GENERATING INNOVATIVE DESIGNS USING QUALITATIVE SPATIAL REASONING

JULIE R. JUPP, RICARDO SOSA
Key Centre of Design Computing and Cognition
University of Sydney, Australia.
{jupp_j, rsos7705, john}@arch.usyd.edu.au

AND

JOHN S. GERO

Abstract. In this paper we present a generative system supported by qualitative spatial reasoning. The approach incorporates qualitative modelling in an evolutionary system to automate the design of novel solutions assessed as compatible with a set of existing designs. The system is presented through an application of door design and demonstrates how development guidelines aimed at preserving a building or streetscape's visual character can be met by novel designs. The results presented in this paper illustrate the generation of novel designs that intuitively capture key characteristics of the corpus of existing designs at a qualitative level. This approach provides the basis for new kinds of design tools.

1. Introduction

The built environment is shaped by a variety of design standards that are defined over time. Design regulations and guidelines are products of an ongoing effort to preserve valued qualities of the built environment and are developed to manage change and ensure that new solutions are compatible with existing designs. In particular, heritage buildings and streetscapes are protected by established design standards that result from multiple factors including historical, social, technical and artistic requirements. As social criteria develop over time, certain design standards evolve. It is possible to describe such standards qualitatively and use these characterisations to guide the design of new solutions. Such solutions can be considered as potentially creative inasmuch as they meet the two main premises of creativity, i.e., novelty and appropriateness (Runco and Pritzker, 1999).

In cases where building alterations and additions or new neighbouring developments are proposed, the designer is required to ensure compatibility and preservation of valued qualities set out by stakeholders including development authorities. It has been argued that such design regulations can constrain new design solutions by imposing homogeneity and limiting creativity (Murcutt et al., 2002). A balance between standards and innovation can be achieved through design processes that generate novel solutions that resemble the desired qualitative characteristics of existing designs.

This paper presents a computational generative system of novel solutions that are compatible with existing designs using qualitative spatial reasoning (QSR). Qualitative spatial reasoning is used to extract and evaluate physical features of existing designs. The model of QSR implemented here incorporates qualitative feature-based descriptions and data mining techniques (Jupp and Gero, 2004). The core idea is that existing designs can be sufficiently characterised by qualitative representations of embedded shape and spatial features. By identifying qualitative features deemed as significant to maintaining salient visual and spatial qualities, we construct a predictive model to evaluate a generative system's output.

2. Design Representation

The example presented in this paper consists of generating novel door designs that capture qualitative characteristics of timber doors from 17th- and 18th-century heritage buildings in the historic centre of Morelia in Michoacan, Mexico. Over 200 stone buildings in Morelia reveal a blend of Renaissance, Baroque and neoclassical architectural elements and have been listed under the World Heritage List of the United Nations Educational, Scientific and Cultural Organization (UNESCO, 1991). As such,

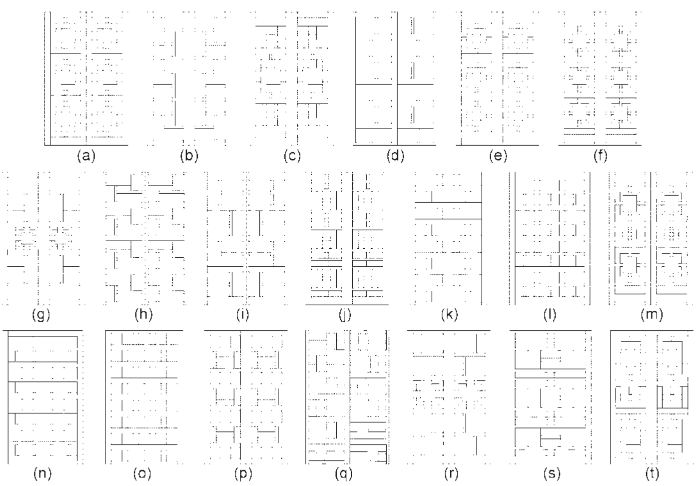

Figure 1. 20 Morelia door designs represented as 2D contour diagrams.

there are strict standards in place aimed at preserving specific design qualities for new building works to maintain a consistent visual character. The objective is to build a computational system to generate new designs of the 'Morelia style'.

For this study, 20 door designs with a variety of arrangements were selected. The study focuses on the restricted but significant domain of two-dimensional (2D) representations. All doors selected are handcrafted single or double leaf timber doors. They are divided into construction components and each door leaf consists of: (i) top and bottom rails; (ii) left and right stiles and (iii) inset panel. Each inset panel is composed of between three and eight frames containing orthogonal patterns. Figures 1(a) to 1(t) illustrate the sample set represented as 2D line contours.

2.1. SPATIAL REASONING IN DESIGN

Spatial reasoning and designing in 2D are inherently linked. Diagrams allow designers to manipulate spatial relations by recognising and interpreting alternatives, searching for salient features, discovering new spatial relations (based on previously unrecognised physical properties) and recalling relevant examples. When reasoning about 2D diagrams, designers presumably intuitively use abstraction, approximation, aggregation and other techniques to generate manageable spatial descriptions upon which to manipulate and base comparisons. A comparative assessment of designs is a judgment process that requires two or more "things" to be decomposed into elements in which they are the same and elements in which they are different.

Since qualitative judgements are typically intuitive and subjective, they usually display no strict mathematical models (Tversky, 1977). Therefore in 2D designing where an observer must compare existing and proposed designs, the observer's intuitive or common sense knowledge is seen as essential in reasoning about the designs and highlights the importance of a qualitative approach. Whilst a host of numerical techniques exist for reasoning about physical characteristics, precise numerical information does not allow the kind of commonsense reasoning necessary for comparing existing and new designs. QSR provides an approach to recognise and compare features significant to the preservation of visual design qualities and upon which to base an assessment of novelty and appropriateness.

In order to automate the generation of both novel and appropriate solutions generative systems need a way to guide the search process. One such way is to use automated reasoning to build models of expected results. The following section introduces the qualitative modelling used for this purpose.

3. Qualitative Modelling

Qualitative modelling is dealt with in two stages: (i) re-representation and feature extraction of physical characteristics; and (ii) automated evaluation using data mining techniques. The qualitative encoding schemata are based on a mixed spatial ontology and employ descriptions invariant to scaling, rotation and shift in patterns. Once encoded in this canonical form, analysis of features using attribute evaluation methods and clustering algorithms can begin. The following sections provide a brief overview of these stages, further details can be found in Jupp and Gero (2004).

3.1. QUALITATIVE FEATURE EXTRACTION

The qualitative encoding schemata are based on landmarks for boundary- and graph-based representations of 2D diagrams that capture relational variations in which abstraction and successive derivatives are represented symbolically. Shape and spatial characteristics are articulated in relation to constraints placed upon contours and subsequent abstracted graph edges. The schemata represent in detail the physicality of shapes and spatial relations as a sequence of symbols from which feature semantics can be derived that are assumed to denote pictorial characteristics. The method of feature extraction is organised cyclically, when more abstract features are identified on the basis of current available features, a new representation is produced.

The encoding schemata have the ability to deal with classes of shape and spatial relations rather than simply instances of them.

3.2. EVALUATION

Clustering of Morelia door designs commences with the assumption that by sampling a number of them it is possible to identify those features and frequencies that distinguish 17th- and 18th- century designs. The type, frequency and sequence of features may be seen as the basis of comparison of new door designs generated by a computational process, here a genetic algorithm. Thus the shape and spatial features identified by the encoding procedure will be the dimensions by which we compare the door designs. The extracted feature values are used to construct a predictive model. The model incorporates Weka 3.4 (Witten and Frank, 2000) classes for attribute evaluation and clustering.

3.3. ATTRIBUTE SELECTION AND CLUSTERING

Attribute selection is an important technique for reducing the dimensionality of the dataset. Using a filter-based feature selection algorithm attribute evaluation was undertaken using Correlation-based Feature Selection (CFS) (Hall, 2000) in conjunction with a Best First search method. CFS evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy. From the features extracted from the encoding procedure two local feature attributes: Iteration_0, Iteration_2, and two global feature attributes: Contains/Contained_by and Overlaps/Overlapped_by were evaluated as the optimal subset of attributes for clustering. This is significant since clustering relies on a combination of feature categories where the ratio of local to global features is 1: 1.

Clustering was performed using the Expectation Maximisation (EM) algorithm. The EM algorithm selects the number of clusters automatically by maximizing the logarithm of the likelihood of future data, estimated using cross-validation. Beginning with one cluster, it continues to add clusters until the estimated log-likelihood decreases. Since there is no access to prior knowledge about the number of clusters in the data, it is not possible to force the EM to generate a desired number of clusters and learning is therefore unsupervised.

The EM algorithm created one set of clusters that partition the data into four groups. Clustering found the correct number of clusters, meaning that the EM algorithm did not lose any, which is possible. The following box text provides a summary of the run information. Cluster visualisation is shown in Figure 2 which illustrates the four clusters produced using a linkage distance tree diagram, calculated using Ward's amalgamation rule (Ward, 1963) with a Euclidean distance measure.

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Number of clusters: 4 (Log likelihood: -12.1934)
Cluster: 1 Prior prob: 0.27
Cluster: 2 Prior prob: 0.21
Cluster: 3 Prior prob: 0.31
Cluster: 4 Prior prob: 0.20
=== Clustering Stats for training data ===
Cluster 1 members: {a,c,e,f,g,m,r}
Cluster 2 members: {b,d,h,i,k,l,n,o,q,s}
Cluster 3 members: {c,t}
Cluster 4 members: {j,p}
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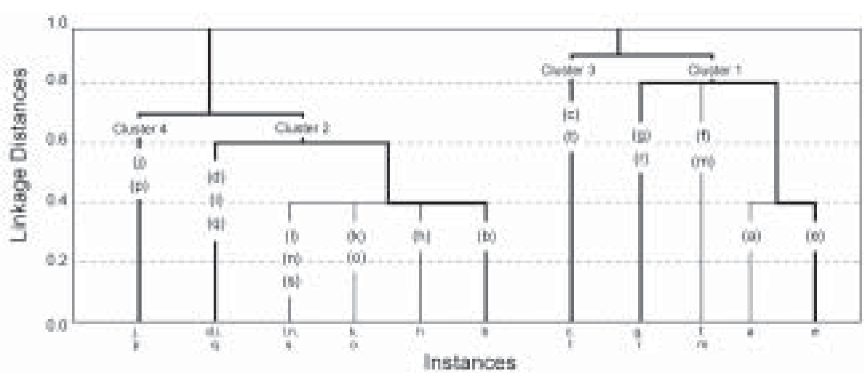


Figure 2 Clustering result for EM algorithm.

Figure 2 shows cluster assignments of the 20 doors for the four selected attributes. Instances closer to one another are assumed to have higher compatibility. Further, the larger the logarithm of the likelihood, or log-likelihood, the better the model fits the data. The predictive model's log-likelihood was -12.2 and indicates a good to average fit. Based on a visual inspection of the four cluster assignments, additional feature attributes were identified as being significant to maintaining pictorial salience if they upheld their cluster assignments. To increase the accuracy of the fitness function a further eight attributes were used in conjunction with the four existing attributes (selected by CFS for clustering) to create four predictive models comprising 12 features as shown in Table 1.

TABLE 1. Four predictive cluster-based models: features and frequencies.

	Indentation	Iteration 0*	Iteration 1	Iteration 2*	Alternation 1	Symmetry	Overall Symmetry	Complete Adjacency	Offset	Meets / Met by	Contains / * Contained by	Overlaps / * Overlapped by
Cluster 1	9 -3	144 -244	35 -20	9 - 16	16 -14	36-61	9-30	67-98	22-9	10-25	9-1	75-105
Cluster 2	NI	108 -300	08 -30	NIL	NI	27-25	NII	58-238	NI	207- 90	NI	62-162
Cluster 3	3 -	125 -140	31 -13	3 - 5	4-1	30-31	1-	75-76	2-1	15-18	5 -	75-76
Cluster 4	NI	115 -220	19 -22	NIL	NI	54-55	NII	125-128	NI	25-26	NI	130-132

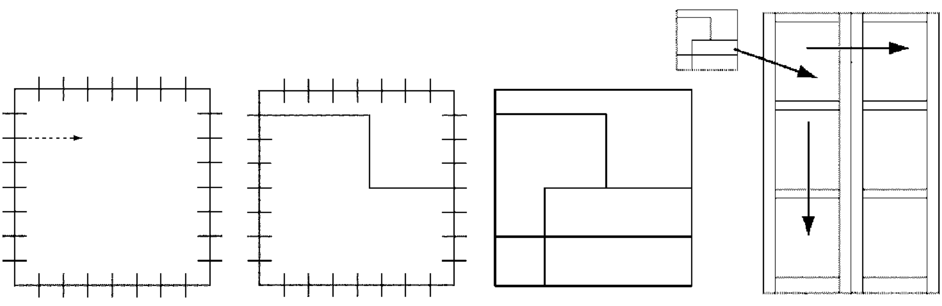
* CFS attributes used for clustering.

Features selected to create these four predictive models are used to define a function that captures the convergent morphological, topological and mereotopological features of the training set. It is possible to evaluate a generative system's output with this qualitative model. The models obtained for these four sub-types of Morelia doors are used to define a multi-objective fitness function (design evaluator) in an evolutionary design system described in the following section. Such a system is expected to generate new instances that match the features that characterise each cluster.

4. Evolutionary Design System

To generate novel and appropriate designs a genetic algorithm is implemented that uses QSR to guide the search of a design space (Bentley, 1999). An initial population of designs is defined as a set of random solutions within a given design representation. In this case the 2D representation of door frames is defined by a border within which a random number of lines are drawn in the following sequence: select a random border point in the grid, continue to draw a line segment in random direction until another existing line is met (including border lines). The range of line number and grid size are set at initial time. In this case given the sample set, the grid size is set to a maximum of 5x5 units and the number of lines is set to a range of 2 to 10 lines. The generation of a random frame is shown in Figures 3(a) to 3(c). An additional frame variable is symmetry and is implemented by a random boolean operator which can cause generated lines to be reflected in vertical and horizontal axes. This last feature was considered necessary in order to seed symmetry in the door population.

Frames are associated to doors at random at initial time and are exchanged between doors during a system run. In addition, the door representation includes configuration properties such as number of leaves (1 to 2), number of frames (3 to 8), types of frames (1 to 2), and frame reflection (horizontal and vertical) as shown in Figure 3(d). Doors are assigned these configuration values at initial time and they remain constant for each door during a system run. When a frame is associated to a door, the former is scaled to fit the respective configuration, i.e. only the qualitative relationship and not the size proportion between shapes is considered.



(a) (b) (c) (d)

Figure 3 Frame representation: A random border point is selected and a line segment is drawn in random direction one grid unit at the time until another line is met.

Every generation of doors is evaluated by a function that assigns each individual a fitness score. The main motivation of this research is to incorporate qualitative spatial reasoning at this stage of the generative process by defining a multi-objective fitness function extracted from the existing designs. Based on their fitness, doors that yield qualitative measurements within the ranges of clusters of Morelia doors are selected to contribute their genetic material for the next generation of solutions. Namely, door designs are rated for their effectiveness based on the feature series identified within the predictive cluster models for the original doors.

The crossover operation combines frames from the selected (fit) doors to form the following generation. Mutation or genetic variation is implemented by random changes of line segments in frames with a low probability of 1%. A number of possible strategies have been developed for every evolutionary step: populations can be seeded with known solutions and different reproduction and selection operators can be combined. In this paper we apply standard single-point crossover and roulette-wheel selection (Goldberg, 2002).

The system is implemented in Java2 and makes use of the following libraries: Colt for random generators and maths (Hoschek, 2002), JGAP for genetic operators (Rotstan, 2004), and JExcel for data output (Khan, 2004). The output of the system consists of images of door designs and spreadsheets with their fitness on all qualitative features.

4.1 SYSTEM RESULTS

A population size of 100 doors was usually found to generate adequate results over 1000 generations. An experimental random seed generator is used applying the Mersenne–Twister algorithm (Matsumoto and Nishimura, 1998) to enable the use of control initial populations with varying genetic operators.

The system was run several times using different random seeds in order to obtain a range of solutions with high fitness values in the four clustering groups described in Section 3. In particular, new solutions that meet the characteristics of clusters 1 and 2 tend to dominate a population. The reason may be that these clusters have a large number of instances and therefore their value ranges are the largest. Also, the specific representation used may benefit the occurrence of these two types of solutions. In order to obtain solutions for clusters 3 and 4 the fitness functions for the competing clusters were ‘turned off’. Clusters 1 and 2 also present some of the best matches for new door designs.

Figure 4 shows a selection of results with high density for all clusters. At first, some of these designs seemed counter-intuitive, however, this can be attributed to the scale of shapes and their proportion to other shapes within frames.

Table 2 shows the distribution of new doors in Figures 4(a) to 4(p) by cluster and their fitness value. Fitness values are estimated as the number of features that match between new doors and the clusters of their membership, i.e. all examples shown have 8 to 11 common features out of the 12 used for evaluation described in Section 3.

The highest mean fitness is registered for new doors of cluster 2 (mean fitness value 0.84) whilst the lowest is cluster 3 (mean 0.7). This demonstrates that with this system it is easier to generate new instances of clusters 2. A reason may be that doors that combine more than one type of frame are more difficult to reproduce possibly because their measurements are a product of combining two qualitatively different frames, whereas doors with a single type of frame are easier to model.

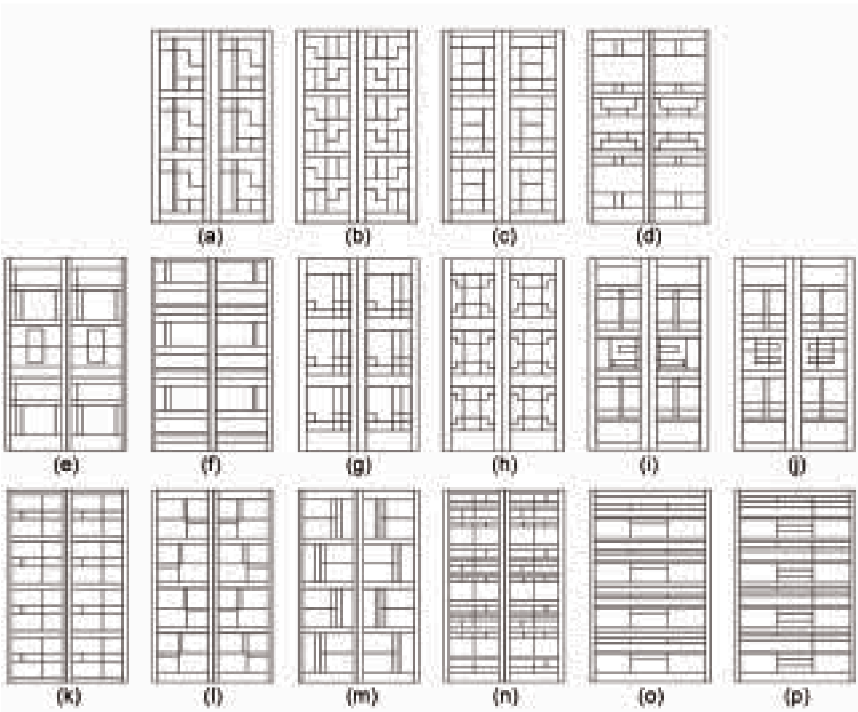


Figure 4. Fittest new-Morelia door designs.

Frame symmetry was resilient in the genetic pool, probably due to the relevance of the local and global (or overall) symmetry criteria defined in the predictive cluster models in Section 3.

TABLE 2. New doors' fitness and cluster membership.

New door	Cluster	Fitness	New door	Cluster	Fitness
a	1	0.66	i	1	0.66
b	1	0.66	j	1	0.66
c	1	0.83	k	2	0.83
d	3	0.75	l	2	0.91
e	3	0.66	m	2	0.91
f	2	0.83	n	4	0.75
g	1	0.66	o	2	0.83
h	1	0.75	p	2	0.75

To confirm the use of QSR in the design generator, Figure 5 shows a set of doors that receive low fitness values for all clusters. These solutions are novel but they do not capture the qualitative characteristics of Morelia doors.

4.2 ANALYSIS

The results presented in this paper illustrate the generation of novel designs that intuitively capture most of the characteristics of the corpus of existing designs at

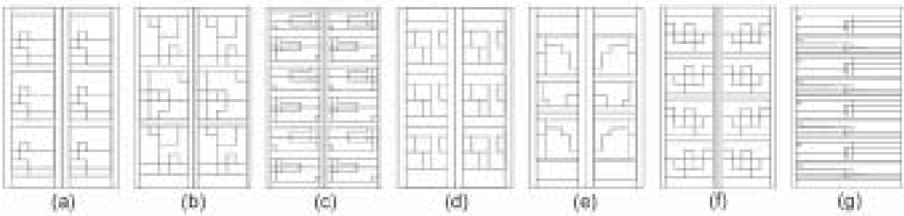


Figure 5. Inverting fitness function to evolve doors that are different from Morelia doors.

a qualitative level. The new doors shown in Figure 4 are significantly different from the original Morelia doors in Figure 1, yet, they show some general resemblance to them. Moreover, the new designs comply with the more particular characteristics of the four sub-groups of original designs, and so can be categorised in similarity and membership.

New doors can have local attributes that are similar to their original counterparts such as L-shapes seen repeatedly in clusters 1 and 3. However, they can yield different qualitative measurements in the global relationships between these shapes such as the door shown in Figure 5(g). In contrast, other new doors can have different local features such as “C”, “I”, “E”, “T” and “stepped” shapes seen in the new doors, yet they have very similar qualitative characteristics at the global level. This can be used as a measure of novelty and is one of the key aspects of applying QSR in generative systems: the capacity to introduce novel local features whilst complying with overall global features visually.

The qualitative model incorporated into the evolutionary system can effectively compare door designs for one or more features and analyses the degree of feature compatibility as well as identifying those features and frequencies that differentiate designs and increase novelty. The quality of these results could be complemented in future work by extending the current qualitative encoding of lengths of contours to include the proportion or scale ratio between regions. The results are promising, given the distinct visual similarities that we may intuitively see from the new door designs.

5. Discussion

The generative system presented in this paper provides the basis for a new kind of design tool. The applications of this approach are wide ranging and include design diagram identification, indexing, retrieval, robust description for 2D diagrams in computational design reasoning and design support systems.

CAD systems are currently unable to aid the designer in the perception of figures and gestalts or in the recognition, categorisation and generation of qualitative design characteristics. The approach presented here can potentially assist designers in useful ways by “amplifying the mind’s eye” (Fish and Scrivener, 1999). A fully automated approach to qualitative modelling in generative systems like the one presented here is required if the advantages of automated and support design systems are to be exploited.

Future work is aimed at conducting cognitive experiments to validate the results of the system with existing designs. Future research will also be aimed at developing a co-evolutionary system where design standards are dynamically transformed by simulated social groups over time (Sosa and Gero 2004). The generative system should adapt to such changes by updating the fitness function accordingly. In this way, the temporary nature of ascription of style is to be captured in a computational system of design.

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