

Investigating the Interplay between Camera Viewpoints, Game Information, and Challenge

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Abstract

Players perceive information about game environments through a virtual camera. While a significant discussion in the industry and in academic research circles has centered around effective camera control, it is focused mainly on occlusion free placement and smooth movement. The relationship between information communicated by the camera about game state and the selection of camera parameters has not been investigated. In this paper, we systematically investigate the effect of different camera profiles on player experience in a 3D prey/predator test-bed game. We describe a constraint-based dynamic camera system that maintains the position and orientation of the camera based on the constraints imposed by given camera profiles. The impact of different profiles on the amount of game information provided to the player and the player's game challenge preferences is investigated through a user experiment. An artificial neural network model of challenge constructed using artificial evolution reveals the non-linear mapping between challenge and information features.

Introduction

Camera control is an important component of player experience in games (Pinelle and Wong 2008). A camera in games provides the player with a means for exploring the game world, getting feedback on her actions, and updating the state of the game. Previous research on camera control techniques have centered around efficient placement of the camera and determination of viewpoint (Christie et al. 2005). Such techniques have mainly focused on efficiency in computing the camera position and view, and ease of use for game players. In the industry, designers have, over the years, settled on specific camera profiles for particular game genres. For example, Real-Time Strategy games have a top-down (bird's eye) camera that can be controlled by the player by moving the mouse around the edges of the screen. First-Person Shooting games give players an option of using an overhead camera just over the shoulder of the player, or a point of view of the player from eye-height of their avatar. The camera settings for games are pre-defined by designers and are maintained the same throughout the game. As the industry moves towards procedurally generated content including levels, characters, dialogues, and game rules, there

is an increasing need for dynamic camera systems that can adapt to procedural content by switching between different camera configurations.

In this paper, we systematically investigate the impact of different camera profiles on the amount of information communicated to the player. For this purpose, we implement a constraint-based camera system and identify variants of the camera based on different values of the *distance*, *height*, and *coherence* camera parameters. The constraint-based camera system maintains the camera at a specified distance, height, and coherence in real time. We present a user study carried out on different camera variants of a 3D prey/predator game called Maze-Ball. In Maze-Ball players control a ball and navigate inside a maze to collect gold tokens while avoiding enemies. Users report pairwise *challenge* preferences for 8 camera variants of the Maze-Ball game. Information about the game state that is provided to the player is recorded and quantified through three measures: visible grid, visible tokens, and visible enemies.

Our analysis shows that camera profiles affect statistical features of game information and that there is no linear correlation between those features and reported challenge. A perceptron is trained using artificial evolution to learn the mapping between features of information and challenge preferences. The highest performing neural network obtained achieves a validation accuracy of 75% on unseen data. This performance is satisfactory given the complexity of the problem — deriving from the subjectivity of human notion of challenge — and the simplicity of the learning mechanism. Analysis of the obtained perceptron model reveals that information about enemies and tokens contribute more to perceived challenge than information about the maze. Moreover, while less information about enemies and the maze lead to higher challenge, less information about tokens available leads to lower challenge.

This work is a step towards developing adaptive camera systems that can modulate the viewpoint to tailor challenge for individual players. The promising results derived from the perceptron model motivate further work on more complex preference models and the design of adaptive mechanisms for automatically selecting appropriate camera profiles to enhance player experience.

Constraint-based Camera Control

Research on camera control that is relevant to our work is research on constraint-based camera systems. For a comprehensive survey of different autonomous camera systems the reader is encouraged to read (Christie et al. 2005). Our work derives from the system developed by Bourne and Sattar (Bourne, Sattar, and Goodwin 2008). Their system uses a constraint solver which exploits the spatial structure of the problem and thereby enables it to be used in real-time environments. It uses a weighted constraint satisfaction problem (CSP) framework. This allows the camera to be used in highly dynamic and interactive environments. The following three constraints are used to control the camera:

- Height. Maintains a relative height relationship with the target.
- Distance. Maintains a relative distance relationship with the target.
- Orientation. Maintains a relative angular alignment between the camera view vector and the target facing vector.

Bourne uses the idea of frame-coherence similar to Halper’s system (Nicholas, Ralf, and Thomas 2001) to maintain smooth camera movements, but instead of using an algebraic incremental constraint solver Bourne introduces a frame-coherence constraint. This constraint evaluates the difference between the distance the camera is planned to move in the current frame and the distance moved in the previous frame.

Maze-Ball Game

Maze-Ball (see Figure 1) is a 3D game developed on the Unity game engine. The player controls a ball and moves it inside a maze. The maze contains a number of golden tokens that the player can pick up to get a reward of 50 points. There are also 10 red colored enemies moving in the maze. Touching an enemy costs the player 25 points. The goal of the player is to maximize her score by gathering as many gold tokens as possible while avoiding being touched by the red colored enemies within a pre-defined time window of 90 seconds.

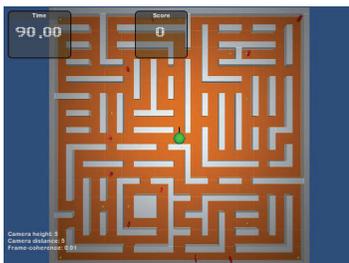


Figure 1: Mazeball game top-down view

The purpose of choosing Maze-Ball for our experiments is two-fold. First, it consists of a minimal interface for an enjoyable game (arrow keys for controlling the character) and a simple visual environment. Second, there is a direct effect of the amount of information available to the player via the camera viewpoint on their movement strategy.

Camera Control in Maze-Ball

A dynamic camera controller maintains the position, orientation, and the field-of-view (FOV) of the camera in a graphical world. Maintaining the camera position and orientation amounts to finding and maintaining the 3D coordinates (x, y, z) for the location and rotation angles for orientation ($pitch, yaw, roll$) to satisfy viewing constraints imposed on the camera by the game design and the environment. Constraint-based techniques have been extensively used in virtual camera control systems (Christie et al. 2005).

The camera system implemented for our experiments is based on a weighted Constraint Satisfaction Problem (CSP) solver framework for satisfying view constraints at each frame (Bourne, Sattar, and Goodwin 2008). The CSP representation used in this framework contains fewer variables in order to make it interactive and efficient. The constraints used are: *distance*, *height* and *frame coherence*. Distance constraint maintains a relative distance relationship with the target (Eq. 1, where d is the current distance, d_d is the desired distance, and Δd is the difference between distance between last position and desired position). Height constraint maintains a fixed height relative to the target (Eq. 2, where h is the current height, h_d is the desired height, and Δh is the difference between last height and desired height). Frame coherence constraint maintains smooth motion across frames and avoids erratic camera movements. Unlike spatial constraints, frame coherence only has a weight that indicates the importance of smooth transitions for the camera. In equation (3) C_c is the coherence value, d_l is the distance traveled in the previous frame, d_p is the distance the camera has to move in the next frame using the current potential solution, f is the frame interval, and C_w is the weight of the constraint. We define a *camera profile* in the context of our game as a triple of distance, height, and frame coherence values. Orientation, which is one of the constraints normally included in constraint-based systems, is not constrained as the default orientation is determined by the position of the player’s ball. The camera is always constrained to maintain the player’s ball in the center of the screen from a behind view.

$$h = (h_d - \Delta h) \quad (1)$$

$$d = (d_d - \Delta d) \quad (2)$$

$$C_c = \frac{|d_l - d_p|}{f} * C_w \quad (3)$$

To geometrically solve the constraints provided by the designer or automatically generated by the system, the constraint solver searches through the 3D space for potential solutions. The algorithm (Algorithm 1) used in our experiments is based on the sliding octree solver proposed by Bourne and Sattar (Bourne, Sattar, and Goodwin 2008). The search starts by generating an octree spatial data structure for the entire domain. The mid-point of each node is then evaluated as the potential camera solution. The solver progressively scales the octree down at each iteration and the octree is slid down to the best evaluated solution that satisfies the given constraints. A collection of desired values for distance, height, coherence, and importance weight of each

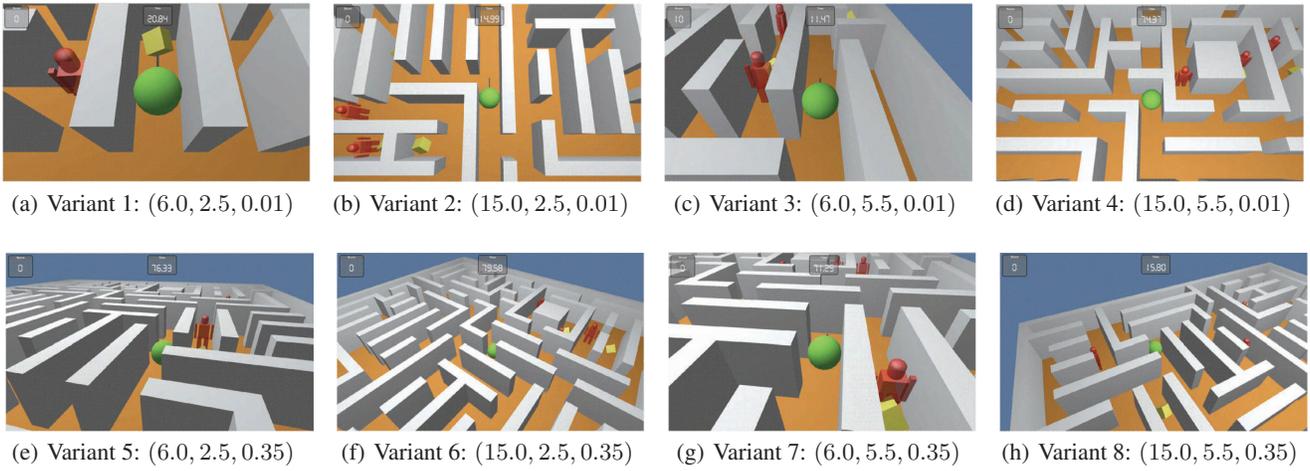


Figure 2: Different camera profile variants used in the user study for the Maze-Ball game. Camera profiles are expressed as value triples of (*distance, height, coherence*).

of these values is termed as a camera profile. By selecting particular values of constraints different camera profiles can be obtained.

```

calculate camera front and right vectors;
calcualte initial domain size;
while current pass less than maximum passes do
  foreach octree node do
    evaluate octree node as potential solution;
    if octree node cost less than best solution cost
      then
        keep octree node as best solution;
      end
    end
  end
  reduce domain size by scaling factor;
  slide direction = (best solution - octree center);
  new octree center += slide direction * domain size;
  increment pass count;
end
return best solution as new camera position;

```

Algorithm 1: Sliding Octree Solver based on Bourne et al. (Bourne, Sattar, and Goodwin 2008)

Choice of camera profile variables

We are interested in evaluating the effect of camera viewpoints resulting from different camera profiles on the perceived challenge for players. For that purpose, given the same virtual setting of the game, we vary camera profiles while keeping the game design, level design, and game mechanics unaltered. Eight game variants are implemented in Maze-Ball by varying distance, height and frame coherence. For each of the three camera control variables, two states (*‘High’* and *‘Low’*) were selected leading to the aforementioned 8 different variants of the game. The range of values for distance and height were determined to cover different well-known camera profiles. Minimum distance is 0 (camera on top of the ball looking down) and minimum height equals to the radius of the ball. Maximum distance

equals half of the edge size of the maze grid and maximum height is determined by the height at which the whole grid is visible when the camera is fixed at the center of the grid. These ranges for distance and height cover several well-known camera profiles in games. For instance, minimum distance combined with maximum height yield a top-down view shown in Figure 1 similar to the pac-man game. Maximum distance combined with minimum height give a 2.5 dimensional view as seen in 3D chess, mini-golf, and billiard games. Minimum values of both distance and height give a first-person view while increasing the distance and height values by a small amount gives a behind-view of the player; a popular camera viewpoint in shooting games. Finally, minimum distance combined with low height values give a top-down restricted view of the world similar to real-time strategy games.

For the purpose of our experiments, we chose two intermediate values for distance and height within the aforementioned ranges. The exact values for distance, height, and coherence for each of the eight variants are illustrated in Figure 2.

Information in Maze-Ball

The Maze-Ball environment consists of a two dimensional grid. Each grid location can either be open or blocked if there is a wall on it. Any open grid location can be occupied by a gold token. The player’s ball and enemies can move along contiguous open grid locations. If the player’s ball moves over the grid location on which a gold token is present, then the gold token is removed and the player is awarded points for collecting the token. If the player and the enemy collide in the same open grid location then the player loses points for touching the enemy. Three information measures are recorded by the game for each playing session

- **Visible Maze I_M :** The number of grid cells that are visible to the player at any time during the game.

- **Visible Tokens** I_T : The number of tokens visible to the player at any time during the game.
- **Visible Enemies** I_E : The number of enemies visible to the player at any time during the game.

We assume that these information measures are directly affected by the choice of camera profiles. Camera profiles with low height values will lead to a smaller part of the maze being visible at any time during the game. Similarly, low distance values will restrict the visibility for grid cells behind the player and further out in front of the player. Coherence values determine how fast the camera sweeps across when the player changes directions or speed. This affects the visibility of the maze during the interval between the successive camera transitions. The analysis presented in Section below verifies these assumptions.

The player’s movement strategy in Maze-Ball is also affected by these three measures of information about the game at any time. The measures can also be efficiently computed and recorded in real-time which makes them appropriate for any adaptive camera controller constructed.

User Study

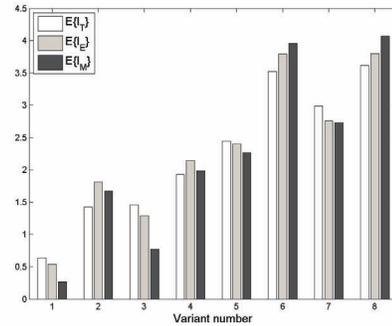
We conducted a user study to solicit pairwise preferences for challenge perceived by players in different variants of Maze-Ball by following the experimental protocol proposed in (Yannakakis, Hallam, and Lund 2008). Thirty-six subjects (males: 20%, females: 80%) aged 21 to 47 years (mean: 27.2 and standard deviation: 5.84) participated in the experiment. Each subject played a predefined set of eight games for 90 seconds each. For each of the four pairs of games A and B , subjects reported their preference for challenge using a 4-alternative forced choice (4-AFC) protocol:

- game $A[B]$ was more challenging than $B[A]$
- both games were equally challenging
- neither of the two games was challenging

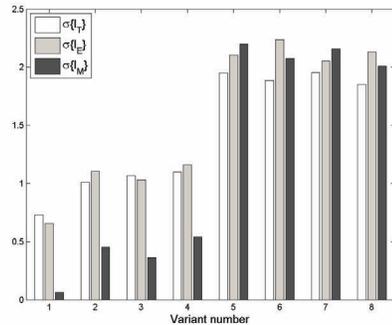
The number of participants is determined by $C_2^9 = 36$, which is the number of all combinations of 2 of 9 variants. The 9th variant has only been used for testing purposes and it is not investigated in this paper. Four preference instances (2 for each order) are obtained for each of the $C_2^8 = 28$ game pairs resulting to $4 \cdot 28 = 112$ pairwise preferences. A clear 2-AFC preference ($A \prec B$ or $A \succ B$) was obtained for challenge in 97 out of 112 game pair preference instances showing that the variants, in the vast majority of instances, generated a dissimilar playing experience with respect to challenge. Data for each information measure (I_M , I_T and I_E) is collected at a sampling rate of two per second during each game played by the subjects. The mean $E\{\cdot\}$ and standard deviation $\sigma\{\cdot\}$ of those recorded values are calculated. More statistical features of those measures could be investigated; however, $E\{\cdot\}$ and $\sigma\{\cdot\}$ provide adequate information for the distribution of those measures required for the aims of this paper.

Order of Play Effects

We check for order of play effects on player’s reported preferences by following the procedure described in (Yan-



(a) Average



(b) Standard deviation

Figure 3: Statistical features of the three information measures over game variants. Values illustrated are averaged across all subjects played the corresponding variant. Feature values for I_M are divided by 20 for illustration purposes

nakakis, Hallam, and Lund 2008). This testing approach is based on the times that the subject prefers the first or the second game of pairs played in both orders. Our statistical analysis shows that the order of play correlation coefficient for challenge equals -0.222 with a corresponding p-value of 0.121. This shows that order of play does not affect reported challenge preferences. These values also suggest that a user’s preference for the first game played and the interplay between reported preferences and familiarity with the game in later preferences are statistically insignificant.

Results and Discussion

A statistical analysis on the relationship between camera profiles and game state information is presented in the first part of this section. Then, the impact of information on reported challenge is investigated by constructing and analyzing a computational model of challenge preferences built on information statistical features; a perceptron is evolved to map features of information to challenge preferences.

Camera Profiles versus Game State Information

We first investigate the relationship between camera profiles and game state information measures. Our assumption is that camera variants with higher distance and height values

provide more information about the world (maze/grid layout, tokens, and enemies).

Figure 3(a) shows the mean (across all subjects) of the average ($E\{\cdot\}$) and standard deviation ($\sigma\{\cdot\}$) values of all three information measures during each of the 8 game variants. It can be seen from the figure that information about the maze is high in variants where distance and height are higher. Odd numbered variants (1, 3, 5, and 7) have lower distance values and generate a correspondingly lower number of grid cells visible. Among these, 5 and 7 have a higher height value resulting to more visible maze cells. As expected, average numbers of visible tokens and enemies (just like $E\{I_M\}$) increase with higher values of distance and height. For both features, information increases for variants with higher frame coherence due to the time taken by the camera to sweep across the maze.

Frame coherence mainly contributes to standard deviation observed in the variants (see Figure 3(b)). The first four variants, with low frame coherence value, have a lower standard deviation because the camera immediately switches to the new orientation and misses the intermediate grid cells. In the last four variants, where coherence is high, the camera slowly adjusts to the desired change in orientation thereby sweeping across the maze landscape providing more information.

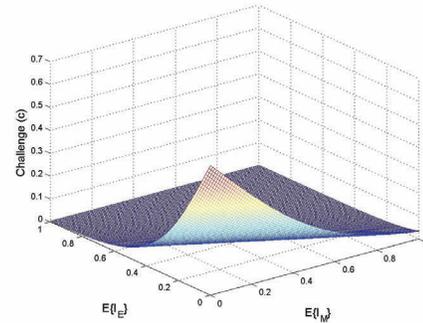
Challenge versus Game State Information

Given the average and standard deviation values for all three information measures the first step in the investigation between reported challenge and information provided by the game is the observation of significant linear correlations between challenge and game state information. For this purpose we follow the test statistic proposed in (Yannakakis, Hallam, and Lund 2008) which checks whether preferences are consistent to a higher value of the statistical feature examined (e.g. average visible number of enemies).

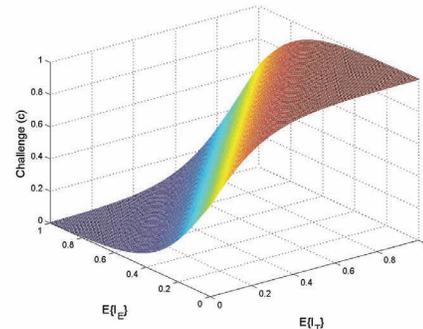
Statistically significant effects were not observed between challenge and any of the six statistical features indicating that challenge does not vary linearly with respect to information provided by the game. This generates the assumption that there is an unknown non-linear function between game state information and challenge generated by the game. Machine learning can be used to automatically approximate this function; the procedure followed is described below.

Perceptron Model of Challenge Given the high level of subjectivity of human preferences and the noisy nature of input data (information features), we believe that a non-linear function such as an artificial neural network (ANN) might approximate well the mapping between reported challenge and input data. Thus, a simple single-neuron (perceptron) is utilized for learning the relation between the six statistical features (ANN inputs) and the challenge value c (ANN output) of a game. Function expressiveness is the main motivation for using a single-neuron instead of a multi-layered perceptron (MLP) in this study. While an MLP can potentially approximate the function investigated with a higher accuracy, speculation of the obtained function is a much simpler task in a single-neuron ANN.

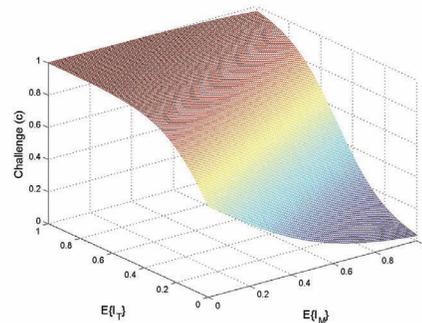
The sigmoid function is employed at the neuron, connection weights take values from -10 to 10 and input values are normalized into $[0, 1]$. Since there are no prescribed target outputs for the learning problem (i.e. no differentiable output error function), ANN training algorithms such as back-propagation are inapplicable. Learning is achieved through artificial evolution by following the preference learning approach presented in (Yannakakis and Hallam 2007). A generational genetic algorithm (GA) (Holland 1975) is implemented, which uses a fitness function that measures the dif-



(a) Challenge with respect to average I_E and I_M



(b) Challenge with respect to average I_E and I_T



(c) Challenge with respect to average I_T and I_M

Figure 4: The function between the challenge value c (ANN output) and three information features (ANN input) derived from the highest performing perceptron.

ference between the subject's reported challenge preferences and the relative magnitude of the corresponding model output values c . Further details on the neuro-evolution mechanism can be found in (Yannakakis, Hallam, and Lund 2008).

To permit evaluation of the performance of a constructed ANN model, the available data is randomly divided into three subsets which are combined to give three training and three, independent, validation data sets each 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 3-fold cross-validation on these training and validation data sets. The highest-performing perceptron achieves a cross-validation accuracy of 71.88% (average of 75%, 71.87% and 68.75%) on unseen data while the corresponding average performance of 10 random ANNs is 48.85%. The obtained performance is satisfactory given the high level of subjectivity of challenge preferences and suggests that additional individual playing characteristics (e.g. average distance from enemies) may be required for higher accuracy approximations. Note that the binomially distributed probability of the 71.88% accuracy to occur at random is 0.01 which demonstrates the robustness of the obtained solution.

The weight values of the highest performing perceptron (75%) connecting the input values of E_{I_E} , E_{I_T} and E_{I_M} to the perceptron are, respectively, -6.465, 6.739 and -3.643. These values show the relative importance of each of the three information measures for reported challenge. On that basis, the average numbers of enemies and tokens visible contribute more to challenge than the average number of maze cells visible. Moreover, it appears that visible enemies and maze cells have a negative contribution to challenge whereas visible tokens contribute positively to the level of challenge. These effects are better illustrated in Figure . As can be seen in that figure, more information about the maze of the game leads to decrease of the challenge value. Similarly more information about the enemy leads to a decrease in reported challenge. More information about the number of tokens, however, results in increased challenge value.

While the interplay between maze and enemy information and challenge is obvious, the positive impact of token information on challenge is unexpected at first glance. This effect generates the assumption that challenge perceived by the player is increased through more visible tokens due to the restricted gameplay time window. Observation of game sessions reveals characteristics of the aforementioned playing behavior; however, further statistical features of gameplay data (e.g. spatial diversity of player position in the maze) will be required to further validate this assumption.

Conclusions and Future Work

This paper presents a first systematic empirical study of the relationships between camera profiles, game state information, and perceived challenge. We presented an implementation of a constraint-based camera system capable of maintaining different camera profiles defined as constrained distance, height, and frame coherence values in a 3D prey/predator game called Maze-Ball. We also designed three heuristics for quantifying the information provided to

the player of Maze-Ball: visible maze, visible enemies, and visible tokens.

An efficient experimental setup was designed and the impact of game information statistical measures was examined against challenge preferences. Our observations show a positive correlation between the amount of information given to the player through a dynamic camera and perceived challenge for the player. As expected, the amount of information determined by the three measures is directly related to camera profiles. Higher distance, height, and coherence settings lead to increase in the amount of information presented on the screen. More information is not, however, linearly related to player's reported challenge values. The perceptron model of challenge constructed on game information and preference data reveals that more information about enemies and maze leads to a decreased challenge value while more information about tokens leads to an increase of game challenge in the test-bed game.

This work is the first step towards finding the link between game state information and adaptive camera control and their interplay with player experience. We believe that this link will be vital for developing intelligent camera control systems that will adapt to game play across game genres. One direct step in the future is to use preference learning algorithms to design ANN player models of reported experience built on statistical features of play and camera controllable parameters. Such models can then be used to control the selected camera parameters for tailoring the game experience.

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