Computational Differentiation and Categorisation of Design Drawings

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Abstract. In this paper we present an approach to the differentiation and classification of two-dimensional design drawings. Our model is based on a qualitative encoding scheme and information theoretic measures. The model utilises information-theoretic tools to measure the similarity and complexity of a hierarchy of drawing descriptions. The descriptive and analytic power of the model is demonstrated by evaluating the different measures for a series of simple sketches and studying the time evolution of architectural plans produced by Frank Lloyd Wright.

1. Introduction

Designing using drawn media is inherently visual and the designer is able to inform further designing by seeing what is there, drawing in relation to it, and seeing again what has been drawn in (potentially) new ways (Schön, 1983). The designer not only visually registers new and existing shape information but also visually reasons about what is drawn, constructing or identifying its meaning about shape physicality and its relations with other shapes. As a consequence of identifying visual patterns the designer is also able to differentiate and categorise them. Representational differentiation and categorisation (of visual patterns) is a direct result of the designer’s visual experience.

In this paper we present methods of computational comparison of designs and establish a formal model through which to differentiate and categorise architectural design drawings. Our approach is similar to applications of author-recognition to written text. Since architectural designs are commonly expressed visually in the form of two-dimensional design drawings, the idea
applied here investigates the possibility of distinguishing between an architect’s drawings and identifying design categories or ‘styles’.

Prediction methods should occur within a framework that melds the dynamics of both transformation and transmission processes. We investigate this idea using three distinct descriptions of two-dimensional drawings using the qualitative schema developed by Jupp and Gero (2004). The schema provides a description of shape and spatial characteristics as sequences of symbols. Symbol strings are analogous to a natural language and provide us with the necessary framework for this study.

There are many different measures that could be used for comparing each level of drawing description. Recently an objective quantitative measure for drawings was constructed by Gero and Kazakov (2001). They demonstrated that by using information theoretic measures it is possible to compare drawings of different designs by a single architect and to compare drawings by different architects. We adopt this set of tools based on information theory to evaluate qualitative feature-based descriptions of design drawings.

In the first part of this paper we present a model that consists of a parsing program and a measurement program. We briefly describe the qualitative schema used to represent architectural plan drawings and summarise the information theoretic tools used for design differentiation and categorization. In the second part of the paper, two experiments using information theoretic measures are presented. The first experiment compares the similarity and complexity of a series of simple sketches. The second experiment uses the technique to distinguish between historically described periods in Frank Lloyd Wright’s design corpus and compares the complexity of Wright’s residential designs over time. We present the results from these experiments and investigate the effects different levels of qualitative representation have on a measure of complexity and similarity. Finally, we discuss the potential benefits the use of differentiation and categorisation methods offer an analysis of style.

2. Differentiation and Categorisation

Differentiation and categorisation are central to the study of art and architecture. To talk of individual artworks and architectural designs would be almost meaningless without first grouping or categorising them according to some distinguishable properties. In design, differentiation and categorisation are basic cognitive processes of arranging designs into groups and finding their derivative or rate of change in visual patterns. Identifying visual patterns from drawings is called shape semantics and plays an important role in organising decisions and providing order.
The need for a formal method of differentiation and classification for individual expression was recognised early in the development of computational analysis and in particular in linguistics and authorship attribution. More recently in the design domain, the development of computational techniques has lead to similar methods of formalising these techniques (Gero and Kazakov, 2001, 2002; Jupp and Gero, 2004). Style is considered here as an ordering principle and allows the array of artefacts to be structured in what would otherwise be a chaotic domain.

2.1 DRAWING ANALYSIS MODEL

Drawings in the form of plans are a standard form of representing an architectural design. However visual patterns within a drawing can be derived at a variety of levels. The type, frequency and sequence of both shape and spatial features may be seen as particular to the individual or period. Without a canonical representation it is not possible to compare drawings or features identified within them. We achieve this by implementing an existing qualitative encoding schema in our model. The parsing program consists of a three class qualitative schema (Jupp and Gero, 2004) and automatically encodes a floor plan. The measurement program consists of a set of information theoretic tools. Figure 1 illustrates the drawing analysis model.

The parsing procedure consists of three discrete sequential processes. These processes are: plan contour and graph generator, shape/space encoder, feature detector, and continues in three cycles until a plan drawing is encoded. The method of feature identification and re-representation is organised cyclically when more abstract features are identified on the basis of current available features, then a new representation on the basis of these new features is produced. The program interprets the plan and determines its morphology, topology and mereotopology, returning sequences of symbols.
This provides three kinds of ‘languages’, which distinguish different shape and spatial characteristics of the drawing.

Once drawings are encoded they represent a plan in a canonical form. The measurements are carried out by integrating the CMU-Cambridge statistical language modelling toolkit (Clarkson and Rosenfeld, 1997). We have implemented two different algorithms for differentiation and categorisation: Shannon entropy and Liv Zempel complexity.

2.1.1. Qualitative Representation

Two-dimensional orthogonal design drawings are represented as a qualitative description of basic elements that describe three levels of information. The schema is based on landmarks for boundary- and graph-based representations that capture relational variations in which abstraction and successive derivatives are represented symbolically. The shape and spatial characteristics are articulated in relation to constraints placed upon plan contours and subsequent topological and mereotopological graphs. The schema represents in detail the physicality of shapes and spaces as a sequence of symbols that is assumed to denote its pictorial characteristics.

At the first level of the hierarchy two basic intersection attributes are encoded into qualitative value signs to describe plan morphology, listed in Table 1.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>The vertex produced by two edges intersecting when viewed from inside the acute angle produced by the intersection of the walls they represent (convex).</td>
</tr>
<tr>
<td>⊥</td>
<td>The vertex produced by two edges intersecting when viewed from the complementary angle (concave, complement of convex).</td>
</tr>
</tbody>
</table>

The relative lengths of segments are incorporated for each of the intersection descriptions which are annotated with a symbol indicating the relative length of the segment, i.e., equal to “s =”, greater than “s +”, or less than “s −”, where s is the symbol value.

At the second level of the hierarchy intersection attributes are encoded into qualitative value signs to describe plan topology. By taking the topology graph, semantics can be added to its edges where they cross shape contours. In addition to the values defined at the previous level i.e., “L”, “⊥”, three new values “T”, “⊥”, “+” are created, listed in Table 2.

TABLE 1: Two qualitative intersection types

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td></td>
</tr>
<tr>
<td>⊥</td>
<td></td>
</tr>
<tr>
<td>+</td>
<td></td>
</tr>
</tbody>
</table>
A COMPUTATIONAL CLASSIFICATION OF DESIGN DRAWINGS

TABLE 2: Three qualitative intersection types

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>The vertex produced by three arcs intersecting when viewed from inside either of the acute angles, (straight/right-angle).</td>
</tr>
<tr>
<td>⊥</td>
<td>The vertex produced by three arcs intersecting when viewed from the complementary angle, (complement of straight/right-angle).</td>
</tr>
<tr>
<td>+</td>
<td>The vertex produced by four arcs intersecting when viewed from inside any of its acute angles, (four right-angles is its own complement).</td>
</tr>
</tbody>
</table>

Characteristics of topologies are represented through the dyad of the five intersection attributes to produce dyad symbols. A dyad symbol is defined as a subset of intersection symbol values describing topological features including: complete adjacency, partial adjacency and offset. The definitions of the three adjacency regularities are provided in Table 3.

TABLE 3: Dyad symbol values

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>A subset of dyad symbols: {L ∧ T ∧ +}; where ( C ) is a semantic symbol value denoting complete adjacency, and the set {n} is labelled according to intersection type: ( C \subseteq {L ∧ T}; {T ∧ T}; {L ∧ ⊥}; {T ∧ ⊥}}; {L ∧ +}</td>
</tr>
<tr>
<td>P</td>
<td>A subset of dyad symbols: {L ^{¬} ∧ T ^{¬} ∧ ⊥ ^{¬}}; where ( P ) is a semantic symbol value denoting partial adjacency, and the set {n} is labelled according to intersection type: ( P \subseteq {⊥ ^{¬} ∧ T ^{¬}}; {L ∧ +}; {T ∧ ⊥}}; {T ∧ ⊥}; {T ∧ +}}; {L ∧ ⊥}; {L ∧ +}</td>
</tr>
<tr>
<td>O</td>
<td>A subset of dyad symbols: {L ∧ ⊥ ∧ ⊥ }; where ( O ) is a dyad symbol denoting offset, and the set {n} is labelled according to intersection type: ( O \subseteq {⊥ ^{¬} ∧ T ^{¬}}; {L ∧ +}; {T ∧ ⊥}}; {T ∧ ⊥}; {T ∧ +}; {L ∧ ⊥}</td>
</tr>
</tbody>
</table>

At the third level the dual topology graph, called a mereotopology graph, is constructed to describe spatial characteristics in relation to the whole. For each edge in the mereotopology graph labels are derived from dyad symbol values corresponding to edges identified in the topology graph. Composite symbol values are produced which describe relations of contact and organisation, such that the properties meets/met-by, contains/contained-by, and overlaps/overlapped-by are identified. Definitions of the three semantic regularities are provided in Table 4.

TABLE 4: Composite symbol values

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>R’</td>
<td>A subset of topology feature types: { C ^{¬} ∧ P ∧ O }; where ( R’ ) is a composite symbol value denoting transfer, the set {n} is labelled according to dyad symbols: ( R’ \subseteq { C ^{¬} ∧ P}; {C ∧ O}; {P ∧ C}}</td>
</tr>
<tr>
<td>S’</td>
<td>A subset of topology feature types: { C }; where ( S’ ) is a semantic composite value denoting correspondence, the set {n} is labelled according to dyad symbols: ( S’ \subseteq { C ∧ C} )</td>
</tr>
<tr>
<td>T’</td>
<td>A subset of topology feature types: { P ∧ O }; where ( T’ ) is a composite symbol values denoting anti-symmetry, the set {n} is labelled according to dyad symbols: ( T’ \subseteq { P ∧ O}; { O ∧ P}}</td>
</tr>
</tbody>
</table>
This converts the drawing into a circular string of codes and creates the common representation for different drawings. The qualitative codes are composed in a similar way to any natural language. A sequence of codes forms a word that may represent a shape or spatial pattern of significance such as a primary shape with protrusions or indentations, the spatial offset of two regions, or a region contained by one or more other regions. This provides an alternative to the numerical representations used in CAD systems and has the ability to deal with classes of shape and spatial features rather than simply instances of them.

Once the drawings are encoded in this canonical form, we can work with the symbol strings that represent these drawings and measure the amount of information they contain.

2.1.2. Information Theoretic Measures

Information theory (Shannon, 1948) is commonly applied in the analysis of natural languages, music, the arts and aesthetics (Attneave, 1959; Moles, 1966; Berlyne, 1971 et al). We use two measures provided by classic information theory: Shannon entropy and Ziv-Lempel complexity. Each of these measures provides an integral value over the whole drawing or set of drawings of its information content. Gero and Kazakov (2001) describe the intuitive idea behind this approach as the more information that is necessary to describe the particular drawing the higher its complexity and the closer to each other are the distributions of features in two shapes, the higher is the degree of similarity between them.

Shannon entropy is based on a simple statistical model of data, which assumes that they are generated by an ergodic Markov source, symbol after symbol or feature after feature. This generation is executed stochastically on the basis of the history of which symbols have been generated. The entropy is calculated as:

\[
En = - \sum_{i,j} P_S(q_i, q_j) \log \text{Prob}_M(q_i, q_j)
\]  

where \( P_S(q_i, q_j) \) is the empirical probability of the symbol \( q_i \) following \( q_j \) in this sentence.

Entropy is a measure that can only be calculated for an ensemble of similar sequences. Thus, if we have a group of similar drawings we can calculate entropy for each symbol sequence. Those that have higher entropy values, will be declared as more complex than the ones with the lower values of entropy. For different groups of drawings the comparison between the symbol sequences can be carried out by computing perplexity. Perplexity, \( PP \), is defined as:

\[
PP = 2^{En}.
\]
The higher the perplexity the further apart are the two generators from each other and less similar are the two symbol strings being compared. When perplexity of one corpus of symbol strings is computed with respect to the other corpus, the mean “distance” between corpuses can be obtained. However the usefulness of Shannon entropy as a complexity measure is limited since it is applied to the process generating the symbol string rather than to the resulting string itself. Therefore Lempel-Ziv compression, LZ, as a complexity measure is utilised as it is defined by the symbol string itself rather than process that created it. LZ has been used to show how individual drawings can be used to track changes over time (Gero and Kazakov, 2001).

The measure LZ (Ziv and Lempel, 1978) is essentially the number of cumulatively distinct words in the symbol string descriptions and determines how far a description can be compressed. The heuristic idea is that the most complex drawings are those ones whose description cannot be compressed. LZ can be computed for individual shapes and spatial relations and can be used to compare characteristics that belong to different categories, for example, belonging to different styles.

3. Applying Model to Architectural Design Drawings

We assume that by sampling a designer’s corpus of two-dimensional plans it may be possible to identify a pattern that distinguishes their designs and their development over time.

We describe two experiments that evaluate each of the three different canonical representations using the objective quantitative measures outlined previously.

3.1 EXPERIMENT 1: SKETCH ANALYSIS

This experiment involves an analysis of simple sketches drawn by a design student. The objective of this experiment is to demonstrate the descriptive power of the drawing analysis model. The strength of the qualitative representational schema enables us to describe sketches at the early stages of designing when objects do not yet have a fixed geometry, only an indicative one based on their topology and mereotopology. The twelve sketches used in this experiment are illustrated in Figure 2.
Figure 2. The twelve sketches used in Experiment 1

The sketches were produced as the result of three criteria: equivalent perimeter shape, equivalent structural description, and equivalent number of shapes (six). Thus, the morphological descriptions of the sketches in Figure 2 are all equivalent, resulting in equivalent measures of similarity and complexity for the first level of analysis. In order to differentiate between sketches and categorise them a measure that relies on descriptions of internal shape features and their spatial relationships, i.e. topological and mereotopological symbol strings, need to be used.

3.1.1 Similarity measure for sketches
The perplexities of the topology and mereotopology symbol strings for the sketches in Figure 2 are shown in Table 5. From this table one can see that the perplexities vary significantly which confirms the discriminatory power of the approach. The higher the perplexity the more complex the sketch.

<table>
<thead>
<tr>
<th>Sketch</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
<th>L</th>
</tr>
</thead>
</table>

Examining the results in Table 5 we can see that for topology sketch “C” has the highest complexity with a perplexity of 4.56. Sketches “E” and “F” have the lowest complexity with a perplexity of 3.36. In Figure 2 we can see that “C” is the only sketch that contains all symbols of the topology alphabet requiring more information to describe the types of adjacency between two shapes. Sketch “E” and “F” contain only four topology symbols, contains the
lowest number of intersections and therefore requires less information to describe the types of adjacencies. A different behaviour is observed in the results for mereotopology perplexities. Sketch “K” has the highest complexity with a perplexity of 4.42 and sketch “B” the lowest complexity with a perplexity of 3.67. The mereotopology string is comprised of an alphabet that describes regions in relation to the whole. The results for mereotopological perplexity suggest an inverse relation between perplexity and the degree of visual order intuitively perceived in the sketches. We can observe that sketch “B” has a low perplexity measure and contains a high degree of visual order. Sketch “K” has a high perplexity measure and contains a low degree of visual order.

In addition, we can also rank perplexities as a percentage of the data set in order to derive categories of similar sketches. The percentile rank for topology and mereotopology perplexities form categories based on the number of standard deviations:

- **Topology categories:** (0: E, F), (0-0.34: H, J, K, L), (0.34-0.68: A, B), (0.68-1.02: C, D, G, I).
- **Mereotopology categories:** (0: B), (0-0.33: A, D, G), (0.33-0.66: E, F, H, J), (0.66-0.99: C, I, L), (0.99-1.32: K).

The percentile rankings identify four different categories for topology and five different categories for mereotopology. The results imply that the similarity of the sketches in Figure 2 changes as a higher level of spatial information is abstracted.

From Table 6 we can see that the topology has a mean perplexity of 3.88 and the mereotopology has a mean perplexity of 4.09. Thus, typically for the sketches in Figure 2 there is a higher mereotopological perplexity than topological perplexity, as can be seen in Table 5 for sketches: E, F, H, J, K and L.

<table>
<thead>
<tr>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topology</td>
</tr>
<tr>
<td>Mereotopology</td>
</tr>
</tbody>
</table>

For those sketches where the inverse condition is true, i.e., sketches: A, B, C, D, G, and I, one spatial characteristic differentiates: the occurrence of four closed regions meeting at a common vertex. We could reason that where this spatial characteristic occurs, there is a higher degree of visual order hence the complexity of the mereotopology description decreases. However, it is significant that there is no dependant correlation between high topological complexity and low mereotopological complexity or vice versa.
For example, we can observe high perplexity measures for both topology and mereotopology in sketch “C” and “I”. Although the mereotopology string is derived from features identified in the topological string, the information abstracted describes another level of spatial characteristics. Therefore perplexity measures for each string type are independent of the previous level’s result.

3.1.2 Complexity measure for sketches

A random symbol sequence will have a characteristic number of distinct words and therefore we can calculate the value of LZ for a given length of the sequence and size of alphabet. This provides a natural scale for LZ and allows the use of an absolute (relative to these two limits) value of LZ for an individual sketch’s topology and mereotopology.

The results for the sketches in Figure 2 are shown in Figure 3. The figure contains two graphs that show the topological and mereotopological empirical dependences on sketches for the LZ complexity and linear regression for each “cluster” identified.

![Figure 3](image)

*Figure 3. The dependence of the maximal LZ for topology and mereotopology on sketches.*

Figure 3(a) indicates that the complexity of the sketches increases with the number of intersections created in the arrangement of shapes. The graph in Figure 3(b) indicates the change in four ranges of complexities produced as the type of spatial relationships increases. We can observe from this graph that there are only slight changes within each range.

The model implemented here is one approach to design differentiation and classification. These simple experiments form the basis for comparisons within an individual architect’s drawing corpus in the following experiment.

3.2 EXPERIMENT 2: ARCHITECTURAL PLAN ANALYSIS

In this experiment we analysed the architect Frank Lloyd Wright’s plan drawings for residential designs span five decades, Figure 4.
Figure 4. Wright’s residential projects over five decades, measured by decade.

Figure 4 represents a time line of each period and number of projects. Decades shown as shaded white represent what we refer to as Wright’s Early and Transition periods. Decades shown as shaded dark grey and light grey represent the two periods described by critics and historians as Prairie, spanning two decades and Usonian. Prairie and Usonian periods are significant since they are identified historically as ‘styles’. Figure 5 shows two plan drawings typical of Wright’s Prairie and two plan drawings of typical Usonian designs.

Figure 5. Wright’s architectural plan drawings: (a), (b) Prairie and (c), (d) Usonian.

Prairie houses were characterized by horizontal lines that are reflected in the geometries of 2D plans. Typically, these structures were built around a central
chimney and consisted of open spaces instead of strictly defined rooms. The Usonian style represented a revolutionary change in domestic planning where the living room and dining room were unified in a single space, and the kitchen was only partially separated from the living area.

A total of 49 plans were coded in the three “sentence” types, morphology, topology and mereotopology. The resulting symbol strings were separated into groups that belong to the different decades in which they were designed. Each drawing was evaluated and the perplexities and compression were calculated.

At the very least we expect to find that the proposed technique is able to differentiate between Wright’s Prairie and Usonian designs for one or more string types. This is based on the assumption that there have been changes in the complexity of drawings Wright produced during these decades. In other words the corresponding measures for plan drawings must be statistically different for one or a combination of the three shape and spatial descriptions.

3.2.1 Similarity measure for FLW
The mean or overall perplexities of the plan drawings from the different time intervals for Wright are shown in Table 7.

<table>
<thead>
<tr>
<th></th>
<th>Early 1890-1900</th>
<th>Prairie 1900-1910-1920</th>
<th>Transition 1920-1930</th>
<th>Usonian 1930-1940</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Morphology</strong></td>
<td>2.03</td>
<td>2.23</td>
<td>2.27</td>
<td>2.35</td>
</tr>
<tr>
<td><strong>Topology</strong></td>
<td>4.02</td>
<td>5.12</td>
<td>5.20</td>
<td>3.36</td>
</tr>
<tr>
<td><strong>Mereotopology</strong></td>
<td>2.97</td>
<td>3.21</td>
<td>3.20</td>
<td>3.29</td>
</tr>
</tbody>
</table>

From the table we can see minor variations within the morphology perplexity as well as mereotopology perplexity, indicating strong similarity in Wright’s morphological characteristics as well as mereotopological characteristics. However the topology perplexity varies more significantly. This indicates that the complexity of the topologies of Wright’s plans fluctuated during the four periods but remained steady over the two decades which correspond to the Prairie style. We can also see for these two decades that the morphological and mereotopological perplexity also remain steady, where for the first of the Prairie decades the perplexities are: 2.23 / 5.12 / 3.21 and the for second decade are: 2.27 / 5.20 / 3.20. These results imply that Wright did not significantly change the complexity of the Prairie style over time.

3.2.2 Complexity measure for FLW
The results of LZ complexity for Wright’s residential designs are shown in Figure 6. The figure contains three graphs that show the empirical dependence on decades of the LZ and their polynomial regressions.

Figure 6(a) indicates that the complexity of plan morphology steadily increased then decreased in the following decade and continued to decrease from 1930-1940. This indicates that the complexity of plan morphology was highest during the two decades of the Prairie style than for the decade of the Usonian style. In Figure 6(b) we can see that the complexity of plan topology increased steadily from the 1890s, peaking around the mid 1910s with the Martin House (1904). From 1910 to 1930, topological complexity decreased and then slightly increased from 1930 – 1940 during Wright’s Usonian style. Figure 6(c) indicates the change complexities for mereotopology, where a steady increase throughout the length of Wright’s practice with a slight trough occurring in the second decade of the Prairie style and the Transition period. From these results we can identify how the morphological, topological and mereotopological strings characterise each design period. Table 8 illustrates the patterns of change as characterised by the levels of complexity: low, medium and high which are scaled on the basis of number of standard deviations.

<table>
<thead>
<tr>
<th></th>
<th>Morphology</th>
<th>Topology</th>
<th>Mereotopology</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Early</strong> 1890-1900</td>
<td>LOW</td>
<td>LOW</td>
<td>LOW</td>
</tr>
<tr>
<td><strong>Prairie</strong> 1900-1910</td>
<td>MEDIUM - HIGH</td>
<td>HIGH</td>
<td>MEDIUM</td>
</tr>
<tr>
<td><strong>Prairie</strong> 1910-1920</td>
<td>HIGH</td>
<td>HIGH</td>
<td>MEDIUM</td>
</tr>
<tr>
<td><strong>Transition</strong> 1920-1930</td>
<td>MEDIUM - HIGH</td>
<td>MEDIUM - HIGH</td>
<td>LOW - MEDIUM</td>
</tr>
<tr>
<td><strong>Usonian</strong> 1930-1940</td>
<td>MEDIUM - HIGH</td>
<td>LOW - MEDIUM</td>
<td>HIGH</td>
</tr>
</tbody>
</table>

These results imply that the drawing analysis model presented here provides the potential to reveal patterns of change for related designs. In this
example one ‘style’ has grown to dominate the design population with distinct and consistent shape and spatial characteristics but is later replaced by another style. By examining changes at key design periods transitions from one dominant ‘style’ to another can be associated with substantial change at a single point, with the affected style varying from transition to transition. We propose that categories that can be derived from information theoretic measures characterize the scale at which transformations occur. Further insights into design transformations may be gained by examining the differences in design sequences between two or more architects.

Discussion

Differentiating between two design drawings and assessing the degree to which they are similar is critical in the development of conceptual design tools and for automated classification and information retrieval. Current CAD systems are unable to aid the designer in the perception of figures and gestalts and in the recognition and categorisation of shape and spatial characteristics.

Typically an individual may categorise objects by associating visual representations which later serve as a semantic framework for related concepts. Consequently information about a newly encountered design is categorized and re-categorised and is integrated with the already formed concepts. Individuals can then differentiate a new design – if it is alike or different from a certain design class. Our ability to identify visual similarities makes past designs relevant to present ones.

The computational model presented here enables the identification of shape and spatial semantics and measures their similarity and complexity in relation to other drawings. Our approach of an objective information theoretic measure for differentiation and classification of design forms the basis of a computational characterisation of style. This approach provides the potential to develop our understanding of style, its role in design and ways of formalising style that extend beyond existing approaches. Computing an architectural plan’s information and distinguishing designer’s styles provides the basis for new kinds of CAD tools that could be used at the conceptual stage of design.

The dynamics identified within the results of our experiments give rise to the characteristics common in the architectural domain by describing patterns of continuous change through time, but approximately constant design diversity at any instant. Although it is of considerable theoretical interest, the patterns that can be identified within and between design corpuses have important implications for designers. The limited diversity of any defined design style at any point in time makes feasible the use of mass
production techniques using only a few design features, but design transformations necessitates a kind of updating of those features. Given that the mass production of new designs may take several months, design efficacy depends on accurately predicting the design style likely to dominate transmission in the future. A future research goal is therefore to develop our model as a prediction technique used to select a design style. The technique we present can be utilized to evaluate those changes in designs and suggests a more systematic approach to predicting design based on style.

Acknowledgements

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References