Interior spatial layout with soft objectives using evolutionary computation

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Abstract—This paper presents the design problem of furniture arrangement in a residential interior living space, and addresses it by means of evolutionary computation. Interior arrangement is an important and interesting problem that occurs commonly when designing living spaces. It entails determining the locations of interior elements such as tables, seating elements, projection screens etc., in order to satisfy objectives. Despite it's commonality, it is a challenging problem that entails mainly soft objectives, related to perception and ergonomics, as well as challenging constraints. This paper is an attempt to address this problem by means of Evolutionary Computation. We discuss the problem formulation focusing on perceptual aspects of the various elements of space. In particular, we formulate a three objective problem with the following objectives: Maximization of visual perception of openings to the outside, maximization of inter-person visual perception, from the seating places, and maximization of the "openness" of space. We provide results from a comparison of two MOEAs, namely NSGA-II and HypE.

Keywords—interior space, interior architecture, multi-objectivity, evolutionary computation, perception

I. INTRODUCTION

The design discipline of Interior Architecture focuses on the elaborated analysis of design problems related to living spaces and applies 'the elements and principles of design' for their solutions [1]. One of the most common and yet overlooked problems in interior architecture is the arrangement of furniture in a living space. As simple as it sounds, the solution of such a problem requires the comprehension of a spatial organization that structures interior space within architectural boundries. Although we recognize the mastery that may occur from an experienced designer spending a significant amount of their creative effort in designing an interior space, we find that it would be beneficial in any case to consider a computational system that could serve as support in the creative process.

The challenge for such a problem as interior design and arrangement is to well define all factors that leads to a successful spatial organization. Quality of a design should incorporate a wide variety of design factors, including, but not limited to, functional, ergonomic, perceptual and aspects of scale. For defining the goals of the computational system, we are inspired by criteria for spatial definiton which were derived

from the definitions presented in [2]. In the following section we explain what we mean with the terms interior space, interior circulation, interior scale, hierarchy and Connections in interior spaces.

II. BACKGROUND

A. Definitions

We first go through definition of some terms in order to contextualize the research.

Interior Space: An interior consists of form and space when boundries are made possible through architectural structure. For our case we take a living space inside an apartment for our interior space.

Interior circulation: The circulation in interior spaces determine the connections between areas. The arrangement of interior elements, entrances to other interior spaces and to outside determines interior circulation.

Interior scale: The scale is related with the immediate environment. For the interiors the scale should be related to the human ergonomics.

Connections in interior spaces: There are three types of connections in an inteior space: visual, functional and structural. Visual connections in an interior space is provided with openings within planes. Doors and windows ensure visual connection in an interior space. The functional connections are determined by the relationships between different activites in a living space such as dining, watching TV, relaxing. Structural connections are defined as the junctions between structural elements such as between floor to wall and wall to ceiling.

B. Previous Works

Computational Decision Support systems for interior layout and furniture arrangement have attracted attention in some sutdies.

In [3], the author proposes a pattern-based mutation scheme, which allows a series of predetermined elements to be interchanged in an indoor environment. However, the positions of the elements are held fixed, and as such the search space is dramatically constrained.
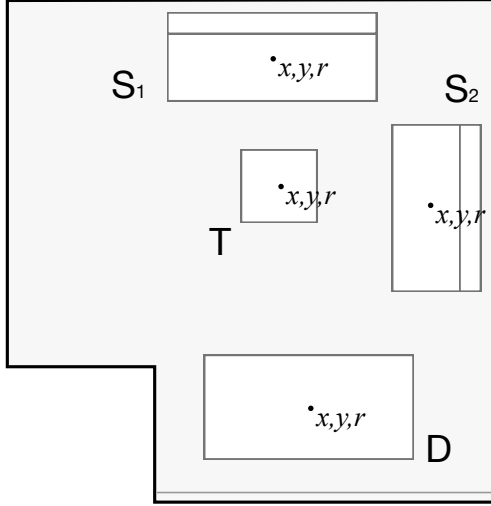
Fig. 1. A graphical scheme of the geometric correspondence between decision variable values and placement of furniture. The lower left corner of the space is occupied by a balcony.

In [4], [5], authors have considered the problem of interior arrangement of office functions and furniture, both in rectangular as well as polygonal spaces. However, their objective functions consisted only of criteria regarding the functionality of the solutions. As such, soft aspects such as perception and openness could not be addresses by this approach.

In [6], authors have considered the placement of furniture in an interior space focusing on ergonomic criteria. They propose addressing the optimization problem by the use of Simulated Annealing algorithm. However, the authors do not discuss the issue of conflicting objectives in the problem at hand.

Lastly, in [7], authors use interior design guidelines to generate a density function with respect to positioning of furniture. They sample the distribution to generate solutions. This approach, while quite unique, does not directly guarantee satisfiability of goals, as well as relying on user input to guide the system.

In view of the works presented above, this paper considers an approach to addressing the interior arrangement problem by means of Soft Computing. In particular, we make use of Visual Perception definitions, and Evolutionary Computation.

III. Problem Formulation

We formulate the interior furniture arrangement problem as a constrained real parameter optimization problem with 16 Decision Variables and three Objective Functions. As will be explained in detail, our decision variables correspond directly to element positions within the space, and objective functions focus on soft aspects of space such as visual perception and the perception of openness.

For simplicity, in the current version of the proposed model we do not consider quality of access in the space, apart from the basic clearance requirements, e.g. around tables, in front of seating elements etc. However, it is our plan to include specific access-related design goals in the near future.

We formulate a scenario that concerns furniture placement in a living room of an apartment residence. The rectangular space has dimensions of roughly 5.5m x 5.0m, with one corner of the rectangle occupied by a balcony. One of the sides of the living room has a large opening to the outside. A diagram of the space in question is available in Fig. 1.

A. Decision Variables

We define a total of 16 decision variables (DVs). For each of the four pieces of furniture to be arranged, correspond three DVs: Two control the position of the element in space, p_x, p_y, and one controls it's rotation, r_{xy}. Position variables form real numbers, while rotation is a discrete variable.

In principle, the scheme described above should be enough to fully describe an instance of our interior space arrangement. However, we have found it is beneficial as for the results, to include four additional variables, which would control the ordering of the furniture with respect to their anchor points. In other words, we first specify four anchor points using the 12 variables discussed above, and subsequently we assign one element to each, according to an ordering, which is itself subject to optimization. This is a trick that has been reported several times in previous works [6], [8], and allows for radical changes in the phenotype to take place with minimal change in the genotype, i.e. furniture positions could be potentially completely re-arranged, through a slight change in two or three DVs. An overview of DVs is available in Table I.

TABLE I.   Decision Variable Notations and Units

Notation	Unit	Interval or Values	No. of DVs	Description
$p_{x,i}$	m	[0.0, 5.5]	4	Position in the X direction
$p_{y,i}$	m	[0.0, 5.5]	4	Position in the Y direction
r_i	rad	{0, π/2, π, 3π/2, 2π}	4	Rotation
o_i	-	[0.0, 1.0]	4	Assignment parameter

B. Objective Functions and Constraints

We define a total of three objective functions (OFs). The first OF regards the visibility of exterior openings from the hypothetical observers occupying two seating positions of the interior space (Sofa A and Sofa B). The second OF regards the inter-person visual perception between occupants of the same seating positions. The third OF regards the perceived "Openness" of the space, which, broadly speaking, corresponds to the existence of a single and unpartitioned area within the space. The solutions are subject to two constraints, g_a and g_b, which ensure feasibility of the solution, with respect to object overlaps. Thus, our problem formulation is as follows:

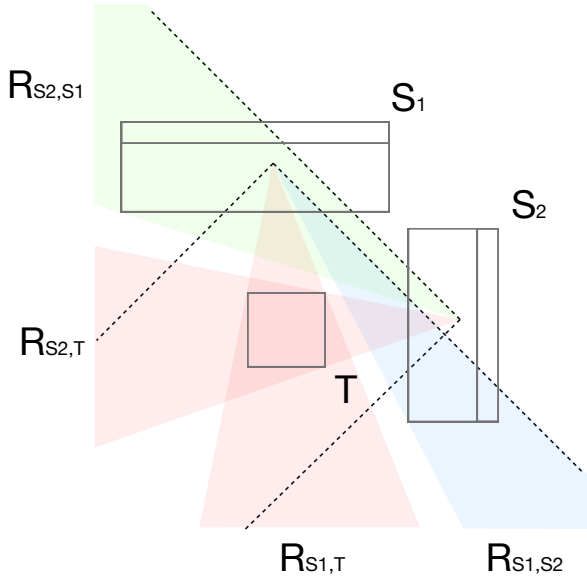$$\max(O_{View}, O_{Vis}, O_{Dist})$$

Fig. 2. An instance of potential furniture arrangement, with visual perception areas being highlighted. For S1, around 20% of the visual area is occupied by S2, and around 40% by table T. For S2, around 35% is occupied by S1, and 30% by table T.

subject to:

$$g_a, g_b \geq 0$$

To evaluate visual perception, we implement the visual perception model introduced by Çiftçioğlu and Bittermann in [9], [10]. The model in question is a probabilistic model that manages to provide a quantitative figure of unbiased observer visual perception, effectively abstracting much of the biological complexity that belies the human faculty of vision.

In the stochastic version of the model, the visual field is defined as a cone with an apex angle of 90 degrees, located at the observer and aligned with their viewing direction. Within the cone, a number of "visual rays" are considered, which are generated according to a uniform random distribution with respect to their angle of departure from the observer. The degree of awareness of a particular object or region in the visual field is then defined as the proportion of visual rays that intersect it, over the total rays considered:

$$p_{s,o} = \frac{\sum_{i=1}^{n} intersect(R_i, O)}{n}$$

In the above formula, S is the spectator, O is the object or region in question, and *intersect* is a function that returns 1 if a ray intersects an object, and 0 otherwise.

For our purposes, we make use of the model to perform four measurements:

1. Perception of observers in sofa S_1 by observers at sofa S_2, R_{S2S1}.

2. Perception of observers in sofa S_2 by observers at sofa S_1, R_{S1S2}.

3. Perception of coffee table by observers in sofas S_1 and S_2 R_{S1T}.

4. Perception of exterior openings by observers in sofas S_1 and S_2 R_{S1E}, R_{S2E}.

The above mentioned measurements are outlined visually in Fig. 2.

Finally, for the first objective, we need to combine visual perception measurements 1, 2, and 3, as outlined above, in a single figure, to produce the actual OF value. We perform this by summing up the individual visual perception measurements, and applying a non-linearity, in our case the logistic function, to the result:

$$O_{Vis} = \frac{1}{1 + e^{-m*(Svis-c)}}$$

$$Svis = P1 + P2 + P3$$

Where P1, P2 and P3 are the individual objeive function values. The last objective concerns, as already mentioned, maximizing the perceived "Openness" of the indoor space. The reason for considering this objective is explained as follows: In order to satisfy the previously explained objectives, namely perception of exterior openings and perception of seating spaces, many different arrangements may be considered. However, some of them include furniture that are placed in such ways that partition the space in smaller areas that are difficult to be used, and furthermore, impede movement through space. Ideally, we would like to have a single, unpartitioned area within the interior, that may be used as required, and would not inhibit movement. In other words, our third objective serves as an indication of the fragmentation of the interior space.

To model this aspect of space, we refer to the following method: N points are distributed uniformly in the boundaries of the space. From each of the points, we measure the distance to each of the geometrical features of the furniture, as well as the boundaries of the space itself, and consider the smallest one, which we term $D_{i,min}$ for the ith point. The final objective function value is given by the largest among the N values of $D_{i,min}$:

$$O_{Dist} = \max_{i=1}^{N}(\min_{j=1}^{k} \|p_i - e\|)$$

Constraints are mainly related to the presence of geometrical overlapping between each one of the furniture in the space, and between the boundaries of the space and the furniture. Overlaps may be caused in both cases by unsuitable position and rotation decision variable values. In order to evaluate the overlaps between furniture, we compare the area of the union of the geometric shapes of the furniture, with the summation of each of the funrniture's area:

$$g_a = \min(0, h(F_1 \bigcup F_2 \bigcup F_3 \bigcup F_4) - \sum_{i=1}^{4} h(F_i))$$

In the above equation, F is the geometrical shape, including orientation, for each of the elements in space and h is a function that takes a geometrical shape as an argument, and gives it's area. With respect to the second constraint, we compare the area of the room to the area of the union of the room with the furniture:

$$g_b = \min(0, h(R) - h(F_1 \bigcup F_2 \bigcup F_3 \bigcup F_4 \bigcup R))$$

In the above equation, R denotes the shape of the space in question, and the rest of the variable names are as previously. This provides an easy way of comparing for overlaps and collisions, as the geometric operations, such as unions, are readily available from the CAD program in use, which is the Rhinoceros 3D program and the associated parametric modeling plugin, Grasshopper. A screenshot of the visual representation of the objective function algorithm is available in Fig. 3.

IV. ALGORITHMS

A. NSGA-II

The Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) is perhaps one of the most widely known algorithms in the field of MOEA. Here we wish to provide a brief overview of the main characteristics of the algorithm, but for a detailed treatise the interested reader is referred to the original NSGA-II publication [11].

NSGA-II is a elitist MOEA that is based on a quick non-dominated sorting procedure to apply selection pressure to the population. In addition, population diversity is ensured by favoring individuals in less crowded areas of the objective function space. This is achieved by means of a Crowding Distance indicator, which indicated the relative crowding among individuals of the same dominance rank. Analytically, the process followed by the algorithm in one generation are as follows:

1. Perform non-dominated sorting.

2. Assign crowding distances to individuals for each Pareto rank.

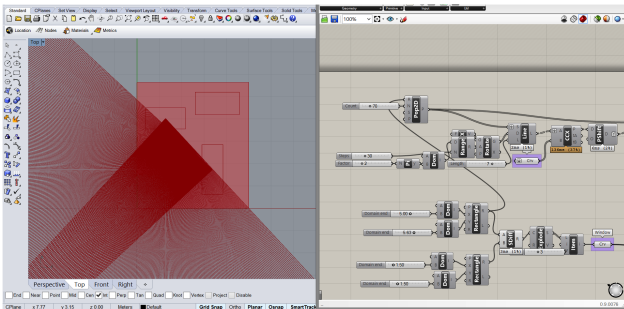3. Perform binary tournament selection and form the mating pool.

Fig. 3. Screenshot of the Geometric Model, the Objective Function computation and Constraint computation scheme in visual format, as developed in the Grasshopper Visual Programming environment.

4. Elitist reduction of the combined previous and current populations.

B. HypE

The Hypervolume Estimation Multi-Objective algorithm (HypE) is an algorithm developed by Bader and Zitzler [12] that belongs to the category of indicator-based MOEAs. The algorithm has been mainly developed to address problems where the number of objectives is high. In these types of problems, Pareto dominace-based algorithms are problematic, due to the decreasing selection pressure that the non-dominance principle is able to apply in many-dimensional spaces.

HypE makes use of the Hypervolume metric, I_h as a fitness assignment scheme. In particular, it measures the hypervolume that can be attributed to each one of the solutions in the population. The corresponding figure, I_{kh}, is assigned as a fitness value to each of the individuals. Selection happens by binary tournament selection. Elitism is enforced by two mechanisms: i. Through Pareto dominance-based comparison of the combined population and ii. through I_h fitness comparison between remaining non-dominated individuals. Analytically, the steps followed by the algorithm for each generation are as follows, given population P:

- Form P' by mating selection through binary tournament using I_h as selection criterion.

- Form P'' by recombination of individuals in P' using genetic operators.

- Environmental selection based on $P \bigcup P''$, using Non-Dominated sorting and I_h.

We make use of a HypE implementation that uses Simulated Binary Crossover and Polynomial Mutation as recombination operators. Both algorithms have been implemented as part of the CIDEA decision support platform [13].

V. COMPUTATIONAL RESULTS AND DISCUSSION

We have performed 10 optimization runs for each of the two algorithms in comparison. The settings for each algorithm are available in Table II. In summary, the algorithms were allowed to run for 140 generations in total, with a population of 140 individuals. The runs were performed on an Intel Core i7 2.2GHz computer with 16GB of RAM.

With respect to the results of NSGA-II, we observed that the algorithm converges to a Pareto front around generation 100. By comparison, the HypE algorithm seems to converge at around generation 110. The solutions present in the final generation of the run, for each of the algorithms, is available in Fig. 4.
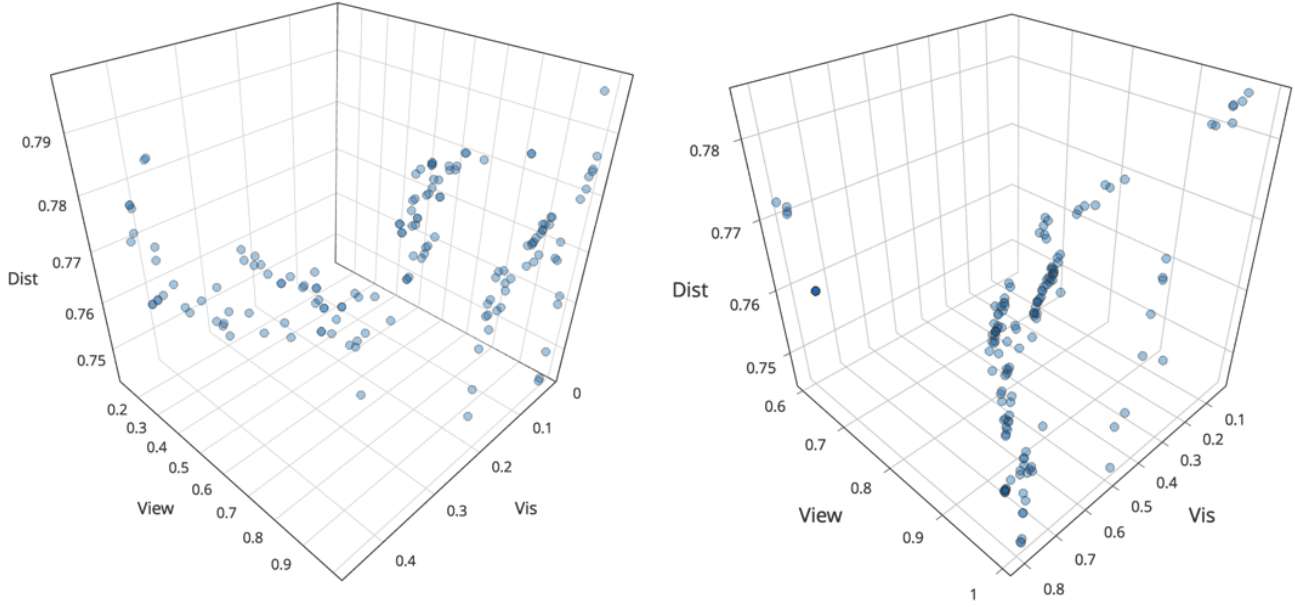
Fig. 4. Final population for the two EAs after 140 generations. Left: NSGA-II, Right: HypE.

other. However, as can be seen in Fig. 4., NSGA-II presents a more uniformly distributed set of solutions.

It has come to our notice that certain designs do not appear on every pareto front, but only once in a while. As such, it can be speculated that the full Pareto front of the problem is not achieved. Or alternatively, it is possible that solutions exist with very similar performance but different decision variable compositions. We speculate that a more advanced method of handling constraints would be also beneficial to the performance of the algorithms, and would result to better approximation of the theoretical Pareto front.

With respect to the architectural qualities of the solutions, we are able to recognize several different types of designs. They are summarized visually in Fig. 5. Several of the design types present indeed plausible arrangements. For instance, Fig.5 top presents a corner arrangement of the sofas near to the exterior opening, with the coffee table in the middle. In the same arrangement, the dining table is placed to the one side of the room, and there is plenty of space for accessing all

TABLE II.   ALGORITHM SETTINGS NSGA-II AND HYPE

Setting	NSGA-II Value	HypE Value
Crossover p	1.0	1.0
Mutation p	0.15	0.15
η Crossover	10	10
η Mutation	30	30
I_h Samples	-	10000

We have performed a Hypervolume comparison for each of the two algorithms. Using a 2-sample t-test, we have confidently concluded that the Hypervolume performance of HypE is superior. This suggests, in our case, that HypE is able to identify a better Pareto front than NSGA-II. The result of the comparison is available in Table IV. The Pareto front in both cases is developed in the dimension of all three objectives, supporting the claim of the objectives being conflicting to each

TABLE III.   DECISION VARIABLE COMPOSITIONS OF SOME NON-DOMINATED INDIVIDUALS FROM THE NSGA-II AND HYPE RUNS

| Item Position (factor of dimension [0,1])								Item Rotation (factor of full circle, [0,1])				Item Assignment (relative order [0,1])				EA
Indexes Correspondence: 1: Couch A, 2: Couch B, 3: Dining Table, 4: Coffee Table																
p_{x1}	p_{x2}	p_{x3}	p_{x4}	p_{y1}	p_{y2}	p_{y3}	p_{y4}	r_1	r_2	r_3	r_4	o_1	o_2	o_3	o_4	
0.686	0.133	0.687	0.576	0.949	0.872	0.244	0.619	0.513	0.950	0.358	0.822	1.0	0.8	0.7	0.7	HypE
0.745	0.722	0.132	0.741	0.467	0.839	0.746	0.242	0.287	0.850	0.759	0.832	0.1	0.4	0.7	0.6	HypE
0.679	0.133	0.693	0.574	0.949	0.872	0.244	0.616	0.510	0.949	0.359	0.822	1.0	0.8	0.7	0.7	HypE
0.705	0.578	0.202	0.248	0.933	0.447	0.790	0.514	0.567	0.568	0.840	0.059	1.0	0.2	0.0	0.9	NSGA-II
0.697	0.898	0.204	0.258	0.933	0.155	0.982	0.667	0.612	0.566	0.832	0.089	1.0.	0.2	0.1	0.6	NSGA-II
0.705	0.588	0.209	0.248	0.945	0.442	0.790	0.514	0.367	0.568	0.840	0.058	1.0	0.2	0.3	0.7	NSGA-II
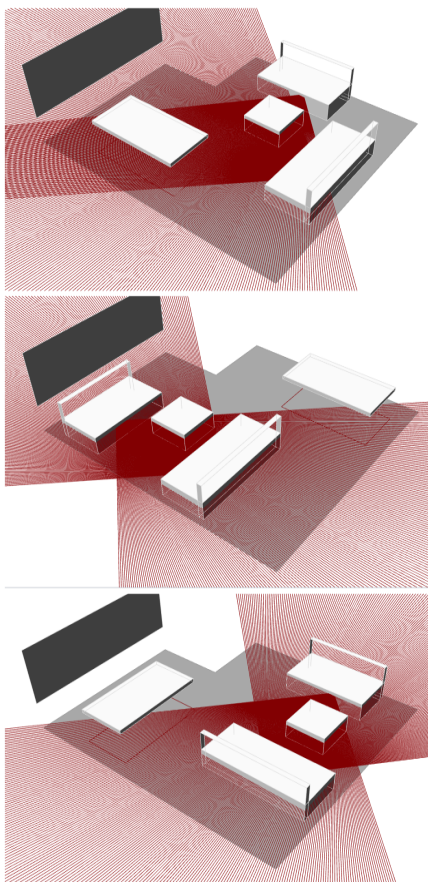
Fig. 5. Promising solutions identified by the proposed approach, using both NSGA and HypE algorithms. Images have been visualized using the Rhinoceros CAD program.
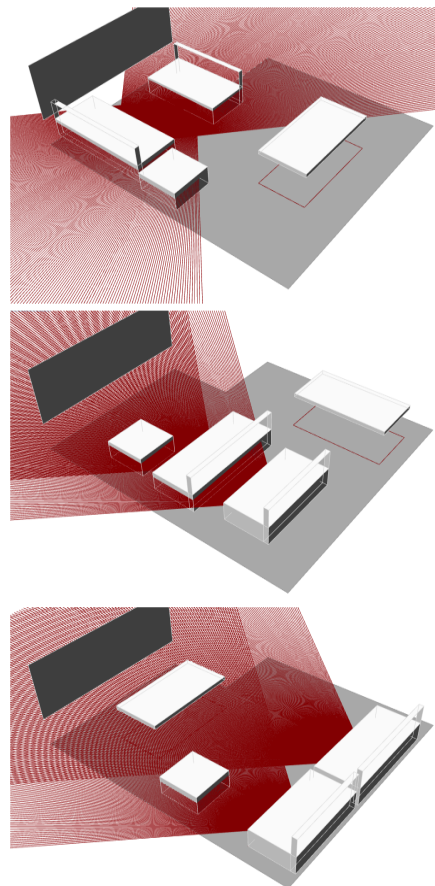
Fig. 6. Solutions that satisfy objective functions specified, but are not plausible from a design perspective. Images have been visualized using the Rhinoceros CAD program.

functions (although this has not been explicitly stated as an objective). In another type of arrangement, the sofas are placed across each other, and the coffee table is placed either between them or on one side. There exist also solutions where the dining table is in fact next to the exterior opening. Naturally, these types of solutions do worse in the Exterior View objective.

TABLE IV. HYPERVOLUME PERFORMANCE FOR NSGA-II AND HYPE

Algorithm	I_h	95% CI
NSGA-II	0.105	0.08 to 0.13
HypE	0.600	0.54 to 0.67

We have also identified solutions that satisfy objectives well, but are not plausible enough to be part of a real design. Some are presented in Fig. 6. For instance, Fig. 6 top, is characterized by an offset arrangement of the sitting sofas, which is not ideal given that there is plenty of space for a more efficient arrangement. Fig 6 center, on the other hand, presents an infeasible, by design standards, arrangement.

The presence of well-performing but not plausible solutions definitely gives a hint for the future elaboration of the

objectives. Specifically, elaboration on the perceptual aspects of room occupants should be central to the development of a more capable interior arrangement system.

VI. CONCLUSION

We presented a method for automatic design of interior space arrangement of furniture, using Evolutionary Computation. We have formulated a Multi-Objective constrained optimization problem, based on three soft, perception-related objectives, and two constraints that ensure plausibility of the solution. We have compared the performance of two MOEAs, namely NSGA-II and HypE, and identified that HypE is superior in terms of Hypervolume performance, however NSGA-II presents a more uniformly distributed solution set.

The qualitative results of our investigation demonstrate interesting design approaches taken by the algorithm, some of which are plausible and close to what a human designer would come up with, and others are ignoring some more elaborate aspects of space planning.

This last observation leads to the most prominent direction for future development of the work, which is the elaboration of the objective functions, by introducing more elaborate

perceptual treatment of the various stimuli found within the space. In parallel to that, a stronger constraint-handling scheme could reveal a wider array of solutions, and lead to more promising and unexpected designs. Finally, it may be worth exploring more rigorously, and formulating as objectives, aspects related to the ergonomics of space.

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