INTERACTING WITH THOUSANDS
A PARAMETRIC-SPACE EXPLORATION METHOD IN GENERATIVE DESIGN

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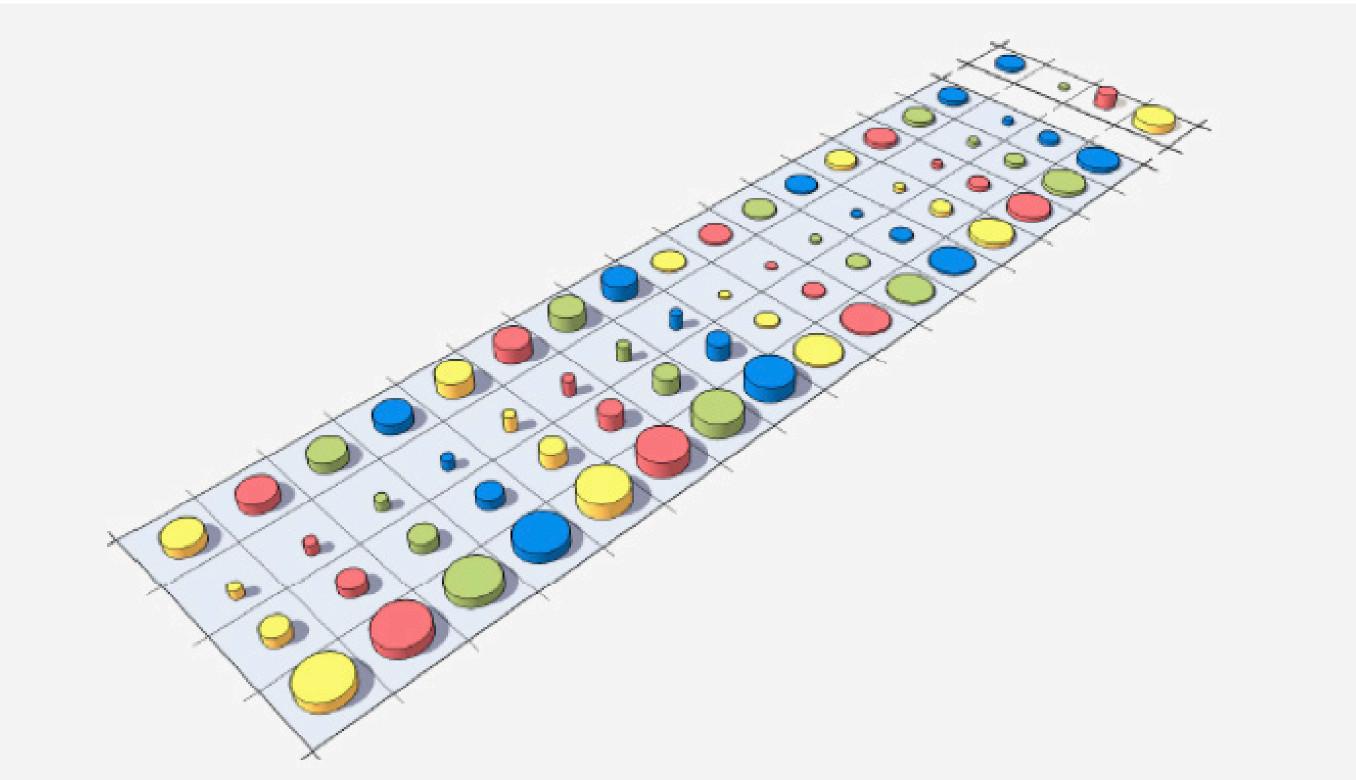


1 A parametric cylinder with four possible heights, radii and color values can create sixty-four alternative solutions

ABSTRACT

Although generative and parametric design methods open possibilities for working with a large number of solutions, there is almost no computational support for designers to directly manage, sort, filter, and select the generated designs. In this study, we propose an approach that presents a similarity-based design exploration relying on similarity indices that aims to reduce and collapse design space into manageable scales. The similarity indices are calculated either before generating solutions by evaluating the input parameter tuples and functions that produce aspects of designs, or after by looking at the solution features. Our goal is to enable designers to identify the design space of interest by incrementally and iteratively studying the solutions in sets, creating subsets through filtering and sorting. We also demonstrate a visualization of a similarity table that presents different interaction opportunities for system design. The approach requires further integration with existing parametric design tools and development of new interfaces.

INTRODUCTION

Simon (1996), Akin (1978), and Woodbury and Borrow (2006) showed that working with multiple alternatives is a central activity in design; therefore we expect computational systems to support such work. The current systems used in practice indirectly support working with multiple solutions (such as through configuration management), and some direct solutions are proposed as prototype systems for demonstration only. They fall under three categories based on where they propose supporting exploration: on the model through side-by-side editing (Hartmann et al 2008); as records in a history of action and states (Jankun et al 2007; Kurlander and Feiner 1991); and on a set of alternatives created by generative methods (Marks et al. 1997; Terry et al 2004). We have yet to know how these prototypes translate into functional systems or the combined effect of the three categories in a task environment that is amenable for design search.

Generative and parametric design methods open possibilities for working with a large set of solutions. Current parametric *CAD* tools are widely used in various stages of design, but mainly for concept generation through a linear process. The challenges of using parametric modeling are prominent; such as it requires a different design paradigm for interweaving the parametric elements, and when they are used in conjunction with one or more plug-ins with generative capabilities, to algorithmically create solutions with limited intervention from designers. The space of alternative solutions that can be generated using a parametric model is high dimensional: due to combinatorial explosion when the number of parameters and their value ranges increase, the growth in the number of possible solutions is polynomial. For a design project with few parameters and a well-defined parameter value ranges, the solution space can easily include thousands of alternatives. The solution space expands with the introduction of new parameters or adding new criteria. However, there is no direct and proper tool support to augment the designers' capability in navigating and managing this space. Hence, as part of a larger research program on working with alternatives, we have developed a similarity-centered method focusing on how we can systematically filter and choose possible alternatives from a large number of solutions generated using a parametric model. We rely on design cognitive and interactive visualization techniques for exploring possible systems features supporting related activities. An informal case study using a parametric model of a residential apartment is presented to illustrate the method.

BACKGROUND AND MOTIVATION: DESIGN TASK ENVIRONMENT AND ALTERNATIVES

Design starts with incomplete and imprecise goals (Akin 1978; Cross 2001) that at the outset can be achieved through many alternative solutions (Foz 1973). As the design goals evolve (Eastman 1968), new constraints and new variables appear (Schon 1983) which demands looking at alternatives systematically. Exploration of alternatives takes place in a task environment that constitutes external representations and the tools that manipulate them. The structure of the task environment influences both (design) problem and solution spaces and consequently, the strategies designers apply in achieving an acceptable solution. In current design practice, the computational design tools present a limited task environment for working with alternatives mainly because most of them interact with representation of "single state (design) model" (Terry et al 2004). If and when we can change the characteristic of this task environment, we envision that we can open up new possibilities for design.

Having to work in task environments with large number of alternatives poses choice overload problem, where the selection mechanism, display strategies, and manipulation techniques become significant factors in shaping the design space. Studies on observing human behavior while working with multiple objects (Clark and Chalmers 1998) for a goal-oriented task, demonstrate that people constantly organize and re-organize objects in their primary workspace and arrange objects based on importance, expected use, or reminders.

Hollan, Hutchins and Kirsh (2000) propose that workspace is a resource that "must be managed, much like time, memory, and energy", and workspace's spatial arrangements must simplify choice, perception, and internal computation. On the similar lines, Smith et al. (2010) propose that the interface solutions for working with multiple designs must be adaptable to provide multiple ways to view alternatives, with an ability to arrange them, group them, tag them, resize them, and reflect on them (Schon 1983; Johnson and Carruthers 2006) individually or collectively.

GENERATIVE TOOLS AND DESIGN EXPLORATION

For comparison and analysis, we have classified design exploration techniques and interfaces into four categories based on their underlying representation used for exploration and their degree of automation in performing exploratory tasks.

PARAMETRIC EXPLORATION

Parameterization provides a mechanism for changing values assigned to different parameters linked to one or multiple design features. Tuning values (Hartmann et al. 2008; Krish 2011) and other input mechanisms have amplified the amount of variability one can achieve in a limited time. Together with linked editing techniques, parametric exploration has become a type of representation on its own.

HISTORY-BASED EXPLORATION

Most of the recent systems now provide rich history keeping mechanism in form of a timeline (Klemmer et al. 2002). The timeline interfaces amplify the opportunities presented to its users. Their interplay facilitates better learning, improved reflection, and flexible design process with minimum premature commitment (Edwards et al. 2000). In addition, interactive histories have enabled playing what-if scenarios: users cannot only go back in time to make corrections but also have a mechanism to try out variations by branching out in the timeline (Terry et al. 2004).

RULE-BASED EXPLORATION

There is a considerable amount of research in this domain with different names; some call it shape grammar (Stiny 1980; Flemming 1987; Heisserman 1994 just to name few) others call it example-based exploration (Lee et al. 2010). However they all share the same principle: the system learns from examples or rules and helps user explore the potentials of the design space. On one hand with minimum computer interference, these systems help motivate exploration by giving related examples, but on the other hand, the suggestions regulated by the semi-automated systems based on shape rules or style grammar, affect the boundaries of design space.

GENETIC ALGORITHMS AND DESIGN EXPLORATION

Genetic exploratory interfaces are generally suited for solving complex parameter optimization problems (Turrin et al. 2011; Josephson and Chandrasekaran 1998). They are often termed as "canonical genetic algorithms". Genetic algorithms are suitable for solving problems in creative design (Xu et al. 2012), such as combining components in a novel, creative way.

EXPECTATIONS FROM *CAD* TOOLS

CAD systems are Creativity-Support Tools and are expected to enable "exploratory processes" for both novices and experts (Shneiderman et al. 2006). However, the current systems inherit the known challenges in *CAD*, they have less emphasis on exploration as discussed in (Shneiderman et al. 2006). Although their interfaces are meant to enrich the design experience, their strength is based on the computation and not necessarily on how designers work. Their actual success against these aspirations is limited to specific and often technically involved strategies. Little research exists on matching these systems and design exploration and the effects of interaction on task performance strategies.

Smith et al. (2010), focus on the interface support in *CAD* tools for generating and managing multiple ideas. They report a set of suggestions based on their empirical findings to improve existing systems:

a. Make it easy to switch between ideas;
b. Provide a way to view multiple ideas at once;
c. Allow users to adapt the interface to their needs and preferences;
d. Provide ways to label the ideas both pictorially and textually;
e. Provide multiple ways to group and classify the ideas;
f. Provide an explicit means for capturing the situation; and
g. Support fluid composition and decomposition of ideas.

Combined with the qualities of creativity support tools, these give an overall direction for development of the next generation *CAD* systems to better support design exploration.

Obviously, developing the next generation of *CAD* tools require a significant effort. Towards contributing ideas, our focus in the paper is to enable designers to access and manage the rapidly growing design space; and if and when possible, enable them to reduce the solutions from thousands to include the most relevant design instances.

APPROACH: USING SIMILARITY INDEXES FOR EXPLORATION

Our goal is to develop computational methods that allow the designers to explore the alternatives by means of filtering and selecting sets in regard to their own "designerly" preferences. Their organization becomes important for accessing, evaluating, sorting, branching, pruning, and cross-pollination. To achieve a final solution, reduction and subordination of alternatives are needed. This calls for system features such as filtering, labeling, sorting, and grouping to reduce solutions to a minimum set of maximally differentiated alternatives. Their visual, logical, temporal organization must help designers generate and select alternatives in different views. Some parametric *CAD* systems can dynamically calculate cost, material complexity, structural robustness etc. of alternative design choices. These data allows better focus on less quantifiable design choices including subjective judgment, but only when they are accessible and visible.

In order to achieve these, we propose a similarity index-based search of design space using similarity matrices taking both independent and derived parameters as input. This approach is feasible in concept exploration as computationally expensive comparison methods using geometry or semantic analysis (such as thermal performance) can be less effective for the rapid search of possible solutions. We operationalize our approach by first introducing a formalism with its basic definitions.

DEFINITIONS

Design instances are unique alternatives generated using any generative algorithm taking a parametric design model as input. All possible design alternatives create a design space, and design instances selected from this design space based on certain selection criteria forms a sub-set of alternatives. When a similarity algorithm is applied on two different design instances, the result reveals the similarity distance between them in a given threshold of similarity or tolerance of similarity. The similarity is calculated based on the independent or derived parameters (such as volume of a box derived from its dimensions). The formal representations of these concepts are:

An independent parameter p has a value v such that
$p::\{ v \mid min_v < v < max_v \mid\mid v \in \{v_1, v_2, v_3 \ldots, v_n\}\}$

A design instance D defined by unique tuples of
p, $D::\{p_1, p_2, p_3 \ldots, p_n\}$

Design space DS includes all possible unique D such that
$DS::\{ D_1, D_2, D_3, \ldots, D_n\}$

Filter f is a rule that takes D to test if it meets the required criteria
$f(D)::\{rule\ expression\ testing\ properties\ of\ D\}$

Design sub-space DSu include every D meeting the criteria defined in a set of filters
$DSu::\{D \in DS \mid f_1(D)\ \&\ f_2(D)\ \&\ f_3(D), \ldots, f_n(D)\ is\ true\}$

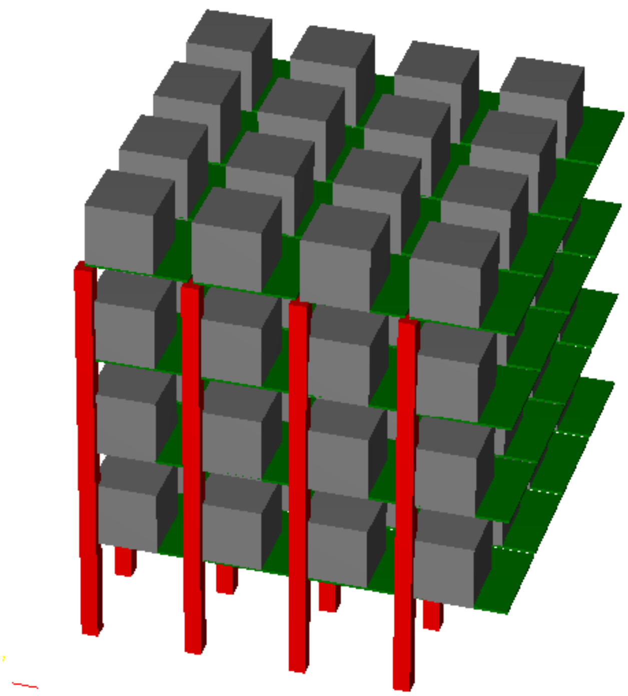
A pair of D be treated as similar if the similarity value S from a similarity algorithm and a set of selection filters satisfied
$S::\{ Di = Dj \mid Di, Dj \in DSub\ \&\ P(Di, Dj) < S_{threshold}\}$

EXAMPLE

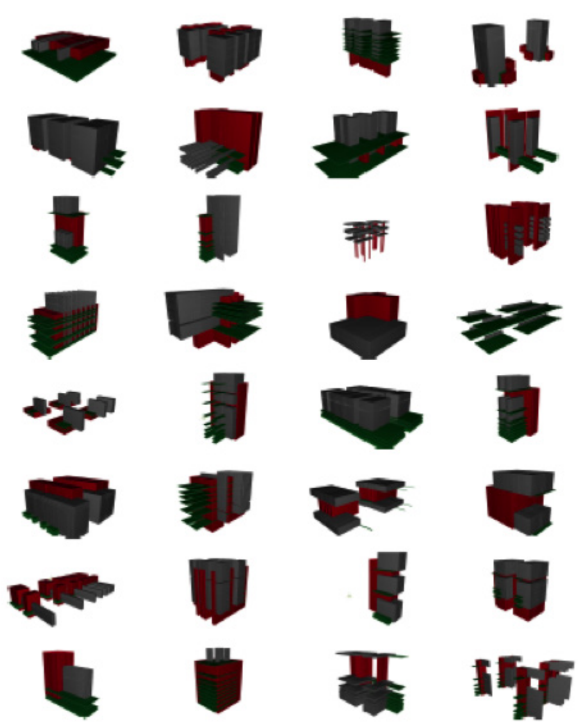
Imagine a parametric cylinder with three independent parameters, as shown in Figure 1, height h, radius r, and color c such that $h = \{0.5, 1, 2, 3\}$, $r = \{1, 2, 3, 4\}$, and $c = \{$red, blue, yellow, green$\}$. The size of possible design space is $|DS| = 64$. If a color filter $f(c)$ $::\{$blue$\}$ is applied, the result is a design sub-space $|DSu|=16$. Let's assume that we apply the Euclidian similarity index on two design instances in the DSu, $D_1=\{h=0.5, r=1, c=\text{blue}\}$ and $D_2=\{h=1, r=3, c=\text{blue}\}$, and assume that we take the similarity threshold 0.7. For the clarity of the example, we standardized the parameters in their given ranges. The calculated similarity index is $E_s(D_1, D_2)=0.5$. In order to decide if these two alternatives are similar under given filtering conditions, the Euclidean index must be above the threshold value 0.7; hence we treat these as different designs. Assume that the same similarity calculation is applied on each pair of D_i, $D_j \in DSu$, the result is a 16x16 similarity matrix that can be visually presented in different formats. The similarity logic can include derived parameters, such as volume, or expanded factors such as color saturations with numeric values. We propose using similarity indices in searching design space by performing selection and comparison operations. The proposed iterative process is described below:

SET PARAMETER AND VALUE RANGES

The designers evaluate and select the parameters or derived parameters to be considered in exploration. The filters can be added into the parameter selection process, which can be expressions or rules.



2a Design model with parametrically defined three types of components



2b Random selection of design alternatives that can be generated using the model

SELECT AND PREPARE SIMILARITY ALGORITHM

Designers choose or define a similarity measurement method to compare how two given design solutions are similar or different. The result is an index value between 0 and 1, where 0 means no similarity and 1 means close similarity. Note that 1 doesn't necessarily show identical solutions. Each similarity measurement method has its own advantages and disadvantages. For example Euclidian similarity index works on absolute distances between different data points; however, each data point is treated equally, hence a weighted method can be preferred. The Bray-Curtis dissimilarity index also uses absolute distances as in the Manhattan method but treats the individual components of data as separate dimensions. There are other statistical similarity calculation methods but their discussion is beyond the scope of this paper.

GENERATE SIMILARITY MATRIX AND VISUALIZE

By computationally comparing each solution to others, a similarity matrix (table) is generated. This is essentially an *n*-by-*n* table half-filled with similarity indices, and columns and rows include design alternatives. One of the main advantages of our method is the ability to compare design similarities without generating the 3D models: comparison of the independent parameters can predict the similarity of a solution to another one. For example, in (Figure 1), the similarities of the cylinders can be calculated without actually generating the cylinder geometries. The models can be generated in any step as needed, which reduces computational time.

CREATE SUBSETS AND REDUCE SCOPE

Once the similarity matrix is created, it can serve as a means to select subsets of designs based on their similarity index values, such as by setting similarity threshold to a certain value or by interactively defining a selection range. The subset can further be treated as possible solution space and its scope can be narrowed. The generated 3D models can be further compared and edited in parallel.

CASE STUDY: A PARAMETRIC MODEL OF A RESIDENTIAL BUILDING

How might a similarity indices and matrix be used in searching design space for choosing potential conceptual design solutions among a large number of possible alternatives? Similarity indices, as mentioned, define how far a solution is from another one. The similarity matrix shows the similarities between all design solutions in one subset of solutions. The interfaces should enable designers to perform the iterative process described in the approach section. Below, we present our initial prototype through a realistic scenario, and describe how it supports selection, comparison, and editing.

DESIGN SCENARIO

We developed a hypothetical design scenario where architects are required to explore design solutions for a residential apartment (Figure 2). The design includes three basic building components: residential units, vertical circulation spaces, and terraces represented by gray, red, and green colors respectively. Each of these components is a parametrically defined rectangular prism. The distance (spread) between the same type of components in the structure is defined by a non-linear function: the distance between the same type of components can vary. For example, the second gray box can be one unit away from the first one, while it can be 1.5 units away from the third depending on the function.

CALCULATING SIMILARITY AND BEHIND THE SCENES

The purpose of this case study is to experiment with different similarity metrics to evaluate whether the proposed approach discussed in *Approach: Using Similarity Indexes for Exploration* is appropriate. Different metrics attempted in algorithms are illustrated below.

ALTERNATIVES GENERATION–STRUCTURE VS. RANDOM SAMPLING

During the first step of the task, the designer must generate a limited number of alternatives to start. We tried both structured and random generation in this case. In the structured generation option, alternatives are created incrementally with a fixed parameter range chosen by the designer, with fixed values or fixed step-sizes. For this case, in order to keep the numbers reasonable for further steps, the designer has to make a deliberate decision to fix some of the less important parameters, varying only twelve parameters of their personal preference. Only two possible values are chosen for the selected twelve parameters, hence results in structure generation of 2 ^ 12 = 4096 alternatives. In the random generation option, we ask the computer to randomly choose a value in the entire range for all parameters on each new alternative generation. The total number of random generations varies during our experimentation with different algorithmic options for filtering scope, as discussed in later sections. A comparison between 4096 alternatives generated by structure and random options unsurprisingly shows:

1. random generation displays more visual variability, and
2. sructure generation is able to reveal the relationships between the visual output and the parameters to someone who has no knowledge about the model.

BRAY-CURTIS DISSIMILARITY–NORMALIZED VS. RAW PARAMETER VALUES

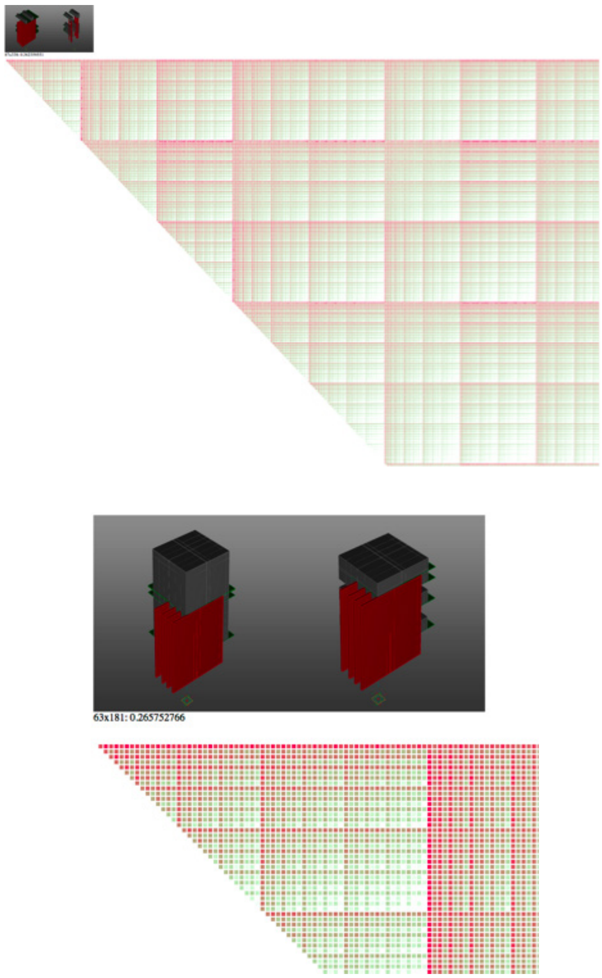
We choose to use Bray-Curtis as part of the exploration. We calculate Bray-Curtis dissimilarity index using normalized and raw parameter values. The advantage of using the normalized values (scaled normalizations from 0 to 1) in the case study was apparent, as it is more reflective of the visual difference between two alternatives on average. Using only the raw parameter values to calculate dissimilarity resulted in some parameters taking more weights in the calculation due to its large raw value. For example, without normalization, a difference of five in parameter (number of cubes) weighs double than a difference of 2.5 in parameter [length of the gray cubes]. But after normalization, they will be the same 0.5, which is a more accurate reflection of the difference on the parameter differences.

FILTERING SCOPE–GLOBAL VS. WITHIN-SET

Global filtering is performed on fixed number generations with the entire dissimilarity matrix calculated, whereas within-set filtering is performed as each alternative is generated with the already selected set. In this case, a global 4096x4096 matrix with each cell containing a Bray-Curtis calculation for the pair, then an average for each alternative's "dissimilarity" against all other alternatives was calculated, a global filtering was done to select the top 1000 most dissimilar alternatives. In the within-set filtering case, dissimilarities are evaluated on a rolling-basis only against those already selected as opposed against all generated solutions. This is beneficial in terms computation time. In this study, we either structurally or randomly select a seed alternative from whatever generation option described in (a), then continue on evaluating the upcoming alternative until 1000 are selected. We only select the upcoming alternative if it has a dissimilarity index above the threshold 0.3 with everything that's already in the selected set. If the upcoming alternative is similar with anything in the set, then we discard it and go to the next alternative.

VISUALIZATION OF DESIGN SPACE USING SIMILARITY MATRIX

After applying a set of filters, the design space for the case project can be significantly reduced. However, still even after the filtering, possible solutions can be significantly large. For the purpose of demonstration, let's assume we have selected 500+ solutions that we wish to explore. The similarity matrix with color-coding (or another type of indicator) can visually describe how each alternative is similar or different from the other alternatives (Figure 3).



3 The Similarity Matrix Showing a Large Number of Alternatives Selected from a Subset for Further Exploration

The matrix includes rows and columns, where each cell is colored to show the degree of similarity or dissimilarity between a pair of alternatives. The color scale can be adjusted to display different range of similarities. The red used in the example shows strong similarity, while white shows weak similarity. The upper right corner shows the pair of alternative solutions selected from the matrix.

The similarity matrix is intended to serve multiple functions:

a. to visualize the similarities between the selected solutions;

b. to pair-wise explore alternatives by selecting colored units;

c. to perform semantic zoom to investigate similarity indices and solutions; and

d. to select ranges to further develop smaller subset of alternatives.

CONCLUSIONS

In this paper we explore possible interaction with a large number of alternatives generated using parametric design models and a method based on similarity indices. The method is computationally robust and presents possibilities for novel interaction on alternatives. Its goal is to prevent or reduce the effect of the combinatorial explosion by applying different heuristics as filters or parametric value constraining. Currently, we are studying how designers work with large number of alternatives through a series of experiments. The findings from these and the similarity-based search methods will enable us to better define the characteristics of future computational design tools.

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IMAGE CREDITS

Figure 1: Sheikholeslami, Mehdi (2009) You can get more than you make. MSc Thesis, School of Interactive Arts & Technology-Simon Fraser University.

Figure 2-3: Image credits to Authors (2014).

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