Optimizing visual properties of game content through neuroevolution

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Abstract

This paper presents a search-based approach to generating game content that satisfies both gameplay requirements and user-expressed aesthetic criteria. Using evolutionary constraint satisfaction, we search for spaceships (for a space combat game) represented as compositional pattern-producing networks. While the gameplay requirements are satisfied by ad-hoc defined constraints, the aesthetic evaluation function can also be informed by human aesthetic judgement. This is achieved using indirect interactive evolution, where an evaluation function re-weights an array of aesthetic criteria based on the choices of a human player. Early results show that we can create aesthetically diverse and interesting spaceships while retaining in-game functionality.

The games industry has often used procedurally generated content in order to increase replayability and cut down on development costs. With the gaming population increasing in size and diversity over recent years (Entertainment Software Association 2011), the need for original content suited to a wider assortment of players of different age, culture and taste has also increased. Experience-Driven Procedural Content Generation (Yannakakis and Togelius 2011) introduces a framework of methods for creating and evaluating experience-centric game content which offers personalized gaming experience within a wide variety of game genres.

In this paper we introduce a number of aesthetic filters for evaluating generated content from the perspective of a player's visual taste and preferences. Using these quantifiable visual properties as the fitness function of a genetic algorithm, the content generator can optimize game elements with the desired visual patterns as dictated either by the player (online) or by a designer (offline). Our approach is unique as it combines neuroevolution with constraint satisfaction (introduced in (Liapis, Yannakakis, and Togelius 2011)) in order to create content which fulfills some minimum requirements while posessing some visual properties deemed important for human perception by studies in cognitive psychology and neuroscience. Most importantly, the paper proposes a novel framework for adapting a user preference model of visual taste by adjusting the importance of each visual property in the content's evaluation based on the choices of one or more players. This allows for an indirect form of interactive evolution, where the player's choices affect the fitness function determining content quality, allowing for a more holistic aesthetic model. The presented framework is inspired by the Galactic Arms Race game (Hastings, Guha, and Stanley 2009), yet it is distinct in that it evolves the spaceships themselves rather than their weapons, controls the generative process through constraints and proposes an indirect form of preference modelling.

This paper builds and extends upon the study presented in (Liapis, Yannakakis, and Togelius 2011) which focuses on the optimization of performance of generated spaceships in a space combat game. The current paper focuses on the optimization of visual properties of the spaceships' form and on the personalisation of a hand-crafted aesthetic model to individual players. However, the methods suggested in this paper are quite generic and not explicitly designed for creating spaceships; therefore results are often abstract shapes.

Related Work

Experience-Driven Procedural Content Generation

The game industry has in many cases preferred procedurally generated to author-created content in order to increase the unexpectedness or unpredictability of a game (and therefore increase its replayability value) in games such as Diablo (Blizzard North 1997) (for dungeons), Borderlands (Gearbox Software 2009) (for items) or Civilization (MicroProse 1991) (for the world map). In recent years, the procedural generation of content is also used during the development of a game to limit development time and cost, with applications like SpeedTree (Interactive Data Visualization, Inc. 2010) and WorldMachine (Schmitt 1992).

Despite its long history within the game industry, the procedural generation of game content has only recently received attention from the academic community. Experience-Driven Procedural Content Generation (EDPCG) is introduced in (Yannakakis and Togelius 2011) as a novel approach to procedural content generation geared towards optimizing the experience of the player. EDPCG is synthesized by four main components: a Player Experience Modeling (PEM) component, a Content Quality component (which evaluates the generated content based on the PEM), a Content Representation and a Content Generator component which usually follows a search-based PCG method (Togelius et al. 2010). The EDPCG approach described in this paper provides an efficient method for constrained optimization, a versatile model for content representation, an evaluation of visual quality rooted in theories of human perception and an inclusive aesthetic model which can be adjusted to the player's preferences.

Interactive Evolution

Many EDPCG projects use an ad-hoc designed fitness function to assess content quality while others use interaction with a human to guide evolution. Interactive Evolutionary Computation (IEC) is "the technology in which EC optimizes the target systems based on subjective human evaluation as fitness values for system outputs" (Takagi 2001) and is used extensively for content whose quality is subjective and difficult to quantify. At its core, IEC utilizes a human user to select individuals which will breed to create a new generation. IEC is limited by the fact that user interest drops as the number of choices they have to make increases. In order to avoid *user fatigue*, most IEC projects find shortcuts for reducing the number of choices imposed on their users.

In the current literature, IEC is used within EDPCG either to provide an indirect player model based solely on gameplay metrics (side-stepping user fatigue) (Hastings, Guha, and Stanley 2009) or to model a direct mapping between the content and a desired player experience which is provided either explicitly (e.g. through self-reports) or implicitly (e.g. through biofeedback) (Pedersen, Togelius, and Yannakakis 2010). The interactive aesthetic model presented in this paper is closer to the latter approach, as it provides a direct mapping between content and visual taste.

Universal principles of visual perception

Many EDPCG (and evolutionary art) projects argue that interactive evolution is a necessity, since purely stylistic or aesthetic preferences are very difficult to recognize. However, research in cognitive psychology and neurobiology has established certain universal properties of form which are ingrained in human perception and are not subject to cultural trends. Ramachandran has suggested "speculative and arbitrary" laws of art, such as *symmetry*, grounded mostly on experiments and empirical studies of the brain (Ramachandran and Hirstein 1999). On the other hand, Arnheim used cognitive psychology to analyze the aesthetic appeal of shapes and paintings within the art domain (Arnheim 1954). Introducing the term *perceptual forces* as the psychological and physical forces that guide the viewers' attention at specific points and along specific axes of an object or scene, Arnheim attempted to identify the most important contributors to the creation of these forces, such as *weight* and *direction*.

Methodology

The type of game content evaluated and optimized is a two-dimensional spaceship (see Fig. 1). The spaceship consists of a single polygon representing the hull, while weapons and thrusters are attached to the edges of this hull. The spaceship must fulfil some minimum requirements; if it does, its aesthetic quality is evaluated based on principles of visual

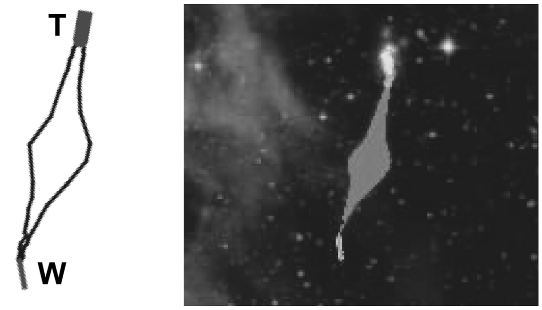


Figure 1: A generated spaceship, in graphical display (left) and within the game environment (right). W represents a weapon and T represents a thruster.

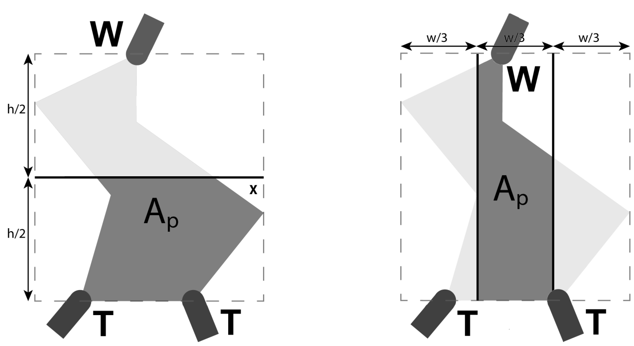
perception. This section presents the process of the spaceship's generation and its evaluation, and the tools for its optimization. For space considerations the spaceship representation and the constrained optimization algorithm used are presented briefly; more details on the methodology followed can be found in (Liapis, Yannakakis, and Togelius 2011).

Representation

The generated spaceships are encoded as Compositional Pattern-Producing Networks (CPPNs) (Stanley 2006) which are specifically designed to represent content with regularities and which are capable of being optimized through artificial evolution. The CPPN receives a sequence of inputs in the form of 2D coordinates (64 equidistant points on a circle) and returns a sequence of outputs corresponding to the points of the spaceship hull's pattern. Each output vector consist of the 2D coordinates X and Y of each point and a value which indicates if the point has a weapon or thruster attached, if any. This sequence of outputs is translated into the spaceship's hull coordinates as well as specific weapon and thruster types according to a collection of game-specific parameters.

Constrained optimization

The CPPNs which encode the generated spaceships are optimized through Neuroevolution of Augmenting Topologies (Stanley and Miikkulainen 2002) in which an initial population of simple networks is iteratively augmented through mutations, with similar networks being grouped together into *species* and sharing their characteristics (links, nodes, weights) through recombination. The presented neuroevolution approach satisfies the constraints imposed by the game environment, the physics engine or the designer by simultaneously evolving two different populations. One population includes all feasible individuals and is optimized according to the objective function detailed in the following section while the other includes all infeasible individuals, and its fitness function is based on the total distance from feasibility for all violated constraints. This two-population neuroevolution builds upon the work of (Kimbrough et al. 2008), which proposes that by minimizing the distance from feasibility for the infeasible population, their members will exist on the



(a) Bottom Half (b) Mid Third (on X axis)

Figure 2: Example weight distributions.

boundary of feasible space, where the optimum solution often lies (Schoenauer and Michalewicz 1996).

Aesthetic evaluation

Inspired from the works of Ramachandran and Arnheim, some of the most important visual properties of the 2D spaceships are *symmetry*, *weight* and *direction*. This paper presents a set of four significant visual properties of the spaceship's hull, while more aesthetic properties, including weapon- and thruster-specific ones can be found in (Liapis 2011). Visual quality is assessed solely on the spaceship hull's shape (ignoring color, lighting and other aesthetic properties) because, with the current representation, the spaceship's form has the greatest representational freedom (and therefore intrinsic value). Additionally, the spaceship hull's shape also determines the spaceship's mass, centroid and alignment of thrusters and weapons, therefore affecting the spaceship's movement pattern and, indirectly, its overall performance.

Symmetry can be measured by reflecting the hull of the spaceship along an axis passing from its midpoint. The fitness score for symmetry is computed as:

$$f_S = A_\cap / A_\cup \tag{1}$$

where $A_\cap$ the surface of the common area in the base and the reflected shape and $A_\cup$ the surface of the area occupied by either the base or the reflected shape.

Weight (or weight distribution) can be measured by calculating the surface of a "focus" part of the spaceship's hull (see Fig. 2). The fitness score for weight is computed as:

$$f_W = \mu_W \left(A_p / A\right) \tag{2}$$

where A_p the surface of the "focus" part of the spaceship's hull and A the surface of the entire spaceship's hull. $\mu_W(x)$ is a membership function indicative of the proximity with the desired weight distribution in the "focus" part.

Direction is measured by the angle of the least squares line of the hull's points (see Fig. 3). The fitness score for direction is computed as:

$$f_D = \mu_D(\phi) \tag{3}$$

where ϕ the angle between the least squares line and the positive Y axis, and μ_D a membership function indicative of the proximity with a desired angle.

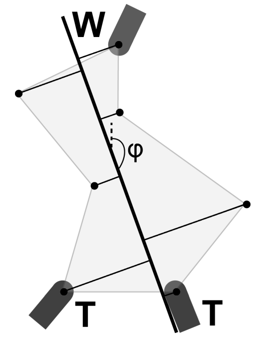


Figure 3: Direction as the least squares line.

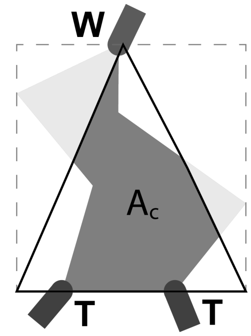


Figure 4: Containment within a triangle pointing forward.

Containment builds on the notion of *weight*, but the "focus" part of the spaceship's hull is determined by a more complex shape acting as a "cookie cutter" (see Fig. 4). The fitness score for containment is computed as:

$$f_C = A_c / A \tag{4}$$

where A_c the surface of the part of the spaceship's hull contained within the designated shape and A the surface of the entire spaceship's hull.

Interactive adaptation of the aesthetic model

The individual fitness scores presented in the previous section can be used on their own to optimize a single visual property such as symmetry or direction, or can be aggregated into a weighted sum representing a more inclusive aesthetic model. By using a weighted sum as the feasible fitness, the constrained optimizer can create content with high scores in many different visual properties. In such cases, the fitness function (also identified as *aesthetic score* or F), is the weighted sum normalized to $[0, 1]$. Using a weighted sum for deriving a single fitness score allows for the weights of this quality approximation to be adjusted in a straightforward fashion based on in-game player's choices. Through this weighted sum, the evolution's objective function subsititutes user input with a personalised aesthetic model and limits user fatigue.

Treating the aesthetic score F as a single artificial neuron with a linear activation function allows this quality approximation to incrementally adjust its weights towards the desired output as dictated by player choices. If a player is presented with a single spaceship, selecting it corresponds to a desired output of 1 and discarding it corresponds to a desired output of 0. If presented with more than one spaceships, the user selects one and discards the others; in order to take both selected and discarded spaceships' visual properties into account, weight adjustment is performed according to eq. (5), which is a variation of the weight update rule, until the selected spaceship has a higher aesthetic score than all unselected ones:

$$\Delta w_i = -\eta \left((F_s - 1) \frac{\partial F_s}{\partial w_i} + \sum_{j=1}^{N_u} \left(F_{u_j} \frac{\partial F_{u_j}}{\partial w_i} \right) \right) \tag{5}$$

where w_i the weight for the i-th visual property, η the learning rate, F_s the aesthetic score of the selected spaceship, F_{u_j}

Table 1: Fitness of the best individual at the beginning and the end of constrained optimization of a single visual property across 5 individual runs.

		f_1	f_2	f_3	f_4	f_5
First feasible	Mean	0.77	0.00	0.00	0.72	0.53
	St.Dev	0.19	0.01	0.00	0.30	0.12
After 100 gen.	Mean	1.00	1.00	1.00	1.00	0.96
	St.Dev	0.00	0.00	0.00	0.00	0.01

the aesthetic score of the j-th unselected spaceship and N_u the number of presented spaceships that were not selected.

Experiments

This section presents the results of the neuroevolutionary constrained optimization algorithm when one or more visual properties are targeted, and concludes with an experiment in adaptive content generation using a player-dependent aesthetic model.

Offline optimization of a single visual property

Each of the visual properties identified in the previous section can be used on their own as a fitness function for feasible individuals in the constrained optimization algorithm. This section demonstrates the optimization process of five different visual properties; these visual properties and their corresponding fitness scores (f_1 to f_5) are as follows:

- f_1 is the fitness score for symmetry (see eq. (1)) with the axis of symmetry being a line parallel to the world's Y axis and passing through the spaceship's midpoint.
- f_2 is the fitness score for weight (see eq. (2)) using the bottom half of the spaceship as the "focus" part (see Fig.2(a)) and $\mu_{W.75}(x) = e^{\frac{-(x-0.75)^2}{2\cdot 0.033^2}}$ as the membership function $\mu_W(x)$.
- f_3 is the fitness score for weight (see eq. (2)) using the mid third of the spaceship (on the X axis) as the "focus" part (see Fig. 2(b)) and $\mu_{W.75}(x)$ as the membership function $\mu_W(x)$ (described above).
- f_4 is the fitness score for direction (see eq. (3)) evaluating proximity with the Y axis and with $\mu_D(x) = |sin(x)|$.
- f_5 is the fitness score for containment (see eq. (4)) using a forward-pointing triangle as the containing form (see Fig. 4).

Table 1 presents the fitness scores of the best feasible individuals at the beginning and the end of a constrained optimization process (after 100 generations), with a population of 250 individuals. The means and standard deviations are calculated from 5 individual runs. The first feasible individual in the population is used in the calculation of initial scores regardless of the generation it occured. Fig. 5 presents the best final individuals among the 5 different runs; since the presence of thrusters and weapons is neither necessary (for functional purposes) nor contributes to the evaluation of visual properties, the generated spaceships have no thrusters or weapons attached.

Table 2: Fitness (F) of the best individual at the end of constrained optimization of five visual properties, and its components (f_1 to f_5) among 10 individual runs.

	F	f_1	f_2	f_3	f_4	f_5
Mean	0.73	0.78	0.89	0.19	0.98	0.80
St.Dev	0.04	0.15	0.31	0.40	0.04	0.10

Each of the five visual properties show different behaviors in their optimization. Because the sequence of points used as input to the CPPN are on a circle which is symmetrical along the X and Y axis, the resulting spaceships (especially with simple networks) are more likely to be symmetrical (f_1) and very unlikely to have the desired weight distribution of f_2 and f_3. Since the membership function of f_2 and f_3 is very specific (returning 0 or near 0 for most shapes and high fitness scores only for shapes with the desired pattern), only the complexification of networks guided by the continuous fitness score f_W can lead to the discovery of individuals with the desired weight distribution. Unlike weight distribution, containment (f_5) has no membership function and therefore many shapes may have average or high fitness scores for it. The same applies to direction (f_4), whose membership function has high scores for many different angles ϕ.

(a) f_1=1.00 (b) f_2=1.00 (c) f_3=1.00 (d) f_4=1.00 (e) f_5=0.98

Figure 5: Best final individuals among 5 independent runs for the different visual properties being optimized.

Offline optimization of multiple visual properties

While the optimization of a single visual property leads to highly fit content, it is only through the combination of different visual patterns that a meaningful spaceship shape can be identified. This section presents an experiment which uses the normalized weighted sum (all weights at 1) of the fitness scores f_1 to f_5 as its objective function F. The results of the optimization process for 100 generations on a population of 250 individuals are shown in Table 2 collected through 10 individual runs, while the progress of the best individual for the most successful run is also presented graphically in Fig. 6.

Fig. 6 shows an overall increase of the aesthetic score F from its initial values; however, Table 2 indicates that not all of the contributing visual properties are optimized to the same degree. The most noteable disparity are the two weight properties (f_2 and f_3). In all the final best individuals f_2 is the highest scoring among the contributing visual properties in all but one runs, while only two runs does the best spaceship have a contribution from f_3; however, both f_2 and f_3 have a very similar behavior when optimized on their own. A number of factors affect this outcome: firstly, f_2 and f_3 have a membership function μ_W which requires a very spe-

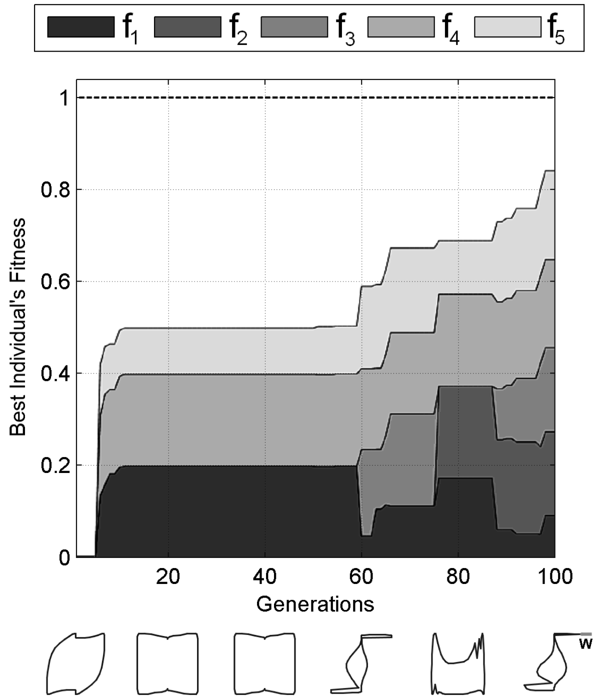


Figure 6: Stacked area plot of the best individual's optimization progress using a model of five visual properties. Also displayed are the phenotypes of the first feasible individual (far left) and the best individuals in 20 generation intervals.

cific visual pattern, so most spaceships will either have a score of 0 or a high score in these visual properties; a spaceship either has the desired weight distribution or it doesn't. Compared to aesthetic properties with a more lenient membership function (μ_D for f_4) or none at all (f_1,f_5), a spaceship with the desired visual pattern for f_2 or f_3 has a large advantage to one that does not; this is not true for the other visual properties. Most shapes have a considerable score for f_1, f_4 or f_5 since their desired visual patterns are much more generic, while most shapes have a score of 0 for f_2 and f_3. By design, therefore, any f_W with the given membership function is expected to dominate the aggregated fitness score if the targeted weight distribution is found; this explains why f_2 is usually optimal in the best final spaceships. On the other hand f_3 is mostly absent from the best individuals because both f_2 and f_3 are pattern-specific: once a spaceship with a high score in f_2 is found, the discovery of a spaceship with a high score in both f_2 and f_3 becomes much less likely. Fig. 6 presents the only run where both f_2 and f_3 have a high score at the end of the optimization process.

As expected, the aggregated approach to optimizing multiple visual properties suffers from dominant solutions; however, it does manage to create spaceships with high fitness scores for most contributing aesthetic properties and can be even more successful with a more sophisticated selection of targeted visual patterns.

Online adaptation of the aesthetic model and the generated content

As a proof of concept for the interactive adaptation of the aesthetic model presented in the previous section, an experiment was conducted using the online adjustment of both the aesthetic model and the content generated based on it.

The experiment revolves around a series of iterations: in each iteration a range of shapes is presented and the user selects the preferred one among them. Based on this selection the aesthetic score is re-evaluated according to eq. (5) and new shapes are evolved from those currently presented using an objective function from the updated aesthetics. In order to make online evolution manageable in terms of time, the initial shapes were loaded from a pretrained collection, the total population (feasible and infeasible) was limited to 40 individuals and the number of generations between each iteration was limited to 5. Furthermore, instead of the inclusive aesthetic model only two visual properties were evaluated and optimized during each iteration. Choosing from a large pool of visual properties, the two properties with "the most different" scores between the selected individual and all unselected ones are chosen and combined together into a weighted sum serving as the objective function for the current iteration. The difference (δ_i) with regards to a visual property i is computed as:

$$\delta_i = \sum_{\substack{k=1 \\ k \neq s}}^{N} |f_{i_k} - f_{i_s}| \tag{6}$$

where s is the selected individual, N is the number of presented individuals and f_{i_k} is the score of individual k for the i-th visual property.

Figure 7: Final results of the online evolutionary session for five different participants.

The experiment included 26 participants, most of which evolved content for 10 to 20 iterations. The same initial spaceship shapes were presented to all participants, while subsequent iterations presented only content which was distinct from each other. Although certain participants evolved content which was not of particular visual interest (variations of skewed circles similar to the CPPN's input), many participants generated very different spaceship shapes at the end of their sessions, both from each other and compared to the initial shapes. For space considerations, Fig. 7 demonstrates the most interesting results of this experiment and showcases the variety of spaceship designs which are driven by personalized aesthetic models of participants. Despite the fact that the framework focuses on genereating aesthetically pleasing spaceships, users were not required to specifically target spaceship shapes but were encouraged to choose any shape they found most appealing. This explains why not many of the final results bear any resemblance to spaceships; the focus of this experiment was the potential of adapting a context-independent personalized aesthetic model. In future work, we will consider explicitly requiring that users choose shapes appropriate for use as spaceship hulls.

Conclusion

This paper presented a constraint satisfaction PCG framework used to optimize the shape of spaceships according to visual properties deemed taste- and context-independent by studies on the field of human perception. By ensuring that constraints imposed by the game engine and a human designer are met by feasible individuals, the content generator operates in a much more limited search space. The visual properties presented in this paper are only a sample of possible quantifiable aesthetic characteristics that have been introduced in (Liapis 2011) pertaining to simplicity, cost, or weapon- and thruster-specific properties. These aesthetic evaluations can be used in conjunction with evaluations of the generated content's performance in game-specific tasks, as presented in (Liapis, Yannakakis, and Togelius 2011), to create both functional and visually appealing spaceships.

Experiments in the optimization of a single visual property have as a whole shown promising results. On the other hand, the aggregation of multiple visual properties in a single fitness score (as a weighted sum) is not guaranteed to generate results with all the required visual patterns. The evaluation of content in the form of a weighted sum allows for the adaptation of this heuristic according to player choices, allowing for the creation of personalized computational models of visual taste. For future work, we will consider a multi-objective evolutionary approach for the optimization of multiple visual properties. The argument for the aggregated approach is the potential for an interactive aesthetic model; however, a lexicographic ordering method could also take the aesthetic model into account by assigning higher importance to visual properties with larger weights.

Although targeted visual properties are often achieved within a number of generations using the proposed constrained optimizer, it should be noted that the resulting shapes are not particularly reminiscent of spaceship hulls. In future work we will limit the current representational freedom to ensure the generation of recognizeable spaceships.

The framework and algorithm proposed is applicable beyond the scope of spaceship design; the visual properties presented in this paper can be applied to any 2D game element. Additionally, the evaluation of content quality can be used as an authoring tool in game development: while the neuroevolutionary constrained optimization of multiple visual properties certainly has room for improvement, the adaptive aesthetic model in the form of a weighted sum can also be useful for evaluating existing content. This aesthetic model can select the most suitable game content for a particular player's visual taste from a collection of pre-generated or procedurally generated content. The player's choices can be used to adapt the aesthetic model much like the experiment presented in this paper and without the need for online evolution of new content. The fact that such a personalized aesthetic model can be combined with the evaluation of competencies in game-specific tasks, which is presented in (Liapis, Yannakakis, and Togelius 2011), allows for a personalized experience where the presented content is to the player's taste and its functionalities are tailored to their playstyle or challenge level.

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