# Feature Selection for Capturing the Experience of Fun

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### Abstract

Several approaches for constructing metrics to capture player experience have been presented previously. In this paper, we propose a generic methodology based on feature selection and preference machine learning for constructing such metric models of the degree to which a player enjoys a given game.

For that purpose, previous and new survey experiments on computer and physical interactive games are presented. Given effective data collection a set of numerical features is extracted from a player's interaction with the game and its physiological state. Then feature selection algorithms are employed together with a function approximator based on artificial neural networks to construct feature sets and function that model the players' notion of 'fun' for the game under investigation. Performance of the model is evaluated by the degree to which the preferences predicted by the model match those 'fun' (entertainment) preferences expressed by the subjects.

The results show that effective models can be constructed using the proposed approach. The limitations and the use of the methodology as an effective adaptive mechanism to entertainment augmentation are discussed.

## Introduction

The principal goal in the reported work is to construct a user model of a class of game playing experience. Specifically, the aim is that the model can predict the answers to which variants of a given game are more or less "fun." This approach is defined as *Entertainment Modeling*. Feature selection is the proposed methodology for choosing the appropriate features extracted from both game-player interaction and the player's physiology. Game play experiences may very well be video recorded and emotions could be recognized by experts or automatically through face gesture detection; however, these approaches are not the focus of this work.

In this work the entertainment model is constructed using preference learning techniques applied to statistical features derived from physiological signals and gameplay data measured during play. The output of the constructed model is a real number in the range $[0, 1]$ such that more enjoyable games receive higher numerical output. This basic approach of entertainment modeling is applicable to a variety of games, both computer (Yannakakis & Hallam 2006) and physical (Yannakakis, Lund, & Hallam 2006), using features derived from physiological data and/or from the interaction of player and opponent measured through game parameters. This paper includes the presentation of successful applications of the proposed experimental protocol for effective data collection, the overview of results from feature selection in both computer and physical interactive games of previous studies and preliminary results of a new set of survey experiments.



## Experiment Setup

This section provides suggestions for effective experimental setup design based on previous empirical studies. According to the experimental design proposed by Yannakakis & Hallam (2007b), the test-bed game under investigation is played in variants. For this purpose, different states (e.g. 'Low', 'High') of quantitative estimators of qualitative entertainment factors (e.g. challenge) are used. The combination of states/number of entertainment factors generates a pool of dissimilar games for the designer to investigate.

### Quantification of Entertainment Factors

Estimators of Malone's (Malone 1981) qualitative entertainment features of *challenge* and *curiosity* have already been reported in the literature for a set of computer and physical interactive games. For instance, in a version of the well-known Pac-Man game the average time before Pac-Man was killed and the standard deviation of these playing-time intervals were considered as measures to represent the level of challenge and the level of curiosity (unpredictability) respectively (Malone 1981) during gameplay (Yannakakis & Hallam 2006).

Likewise, in the physical interactive play domain, the Bug-Smasher game (Yannakakis, Hallam, & Lund 2006) has been designed on the Playware (Lund, Klitbo, & Jessen 2005) physical game platform and used for capturing children's reported experience of "fun". In this game, children have to smash as many bugs as possible by stepping on lighted tiles (bugs) that appear on a $6 \times 6$ tiled floor. Bug-Smasher has been used as a test-bed in previous work; fur-

ther details can been found in (Yannakakis, Lund, & Hallam 2006; Yannakakis, Hallam, & Lund 2006) and (Yannakakis & Hallam 2007a). In Bug-Smasher the speed that the bugs appear and disappear from the game and their spatial diversity in the game field were the estimators of challenge and curiosity respectively (Malone 1981).

In both examples, the former estimator provides a notion of a goal whose attainment is uncertain while the latter estimator effectively portrays a notion of unpredictability in the subsequent events of the game.

### Experimental Protocol

By experimental design (see (Yannakakis & Hallam 2006; Yannakakis, Lund, & Hallam 2006)), each subject plays against $k$ of the selected $n$ variants of the game in all permutations of pairs. Thus, $C_k^n$ is the required number of subjects to cover all combinations of $k$ out of $n$ game variants. More specifically, each subject plays games in pairs (game $A$ and game $B$) — differing in the levels/states of one or more of the selected entertainment factors — for a selected time window. Each time a pair of games ('game pair') is finished, the subject is asked whether the first game was more "fun" than the second game (pairwise preference). Subjects are not interviewed but are asked to fill in a questionnaire, minimizing the interviewing effects reported in (Mandryk, Inkpen, & Calvert 2006). To minimize any potential order effects we let each subject play the aforementioned games in the inverse order too. Statistical analysis of the effect of order of game playing on subjects' judgement of entertainment projects the level of randomness in subjects' preferences (see (Yannakakis 2005)). Randomness is apparent when there is an indifferent preference in the pair $(A, B)$; i.e. $A \succ B$ and $B \succ A$. Order effects of any type should be insignificant in the ideal case study.

The playing time window chosen should be a compromise between effective data collection (long enough subject-game interaction to support a relative judgement) and not overstretching subjects (especially children whose time is a valuable commodity). If physical activity games are under investigation each subject's total playing time should not surpass significant periods of energetic physical play.

All subjects should be given the same instructions by an experimenter who is unaware of the purpose of the experiment. No further oral or eye-contact communication during experiment tasks and questionnaire should be present, minimizing experimenter expectancy effects (Rosenthal 2003).

Emotion, such as entertainment, capture is considered, in general, a hard problem mainly because understanding emotion is hard (Picard, Vyzas, & Healey 2001). Capturing reports of playing experiences or emotions is still tough since data obtained embed experimental noise and subjectivity. To capture the subjects' preferences for the game variants played, a 2-alternative forced choice (2-AFC) approach is used since it offers several advantages for a subjective entertainment capture: it minimizes the assumptions made about subjects' notions of "fun" and allows a fair comparison between the answers of different humans. Since the focus is to construct a model relating reported entertainment preferences to individual playing features that generalises over the reports of different players 2-AFC is preferred to a ranking approach (Mandryk, Inkpen, & Calvert 2006). Forcing the choice of subjects generates experimental noise, in that the subject may have no significant preference for one or other of the game variants played yet must nevertheless express a preference; however, insignificant order effects provide evidence that the experimental noise generated in this way is random.

### Data Collection

Individual player models can be constructed through several types of data collected during play. The two main categories explored in this paper are data obtained through the interaction between the user and the game platform and data obtained from the user's physiological state. The former includes extracted features from the user's playing behavior derived from responses to any game opponent behavior. The latter refers to real-time recordings of physiological signals affected by sympathetic arousal (Mandryk, Inkpen, & Calvert 2006). For instance, ElectroCardioGram (ECG), Blood Volume Pulse (BVP), Galvanic Skin Response (GSR), respiration and jaw-electromyography (EMG) are the most popular physiological signals used for emotion/affect recognition (Picard, Vyzas, & Healey 2001; Mandryk, Inkpen, & Calvert 2006) of emotions corresponding to high arousal and positive valance.

Day-dependence and methodological conditions in capturing and classifying emotions when using physiological signal data raised by Picard, Vyzas, & Healey (2001) should be satisfied for effective physiological signal data collection. Moreover, experiments held should meet the majority of the five factors for eliciting genuine emotion as presented in (Picard, Vyzas, & Healey 2001). Note that in the presented studies subjects played all their assigned games on the same day, mitigating day-dependence effects on their physiology (Picard, Vyzas, & Healey 2001). Cultural differences in the impact of affect on physiology may also be present but are not examined here.

Playing experience recognition through video recordings is also apparent in some studies (Lazzaro 2004); however, real-time emotion recognition and game adaptation is disregarded through this approach. Moreover, automatic emotion recognition from facial expressions/gestures (Kaiser, Wehrle, & Schmidt 1998) is a possible alternative direction to investigate; however, it is not the focus of this paper.

## Feature Selection Methods

Two different feature set selection schemes are used and compared in the studies presented in this paper. Given the features extracted from obtained data, the *n Best Features Selection* (nBest) and the *Sequential Forward Selection* (SFS) methods are applied. The nBest selection method picks the n individually best features (with regards to a performance function) from the feature subset. The SFS method, by contrast, is a bottom-up search procedure where one feature is added at a time to the current feature set. The feature to be added is selected from the subset of the remaining features so that the new feature set generates the maxi-

mum value of the performance function over all candidate features for addition (Devijver & Kittler 1982).

The SFS method is used since it has been successfully applied in a wide variety of feature selection problems yielding high performance values with minimal feature subsets: see (Haapalainen *et al.* 2005), for example, for further discussion and application to the classification problem of process identification in resistance spot welding. On the other hand, the nBest method is used for comparative purposes, being the most popular technique for feature selection. More advanced methods such as Sequential Floating Forward Search (SFFS) and Fisher Projection (FP) could be used and results could be compared to the existing studies.

## Machine Learning Mechanism Selection

The proposed approach to entertainment modeling is based on selecting a minimal subset of individual features and constructing a quantitative user model that predicts the subject's reported entertainment preferences. The assumption is that the entertainment value $y$ of a given game, which models the subject's internal response to playing the game, that is, how much fun it is, is an unknown function of individual features which a machine learning mechanism can learn. The subject's expressed preferences constrain but do not specify the values of $y$ for individual games but we assume that the subject's expressed preferences are consistent.

Constraint satisfaction algorithms cannot solve the problem since the variable $y$ under the constraint $y_A > y_B$ for any two given games $A$ and $B$ has no specific domain values. Likewise, any machine learning which is based on learning a target output is inapplicable since target outputs are unknown. By the use of a ranking approach numerical values for the $y$ variable could be available; however, ranking is an undesired method for the self-report design of comparative "fun" analysis for the disadvantages mentioned earlier.

Preference learning (Doyle 2004) is the only applicable type of machine learning for this constraint classification problem. There are several techniques that learn from a set of pairwise preferences such as algorithms based on support vector machines and perceptron modeling (Fiechter & Rogers 2000). However, given the high level of subjectivity of human preferences and the highly-noisy nature of input data (game-interaction and physiology), we believe that more complex non-linear functions such as Artificial Neural Networks (ANN) would serve our purposes better. Thus, feedforward multilayered perceptrons or alternatively Fuzzy Neural Networks (Fuzzy-NN) for learning the relation between the selected player features (ANN inputs) and the "entertainment value" (ANN output) of a game are used in the studies presented here. Since there are no prescribed target outputs for the learning problem (i.e. no differentiable output error function), ANN training algorithms such as backpropagation are inapplicable. Learning is achieved through artificial evolution in the studies presented here. Other preference learning approaches are considered for comparison as a direction for future work.

Features selected by each feature selection algorithm constitute the input vector of the evolving ANN. The feature selection procedure followed here evaluates the usability of each one of the features available and obtains the minimal feature subset that performs best in the classification between games reported as entertaining and games reported as non-entertaining.

To evaluate the performance of each feature subset the available data is randomly divided into training and validation data sets consisting of 2/3 and 1/3 of the data respectively. The performance of an ANN model is measured through the average classification accuracy of the ANN in three independent runs using the leave-one-out cross-validation technique on the training and validation data sets.

## Game-Player Interaction

This section briefly presents reported entertainment user models in both prey/predator computer and physical interactive games. Obtained models are grounded solely on game-player interaction data.

### Prey/Predator Computer Games

The quantitative impact of the factors of challenge and curiosity on human reported entertainment have been investigated through experiments with a Pac-Man version prey/predator game (Yannakakis & Hallam 2006). In that study, two neuro-evolution approaches for modeling entertainment in real-time were examined: feedforward ANN and Fuzzy-NN. Both approaches managed to map successfully between quantitative estimators of challenge and curiosity and the notion of human gameplay satisfaction. Moreover, validation results obtained showed that the fittest feedforward ANN gets closer to human notion of entertainment than both the $I$ (i.e. interest) value introduced in (Yannakakis & Hallam 2004; Yannakakis 2005) and the fittest fuzzy-NN. However, more extracted features and a more detailed game and playing feature selection would probably yield a better approximation of reported satisfaction.

### Physical Interactive Games

Survey experiments in the Playware physical game platform have been held using the Bug-Smasher game as a testbed and children as subjects (Yannakakis, Lund, & Hallam 2006). Feature extraction of player-game interaction data is constrained on the design of the Playware game platform since the only input to the system is through a Force Sensing Resistor (FSR) sensor on each tile. Pressed tile events are recorded in real-time and a selection of nine personalized (individual) player features are calculated for each child (see (Yannakakis, Lund, & Hallam 2006) for further details).

Single feature investigation in (Yannakakis & Hallam 2007a) shows that the average response time of the child's interacting with the game platform generates the highest cross-validation performance (62.22%) on unknown data. When nBest and SFS selection methods for multiple features are applied the best cross-validation performance (77.77%; average of 70%, 73.33% and 90%) is achieved when the ANN input contains the average response time, the variance of the pressure forces recorded from the FSR sensor, the number of interactions and the quantitative means for

the game controllable feature of curiosity. The binomial-distributed probability of this performance to occur at random is 0.0019 demonstrating statistical significance and providing evidence for this solution's robustness. Moreover, SFS appears to generate feature subsets that yield higher validation performance than feature subsets generated by nBest.

Difficulties in obtaining higher classification accuracy are found in experimental noise in both the recorded features and the children's answers on self reports. Even though comparative fun analysis is a reliable and established method for capturing reported entertainment in computer (Yannakakis 2005) and physical interactive (Yannakakis, Lund, & Hallam 2006) games, it generates a significant amount of uncertainty in subjects' reported answers. Uncertainty appears when the two games played are not significantly different with regards to the entertainment value they generate for the player and therefore cannot be distinguished. In this circumstance, players appear to express a random preference. This 'dilutes' the data in which genuine preferences are expressed from the point of view of the machine learning algorithm.

Further analysis on the obtained best performing feature subset showed that fast children (low average response time) appear to enjoy average and high curiosity values. On the other hand, slow children appear to prefer low curiosity levels. High curiosity is rarely preferred by slow children and this occurs only when the number of their interactions with the playground is low (Yannakakis & Hallam 2007a).

The obtained effects of curiosity in reported entertainment are consistent, in part, with earlier sets of experiments on the Bug-Smasher game (Yannakakis, Lund, & Hallam 2006). In that study the relation between challenge, curiosity and average response time was reported through a lower scale experiment of 28 children. It was found that fast children liked games independently of curiosity whereas children reacting slowly with the playground preferred games of low curiosity levels.

## Player's Physiology

Even though entertainment is a highly complicated mental state it is correlated with sympathetic arousal (Mandryk, Inkpen, & Calvert 2006) which can be captured through specific physiological signals such as heart rate and skin conductivity, as reported by researchers in the psychophysiological research field (Zuckerman 2006). While the emotional impact on a subject's physiological state during computer game playing is well reported in the literature (see (Mandryk, Inkpen, & Calvert 2006) among others), such studies are inexistent in the physical play domain.

Motivated by the lack of entertainment modeling approaches grounded on player's physiological state in physical interactive games the Playware game platform has been used for recoding physiological signals of children during play (Yannakakis, Hallam, & Lund 2006). In that study the following statistical parameters are extracted from Heart Rate (HR) signals recorded while children were playing Bug-Smasher: the average HR $E\{h\}$, the standard deviation of HR $\sigma\{h\}$, the maximum HR max$\{h\}$, the minimum HR min$\{h\}$, the correlation coefficient $R_h$ between HR recordings and the time $t$ in which data were recorded, the autocorrelation (lag equals 1) of the signal $\rho_1^h$ and the approximate entropy ($ApEn_h$) (Pincus 1991) of the signal. In addition, three different regression models were used to fit (least square fitting) the HR signal: linear, quadratic and exponential. The additional features were the parameters of the three regression models mentioned above. Statistical analysis showed that average HR appears to be the only feature examined that is significantly correlated to reported entertainment ($r = 0.4146$, p$= 0.0057$). This interplay between engagement, physical activity and entertainment demonstrated in (Yannakakis, Hallam, & Lund 2006) is consistent with the significant correlation between the average response time of children interacting with Playware games and reported entertainment (Yannakakis, Lund, & Hallam 2006).

The HR signal feature (average HR) found to correlate with self-reported entertainment preferences also correlates with physical activity (Yannakakis, Hallam, & Lund 2006). (This is unsurprising, since one would expect a more enjoyable game to induce greater physical effort from the player.) However, it is then unclear whether constructed user models would distinguish more and less enjoyable games on the degree rather than the kind of physical activity they engender. To control for this and subtract any elements of physical activity from the physiology of entertainment, an objectively (by human-verification) non-entertaining form of physical activity is tested. Preliminary results have shown that user ANN models able to predict children's preferred game variants given suitable HR dynamics feature representations can indeed be constructed and that such models not only distinguish game-play from game-like non-entertaining physical activity but also generalize (to some extent) over children's individual preferences (Yannakakis, Hallam, & Lund 2007).

### Player's Physiology Beyond Heart-Rate

This section presents an initial statistical analysis on data collected through a new survey experiment using the proposed experimental protocol on the Bug-Smasher game. In this experiment physiology data collection expands to Blood Volume Pulse (BVP) and Skin Conductance (SC) signal recordings. Seventy two children participated each playing a pair of variants of the Bug-Smasher game in both orders.

The features extracted from the obtained signals include the fifteen statistical parameters of the HR signal presented in previous studies (see section 'Player's Physiology' and (Yannakakis, Hallam, & Lund 2006)). The additional features for each signal type are as follows:

**HR** The initial HR recording $h_{in}$, the last HR recording $h_{in}$, the time when maximum HR occurred $t^h_{max}$, the time when minimum HR occurred $t^h_{min}$, the difference $t^h_{max} - t^h_{min}$.

**BVP** The average BVP $E\{b\}$, the standard deviation of BVP $\sigma\{b\}$, the maximum BVP max$\{b\}$, the minimum BVP min$\{b\}$, the average inter-beat amplitude $E\{IBAmp\}$, the mean of the absolute values of the first and second differences of the raw BVP (Picard, Vyzas, &

Healey 2001) ($\delta^b_{|1|}$ and $\delta^b_{|2|}$ respectively) and the following Heart Rate Variability (HRV) parameters:

- HRV - time domain: the standard deviation of RR intervals $\sigma\{RR\}$, the fraction of RR intervals that differ by more than 50 msec from the previous RR interval $pRR50$, the root-mean-square of successive differences of RR intervals $RMS_{RR}$ (Goldberger *et al.* 2001).
- HRV - frequency domain: the frequency bands' energy values derived from power spectra obtained using discrete Fourier transformation; energy values are computed as the integral of the power of each of the following four frequency bands (see (Goldberger *et al.* 2001; 2000) among others):
  - High Frequency (HF) band: $(0.15, 0.4]$ Hz.
  - Low Frequency (LF) band: $(0.04, 0.15]$ Hz.
  - Very Low Frequency (VLF) band: $(0.0033, 0.04]$ Hz.
  - Ultra Low Frequency (ULF) band: $[0.0, 0.0033]$ Hz.

**SC** All extracted features used for the HR signal. Additional features include the mean of the first and second differences of the raw SC ($\delta^s_1$ and $\delta^s_1$ respectively) and the mean of the absolute values of the first and second differences of the raw SC ($\delta^s_{|1|}$ and $\delta^s_{|2|}$ respectively).

To identify statistically significant correlations between children's notion of entertainment and any of the aforementioned individual physiological features, the following null hypothesis is formed: The correlation between observed children judgement of entertainment and recorded physiological signal features, as far as the different game variants are concerned, is a result of randomness. The test statistic is obtained through $c(\overrightarrow{z}) = \sum_{i=1}^{N_s}\{z_i/N_s\}$, where $N_s$ is the total number of game pairs played and physiological signals were properly recorded ($N_s = 137$ for HR, $N_s = 115$ for BVP and $N_s = 85$ for SC) and $z_i = 1$, if the subject chooses as the more entertaining game the one with the larger value of the examined feature and $z_i = -1$, if the subject chooses the other game in the game pair $i$.

| HR | $c(\overrightarrow{z})$ | BVP | $c(\overrightarrow{z})$ | SC | $c(\overrightarrow{z})$ |
|---|---|---|---|---|---|
| $E\{h\}$ | **0.224** | $\delta^b_{\|1\|}$ | **0.216** | $E\{s\}$ | 0.167 |
| $\max\{h\}$ | **0.209** | $\delta^b_{\|2\|}$ | **0.216** | $\gamma_s$ | 0.119 |
| $\min\{h\}$ | 0.179 | HF | **-0.216** | $\sigma\{s\}$ | -0.119 |
| $B$ | 0.119 | LF | -0.187 | $t^s_{max}$ | -0.095 |
| $ApEn$ | 0.104 | $\sigma\{RR\}$ | -0.172 | $t^s_{min}$ | -0.071 |

Table 1: Correlation coefficients between reported entertainment and individual physiological features. For reasons of space, the five highest absolute $c(\overrightarrow{z})$ values for each physiological signal type are ranked and presented here. $\gamma_s$ is the parameter of the quadratic regression ($s_Q(t) = \beta_s t^2 + \gamma_s t + \epsilon$) on the SC signal which quantifies the rotation angle with respect to the x-axis of the quadratic curve. Statistically significant effects appear in bold.

Table 1 demonstrates the five highest (absolute value) correlation coefficients between reported entertainment and physiological features for each signal type. Specifically, significant corrections are observed between average and maximum HR and reported entertainment. These effects are consistent with the significant correlations of both $E\{h\}$ and $\max\{h\}$ on data obtained from previous experiments using the Bug-Smasher game (Yannakakis, Hallam, & Lund 2006; 2007). Within the BVP signal features, significant effects are observed on the mean of the absolute values of both the first and the second differences of the raw signal ($\delta^b_{|1|}$, $\delta^b_{|2|}$) and on the energy of the HF band. On the contrary no significant effect appears in the class of SC features. As a general observation, features extracted by BVP signal appear to be the most correlated with reported entertainment.

Obtained effects demonstrate that the higher the $\delta^b_{|1|}$ and $\delta^b_{|2|}$ values, the steeper the BVP signal and the higher the expressed "fun" of children. Moreover, the lower the energy of the HRV HF band which is driven by respiration and appears to derive mainly from vagal activity (Goldberger *et al.* 2001) the more children appear to be entertained. Specifically, the energy of the HF range, representing quicker changes in HR, is primarily due to parasympathetic activity of the heart which is decreased during mental or stress load (Rowe, Sibert, & Irwin 1998; Goldberger *et al.* 2001). This derives the conclusion that high mental or stress load and not physical activity appear to be the factors that guide a child to prefer a game variant more than another.

These effects project a linear relation between the above-mentioned features and reported entertainment which may (or may not) provide insights for the appropriate set of features which would feed a successful non-linear model of reported entertainment built via preference learning. However, no safe conclusion can be derived for the appropriate feature subset before the proposed methodology is applied. Note that previous studies have seen both outcomes (see (Yannakakis, Lund, & Hallam 2006; Yannakakis, Hallam, & Lund 2007)): consistency (or not) of highly correlated features with reported entertainment with the obtained feature set through feature selection and preference learning.

## Conclusions

The entertainment modeling approach based on preference learning proposed here has demonstrated generality over various types of game including computer and physical activity games. Moreover, previous studies have shown that feature selection combined with preference learning contributes to the generation of more effective entertainment models for the player. The statistical effects obtained from the survey experiment presented here provide some first insights for the physiology of entertainment. Higher average and maximum HR, steeper blood volume signals and quicker changes in HR appear to correlate with higher levels of reported entertainment in children. However, no safe conclusions can be derived before feature selection is applied and the non-linear function between the selected feature subset and subject's preferences on 'fun' is generated.

The proposed approach can be used for adaptation of the game's entertainment features according to the user's individual playing style and physiological features in real-time

in physical or computer games. The key to this is the observation that the models (e.g. ANNs) relate features to an entertainment value. It is therefore possible in principle to infer what changes to game features and furthermore to player individual features will cause an increase in the interestingness of the game, and to adjust game parameters to make those changes. For further discussion on this future direction the reader may refer to (Yannakakis & Hallam 2006; 2007a; 2007b)

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