Environment Optimization using Different Measures

Glen Berseth
University of California Berkeley
gberseth@berkeley.edu

1 Extended Abstract

When designing, architects explore a broad set of options to identify the solutions that better satisfy a set of performance criteria while abiding by specific constraints [Kalay, 2004]. This process is iterative where by design solutions are developed and then progressively tested and refined to maximize the overall design performance [Rittel, 1971].

These approaches, however, suffer from two significant limitations. First, with few exceptions [Haworth *et al.*, 2017; Nagy *et al.*, 2017], they do not account for how people act and interact in these environments. This limitation is arguably one of the most critical design criteria: a building that does not support human needs will likely cause users' dissatisfaction and lack of productivity. However, incorporating human movement aspects in an optimization process is very complicated since human factors are hard to quantify.

Second, these approaches tend to produce optimal solutions given a set of encoded constraints while excluding the designer from evaluating intermediate design options. However, in the design process, both design goals and constraints cannot always be specified beforehand, at the beginning of the optimization process. Due to the ill-structured nature of design problems, design goals and constraints can be discovered in the process of synthesizing new solutions [Rittel and Webber, 1973]. For this reason, a trade-off should be found between automation and control, whereby designers are actively participating in the optimization process and can contribute to it utilizing *tacit knowledge*–knowledge that is built with practice and can be difficult to communicate or formalize [Schön, 1987].

To address these issues, we propose IDOME. This user-in-the-loop computer-aided design tool employs architectural optimization with diverse exploration to help architects and designers explore, analyze, and improve their work to maximize human-related parameters. A key aspect of our approach is that the optimization process itself is tuned for exploring alternatives (diversity) rather than merely producing one optimal design at each invocation. The user creates a graph (Figure 1) from the building layout to indicate the structural components that should be optimized.

In this work, we use three well-established metrics to capture how people interact with and navigate in an environment: visibility, accessibility, and organization of space [Bafna, 2003]. These metrics make up a part of the Space-Syntax suite of tools and methodologies for analyzing environment designs. The system, however, can incorporate other kinds of metrics. For example, current data-driven methods that can model additional detail in the motion and behaviour of humans [Peng *et al.*, 2017] or popular crowd simluation methods [Feng *et al.*, 2016].

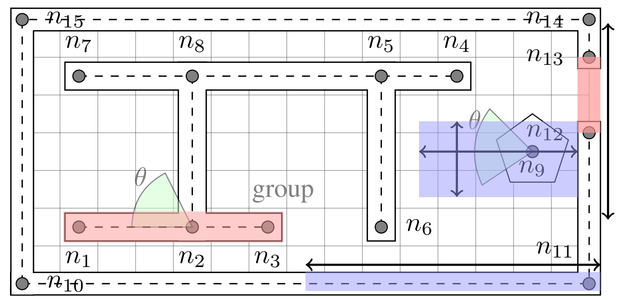

Figure 1: A floor plan and the corresponding graph parametrization of the walls, doors and other rigid elements. User-selected nodes of the graph, n_i, can be grouped, translated, scaled, and rotated within user defined bounds shown in colour and with arcs and arrows.

To solve the optimization process for a diverse set of candidate solutions, we introduce a diversity term in the objective formulation. This diversity term requires the solver to *focus* the search to meet optimality criteria, while simultaneously *broadening* its exploration to maximize the diversity of its candidate solutions. The process of balancing multiple objectives during optimization is a well-known challenge, which is rendered even more difficult by the presence of a diversity term. To address this issue, we propose a hierarchical multi-objective optimization algorithm that balances optimality and diversity while remaining efficient for interactive use without the need for hand-crafted exploration methods.

Unlike a standard optimization approach that produces a single design solution $\mathbf{p}^*$, IDOME produces a set of optimal solutions $\mathcal{D}^* = \{\mathbf{p}_1, ..., \mathbf{p}_n\}$ whose members differ from each other. For efficiency, instead of augmenting the parameter vector $\mathbf{p}$ with additional elements for each member of the diversity set, a round robin technique is used, where one member in $\mathcal{D}$ is optimized at a time while keeping the other parameters members constant.

2 Diverseity Optimization

In practise, enforcing diversity can still lead to a clustering of solutions [Agrawal *et al.*, 2014]. To avoid clustering, we impose a minimum distance between members of $\mathcal{D}$ which is defined as follows:

$$div(\mathbf{p}_m, \mathcal{D}) = k(\sum_{j \in \mathcal{D}} dn(\mathbf{p}_j, \mathbf{p}_m)) - k_m\, d(\mathbf{p}_m, \mathcal{D}), \tag{1}$$

$$d(\mathbf{p}_m, \mathcal{D}) = (\min(0, \min_{j \in \mathcal{D}, j \neq m}(dn(\mathbf{p}_j, \mathbf{p}_m)) - d_{min}))^2, \tag{2}$$

where $dn(\cdot, \cdot)$ normalizes its arguments over the parameter constraints before computing their Euclidean distance, and $d(\mathbf{p}_m, \mathcal{D})$ is the minimum distance between $\mathbf{p}_m$ and all other members in $\mathcal{D}$. Equation 2 ensures that diverse members don't cluster by adding a cost when the closest neighbours are less than d_{min} away. The terms d_{min}, k and k_m are experimentally determined hyper-parameters that control the influence of the diversity term.

3 Hierarchical Optimization Formulation

For a set of optimal solutions, $\mathcal{D}$, the objective vector is aggregated over the entire set. This results in the following multi-objective optimization problem:

$$\mathcal{D}^* = \arg\max_{\mathcal{D} \subset \mathcal{P}} \sum_{\mathbf{p} \in \mathcal{D}} \langle -g(\mathbf{p}), K(\mathbf{p}), -D(\mathbf{p}), H(\mathbf{p}), div(\mathbf{p}, \mathcal{D}) \rangle, \tag{3}$$

$$\text{s.t. } C(\mathbf{p})$$

where $C(\mathbf{p})$ are the parameter bounds specified by the user and $g(\mathbf{p})$ is a combination of user defined constraints. Solving this problem ideally produces a set of solutions with maximum spatial objectives, minimum penalties, and maximum diversity.

4 Discussion

Our framework can serve in a range of assisting roles, from an efficient way to evaluate alternative configurations that accomplish similar objectives, all the way to a design exploration assistant. We have integrated IDOME within an industry-standard architectural design system, Autodesk Revit®. Our results demonstrate the value of our approach to iteratively optimizing and refining architectural design options in a computing-efficient manner. We devise a series of user studies to evaluate the efficacy, usability, preference and usefulness of the proposed approach. To demonstrate efficacy, a user design study showed that subjects using IDOME were able to produce more optimal designs in comparison to subjects who didn't use IDOME and that users with the diversity exploration choices performed on par with single optima (Figure 2). We evaluate usability with an industry-standard usability survey, immediately following a general use design session, which suggests that novices could use our system with minimal training and found it useful. We performed two studies to evaluate the usefulness of the system. The first was an expert preference survey, which showed that experts preferred IDOME derived designs. The second was a general use session followed by an expert usefulness survey, which suggests that experts found the IDOME approach, the visualizations, and the diversity exploration useful.

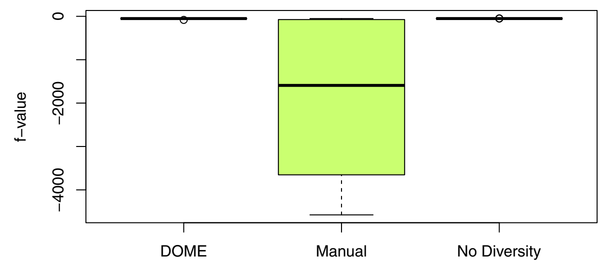

Figure 2: In this task, IDOME helped produce designs with consistently higher objective measures than manual design, and on par with single outcome optimization.

References

[Agrawal *et al.*, 2014] Shailen Agrawal, Shuo Shen, and Michiel van de Panne. Diverse motions and character shapes for simulated skills. *IEEE Transactions on Visualization and Computer Graphics*, 20(10):1345–1355, Oct 2014.

[Bafna, 2003] Sonit Bafna. Space Syntax: A Brief Introduction to Its Logic and Analytical Techniques. *Environment and Behavior*, 35(1):17–29, 2003.

[Feng *et al.*, 2016] Tian Feng, Lap-Fai Yu, Sai-Kit Yeung, KangKang Yin, and Kun Zhou. Crowd-driven mid-scale layout design. *ACM Trans. Graph.*, 35(4):132:1–132:14, July 2016.

[Haworth *et al.*, 2017] Brandon Haworth, Muhammad Usman, Glen Berseth, Mahyar Khayatkhoei, Mubbasir Kapadia, and Petros Faloutsos. Code: Crowd-optimized design of environments. *Computer Animation and Virtual Worlds*, 28(6):e1749, 2017.

[Kalay, 2004] Yehuda E Kalay. *Architecture's new media: Principles, theories, and methods of computer-aided design*. MIT Press, 2004.

[Nagy *et al.*, 2017] Danil Nagy, Damon Lau, John Locke, Jim Stoddart, Lorenzo Villaggi, Ray Wang, Dale Zhao, and David Benjamin. Project discover: An application of generative design for architectural space planning. In *SimAUD 2017 Conference proceedings: Symposium on Simulation for Architecture and Urban Design*, 2017.

[Peng *et al.*, 2017] Xue Bin Peng, Glen Berseth, KangKang Yin, and Michiel van de Panne. Deeploco: Dynamic locomotion skills using hierarchical deep reinforcement learning. *ACM Transactions on Graphics (Proc. SIGGRAPH 2017)*, 36(4), 2017.

[Rittel and Webber, 1973] Horst WJ Rittel and Melvin M Webber. Dilemmas in a general theory of planning. *Policy sciences*, 4(2):155–169, 1973.

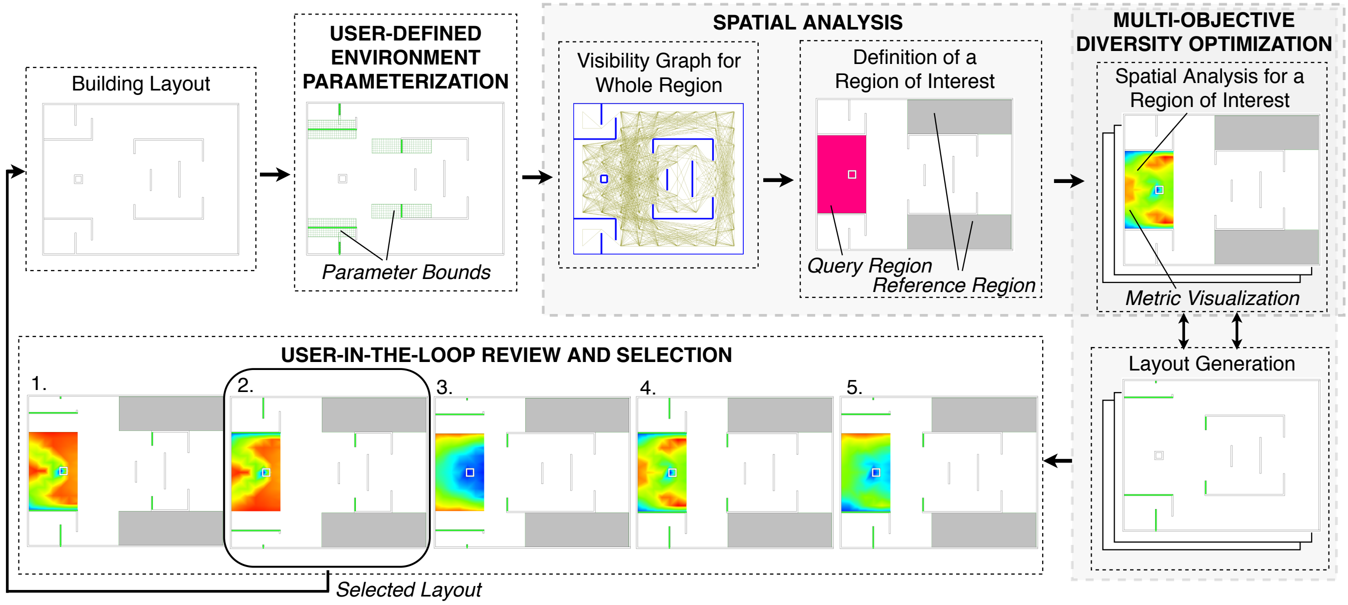

Figure 3: IDOME Framework Overview. With an initial environment design, the user specifies permissible alterations to the layout as bounds on the degree to which different environment elements can transform. The user then specifies one or more focal regions in the environment for which different spatial measures are computed to quantify visibility, accessibility, and organization of the space. A multi-objective hierarchical diversity optimization produces a set of diverse near-optimal solutions concerning user-defined optimality criteria, from which the user may select one and repeat the process as desired.

[Rittel, 1971] Horst Rittel. Some principles for the design of an educational system for design. *Journal of Architectural Education*, 26(1-2):16–27, 1971.

[Schön, 1987] Donald A Schön. *Educating the reflective practitioner*. Jossey-Bass San Francisco, 1987.