Automated Interior Design Using a Genetic Algorithm

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Figure 1: Interior scene automatically populated by furniture objects using our method. Generated interior design is shown with original materials (left) and with new material assignment which was automatically optimized to achieve consistency and color harmony (right).

ABSTRACT

In this paper, we present a system that automatically populates indoor virtual scenes with furniture objects and optimizes their positions and orientations with respect to aesthetic, ergonomic and functional rules called interior design guidelines. These guidelines are represented as mathematical expressions which form the cost function. Our system optimizes the set of multiple interior designs by minimizing the cost function using a genetic algorithm. Moreover, we extend the optimization to transdimensional space by enabling automatic selection of furniture objects. Finally, we optimize the assignment of materials to the furniture objects to achieve a unified design and harmonious color distribution. We investigate the capability of our system to generate sensible and livable interior designs in a perceptual study.

CCS CONCEPTS

• **Computing methodologies** → *Graphics systems and interfaces*;

KEYWORDS

computational design, interior design, furniture arrangement, scene modeling, virtual environments

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1 INTRODUCTION

Interior design, including the selection of furniture objects, their layout and materials, is a challenging task which requires professional designers. While producing excellent results, professional interior design, done by artists, is a time-consuming process. With the growing popularity of large-scale virtual 3D environments for architectural visualization and the game industry, the manual interior design of virtual scenes becomes prohibitively expensive in terms of time and resources. Therefore, methods for automated interior design are necessary to speed up this process.

The problem of automated interior design was recently addressed by stochastic optimization methods [Merrell et al. 2011; Yeh et al. 2012; Yu et al. 2011]. Majority of previous methods are limited to search in fixed-dimensional space of furniture configurations while the furniture objects are selected by the user. Recently, this limitation was addressed by [Yeh et al. 2012]. The authors used a Markov chain Monte Carlo algorithm to deal with the problem of transdimensional search space. However, the drawback of this method is that it requires the parameters and relationships of the

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objects to be defined by imperative programming which is not intuitive for artists.

In this paper, we propose a novel method for automated interior design based on genetic algorithm optimization. Our method automatically generates interior design for a given room in two steps: In the first step, furniture objects are selected and positioned into the room in an iterative optimization process. In contrast to previous optimization-based methods [Merrell et al. 2011; Yu et al. 2011], our method is capable of selecting the appropriate furniture objects fully automatically. Moreover, our method is faster than state of the art method for objects selection and layout optimization [Yeh et al. 2012]. Our system determines the optimal layout by optimizing the cost function formed by the extended set of interior design guidelines. In the second step, the material assignment is optimized to achieve harmonious color configuration and consistent material types. Figure 1 shows the results of both interior design steps in our system.

Automated furniture layout optimization exhibits several nontrivial problems: High dimensionality of the search space, infinite space of possible furniture configurations and the majority of possible furniture configurations being unacceptable in terms of intersections, ergonomics, aesthetics or functionality. We solve the problem of high dimensionality by utilizing a genetic algorithm which is capable of optimizing multiple dimensions simultaneously. The problems of infinite search space and unacceptable furniture configurations are addressed in our method by utilizing interior design guidelines. Design guidelines for semi-automated furniture layout were previously used by Merrell et al. [2011]. In our work we extend the set of design guidelines by new ones, suggested in interior design literature and by professional interior designers in an expert study. In addition to forming a cost function, we used these design guidelines to form a set of mutations which are used to alter the interior designs in each iteration. These mutations aid the interior designs to evolve towards desired configurations by a stochastically-driven heuristic.

Material selection plays an important role in interior design. The selected materials of furniture objects should be consistent across the room and they should form a harmonious color configuration conforming to a specific style. Unfortunately, various 3D furniture models contain different materials which may not fit together if used in one room. Therefore, automated material assignment is required. We present a fast method for optimization of material assignment based on greedy cost minimization. The cost function is inspired by the works of Donovan et al. [2011] and Chen at al. [2015] which measure the color compatibility using a data-driven approach. The novelty of our material selection is a new labeling strategy based on material names and material categories. Additionally, we proposed to use a unification step to increase the visual compatibility of materials in the scene.

In order to evaluate the proposed method for automated interior design, we performed a perceptual study based on a subjective, two-alternative, forced-choice preference. The participants were asked to select their preference between interior designs created by professional artists and the ones created by our system. The results of this study suggest that our method generates sensible interior designs, close to the ones done by professionals for particular scenes.

The main contribution of this paper is a novel method for automated interior design based on a genetic algorithm. Our system achieves the full automation in generation of interior designs. Moreover, our genetic algorithm optimizes multiple designs simultaneously which allows the user to select from multiple sensible results. An additional contribution of this paper is an automatic material assignment which improves the visual quality and aesthetic look of the resulting design.

2 RELATED WORK

Automated Interior Design. Automated interior design is an active area of research in which the variety of approaches have been presented. The majority of them focuses on the layout of furniture objects in an automated or semi-automated fashion. These methods can be classified into three distinct categories: Procedural methods, data-driven methods, and optimization-based methods.

The methods from the first category are fast methods based on procedural layout generation [Akazawa et al. 2005; Germer and Schwarz 2009; Tutenel et al. 2009]. They use the set of rules, constraints and procedures for positioning of furniture objects in relation to the room and already arranged objects. The drawback of these methods is that they do not consider ergonomic factors which makes them prone to generation of uninhabitable arrangements.

Data-driven methods address the interior design problem by utilizing information from existing layouts [Fisher et al. 2012; Guerrero et al. 2015; Zhao et al. 2016]. These approaches require a set of user-created layout examples to generate new plausible arrangements of objects. The advantage of our method over example-based methods is that our method is fully automatic and does not require the manual layout creation. Recently, two methods were proposed which model 3D interior scenes based on the human activities performed in these scenes [Fisher et al. 2015; Ma et al. 2016]. The first method requires a 3D scan of the real environment to populate the virtual space with objects and the second one needs the initial scene layout to augment this layout by additional objects.

Optimization-based methods generate realistic furniture arrangements by optimizing a cost function. Typically, this cost function includes ergonomic, aesthetic and functional terms. The methods for the optimization of furniture arrangement based on evolutionary computing were proposed in [Akase and Okada 2013; Sanchez et al. 2003]. Similarly to these methods, our method also utilizes evolutionary computing, however, in contrast to them, it generates the final arrangement automatically without user assistance. Two methods for the creation of realistic and livable furniture layouts were presented in previous research [Merrell et al. 2011; Yu et al. 2011]. The first one utilizes simulated annealing to optimize the furniture arrangement in a given room. The second method [Merrell et al. 2011] assists a user in creating an optimized interior design by sampling the cost function based on interior design guidelines. The drawback of both methods is that none of them can automatically identify the optimal set of furniture objects for a specific room and this set has to be selected manually. In contrast to that, our method is fully automatic, including the selection of furniture objects and optimization of their arrangement. Similarly to the method of [Merrell et al. 2011] we use interior design guidelines to form a cost function. We extended this set of design guidelines by 3 new principles suggested in literature and by professional designers in an expert study. Moreover, we introduced 8 new mutations (moves) which enable faster exploration of search space.

The problem of automatic furniture selection and layout, requiring transdimensional optimization, was addressed in past by Yeh et al. [2012]. The authors proposed to use a stochastic Markov chain Monte Carlo sampling to explore the space of possible furniture configurations. In their system, the constraints of furniture objects are defined in an imperative programming language. The advantage of our method over [Yeh et al. 2012] is that in our system the furniture constraints are specified in an user-friendly interface as parameters.

In addition to furniture layout, material selection is an important step in interior design process. A method which automatically suggests materials for 3D objects was presented by Jain et al. [2012]. This method uses a data-driven model of shape-material relation to suggest a new material for a given object. Chen et al. [2015] presented a method for automatic material suggestion for indoor scenes. The authors used a set of local material rules and global aesthetic rules to be optimized to achieve visually plausible material suggestions. Similarly to our method, they used a data-driven approach for the calculation of color harmony [O'Donovan et al. 2011].

Interior Design Guidelines. Interior design guidelines are one of the key factors used by interior designers when creating a new design for a specific room. Therefore, an extensive literature exists which discusses these guidelines. In order to form the cost function in our optimization, we created mathematical expressions representing the guidelines used in professional interior design [Ballast 2013; Mitton and Nystuen 2011; O'Shea et al. 2013] as well as the ones previously presented in the area of computer graphics [Merrell et al. 2011]. Additionally, the mutations in our genetic algorithm are also based on interior design guidelines.

3 FURNITURE LAYOUT OPTIMIZATION

Our method for automated interior design utilizes a genetic algorithm [Holland 1992] to select and arrange furniture objects in a given room. The proposed genetic algorithm optimizes the population of interior designs (individuals). We use the set of design guidelines to form our cost function which assesses each individual interior design in terms of ergonomics, aesthetics and functionality. The goal of our genetic algorithm is to find a set of furniture objects and their arrangement, for a given room, which minimizes the cost function.

3.1 Genetic Algorithm

Our genetic algorithm is optimizing the population of furniture layouts in a process which is mimicking evolution in nature. The population is initialized by layouts with randomly selected furniture objects from the database. The probability of an object being selected for the room is proportional to the importance of this object for a specific room (See Section 3.2). Additionally, the position and rotation of each object is randomly chosen. After the population is initialized, the following steps are iteratively performed: Evaluation of the cost function, selection of the best individuals, creation of new individuals by crossover, and altering individuals by mutations. The outline of the algorithm is depicted in Figure 2. Any change in interior design causing objects intersection is rejected during our optimization.

We employ an island model genetic algorithm [Grosso 1985] which is designed to favor exploring the space of possible furniture layouts over narrowly searching within profitable regions. The island model genetic algorithm subdivides the whole population to multiple sub-populations (islands). All islands are evolving separately with rare interactions between them. These interactions typically include migration of the best individuals amongst islands. As a migration strategy, we use an approach similar to [Andalon-Garcia and Chavoya 2012] which migrates the best individual from each island to the next island in each n-th iteration. We set n to 10 in our implementation. We used four islands in our experiments each containing 50 individuals.

3.2 Furniture Categories

We classify all furniture objects into distinct categories in our genetic algorithm optimization. These categories correspond to the types of objects, e.g. *"chair"* or *"table"*. All objects from one category share the same properties which are used in the expressions representing interior design guidelines. These properties correspond to the measurements and relations used in the professional design practice [Merrell et al. 2011; O'Shea et al. 2013; Panero and Repetto 1975]. The cost function (Section 3.3) uses object properties to assess the fitness of each design with respect to design guidelines. The following properties are used in our method for each category of objects:

- **Clearance constraints: front, back, left, right.** Clearance constraints specify the empty space around the furniture object required for its comfortable use. In our experiments, we used values suggested in previous research [Merrell et al. 2011].
- **Probability of standing against a wall.** This probability specifies how important is it for an object to stand near the wall.
- **Possible parents.** This property contains the list of object categories which can be possible parents of a current object. Additionally, the minimum and maximum distance to a parent is used and the orientation towards the parent is specified (front or side).
- **Probability of having a parent.** It represents importance for the object of being in a group relationship with the other objects.
- **Room importance.** This property states how important an object is for a specific room. For example a bed has to be present in a bedroom, thus having importance 1.0 for this room.
- **Desired count.** Each category contains a minimum required and maximum allowed number of objects of this category in a specific room. For example a maximum of one television can be in a living room.

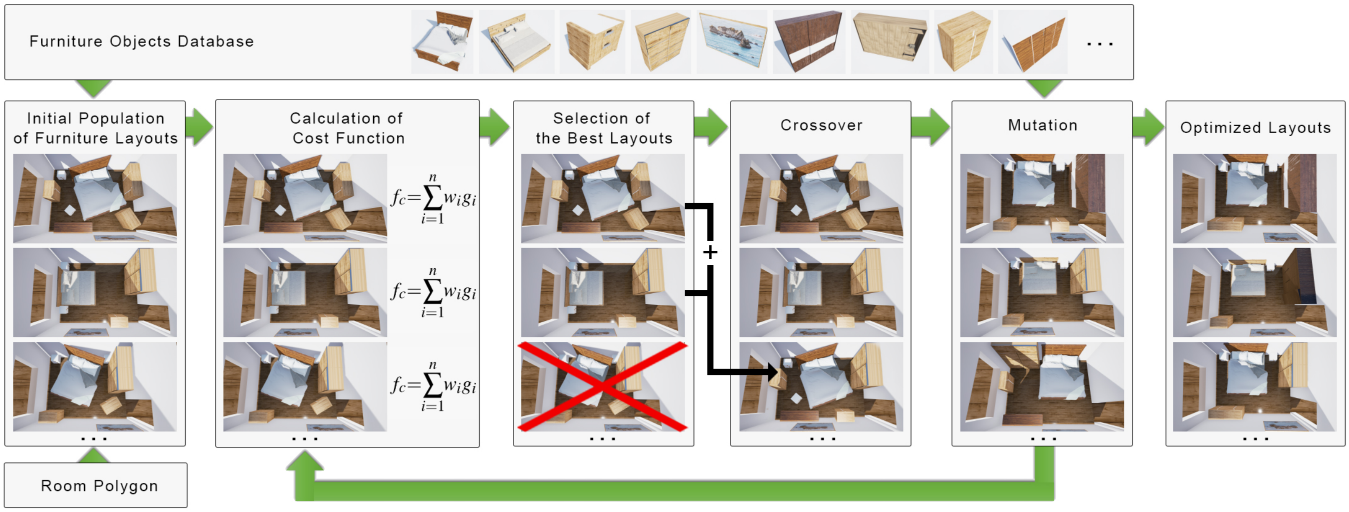

Figure 2: The overview of our genetic algorithm for automated furniture layout. Each step illustrates the evolution of the set of interior designs. Calculation of the cost for each interior design uses the weighted sum of the design guidelines terms. The algorithm iteratively optimizes the population of furniture layouts.

Having the categories of objects, the user can simply add any number of 3D furniture objects to the database by specifying their geometry, category, and front direction (2D vector in a ground plane). New categories can also be added by the user. For each new category of objects the above listed properties have to be specified.

3.3 Cost Function

The cost function in our furniture layout optimization is based on interior design guidelines. We firstly studied the literature in the area of interior design [Ballast 2013; Merrell et al. 2011; Mitton and Nystuen 2011; O'Shea et al. 2013] to summarize the design guidelines used in professional design practice. Then, we conducted an expert study which investigated the frequency of use for these guidelines. Eight professional designers participated in our study. They were asked to state the frequency with which they use each guideline. Additionally, they could suggest other guidelines to be added. According to the results of this study, we selected the most frequent guidelines and added the new recommended ones to form the set of interior design guidelines, used as terms in our cost function. Each guideline is represented as one expression. The cost function, to be minimized in our optimization, is then defined as a weighted sum of these expressions:

$$f_c = \sum_{i=1}^{n} w_i g_i \tag{1}$$

where f_c stands for the cost function, w_i are the user-specified weights and g_i represents particular design guidelines expressions defined below. These expressions utilize object properties (Section 3.2) and oriented 3D bounding boxes surrounding the objects. The bounding boxes are used to prevent intersection of objects and define the areas around the objects. Bounding boxes are evaluated in 3-dimensional space to allow furniture pieces to be organized also in a vertical dimension (See Figure 3). The following design guidelines are summed in the cost function:

Clearance. Furniture objects require an empty space around them to be used for their primary function. Some objects require direct access from one or more sides. The clearance guideline represents this requirement. We model the clearance guideline as the amount of overlap between objects' bounding boxes extended by clearance constraints:

$$g_c = \frac{1}{|\mathcal{A}|\,(|\mathcal{A}|-1)} \sum_{b_1, b_2 \in \mathcal{A} : b_1 \neq b_2} \frac{V(b_1 \cap b_2)}{V(b_1)} \tag{2}$$

The clearance expression is evaluated in a pairwise manner. b_1 and b_2 are extended bounding boxes from the set $\mathcal{A}$. The set $\mathcal{A}$ contains extended bounding boxes of all furniture objects in one furniture layout in union with bounding boxes of walls, windows and doors. Function V returns the volume of the 3D geometric shape. $|\mathcal{A}|$ denotes the size of set $\mathcal{A}$.

Circulation. The circulation guideline expresses the need of furniture objects to be physically accessible by humans to serve their function. No part of the room should be blocked to be livable and usable for humans. We express this guideline by the number of objects which are not accessible from the entrance of the room. In order to calculate this number, we need to employ a path finding algorithm and evaluate if the path exists from the entrance to the furniture object. Our method uses backtracking to find the possible paths in a discrete space. This is done in three main steps: In the first step all furniture objects and walls are projected to the ground plane and rasterized into a 2D grid. In the second step, we apply a dilation operation on these projections to account for the body size. This operation dilates the discrete projections by a disk of the specified human body radius. In the third step the front sides of the furniture objects are marked in a grid as targets to be accessed by

Figure 3: The painting above the bed demonstrates the capability of our system to arrange objects also in vertical space. This benefit is due to the utilization of 3D oriented bounding boxes for collision detection.

the path starting from the room entrance. Then, the backtracking algorithm is started. The algorithm returns the number of accessible targets n_a. We mark the total number of furniture objects present in current layout as n_t. The expression for the circulation guideline can be then written as:

$$g_r = 1 - n_a/n_t \tag{3}$$

We pose a hard constraint for all layouts in the population to contain at least two furniture objects. Therefore, $n_t > 1$ holds for all defined equations and division by zero is avoided.

Group Relationships. The furniture objects in interior design can be grouped based on their function and type. Often a group of objects has their parent (e.g. the chairs are located around the table). The spatial organization within a group conforms to the specific requirements. One of these requirements is the comfortable conversation of people [Merrell et al. 2011]. Comfortable conversation depends on placement of seats which should support eye contact and normal speech volume (i.e. limited distance). We express the group relationships cost in terms of average distance of objects of the same type:

$$g_g = \frac{1}{|C|\,(|C|-1)d_r} \sum_{\vec{c}_1, \vec{c}_2 \in C : \vec{c}_1 \neq \vec{c}_2} G(\vec{c}_1, \vec{c}_2)|\vec{c}_1 - \vec{c}_2| \tag{4}$$

where d_r is the diagonal size of the room in the ground plane. C is the set of all centers of furniture objects in the room. Function $G(\vec{c}_1, \vec{c}_2)$ returns 1 if the centers $\vec{c}_1, \vec{c}_2$ belong to the objects of the same category and 0 otherwise. $|\vec{c}_1 - \vec{c}_2|$ represents the size of the vector. Additionally to the cost function, the group relationships are also modeled in the mutations of the genetic algorithm. This ensures that the objects which require a parent tend to have one.

Alignment. In interior design, the objects should be properly oriented and aligned to their supporting surfaces. For example the cupboard should be oriented by its back side towards a wall. Additionally, the furniture objects should be aligned to the other objects. We model the alignment guideline by the variance of the angles between front vectors of objects in combination with a probabilistic distance measure between objects and their nearest wall. The alignment term is evaluated in a pairwise manner:

$$g_a = \frac{1}{|\mathcal{V}|\,(|\mathcal{V}|-1)} \sum_{\vec{v}_1, \vec{v}_2 \in \mathcal{V} : \vec{v}_1 \neq \vec{v}_2} (\alpha - \overline{\alpha})^2 + g_w \tag{5}$$

$$\alpha = 1 - 0.5(\vec{v}_1 \cdot \vec{v}_2 + 1) \tag{6}$$

α is proportional to the angle between two front vectors $\vec{v}_1$ and $\vec{v}_2$. $\mathcal{V}$ is the set of front vectors of all furniture objects. We also include the front vectors of room walls into $\mathcal{V}$ to allow furniture objects to be aligned with walls. $\overline{\alpha}$ is the mean value of α for all vectors in $\mathcal{V}$. Equation 6 remaps the cosine of the angle between $\vec{v}_1$ and $\vec{v}_2$ from range (-1,1) to (0,1) to be usable as a term of the cost function.

In addition to appropriate alignment of furniture objects, some of them should stand against a wall. Thus, we add the wall distance term g_w to the alignment cost. This term is using the probability of standing against a wall p_w defined for each object category (Section 3.2).

$$g_w = \frac{1}{|\mathcal{P}|\,d_r} \sum_{\vec{p}_b \in \mathcal{P}} p_w|\vec{p}_b - \text{proj}(\vec{p}_b)| \tag{7}$$

$\vec{p}_b$ is the point on the back side of the furniture object. The set $\mathcal{P}$ represents the set of these back points from all furniture objects present in current interior design. The function $\text{proj}(\vec{p}_b)$ projects back point $\vec{p}_b$ to its closest wall and returns this projected point. d_r is the diagonal size of the room in the ground plane. If the room is not rectangular, then d_r is calculated as the diagonal size of the room's bounding box.

Distribution and Rhythm. According to this guideline, the furniture objects should be properly distributed in space and the frequency of this distribution should follow a rhythm. For example the paintings should be distributed along a line on the wall with the rhythmically repeating distances between them. We model the cost for this guideline as a variance of the relative distances between pairs of objects:

$$g_d = \frac{1}{|C|\,(|C|-1)} \sum_{\vec{c}_1, \vec{c}_2 \in C : \vec{c}_1 \neq \vec{c}_2} (d - \overline{d})^2 \tag{8}$$

$$d = \frac{|\vec{c}_1 - \vec{c}_2|}{d_m} \tag{9}$$

d stands for relative distance between two points which is the Euclidean distance divided by the maximum distance d_m between two objects in the scene. $\overline{d}$ is the mean relative distance between all pairs of objects in the interior design.

Viewing Frustum. In an optimized layout, some objects should be visible from the others for their primary function (e.g. television should be visible from sofa). In our method these objects conform to the parent-child relationship. Therefore, we calculate the viewing frustum cost by casting rays between all parent-child pairs and count the number of intersecting rays with other furniture objects. We denote the number of intersecting rays as n_i and the total number of objects in interior design as n_t. The viewing frustum cost can be calculated as $g_v = n_i/n_t$.

Functional Needs. Furniture objects in a room serve for particular functions or activities in this room. Therefore, a specific room should contain interior objects which are important for activities in this room. For example the living room should contain the TV and sofas. Our expression for functional needs consists of two terms:

$$g_f = \frac{1}{2}\frac{\sum_{i_o \in \mathcal{I}} 1 - i_o}{|\mathcal{I}|} + \frac{1}{2}\frac{\sum_{o_c \in O} \Delta(o_c)}{|O|} \tag{10}$$

The first term in Equation 10 is related to the room importance (Section 3.2) of all furniture objects present in a current design individual. This term assigns higher cost to the objects which are less important for the current room. The importance cost sums up the importance values i_o of objects present in the design individual. I is the set of these importance values. The second term is related to the desired count of objects of a specific category in a room (Section 3.2). Function $\Delta(o_c)$ calculates the difference between objects count of category o_c and the desired objects count of this category. The set O represents all categories present in the current interior design.

Proportion. The furniture objects should have appropriate proportions to the specific room and to each other. Additionally, if there is too much of empty space in a room, new objects should be generated. We model the cost for this guideline as the ratio of the volume covered by the objects to the room volume:

$$g_p = \frac{\max(r_v - V_o/V_r, 0)}{r_v} \tag{11}$$

V_o is the volume of all furniture objects together and V_r is the total volume of the room. These two volumes are compared with the required ratio of the volume covered by furniture r_v. We used the values of r_v between 0.2 and 0.35 in our experiments. We empirically found these values to work the best for our optimization. The volume V_r depends also on the room height. Therefore, higher furniture objects are preferably selected for higher rooms according to the proportion guideline.

The defined design guidelines play an important role in the optimization of furniture layout. In our experiments we set the weights for all guidelines to 1.0 except circulation with weight 1.1 and proportion with weight 2.5. The weight for proportion was increased because this guideline is essential for inserting objects to the scene.

3.4 Selection

Our genetic algorithm optimization is advancing every iteration by creating a new generation of furniture layouts from the current population. In order to select the design individuals which will survive to the next generation, we use a tournament selection [Miller et al. 1995]. In the tournament selection, each individual to survive is identified in two steps: First, k individuals are randomly selected from the island's sub-population. Second, the individual with the lowest cost value, from these k selected ones, is the winner of the tournament and proceeds to the next generation. We set $k = 6$ in our implementation. By this method our algorithm selects 70% of the population to proceed to the next generation. The remaining 30% is generated by crossover from the selected parents. Finally, we apply mutations to 50% of this newly created population.

3.5 Crossover

Crossover is a computational operation analogous to reproduction in nature in which a new offspring is created from two parents by combining their genomes. A genetic algorithm uses crossover to create a new individual from random sub-parts of selected parents. In the domain of furniture layout, an individual is formed by the configuration of furniture objects. Therefore, crossover can be naturally performed by selecting random furniture objects from each parent layout and combining them together to form a new furniture layout. In our method, 30% of the new generation is formed by crossover from 70% of the selected individuals. Parents for crossover operation are chosen randomly. A new individual is formed by exchanging approximately half of the furniture objects from the first parent with objects from the second parent. If the furniture object from the second parent has children, these children are also inserted to the new individual. The selected furniture object is not inserted into the new individual in case of causing intersections with already existing objects.

3.6 Mutations

At the end of each iteration, our algorithm mutates 50% of the design individuals by random mutations to favor the exploration of new furniture configurations. The following mutations are used in our method to alter the individuals:

(1) Randomly change the position of furniture object.
(2) Randomly change the orientation of furniture object.
(3) Align furniture object with the closest object.
(4) Align furniture object with the closest wall.
(5) Snap furniture object to the closest object.
(6) Snap furniture object to the closest wall.
(7) Connect furniture object with one of possible parents.
(8) Add new children to the parent object.
(9) Add new furniture object to the design individual.
(10) Remove random object from the design individual.

The mutations 1 to 5 are executed for each furniture object in the interior design with the probability of 0.3. We set this probability empirically based on the results of our experiments. Mutation 6 is performed on each object with the probability given as the property of a specific object category (See section 3.2). Mutation 7 is executed for each furniture object with the probability of having a parent, defined for the specific object category. Mutation 8 is performed on each object with the empirically set probability of 0.6. Finally, the probabilities of adding and removing the objects to/from the design are set to 0.5 and 0.1 respectively. If the mutations 8 and 9 are adding a new child object to a design, we use a special heuristic to achieve the alignment of children around parent object (e.g. the chairs around the table). This heuristic positions the child objects to the opposite sides of the parent object and aligns them based on their count. We accept only mutations which do not cause intersections of objects.

4 MATERIAL OPTIMIZATION

The second step in our system is the optimization of material assignment to the furniture objects and to the room. Our main goal is to reach consistency of the selected materials in a room and harmonious colors. We achieve the consistency of materials by introducing surface categories and selecting one common material for all surfaces which belong to a particular category. We use the following categories of surfaces in our experiments: Fabric, wood, glass, chrome, metal, plastic, ceramic and stone. Our method uses the database of materials to randomly assign one material to each surface category.

Additionally, we use the material names from the imported geometric models to identify the surfaces from specific categories. The surface is assigned to a category if the category name matches part of the material name on this surface. This method groups the surfaces with the same category. The color harmony of the materials in a room is then achieved by optimizing the material assignment for each category with respect to a data-driven cost function. Our cost function models color compatibility between the colors present in the scene. We use a greedy algorithm to minimize this cost function. Following steps are performed in each iteration of the optimization:

(1) Randomly select a material for each category and assign it to the surfaces of this category.
(2) Render the scene from four viewpoints aligned with room corners.
(3) Extract 5 dominant colors from the rendered images.
(4) Evaluate color compatibility in the scene by calculating the cost of the extracted 5-color palette.
(5) If the cost function of newly assigned materials is lower than the previously assigned ones, accept this new material configuration.

4.1 Color Compatibility

The optimization of materials uses color compatibility to assign cost to each material configuration in the scene. We employ a data-driven method, inspired by [Chen et al. 2015; O'Donovan et al. 2011], to calculate color compatibility in the scene. Our method uses color palettes, consisting of 5 colors, to represent dominant colors in the scene. The colors in color palettes are represented in CIELab color space. We extract a color palette from rendered images of the scene by k-means clustering. Then, we use the database of harmonious color palettes to calculate the cost of the extracted color palette. The interior design scene with its extracted color palette can be seen in Figure 4.

The cost of the extracted color palette f_p is calculated by the weighted distance to the k-nearest color palettes from our database of harmonious colors:

$$f_p = \sum_{i=1}^{k} (1 - r_i)|p_i - p_e| \tag{12}$$

p_i is the i-th closest color palette to the extracted palette p_e and r_i is the rating of the palette p_i. The ratings in our database are normalized. We used $k = 10$ in our experiments. The distance of palettes $|p_i - p_e|$ is calculated as the sum of distances between individual colors in palettes in CIELab color space:

$$|p_i - p_e| = \sum_{c=1}^{5} |p_{ic} - p_{ec}| \tag{13}$$

where p_{ic} and p_{ec} are c-th colors from the corresponding palettes. The distance $|p_{ic} - p_{ec}|$ is the Euclidean distance in the CIELab color space. The colors in all palettes are ordered by the L value to calculate distances between corresponding colors.

Figure 4: Top: The optimized layout and materials of interior design by our system. Bottom: The extracted 5-color palette.

Color Compatibility Database. Our database of harmonious colors consists of 100000 color palettes with assigned ratings. This database was formed by using harmonious color palettes, created by artists, obtained from the online resource www.colourlovers.com. We downloaded 500000 color palettes with user ratings from the Colourlovers website. These palettes contain colors used in general design tasks including webdesign, architectural design, interior design, etc. Similarly to [Chen et al. 2015], we used an image-based approach to select the palettes suitable for interior design. We downloaded 10000 images of interior designs from the internet and extracted their dominant color palettes by k-means clustering. Then, the interior design suitability rating r_e of each palette from Colourlovers was calculated as the average distance to the k-nearest color palettes from the extracted interior design palettes. The extracted palettes were added to the downloaded ones to form the initial database of harmonious colors. Each palette from this database was assigned a new rating r_i calculated as $r_i = 0.6r_e + 0.4r_c$ where r_e is the rating extracted from interior design images and r_c is the user rating from the Colourlovers database. Both ratings were first normalized by the maximum values. The weights 0.6 and 0.4 were set empirically. The palettes extracted from images had assigned the user rating r_c of 1.0.

Finally, our database of harmonious color palettes was formed by selecting 100000 color palettes with the best ratings r_i. This database was used in our greedy material optimization to select the material configuration with harmonious colors. The results of interior designs before and after our material optimization can be seen in supplementary files. Additionally, the capability of our system to optimize not only the materials of furniture objects but also the materials of walls and floor is demonstrated in Figure 4.

5 RESULTS

We implemented the presented algorithms in Unreal Engine 4 and our experiments were executed on a desktop PC with the 3.2 GHz hexa-core CPU and GeForce GTX 980 graphics card. We evaluated the performance of our system in three different rooms: Kitchen, living room and bedroom. Firstly, our system automatically furnished these rooms with interior objects and then it selected consistent materials with harmonious colors for the scenes. Additionally, we conducted a perceptual study to assess the quality of generated interior designs. The interior designs, generated by our system, can be seen in Figure 1, Figure 3, Figure 4 and in supplementary files.

The computational times of our methods for all furnished scenes are shown in Table 1. We used 42 3D models of furniture objects and 16 furniture categories in our experiments. In addition to the object database, a material database was employed which consists of 80 materials for furniture objects, 19 materials for room walls, and 15 materials for floor. The resolution of rendering from room corners in material optimization was 256x256 for each camera.

Table 1: Computational time of our system. Iter. denotes the number of iterations in our genetic algorithm. This number was determined empirically for each scene as a tradeoff between optimality of the cost and variability of the results.

Scene	Iter.	Layout opt.	Material opt.
Kitchen	20	12 s	14 s
Living room	100	51 s	15 s
Bedroom	30	16 s	14 s

Additionally, we evaluated the scalability of our genetic algorithm by plotting the dependency of computational time on the number of iterations (Figure 5). The resulting graph indicates the linear dependency of time on iterations count.

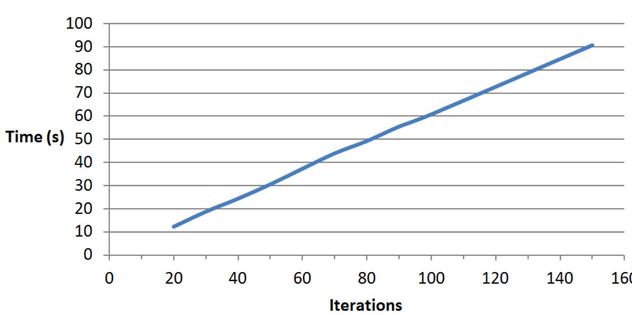

Figure 5: Dependency of computational time of layout optimization on the number of iterations. The time was measured using the kitchen scene.

5.1 Perceptual Study

We evaluated the capability of our system to generate sensible and livable interior designs by conducting a human-oriented perceptual study. The main goal of this study was to investigate if there is a significant difference between the interior designs created by our system and the ones created by professional interior designers. Therefore, we asked two interior design artists to manually furnish our virtual testing rooms for comparison with our algorithm. Secondly, they were asked to also manually assign materials to the objects in the scenes. The database of available furniture objects and materials was the same for both our algorithm and the artists. We used three test scenes to compare our algorithm with manually-created interior designs: Kitchen, living room, and bedroom. Two conditions, with original materials and with optimized materials, were evaluated for each test scene. In total 6 scenes had to be evaluated. 30 users participated in our perceptual study, including 23 males and 7 females, in age from 23 to 49.

Study Design. Our null hypothesis H_0 was that there are no significant differences of user preference between automatically created interior design and manually created interior design. The alternative hypothesis H_1 was that there are significant differences of preference between these two conditions. We conducted our experiment using a subjective, two-alternative, forced-choice preference approach similar to [Jimenez et al. 2009; Yu et al. 2011].

Procedure. Our perceptual study was conducted in the form of an online questionnaire. Each question of the questionnaire showed two interior designs for side-by-side comparison by the user, one created by our system and one created by the artists. Each interior design was represented by three images: Two images from the first-person perspective and one image from the top. For each question the user had to select which interior design, from two alternatives, would he/she prefer to live in. The questionnaire consisted of 6 questions, three for furniture layout with original materials and three for furniture layout with optimized materials. The order of the questions was randomized. The sides (left, right) of automatic and manual designs were also randomized.

Outcome and Analysis. The main focus of our study was to validate the quality of interior designs created by our system. Thus, we investigated if our designs are close to the ones created by professionals in terms of user preference. If there are scenes with no statistically significant difference in preference between our designs and manual designs, our system may be considered successful.

We used a Chi-square nonparametric analysis to determine any statistical significance in each of our 6 conditions (3 rooms, without and with material assignment). The Chi-square analysis in one-dimension was used for each of these conditions separately. Each condition contained 30 preference answers, thus the frequencies of preferences were compared to an expected 15/15 result. The Chi-square values were computed and tested for significance. The results of this analysis are shown in Table 2. Additionally, the measured frequencies of user preferences are shown in Figure 6.

The results of the Chi-square analysis suggest that there is no clear winner, amongst our method and the manual design, which would significantly outperform the other in all tested scenarios. The kitchen scene results are particularly interesting because our method significantly outperformed the manual design for the layout scenario ($p = 0.028$) with 21 votes in favor of our method and only 9 votes which preferred manual design. Additionally, there was no significant difference for the kitchen scene in the scenario with optimized materials. In case of the living room scene, the manual design significantly outperformed our method in the layout scenario. However, after material assignment, our method was able to revert this trend and got even more preferences than the manual design. In this case, the difference was not statistically significant. In the bedroom scene, the manual design significantly outperformed our method in both layout and material conditions. We hypothesize that the preference of the manual design in this case was caused by the algorithm positioning the bed side close to the wall. Nevertheless, our algorithm can suggest layouts for the bedroom scene where the bed can be accessible from both sides.

In summary, 3 scenarios in our experiment showed significant preference of the manual design over our method and 3 scenarios showed either no statistical significance or preference of our method. Thus, we conclude that our method can generate sensible and livable interior designs which are comparable to manually-created ones for particular scenes. Additionally, the extension of our cost function and further experiments would be vital for generalizing the preference of our method in all interior spaces.

Table 2: The results of the Chi-square analysis. Values in boldface indicate significant difference (level of significance = 0.05). The left column shows the results for layouts with original materials and the right column shows the results for layouts with optimized materials. Please note that while the result of the layout with original materials in the kitchen is significant, the users preferred the design generated by our system rather than the one created by the artist. This preference can be seen in Figure 6.

	Layout only		Layout + materials	
Scene	χ^2-value	p-value	χ^2-value	p-value
Kitchen	**4.800**	**0.028**	0.133	0.715
Living r.	**6.533**	**0.011**	0.133	0.715
Bedroom	**19.200**	**< 0.001**	**6.533**	**0.011**

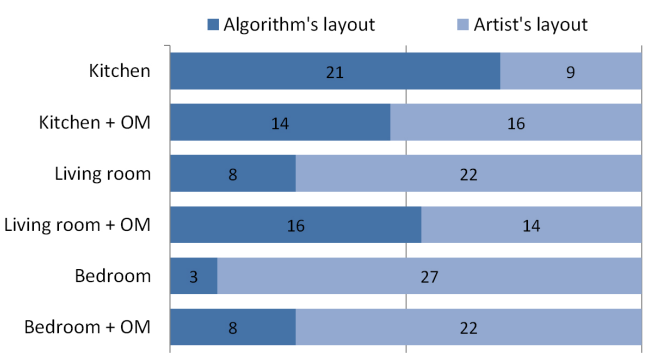

Figure 6: Frequencies of user preferences in our study. Each of the 6 displayed conditions represents the preferences amongst answers of 30 participants. The conditions of kitchen layout and living room layout with optimized materials show the preference of our method before the manual design. In the other conditions, the manual design was preferred. OM stands for optimized materials.

6 DISCUSSION

The results of perceptual study indicate that our method is capable of producing sensible and livable interior designs. In the kitchen scenario, our method was able to significantly outperform the manual design in terms of the user preference. Additionally, in the living room and bedroom scenes our method for automated material assignment increased the frequency of preference of our generated designs (Figure 6).

Based on the varying significance values and trends in user preference, we can hypothesize that the quality of the generated interior design depends on the type of the room. Our algorithm performed very well in the kitchen scene while it was not preferred by participants in the bedroom scene. Therefore, future investigations can help to identify the source of this variability and consequently extend the cost function.

We implemented our methods in Unreal Engine 4. Thus, our algorithms can be easily integrated into video games, virtual reality systems, or other real-time applications to generate large-scale indoor virtual environments. Moreover, the generated interior designs can be easily edited by the artists, using the Unreal Editor.

7 CONCLUSION

We have presented novel methods for automated furniture layout and material assignment in interior scenes. The advantage of our methods over state of the art is that our system can automatically add furniture objects to the room. This object addition is implemented as a mutation of interior design in our novel genetic algorithm. Moreover, we have presented and implemented an extended set of interior design guidelines which form the cost function. Our results show that the optimization of this cost function by the genetic algorithm leads to consistent and livable interior designs. Finally, the results of our perceptual study suggest that our methods can generate interior designs which are close to the ones created manually by professional designers for specific scenes.

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