the presence of individual player characteristics. Results demonstrate that the ANN maps a function whose qualitative features are consistent with Malone's corresponding entertainment factors in that non-extreme levels of challenge and curiosity generate highly entertaining games. Moreover, we show that player's response time has a positive impact on providing a more accurate model of player satisfaction where children (classified by their response time) project different requirements on the levels of the examined entertainment factors for the game to be entertaining. The generality of the proposed methodology and its extensibility to other genres of digital entertainment are discussed as well as its applicability as an efficient AI tool for enhancing entertainment in real-time is outlined.

II. Entertainment Modeling

The current state-of-the-art in machine learning in computer games is mainly focused on generating human-like [1] and intelligent characters (see [3], [11], [12] among others). Even though complex opponent behaviors emerge through various learning techniques, there is no further analysis of whether these behaviors contribute to the satisfaction of

the player. In other words, researchers hypothesize that by generating intelligent opponent behaviors they enable the player to gain more satisfaction from the game. According to Taatgen et al. [13], believability of computer game opponents, which are generated through cognitive models, is strongly correlated with enjoyable games. These hypotheses may well be true; however, since no notion of interest or enjoyment has been explicitly defined, there is no evidence that a specific opponent behavior generates enjoyable games. This statement is the core of Iida's work on entertainment metrics for variants of chess games [14].

Previous work in the field of entertainment modeling is based on the hypothesis that the player-opponent interaction — rather than the audiovisual features, the context or the genre of the game — is the property that primarily contributes the majority of the quality features of entertainment in a computer game [10]. Based on this fundamental assumption, a metric for measuring the real-time entertainment value of predator/prey games was established as an efficient and reliable entertainment ('interest') metric by validation against human judgement [15], [16]. According to this approach, the three qualitative criteria that collectively define entertainment for any predator/prey game are: the appropriate level of challenge, the opponent behavior diversity and the opponents' spatial diversity.

Currently there have been few attempts for adjusting the game's difficulty by reinforcement learning [17] in a fighting game or by the use of genetic algorithms [18] in the 'Snake' game. However, these studies are based on the empirical assumption that challenge is the only factor that contributes to enjoyable gaming experiences.

Following the theoretical principles reported from Yannakakis and Hallam [10], this paper is primarily focused on the game opponents' behavior contributions to the real-time entertainment value of the game. However, instead of being based on empirical observations on human entertainment, the work presented here attempts to introduce quantitative measures for Malone's entertainment factors of challenge and curiosity and extract the mapping between the two aforementioned factors and the human notion of entertainment based on experimental data from a survey with children playing with Playware playground (see Section III).

III. Playware Playground

Children's and youth's play has seen major changes during the last two decades. New emerging playing technologies, such as computer games, have been more attractive to children than traditional play partly because of the interactivity and fantasy enhancement capabilities they offer. These technologies have transformed the way children spend their leisure time: from outdoor or street play to play sitting in front of a screen [19]. This sedentary style of play may have health implications.

A new generation of playgrounds that adopt technology met in computer games may address this issue. More specifically, intelligent interactive playgrounds with abilities of adapting the game according to each child's personal preferences provide properties that can keep children engaged in entertaining physical activity. On that basis, adjusting the game in order to increase a child's entertainment can only have positive effects on the child's physical condition. The Playware playground is built along these primary concepts.

Fig. 1. The tiles used in the Playware playground.

A. Playware Technology

The Playware [8] prototype playground consists of several building blocks (i.e. tangible tiles — see Fig. 1) that allow for the game designer (e.g. the child) to develop a significant number of different games within the same platform. For instance, tiles can be placed on the floor or on the wall in different topologies to create a new game [8]. The overall technological concept of Playware is based on embodied AI [20] where intelligent physical identities (tiles) incorporate processing power, communication, input and output, focusing on the role of the morphology-intelligence interplay in developing game platforms.

1) Specifications: The Playware tile's dimensions are 21 cm x 21 cm x 6 cm (width, height, depth) and each incorporates a Atmel ATmega 128 microcontroller. To support a 4-way communication bus a Quad UART chip (TL16C754BPN) is interfaced to the serial USART on the microcontroller. The Quad UART is furthermore interfaced to a multichannel line driver/receiver (MAX211) in order to support RS-232 level connections between the tiles.

Visual interaction between the playground and children is achieved through four light emitting diodes (LEDs) which are connected to the microcontroller. In this prototype game world, users are able to interact with the tiles through a Force Sensing Resistor (FSR) sensor embedded in each tile. A rubber shell is used to cover the hardware parts of the tile and includes a "bump" indicating the location of the FSR sensor (i.e. the interaction point) and a plexiglass window for the LEDs (see Fig. 1).

B. Systems Related to Playware

The Smart Floor [21] and the KidsRoom [22] are among the few systems that are related primarily to the conceptual level of the Playware tiles. The first is developed for transparent user identification and tracking based on a person's footstep force features and the latter is a perceptually-based, multi-person, fully automated, interactive, narrative play room that adjusts its behavior (story-line) by analyzing the children's behavior through computer vision. As far as the concept of intelligent floors consisting of several building blocks is concerned, the Z-tiles [23] are closely related to Playware. However, the Z-tiles are mainly used as input devices only whereas Playware comprises building blocks that offer interactivity by incorporating both input and output devices.

C. Bug-Smasher Game

The test-bed game used for the experiments presented here is called 'Bug-Smasher'. The game is developed on a 6 x 6 square tile topology (see Fig. 2). During the game, different 'bugs' (colored lights) appear on the game surface and disappear sequentially after a short period of time by turning a tile's light on and off respectively. A bug's position is picked within a radius of three tiles from the previous bug and according to the predefined level of the bugs' spatial diversity (see Section IV). Spatial diversity is measured by the entropy of the bug-visited tiles which is calculated and normalized into $[0, 1]$ via (1)

$$H = \left[-\frac{1}{log36} \sum_i \frac{v_i}{V} log\left(\frac{v_i}{V}\right) \right] \quad (1)$$

where v_i is the number of bug-visits to tile i and V is the total number of visits to all visited tiles (i.e. $V = \sum_i v_i$). If the bug visits all tiles equally then $v_i = V/36$ for all 36 tiles and H will be 1; if the bug visits exactly one tile, H is zero.

The child's goal is to smash as many bugs as possible by stepping on the lighted tiles. Different sounds and colors represent different bugs when appearing and when smashed in order to increase the fantasy entertainment factor [5]. Moreover, feedback to the player, which is essential for a successful game design [5], is provided through different characteristic sounds that represent good or bad performance.

IV. Experimental Data

The Bug-Smasher game has been used to acquire data of human judgement on entertainment. Two states ('Low' and 'High') are used for each of the three entertainment factors of challenge, curiosity and fantasy summing up to 8 different game states. While the fantasy factor is also investigated through this survey, the focus of this paper is on the opponent (bug) contribution on entertainment and, therefore, only the relation between challenge, curiosity and entertainment is reported here.

We consider the speed (S — in sec^{-1}) that the bugs appear and disappear from the game and their spatial diversity (H) on the game's plane as appropriate measures to represent the level of challenge and the level of curiosity (unpredictability) respectively [5] during gameplay. The former provides a notion for a goal whose attainment is uncertain — the higher the S value, the higher the goal uncertainty and furthermore the higher the challenge — and the latter effectively portrays a notion of unpredictability in the subsequent events of the game — the higher the H value the higher the bug appearance unpredictability and therefore the higher the curiosity.

Fig. 2. A child playing the Bug-Smasher game.

To that end, 28 children — $C_2^8 = 28$ being the required number of all combinations of 2 out of 8 game states since, by experimental design, each subject plays against two of the selected game states in all permutations of pairs — whose age covered a range between 8 and 10 years participated in an experiment. In this experiment, each subject plays two games (A and B) — differing in the levels of one or more entertainment factors of challenge, curiosity and fantasy — for 90 seconds each. Each time a pair of games is finished, the child is asked whether the first game was more interesting than the second game i.e. whether A or B generated a more interesting game. The child's answers are used to guide the training of an ANN model of entertainment (see Section V). In order to minimize any potential order effects we let each subject play the aforementioned games in the inverse order too. Statistical analysis of the subjects' answers shows that the order effect on children judgement on entertainment is not statistically significant ($r_c = -0.0714$, p-value$= 0.3444$).

Since at the current implementation of the Playware the only input to the system is through the FSR sensor, quantitative individual playing characteristics can only be based on three measurable features: the state (position and LEDs color) of a pressed tile, the time that a tile-press event took place and the pressure force on a pressed tile.

Pressed tile events are recorded in real-time and a selection of personalized playing features are calculated for each child. These include the total numbers of smashed bugs P and interactions with the game environment N_I; the average response time $E\{r_t\}$; the average distance between the pressed tile and the bugs appearing on the game $E\{D_b\}$; the average pressure recorded from the FSR sensor $E\{p\}$; and the entropy of the tiles that the child visited H_C.

A. Statistical Analysis

The aim of the statistical analysis presented here is to identify statistically significant correlations between human notion of entertainment and any of the aforementioned individual quantitative playing characteristics. For this purpose the following null hypothesis is formed: The correlation between observed human judgement of entertainment and recorded individual playing characteristics, as far as the different game states are concerned, is a result of randomness. The test statistic is obtained through $c(\overrightarrow{z}) = \sum_{i=1}^{\mathbf{N}} \{z_i/\mathbf{N}\}$, where $\mathbf{N}$ is the total number of game pairs played and $z_i = 1$, if the subject chooses as the more entertaining game the one with the larger value of the examined characteristic and $z_i = -1$, if the subject chooses the other game in the game pair i.

Table I presents the $c(\overrightarrow{z})$ values and their corresponding p-values for all above-mentioned personal characteristics. Average response time appears to be the only characteristic examined that is significantly — significance equals 10%, high significance equals 5% in this paper — correlated to entertainment. The obtained effect of $E\{r_t\}$ appears to be commonsensical since the Bug-Smasher game belongs to the genre of action games where reaction time tends to have a significant effect on the level of engagement of the user [24].

The first attempt to include subjectivity in entertainment modeling, presented in this paper, will be through investigating the impact of entertainment factors on entertainment according to the average response time $E\{r_t\}$. The choice of this specific measure, instead of others examined, is made due to its demonstrated statistically significant effect to entertainment.

TABLE I

CORRELATION COEFFICIENTS BETWEEN ENTERTAINMENT AND INDIVIDUAL GAMEPLAY QUANTITATIVE CHARACTERISTICS. P IS THE TOTAL NUMBER OF SMASHED BUGS; N_I IS THE TOTAL NUMBER OF INTERACTIONS; $E\{r_t\}$ IS THE AVERAGE RESPONSE TIME; $E\{D_b\}$ IS THE AVERAGE DISTANCE BETWEEN THE PRESSED TILE AND THE BUGS APPEARING ON THE GAME; $E\{p\}$ IS THE AVERAGE PRESSURE RECORDED FROM THE FSR SENSOR AND H_C IS THE ENTROPY OF THE TILES THAT THE CHILD VISITED.

Characteristic	$c(\overrightarrow{z})$	p-value
P	-0.0384	0.4449
N_I	0.1923	0.1058
H_C	-0.1153	0.2442
$E\{r_t\}$	-0.2307	0.0631
$E\{p\}$	0.0769	0.3389
$E\{D_b\}$	-0.0384	0.4449

V. EVOLVING ANN

A fully-connected feedforward ANN for learning the relation between the challenge and curiosity factors, the average response time of children and the entertainment value of a game has been used and is presented here. The assumption is that the entertainment value y of a given game is an unknown function of S and H (and perhaps $E\{r_t\}$), which the ANN will learn. The children's expressed preferences constrain but do not specify the values of y for individual games. Since, the output error function is not differentiable, ANN training algorithms such as back-propagation are inapplicable. Learning is achieved through artificial evolution [25] and is described in Section V-A.

The sigmoid function is employed at each neuron, the connection weights take values from -5 to 5 and all input values are normalized into [0, 1] before they are entered into the ANN. In an attempt to minimize the controller's size, it was determined that single hidden-layered ANN architectures, containing 10 hidden neurons, are capable of successfully obtaining solutions of high fitness.

A. Genetic Algorithm

A generational genetic algorithm (GA) [26] is implemented, which uses an "exogenous" evaluation function that promotes the minimization of the difference in matching the human judgement of entertainment. The ANN is itself evolved. In the algorithm presented here, the ANN topology is fixed and the GA chromosome is a vector of ANN connection weights.

The evolutionary procedure used can be described as follows. A population of N (N is 1000 in this paper) networks is initialized randomly. Initial real values that lie within [-5, 5] for their connection weights are picked randomly from a uniform distribution. Then, at each generation:

Step 1 Each member (neural network) of the population gets two triples of (S, H, $E\{r_t\}$) values one for A and one for B and returns two output values, namely $y_{j,A}$ (output of the game against opponent A) and $y_{j,B}$ (output of the game against opponent B) for each pair j of games played in the survey ($N_s = 56$). When the $y_{j,A}$, $y_{j,B}$ values are consistent with the judgement of subject j then we state that: 'the values agree with the subject' or that there is 'agreement' with the subject throughout this paper. In the opposite case, we state that: 'the values disagree with the subject' or there is 'disagreement.'

Step 2 Each member i of the population is evaluated via the fitness function f_i:

$$f_i = \sum_{j=1}^{N_s} \begin{cases} g(d_j, 30), & \text{if agreement;} \\ g(d_j, 5), & \text{if disagreement.} \end{cases} \quad (2)$$

where $d_j = y_{j,A} - y_{j,B}$ and $g(d_j, p) = 1/(1 + e^{-pd_j})$ is the sigmoid function.

Step 3 A fitness-proportional scheme is used as the selection method.

Step 4 Selected parents clone an equal number of offspring so that the total population reaches N members or reproduce offspring by crossover. The

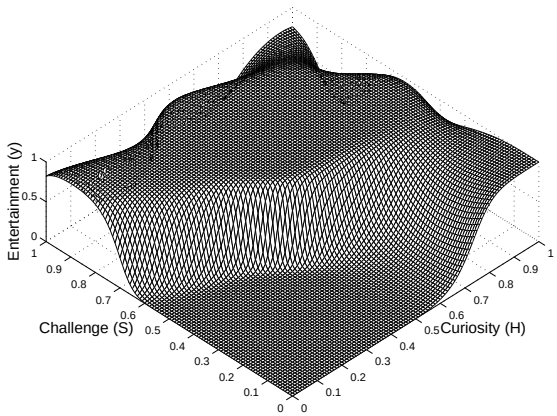


Fig. 3. Fittest ANN ($f = 22.82$) trained on absence of individual playing characteristics.

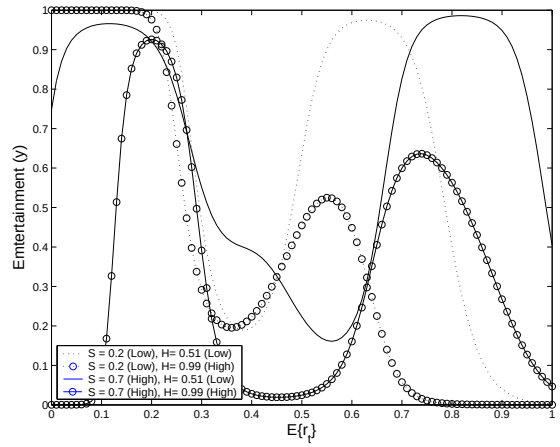


Fig. 4. Fittest ANN ($f = 52.68$): Entertainment over average response time for both states (*Low*, *High*) of each entertainment factor S and H.

Montana and Davis [27] crossover operator is applied with a probability 0.4.

Step 5 Gaussian mutation occurs in each gene (connection weight) of each offspring's genome with a small probability $p_m = 1/n$, where n is the number of genes.

The algorithm is terminated when either a good solution (i.e. $f_i > 54$) is found or a large number of generations g is completed ($g = 10000$).

VI. Results

Results obtained from the ANN evolutionary approaches are presented in this section. In order to diminish the non-deterministic effect of the GA initialization phase, we repeat the learning procedure ten times — we believe that this number is adequate to illustrate a clear picture of the behavior of the mechanism — with different random initial conditions.

A. Objective Entertainment Value

The experiment presented here tests the hypothesis of the existence of an objective notion of entertainment given the level of challenge and curiosity in a game. Thus, the aim here is to extract a mapping between challenge, curiosity and entertainment independently of player individual characteristics ($E\{r_t\}$ values are not included in the ANN input vector). Given the 30 pairs of games, where the games have different levels of S and/or H, an ANN is evolved by following the approach presented in Section V-A. The fittest ANN found was able to correctly match only 20 out of 30 children answers on entertainment. Such a poor fitness indicates the difficulty of adjusting values of challenge and curiosity for inferring entertainment values in an objective manner (without the presence of individual characteristics). The relation between bug speed (S), bug spatial diversity (H) and the game's entertainment value (y) is illustrated in Fig. 3.

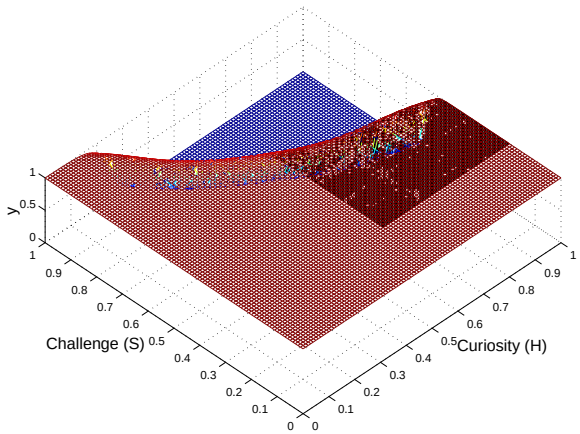
Despite the best solution's poor fitness, the correlation between entertainment, challenge and curiosity generated through the evolved ANN (see Fig. 3) appears to follow the qualitative principles of Malone's work [5]. According to these, a game should maintain an appropriate level of challenge and curiosity in order to be entertaining. In other words, too difficult and/or too easy and/or too unpredictable and/or too predictable opponents to play against make the game uninteresting. As seen from Fig. 3, average levels of challenge ($0.5 < S < 0.8$) and curiosity ($0.3 < H < 0.9$) generate high entertainment values objectively. Moreover, it appears that games of the lowest challenge level ($S \approx 0$) combined with the highest curiosity level ($H \approx 1$) may yield high entertainment values.

B. Response time

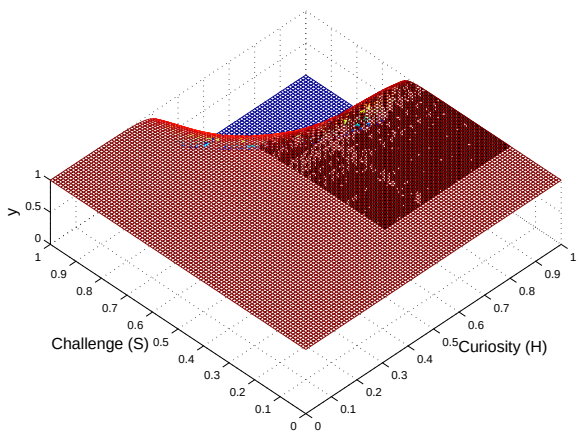
As previously presented in Fig. 3, extreme values of challenge and curiosity appear to generally generate low values of player satisfaction. However, what it still needs to be extracted are the appropriate levels of challenge and unpredictability required by individual players for a game to be entertaining.

This section presents experiments where individual characteristics are present in the evaluation of entertainment. Thus, the average response time of the child is included in the input vector of the ANN which is evolved by following the approach presented in Section V-A. For space considerations, only the fittest solution is presented in this paper. Note that, the qualitative features of the lines and surfaces plotted in Fig. 4 and Fig. 5 appeared in all ten learning attempts.

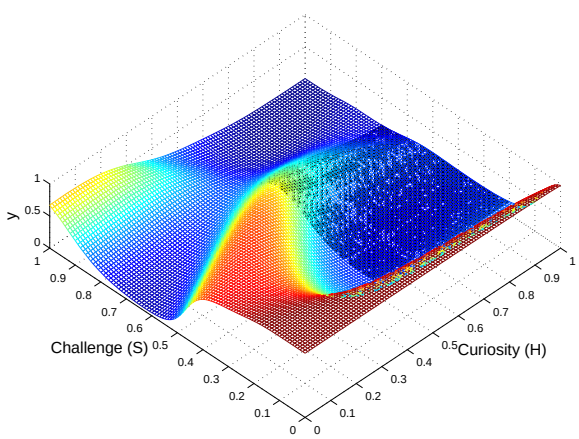
More specifically, Fig. 4 illustrates that challenge has a higher impact on children's notion of entertainment than curiosity. In fact, low levels of curiosity appear to entertain children more. This could be explained through the fact that for the game experiments presented in this paper the *High* value for H is the highest possible value of entropy ($H \approx 1.0$). This level of bugs entropy appears to generate too unpredictable games for the majority of children and, therefore, confusion during play and furthermore less satisfaction. Fig. 4 also shows that highly entertaining games are generated when challenge is *Low* and children are fast



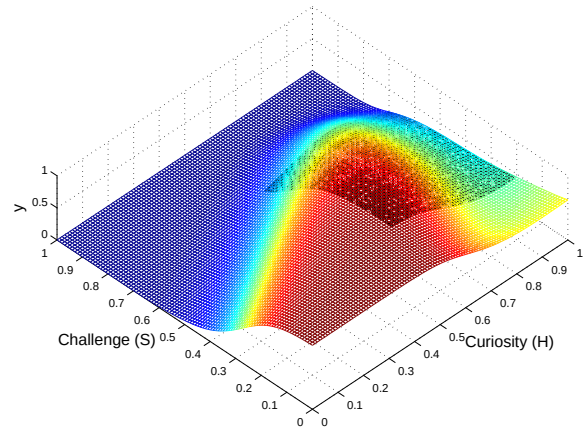
(a) $E\{r_t\} = 0.0$



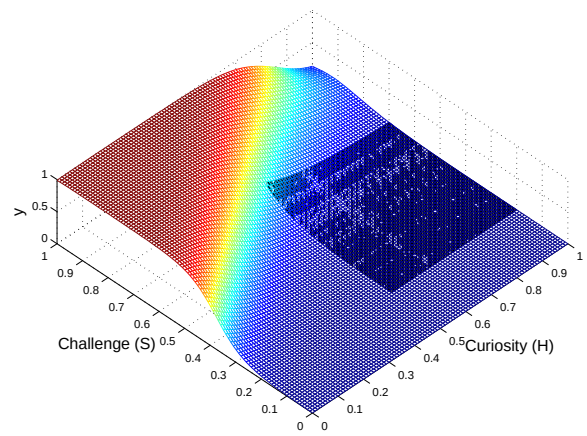
(b) $E\{r_t\} = 0.1$



(c) $E\{r_t\} = 0.356$



(d) $E\{r_t\} = 0.6$



(e) $E\{r_t\} = 1.0$

Fig. 5. Fittest ANN ($f = 52.68$): ANN output y (entertainment) with regards to S and H for 5 values of $E\{r_t\}$. The shadowed area corresponds to the surface within the *Low* and *High* states of the S and H values.

in their average response time ($E\{r_t\} < 0.3$) and when $0.5 < E\{r_t\} < 0.7$. On the other hand, when children are reacting slowly ($0.7 < E\{r_t\} < 1.0$), high values of entertainment y are generated when challenge is *High* in the game. *High* challenge combined with *Low* curiosity has also the most positive impact on entertainment in children whose average response time lies between 0.3 and 0.4.

Fig. 5 illustrates the trained ANN output with regards to challenge and curiosity for five characteristic $E\{r_t\}$ values: the two boundaries (0 and 1), the median (0.356) and two values (0.1 and 0.6) that determine the interval within the 82.14% (92 values) of the average response times are recorded. Values outside this interval correspond to a 8.93% (10 values) of very fast ($E\{r_t\} \leq 0.1$) and a 8.93% (10 values) of very slow ($E\{r_t\} \geq 0.6$) children.

If we make the generic assumption that response time cor-

relates with perception time then one would expect that the faster the perception ability of a child the higher its demand for faster (more challenging) and more unpredictable (higher curiosity) games. However, Fig. 5 illustrates the inverse case since it appears that faster children have a preference for games of lower challenge and curiosity (see Fig. 5(a)) whereas slower children appear to prefer games of high challenge (see Fig. 5(e)). Therefore, this assumption seems to be ruled out for this case study or the aforementioned correlation is insignificant.

In order to demonstrate a clearer image of the child's behavior with regards to its recorded response time, we calculate the correlation coefficients between $E\{r_t\}$ and the measurable individual child characteristics previously mentioned in Section IV-A. As seen from Table II, the correlation coefficient r_c between $E\{r_t\}$ values and their corresponding sample size (total number of interactions N_I) shows a statistically high significant tendency for fast-reacting and slow-reacting children to interact more and less frequently with the game environment respectively. Moreover, $E\{r_t\}$ values correlate significantly with the child's spatial diversity on the game surface ($r_c = 0.3305$, p-value = $7.82{\cdot}10^{-4}$) and the average pressure on the tiles ($r_c = 0.2175$, p-value = 0.0296) as well as correlate inversely with the child's performance measure P ($r_c = -0.4058$, p-value = $2.80{\cdot}10^{-5}$). These indicate that the faster the response time the less children tend to move around on the game surface, the less their pressure on the tiles and the higher their performance.

To summarize given the r_c values on Table II, it can be assumed that low $E\{r_t\}$ values correspond to a rather static behavior of children pressing faster and more frequently few tiles which results to higher performance, whereas high $E\{r_t\}$ values correspond to children that move on larger and decisive (and powerful) steps, covering much of the game surface and taking their time for their next step which as a strategy results to lower performance.

The aforementioned quantitative indications about children behavior do also match the video-recorded playing behavior. Thus, it can be derived that when $E\{r_t\}$ is low, static children cannot easily cope with too challenging and too unpredictable games. Therefore, it appears that such games are not entertaining for children of this category (see Fig. 5(a), Fig. 5(b)). On the other hand, when a child's $E\{r_t\}$ value is high, the child appears to prefer games of low curiosity at a level of challenge higher than average (see Fig. 5(e)). The reason for such a preference might be that too unpredictable games require more motion from children in the Bug-Smasher game and, therefore, these games become very tiring for children that tend to cover uniformly the game's surface.

Finally, low levels of challenge combined with average levels of curiosity or high levels of challenge combined with low levels of curiosity appear to be the preferred game states for children whose $E\{r_t\}$ values are between 0.1 and 0.6 (see Fig. 5(c) and Fig. 5(d)).

TABLE II

CORRELATION COEFFICIENTS BETWEEN $E\{r_t\}$ AND OTHER INDIVIDUAL GAMEPLAY QUANTITATIVE CHARACTERISTICS. P IS THE TOTAL NUMBER OF SMASHED BUGS; N_I IS THE TOTAL NUMBER OF INTERACTIONS; $E\{r_t\}$ IS THE AVERAGE RESPONSE TIME; $E\{D_b\}$ IS THE AVERAGE DISTANCE BETWEEN THE PRESSED TILE AND THE BUGS APPEARING ON THE GAME; $E\{p\}$ IS THE AVERAGE PRESSURE RECORDED FROM THE FSR SENSOR AND H_C IS THE ENTROPY OF THE TILES THAT THE CHILD VISITED.

Characteristic	r_c	p-value
P	-0.4058	$2.80{\cdot}10^{-5}$
N_I	-0.4324	$7.01{\cdot}10^{-6}$
H_C	0.3305	$7.82{\cdot}10^{-4}$
$E\{p\}$	0.2175	0.0296
$E\{D_b\}$	0.0494	0.6249

VII. CONCLUSIONS & DISCUSSION

This paper introduced quantitative metrics for entertainment primarily based on the qualitative principles of Malone's intrinsic factors for engaging gameplay [5] and individual game play features. More specifically, the quantitative impact of the factors of challenge and curiosity and the average response time on children's entertainment were investigated through the Bug-Smasher game played on the Playware playground. Moreover, the advantages of play on interactive intelligent playgrounds were stated and experiments within the Playware platform were introduced in this paper.

The evolved ANN approach for modeling entertainment in real-time examined demonstrates qualitative features that share principles with Malone's theory on efficient game design [5]. The fittest ANN solution manages to map successfully between the entertainment factors of challenge and curiosity and the notion of human gameplay satisfaction on the absence of individual player characteristics and demonstrated that non-extreme values for the entertainment factors generate highly entertaining games. In addition, the learned mapping with regards to the children's average response times showed that fast responding children show a preference for low challenge games of low curiosity whereas slow responding children tend to prefer games of high challenge and low curiosity.

The current work is limited by the number of participants in the game survey we devised. Therefore, not all regions of the challenge-curiosity search space were sampled by human play which therefore yielded poor ANN generalization for these regions. Limited data also restricted the sensible number of inputs to the learning system. More states for the measurable metrics of challenge and curiosity need to be obtained and other measures — e.g. average distance between the bugs instead of speed for measuring challenge — need to be investigated in a future study. The challenge that arises here is that the number of subjects required for experiments like the one reported here is factorial with respect to the number of states chosen for the entertainment

factors and the total number of entertainment factors under investigation. Moreover, Malone's entertainment factor of fantasy is omitted from the results in this paper since the focus is on the contribution of the opponent behaviors to the generation of entertainment; however, fantasy's impact on entertainment is planned to be reported in a forthcoming analysis.

The entertainment modeling approach presented here demonstrates generality over the majority of action games created with Playware since the quantitative means of challenge and curiosity are estimated through the generic features of speed and spatial diversity of the opponent on the game's surface. Thus, these or similar measures could be used to adjust player satisfaction in any future game development on the Playware tiles. However, each game demonstrates individual entertainment features that might need to be extracted and added on the proposed measures and therefore, more games of the same and/or other genres need to be tested to cross-validate this hypothesis. The proposed approach can be used for adaptation of the game opponents (e.g. bugs) according to the player's individual playing style (reaction time) and as far as the challenge and curiosity factors of entertainment are concerned. Given the real-time average response time of a child, the partial derivatives of $\vartheta y/\vartheta S$ and $\vartheta y/\vartheta H$ can be used to appropriately adjust the speed and the entropy of the opponent respectively for the entertainment value y to be augmented.

Such a direction constitutes an example of future work on Playware, computer and educational games. The level of engagement or motivation of the user/player/gamer of such interactive environments can be identified and increased by the use of the presented approaches. Apart from providing systems of richer interaction and qualitative entertainment [4], such approaches can generate augmented motivation of the user for deep learning in learning environments that use games (i.e. edutainment).

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