Computational Intelligence in architectural and interior design: a state-of-the-art and outlook on the field

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Abstract. Tasks in architectural and interior design range from defining the building floor plans and ensuring desired functionality, to deciding furnishing styles and arrangement choices; all to best fit certain pre-established purposes. The process of design, as a whole, has remained hard to master for computer-based optimization in general and for computational intelligence approaches in particular. Numerous attempts to tackle different subfields of this problem in a machine learning fashion have emerged over the last few years, aiming to offer partial automatization of human tasks, personalized support for specialists in field and professional guidance for amateurs. In this paper, we present an overview of current advances of computational intelligence in architectural science with a focus on interior design. We describe various learning models applied to interior design challenges such as furniture type selection, style compatibility, furniture arrangement, or ornamental decoration. This is accompanied by the description of ongoing research towards the development of a commercial robust and scalable solution for automatic furniture arrangement, given a room plan.

Keywords. Architectural design, interior design, computational intelligence

Introduction

Architecture has been an endeavour at the heart of human societies throughout history. Architectural theory, and the use of mathematics and geometry as an integral part of it, can be traced back to ancient cultures in India, Egypt and Greece [1].

This well-established field has undergone continuous progress in different fronts, from the use of materials to engineering and design. Modern architecture can be said to have undergone a further radical change through the adoption of computer-based methods for both engineering and design. Interestingly, the pervasive introduction of increasingly sophisticated methods of computer-aided design (CAD) and engineering (CAE) temporarily displaced mathematics from its central role in architectural practice. As remarked in [2], this seems to be a trend currently in the process of reversion, paradoxically due to the formal complexity allowed by CAD systems, which begs for the use of parsimonious data models.

This need of data modelling has naturally led to a more recent step forward in the use of computers in architecture, which is the integration and application of computational intelligence (CI) approaches in design processes, so as to answer an older question posed by MacCallum [3]: does intelligent CAD exist? Note that research on the use of Machine Learning (ML) in design was already quite active in the 1990's [4]. In the architectural engineering field, artificial intelligence (AI) is currently present in subfields such as building design, interior furniture organization, ornamental decoration and style, aiming to offer automatization of human tasks, personalized support for specialists in field, professional guidance for amateurs, etc.

In this brief paper, we review the present capabilities of AI, with a focus on CI and ML, in the field of architectural design and, more specifically, in interior design, including an examination of the underlying data models. We expose the models' strengths and limitations; their dependency on the specific context; their similarities and evolution across design main subfields; and the possibilities opened by the potential combinations of methods.

This overview across fields is a first contribution of our ongoing research leading to the development of a real-world, commercial solution to offer automatic custom room plan-adapted furnishing suggestions to clients. Besides, the models behind the solution must be robust and scalable in order to incorporate the numerous existing furniture options and to fit various room layouts. Furnishing options must comply not only with user preferences, but must also be able to incorporate professional design expert knowledge -learned and incorporated by the model, resulting in suggestions as close to professional design as possible.

The remaining of the paper is structured as follows: in section 1, we present a brief overview of the main subfields of architectural building in which CI models have been applied. We do the same for interior design in section 2, highlighting the connections with building design models and detailing model capabilities, contextual constraints and limitations in several sub-fields, including furniture selection and arrangement, furniture style assessment and ornamental decoration. Section 3 describes our own work-in-progress on a CI model aimed to tackle the room interior furnishing problem, including furniture selection and arrangement, in two stages: a data-driven, probabilistic phase, followed by a stochastic optimization process.

1. Architectural design and computational intelligence

1.1. Design as a learning problem

One of the earlier studies introducing the concept of model learning in design from an AI perspective can be found in [5] and it addresses the relationship between the design phenomenon and the possibility of learning in this context, in a way that would benefit the designer. The model is based on an analytical, formal representation of cognitive activities in design. The resulting system, LinD, tested various correlations and learning areas that can be further exploited in a learning fashion, including: abstraction / detailing, association / disassociation, derivation / randomization, generalization / specialization, and similarity measurement. This study is especially relevant for it emphasizes that design implies learning hidden and often complex patterns from observed data.

Some of the most common tasks addressed in this field include the automatization of floor plan generation (layout of the spatial allocation) and exterior building layout design (overall construction form and exterior façade) The models detailed next mainly focus on applications to floor plan design and building overall-shape manipulation.

1.2. Overview and evolution of architectural design models

Non-learning algorithms: Floor plan generation, also known as the spatial allocation problem, can be defined as the process of designing the layout of an architectural space. Many classical algorithms tackle it by starting from specifying some constraints, such as desired number of rooms, pre-configured rooms sizes and by exhaustively enumerating all feasible possibilities. Because of their exponential growth in complexity, these methods become infeasible for complex scenarios. As a result, the spatial allocation problem is restricted to building simplistic, regular layouts with rigorous specifications such as those of schools, health facilities, etc. [6]. Other approaches, focused on locally optimizing an initial room manual arrangement, treat the problem in a similar fashion to the design of VLSI circuit layouts [7]. The main limitation of such methods is the need of an expert to manually design the initial layout.

Procedural architecture: The shape grammars paradigm has been used for both automating floor plan generation and procedural building exterior layout design [8,9,10]. However, the main drawback of using grammars is the need to introduce all the grammar rules manually. Moreover, the static nature of such rules limits the model to produce new layouts as valid, plausible variations, to assist the designer with continuous suggestions.

Probabilistic approaches: In responde to the challenges regarding solution space dimensionality, problem complexity, and rigidness of complete specification of the layout rules, various data-driven probabilistic models have emerged. Their main advantages include: the possibility of incompletely specifying the layout requirements; the ability to fix arbitrary constraints and sample from the probabilistic network the rest of the parameters; the definition of a model for training on real world data followed by sampling reasonable layout characteristics, such as adjacency relations, number, types and sizes of rooms; and the fact that discretely sampling from the probabilistic model overcomes, in a heuristic manner, the performance impact caused by searching or exploring the large, complex solution space. Probabilistic models have successfully been used in architectural design for representing learnable relations between complex objects' components [11] and learning plausible room sizes and arrangement dependencies [12].

Stochastic optimization: It could be argued that the probabilistic approach alone, as well as other similar methods for specifying layout requirements such as constraints set [13] show limitations including the lack of ability to capture architectural style, room functionality, and produce raw estimations. Thus, the goal to capture and reproduce plausible, real-world ready results, is usually conducted through a final step of stochastic optimization, given a set of constraints and a goal function -representing the goodness of the layout [12]. Other approaches use Simulated Annealing (SA) [14] and Monte Carlo Markov Chain (MCMC) to explore the vast space of solutions and produce plausible yet diverse city scale results [15]. Stochastic optimization was successfully applied to furniture arrangement [16] and for the optimization of interior ergonomics [17].

Evolutionary computation: Genetic algorithms have also been applied to both the layout generation problem [14] and building façade definition [18]. Although this powerful paradigm has not yet shown promising results in the architectural engineering field, failing at providing real-world inspired solutions [14] and yielding poor overall performance and generalization [18], it is still worth considering for its strength to generate diverse, highly customized, user preference oriented results as opposed to standard, designer guided blueprints.

Generative models: The problem of generating diverse building models in a scalable fashion resulting in virtual worlds (with applications such as game-environment construction) has been addressed through methods that aim at learning from existing, real-world entities to generate new feasible ones. The study reported in [11], for instance, focuses on generating various new plausible object models from a few, real ones by evolving new compatible components. This is accomplished through a probabilistic model linking properties of the components' shapes and learning the plausible variations within a context. In [19], the authors created a model able to, first, determine the space of plausible, local variations of building layout and, second, merge such local derivations through a linked transitions graph with valid pathways at a global level, enabling easy transition in the building space neighborhood. As compared to the previous explored trends, in which the focus was optimizing layout details, the goal here is generating considerably more models while preserving overall consistency and diversity, starting from only a few ones. The realistic generation capabilities and cross-components similarity learning of these models also have application to interior design for ornamental decoration of rooms [20], where new artifacts need to be generated and well-placed in the room preserving user preferences and the overall style [21] and functionality of the space. However, rigorous hard-constraints need to be enforced for the generation of real-world models in order to maintain their complex functionality. As a result, the application of this type of methods is still mostly for the design of virtual environments.

2. Interior design and computational intelligence

Although addressing a distinct problem, interior design has experienced a parallel evolution to architecture in terms of adoption of computer-based approaches and the use of AI methods. It shares the main goals of architectural design, including the partial automatization of tasks and the design of frameworks to assist professional interior designers by incorporating expert knowledge. The main components of such automatization process to create fully functional furnished rooms are also the main research directions in interior design:

Furniture selection: Automatically deciding what type of furniture entities are right for a given room. This problem should consider the room type (e.g. kitchen, bedroom, living room), the desired functionality to incorporate (e.g. sleeping, work, leisure) and users' preferences (e.g. percentage of furnishing space, life style, developed activities within the room).

Furniture arrangement: Naturally following furniture selection, the task of automatically arranging the furniture includes, besides the hard constraints (e.g. room type regulations, physical space available, ergonomics), soft (subjective) constraints like personal life style, daily activities, arrangement tastes. Given the strong interdependencies between this and the former problem, moving back and forth to reach a desired solution (e.g. deciding on a different size furniture piece to best fit in place and, contrarily, first fixing certain furniture types to later determine their position) is often necessary and, therefore, they can be combined into a single challenge.

Style compatibility: In order to obtain a realistic, professional-looking interior design, the overall appearance of the synthesized room is an important factor. Challenges in this area include automatically assessing style compatibility between furniture pieces; both in terms of same objects and across different object types.

Ornamental decoration: In the light of the continuous attempt to automatize design in all perspectives, ornamental decoration challenges include deciding the types of artifacts, their placement according to user preferences and overall usage, personal arrangement style: agglomerative vs. sparse, ordering degree, etc.

We focus next on describing promising models in each of these components, building upon the more general overview of the models described in the previous section.

2.1. Furniture selection and arrangement

Data-driven and probabilistic approaches: Interior design is characterized by complexity, which often results in a very large solution space that can be efficiently explored or estimated through learning probabilistic models [11,22], although at well-known costs, such as ambiguity, crude estimations of parameters for complex scenarios, or failure to capture the problem in all its dimensions.

Specifically, when dealing with furnishing a room, including both selection and arrangement of objects, most data-driven approaches include a probabilistic model such as Bayesian networks or Gaussian Mixture Models (GMM) [23], which capture aspects of the data that hard to express in an analytical manner.

In [23], Fisher *et al.* used a Bayesian model for learning the furniture occurrence in different types of rooms and a GMM for capturing arrangement patterns. Although in this case the system is initially trained on a fairly small, user-provided data set, its limitations in capturing robust, abstract patters are compensated in a later stage of training on an automatically enlarged data set, to which relevant, similar scenes are included. Another important contribution of this study is a clustering algorithm, trained on a large database of scenes, able to capture contextual similarity resulting in an efficient, reliable grouping of interchangeable objects. This helps in scene variation and solutions diversity, also helping the model to avoid overfitting. Another key aspect of this model is the training in two stages, which compensates for the lack of data and the absence of diversity through enlarging the initial data set with similar scenes from a large database, in an automatic fashion, based on context similarity.

Another data driven approach, with a novel contribution for capturing furniture grouping functionality, can be found in [24] and is based on a new concept of "Wall Grid Structure" (WGS) that addresses the same problem as in our ongoing research, reported in section 3, namely furnishing an empty room given its plan. The algorithm consists of two main stages: the *learning stage*, using a database of same-type rooms from Google Warehouse followed by a *synthesize stage* that consists of furnishing the desired room. Focusing on the learning stage, the author introduces the concept of "functional groups (FGs)", necessary in order to obtain a unique and compatible artistic style of the object collections, rather than putting objects together only by functionality. These FGs contribute to reduce overall scenario complexity, by removing certain degrees of freedom, hard to capture in all their completeness in the learning phase (e.g. a table should have all the chairs the same model, and the overall look and feel should be pleasant).

The FGs are represented as graphs and treated as a single entity in the next steps in the model. Grouping furniture pieces in sets (FGs) that preserve functionality and style while reducing problem complexity and boosting scene quality represents an inspiration for addressing the size of the furniture database in our own scenario. Compared to GMM, the WGS-based model learns bi-directional linkage probabilities of model categories and positions, being able to find one given the other. In the synthesizing step, the appropriate WGS is computed for the given room, followed by probabilistic suggestion of FGs: first one main FG (e.g. a bed in a bedroom, a table in a conference room), followed by a "supplementary" one to complete the room.

Although probabilistic models have successfully been used to capture abstract patterns in data-driven approaches, the synthesizing real-world-ready scenes remains an open problem. Moreover, a pure data-oriented model is still far from capable of capturing rigorous and stylish furnishing subtleties.

Stochastic optimization: In the light of these challenges, other analytical approaches have emerged, aiming to produce a mathematical formulation of both hard constraints (e.g. related to architectural feasibility and regulations) and soft subjective constraints. These approaches are usually based on stochastic optimization models such as SA [16] or MCMC [17], defining an energy function that presumably incorporates defined constraints -which aim to encapsulate underlying rules and patterns that designers apply in their work. They typically include a research phase dedicated to determining such rules as well as ways to analytically translate and combine them in density functions and tackle the interior design challenge from a more structured, algorithmic angle, as opposed to the looseness allowed by data-driven approaches. These methods usually define a set of steps that aim at efficient, iterative, convergence, while having a *reset* mechanism to avoid getting stuck in local minima.

In our own research, we also draw inspiration from such methods, because of their ability to incorporate specific, important design guidelines that help fine-tuning the potentially rough approximations obtained in the initial data-driven stage, through optimization.

Related work is presented in [16], where furniture arrangement is accomplished through an iterative optimization approach, given a complete specified room plan and a finite set of fixed entities. The system learns a priori various features regarding the objects such as visibility, availability space, common usage, hierarchy and positioning (absolute and relative to other objects). In this work, SA is accompanied by a Metropolis-Hastings state-search step to minimize a cost function, which integrates the most relevant features claimed by authors to be necessary to obtain a realistic, "human-approved" room layout, such as accessibility, visibility, pathways connecting doors, pairwise object constraints A possible set of steps designed to iterate through the furniture configurations solution space is defined in [16] includes: a) small objects rotations and translations, which contributes to convergence; b) swapping objects, used for avoidance of local minima; and c) moving pathways control points.

Similar work was carried out in [17], where a software-guided interior synthesis system based on an MCMC sampler was presented. Such framework aims at guiding a user to furnish a room in a professional-like manner, by incorporating functional and visual criteria to the offered suggestions. The system has the capability to allow the user fix, at each step, any desired furniture piece, and receive positioning suggestions for the other ones accordingly. As in [16], the system incorporates pre-established interior guidelines, expressed analytically through independent terms and combined in a density function. The criteria used in this model are split in functional terms (including: a) clearance (e.g. objects are accessible and not blocked; b) circulation, which ensures that the main flows and room utility are not affected by furniture positioning; c) pairwise relationships, defined between dependent (coupled) furniture pieces (e.g., table with chairs, TV with sofa); and d) conversation feature, which supports furniture arrangements that encourage socialization aspects: conversations and collective activities), but also in visual terms (including: a) balance and room symmetry ; b) alignment -exact positioning and orientation of furniture relative to close proximity-; and c) emphasis, describing the point in the room with "layout dominance" (e.g., a fireplace, a TV, or a painting).

Evolutionary computation: An interesting CI approach using GAs was presented in [25]. The authors focus on obtaining a unique arrangement in which the user tastes are the main priority, rather than on a more standard, designer-oriented model. This is always a tradeoff and comes at a cost of much more user involvement to evaluate each generation of individuals, maximizing both user preferences and ergonomics. Specifically, as in genetic modeling, the process of obtaining the final layout is an iterative one, each stage involving the evaluation of current room layouts, followed by the generation of new ones through selection -using a fitness function based on defined ergonomics and user feedback, cross-over and mutation-classical approach, facilitated by a gene-like representation of the room furniture arrangement: comprising each piece of furniture's coordinates and angles, expressed as binary features.

2.2. Style compatibility

Focusing specifically on style comparison across different furniture types, the recent work of Liu *et al*. [21], presents a novel approach for computing object compatibility. Although much research in the area of 3D models similarity can be found in the literature, this work focuses on furniture compatibility detection across different kinds of furniture, rather than within-class compatibility. The proposed algorithm is based on representing models as "part-aware geometric feature vectors", as opposed to mixing features in a general representation. The authors report that this helps to obtain features that measure the style/aspect of the objects rather than the shape, which is important for discouraging low scores for objects in the same class and results in focusing on compatibility rather than similarity. The objects (always belonging to different classes) are compared in an asymmetric fashion, decoupling the need for objects in different classes to preserve entity structure and therefore allowing more complex objects (e.g. with more parts) to be represented in a higher-dimensional space. As a consequence, when comparing two objects, they are initially projected in a common k-dimensional space by multiplying each with the class-specific, pre-learned matrix, followed by distance measurement.

2.3. Ornamental decoration

Generative oriented models: An area related to room layout generation is that of automatic ornamental decoration. Although it may be seen as an optional feature, it is particularly important for transforming an empty room into a livable one. Specifically, the aim is to populate the empty furniture pieces (e.g. as shelves, wardrobes, tables, walls) with adequate artifacts, preserving the style and overall arrangement while suggesting utility and functionality as a whole. Consideration of user preferences and personal arrangement styles is another decisive factor in achieving a pleasant layout. A data-driven, ML approach in this area was presented in [20]. As stated by authors, obtaining a unique solution through a stochastic optimization procedure is an unfeasible task, resulting in lack of diversity in artifacts types and forms and very similar decoration results. Therefore, compared to furniture synthesis models, a valid space of solutions is defined here using a set of inequality constraints, and the optimization process aims at bringing the solution within this valid space, as opposed to a point in the search space. Optimization steps such as object addition, deletion and interchange are defined and applied in random order sequences in order to drive the solution towards the goal while ensuring diversity.

3. Ongoing research: proposed model

As mentioned in the introduction, this brief review of the state-of-the-art on the use of AI (with a focus on CI and ML) in architectural and interior design serves as a background for our work-in-progress, which aims to tackle the room interior furnishing problem, including furniture selection and arrangement. At his point, we propose a preliminary model designed in two stages: a data-driven, probabilistic model-based one, followed by a stochastic optimization one. Pipelining these two strategies will entail a first phase of capturing underlying patterns through a data learning technique, ensuring generalization (i.e. exploration), followed by a second phase of specialization (e.g. exploitation) aiming at more refined results that abide to style criteria and strict regulations. This strategy will help avoid data overfitting in the first stage while assuring model convergence in the latter.

3.1. Data-driven probabilistic learning phase

Specifically, the initial stage will comprise a probabilistic model able to capture abstract trends in real-world data such as furniture type occurrence and arrangement patterns and output a variety of realistically furnished room scenes, with diversified furnishing options, styles and functionality.

Dealing with a complex, high dimensionality solution space, energy-based optimization models are not a feasible option for its exploration. This approach has the strength to efficiently sample the problem parameters, offering a loosely, yet structured representation of the underlying patters governing the problem (i.e. occurrence and arrangement of furniture). Other advantages include the ability to incompletely specify the initial parameters and "fix" certain ones to obtain reasonable approximations for the others.

Limitations, such as often producing crude estimations of the parameters, ambiguity, inability to capture all problem complexity, are addressed through stochastic optimization in the second part of the model, which now becomes feasible, after initially reducing the problem dimension through discrete sampling and thus roughly estimating the solution set. Results obtained at this point, despite incorporating main scene targets, might lack certain subtleties such as style uniformity across all furniture pieces, general alignment, maximum accessibility and functionality of furniture pieces, right balance of entities (e.g. table dimensions having appropriate number of chairs) or preferred furniture rotations towards right angles (e.g. parallel to main room axes).

3.2. Stochastic optimization phase

Automatic fine-tuning of the previous phase results can be achieved through the stochastic optimization of an energy function, using a predefined set of steps. Inspired from previous work, the density function should encapsulate, in an analytical way, specific and important rules in areas like: ergonomics, designer guidelines, psychological factors, safety regulations. Besides these, the energy function might also include terms expressing personal preferences, such as: furnishing percentage, cardinal orientation of certain objects (e.g. bed should face north), type and amount of goods to be deposited in that room, etc.

Because stochastic optimization models are known to be prone to get stuck in local minima, the step set should include both “converging ones” (e.g. that drive the solution towards a lower energy, such as furniture small movements and rotations, replacing pieces with similar ones, deletion attempts) and “resetting ones” (e.g. that produce a jump, associated with an energy spike, such as: swapping furniture positions, adding new furniture types, etc.) Consequently, this model step aims at fine-tuning the preliminary obtained scenes through a step-by-step optimization, resulting in professional-like furniture layout options.

4. Conclusions and future work

Architectural and interior design have become strongly computer-based activities over the last few decades. Almost in parallel, CI techniques have incrementally found their niche in these disciplines. In this paper, we have presented a brief overview of the current state-of-the-art in the diverse forms of application of CI methods in these fields of design. Various models, applied to challenges such as partial automatization of human tasks, personalized support for specialists in field, etc. have been described, including an overview comparison of their strengths and limitations.

In contrast to the dominant trend towards automatic generation of detailed, complete and feasible virtual environments, we have also succinctly described our ongoing research towards the development of a commercial solution for automatic generation of furnishing suggestions to potential customers, according to personalised room plans. The model comprises two stages: a data-driven, probabilistic learning phase for generating custom, plausible room layouts, followed by a stochastic optimization for fine-tuning the previous obtained solutions. Imposed by the expected real-world use, numerous challenges have to be addressed, such as high scalability, robustness, flexibility and customization - incorporating various preferences such as furnishing choices, desired functionality and usability.

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