Let's Look at Style:

Visual and Spatial Representation and Reasoning in Design

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Abstract. This chapter explores the perception and modeling of style in design relating to visuo-spatial representation and reasoning. We approach this subject via cognitive and contextual considerations significant to the role of style during designing. A designer's ability to represent and reason about design artifacts visually and spatially allows meaningful 'chunks' of design information to be utilized relative to the designer's task and context. Central to cognitive and contextual notions of style are two issues, namely the level of semantic interpretation, and the comparative method's degree of contextual sensitivity. This compound problem requires some explicit and cognitively plausible ordering principle and adaptive measure capable of allowing for dependencies in reasoning about similarities. This chapter first investigates the perception of style in relation to these modeling requirements before demonstrating and testing their implementation. We then discuss style in relation to design tasks and how they can be supported via the classification and retrieval of designs from large databases of visuo-spatial information.

1. Introduction

The term style is polysemous and can refer to ideas concerning the product, process, modality, period, region, society, culture, etc. The conceptualization of style explored in this chapter is based on the visual and spatial perception of an artifact's style. That is, when we are consciously aware of the similarity between artifacts it becomes a concept in its own right and is what we referred to as 'style' [1]. Our study of style therefore proceeds using a product or object-based viewpoint. A well accepted definition of this perspective, characterizes style as an ordering principle that allows artifacts to be structured according to some set of criteria [2].

In design, the comparison of artifacts and assignment of formal or ad-hoc styles plays a crucial role. Across a range of different design domains, such as architecture, industrial design and graphic design, an individual's abilities to perceive, (detect and recognize) shapes, their spatial relationships and the similarities between them are important cognitive 'mechanisms'. These cognitive abilities are integral to, for example, Architectural and Art History in enabling the formal recognition and labeling of styles such as 'Romanesque', 'Gothic' and 'Baroque'.

However, these abilities also play an essential role in the design process allowing ad-hoc styles to be applied so as to structure information and create categories of visuo-spatial information whilst designing. Two-dimensional (2D) design diagrams, such as architectural plan and elevation diagrams, are an interesting instance of the artifacts that designer's typically reason about and between during designing. Architectural design diagrams are an attractive application area for studying style via visual and spatial representation and reasoning because they capture and convey designs of the built environment using properties of constituent geometric components, allowing tractable investigations and modeling.

Accordingly, this chapter explores the perception and modeling of style in design, and asks: what makes the style of a design diagram perceptible and how can we model style such that the automated analyses of designs are sensitive to (and therefore useful within) the designer's context?

We approach the first part of this question, from a qualitative feature-based standpoint. The perception of design style requires judgments of visuo-spatial similarity such that two or more artifacts can be decomposed into elements in which they are the same and elements in which they are different. Researchers have shown that the information utilized by human observers during visuo-spatial reasoning is typically qualitative in nature [3]. In other words, in judgments of physical similarity, reasoning is typically intuitive and based on the individual's commonsense knowledge [4, 5, 6].

The second part of the question, how can we model style, is a computational analysis problem that depends largely on the design domain of interest, the database in question, and the amount of *a priori* information available. We approach this analysis-based problem in light of a number of cognitive and contextual considerations which are significant to how the boundary of a style can be drawn differently according to the design task. In building on the foundation of qualitative re-representation we underscore the importance of the preservation of salient design feature semantics. Our approach therefore also emphasizes the contextual properties of comparative visuo-spatial analyses. Accounting for context is important since during designing, designers are capable of perceiving a design artifact's physical characteristics, interpreting their feature semantics, assigning higher importance/weighting to certain features and comparing each design using a number of different visual and spatial dimensions – and all relative to their design task. How similarities are perceived and where the boundaries of a design style are drawn by a designer may be influenced by the designer's intentions and goals. Interpreting a diagram and distinguishing some design style can be dependent on the relevance of physical characteristics relative to the designer's context.

In considering both cognitive and contextual aspects of style this chapter's main objectives are highlighted, namely to (1) bridge the gap between the low-level structural features of design artifacts and the high-level semantics used by designers to understand design content; and (2) develop a model of style which is cognitively plausible and sensitive to context. Addressing these issues is critical to creating a digital characterization of style which is useful to designers.

1.2 Overview

The remainder of the chapter presents our investigation into the visuo-spatial perception and modeling of style. Section 2 continues with an examination of style in relation to the properties of similarity, explores the case for qualitative reasoning and presents our earlier research on computational stylistics in design. Section 3 outlines a digital characterization of style and method of analysis. Sections 4 briefly presents the details of the approach. This section firstly reviews the basics of a qualitative encoding schema for representing visual and spatial information and deriving feature and shape semantics. Secondly we present the technique for assessing design diagrams using multi-dimensional datasets and an artificial neural network. Section 5 tests the model's cognitive plausibility and contextual sensitivity so as to investigate the qualitative, multi-dimensional and context-dependent approach to visuo-spatial reasoning. Lastly, in Section 6 we discuss the results of our experiments in relation to an object-viewpoint of style and current perspectives within and outside the design field. The aim of this discussion is to analyze our results and the insights that can advance our understanding of style with regard to how designers may be assisted in visual and spatial reasoning design tasks. Whilst a number of hypotheses and results are validated, others suggest specific areas for future experimentation.

2. Perception of Design Style

Identifying the style of a design is a judgment process. Human observers are able to search for, recognize, and interpret salient features in design diagrams (as well as all other visually and spatially perceptible artefacts) enabling the detection of physical resemblance and ultimately the identification of a member or many members of a style. Design artefacts can be described as belonging to the same style to the degree that they have a particular dimension in common and are not differentiated by any distinctive one, that is, the degree of their similarity. An object viewpoint of style can therefore be closely coupled to the concept of similarity; and approaching style via this related concept raises important properties surrounding visuo-spatial similarity detection and the nature of reasoning used in making comparisons.

2.1 Style and Similarity

The last 40 years of research surrounding the concept of similarity has provided a variety of insights on both theoretical and empirical levels; see [7, 8, 9, 10]. However, ongoing debate persists regarding the cognitive (or psychological) and contextual properties of similarity. Many studies centre on the analysis of whether similarity satisfies properties of triangle inequality, symmetry and minimality in relation to the metric distance function utilised for comparative analysis; whilst others focus on contextual aspects related to visual and spatial reasoning.

Triangle inequality is one of the most common properties of similarity explored by researchers; see [7, 8, 11, 12]. Triangle inequality implies that if *a* is similar to *b*, and *b* is similar to *c*, then *a* and *c* cannot be very dissimilar from each other. Looking at an example of this property, if the Frank Lloyd Wright plan shown in Fig. 1a is similar to the Louis Kahn plan in Fig. 1b; and if the Louis Kahn plan in Fig. 1b is similar to the Alvar Alto plan shown in Fig. 1c, then the Frank Lloyd Wright plan must be somehow similar to the Alvar Alto plan. However whilst it is possible to recognise similarities between plans in Fig. 1a and 1b and between plans in Fig. 1b and 1c intuitively, this statement is hard to accept, as can be seen in the case of the plans shown in Fig. 1a and 1c.

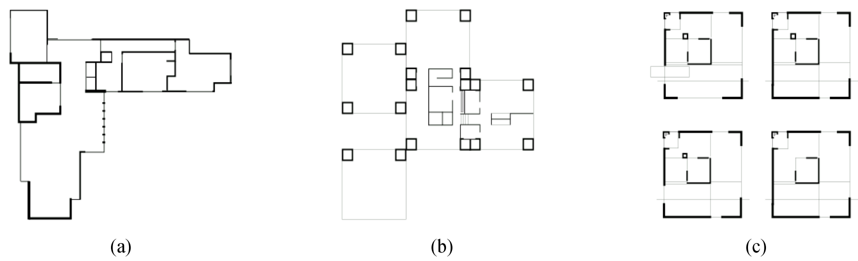


Fig. 1. Frank Lloyd Wright, Louis Kahn, and Alvar Alto residential plan design diagrams

This example illustrates that similarity is not always transitive and triangle inequality fails due to the different emphasis on features and dimensions that are used to evaluate similarity [11, 12]. In the example above plan topology is the basis of the similarity between the Frank Lloyd Wright plan (Fig. 1a) and the Louis Kahn plan (Fig. 1b); whereas plan morphology is the basis of similarity between the Louis Kahn plan (Fig. 1b) and Alvar Alto plan (Fig. 1c).

Further, similarity is not always a symmetric relation [7]. That is, the similarity between *a* and *b* does not always equal the similarity between *b* and *a*. In the naïve view of the world, similarity defined in terms of conceptual distance is frequently asymmetric [13]. Asymmetry of similarity may result from the type of features characterising two objects [11]. Returning to the example in Fig. 1 we can see that the shape features that make up all three plans differ. Fig. 1a is composed of rectangles and complex L-shapes, and in Fig. 1b varying sizes of square shapes are dominant, whereas in Fig. 1c there are a combination of squares and rectangles.

Another property of similarity distance models is minimality. The property of minimality implies that the distance in similarity between *a* and itself will be less than the distance in similarity between *a* and *b*. Although most studies assume that similarity satisfies minimality, Tversky [7] argues that the same self-similarity for all objects implied by the minimality property does not hold for some similarity evaluations. For example, the variation of self-similarity may be related to prototypical characteristics of the design artefact within the domain. Consequently, the measure of similarity between a design and itself may be related to the status of the artefact within the domain [11]. Here we assume that similarity most often satisfies the minimality property, because what matters is that the self-similarity must be larger than the similarity between two different objects.

In addition to these cognitive properties of similarity, there are also related contextual aspects. Studies have found that the similarity of representations is influenced by contextual dependencies [14]. Context in a design environment is a set of circumstances or facts that surround a particular design task.

Other studies have demonstrated that similarity processing often depends on context [15] and increasing consensus therefore regards similarity as a context dependent property [10, 16]. These views are particularly relevant in design since the designer operates within a context and their perception and judgement of design similarities are influenced by it. Yet they have largely been overlooked in modeling an object view of style and its analysis [17, 18].

Correspondence refers to when subjects pay more attention to those features that are similar in the assessment of objects, or pay more attention to distinctive features in the assessment of difference [7, 11]. Applying this notion to design, the similarity between two diagrams is only be established when their features are placed in correspondence, which is determined by their distribution. The degree of correspondence will depend on their consistency in relation to other diagrams in the set, as demonstrated by the example plan diagrams of Fig. 1. The matching of corresponding features has a greater contribution to the similarity rate than the matching of features that do not correspond [19, 20] .

Another contextual aspect that can influence similarity assessment is classification itself. The diagnostic value of a feature is determined by the frequency of its classification that it is based on. Thus, similarity has two faces, causal and derivative. It serves as a basis to classify objects, but can also be influenced by the adopted classification [7]. The effects of the range and frequency of similarities are also associated with categorical judgements along any single dimension.

2.2 Style and Reasoning

How human observers reason about and between the similarity of artifacts is a main concern in an understanding the perception of style. Psychologists and cognitive scientists have pursued questions of how people classify objects, form concepts, solve problems and make decisions based on perceived similarity [see: 7, 8, 9, 10, 15, 16, 21, 22]. Much of this debate has surrounded the investigation of the variables used for reasoning and the different forms of reasoning.

However, in design research, there is still a lack of understanding of how designers classify, form concepts and make decisions based on the similarity perceived between two or more designs. Tversky [23] has shown in cognitive experiments that when reasoning about design diagrams, individuals are able to make comparisons across a variety of dimensions intuitively using abstraction, approximation, aggregation and other techniques to generate manageable spatial descriptions. However, a deeper understanding of the nature of visuo-spatial comparisons and forms of visuo-spatial reasoning in the design domain is lacking [24].

Our own cognitive studies in the design domain investigating the process of visuo-spatial categorisations have shown that during designing, ad hoc visual sorting of 2D design diagrams largely depends on an initial similarity assessment which is then later revised [24]. From this regard, the high-level semantic content contained in design diagrams often results in the initial assessment being revised a number of times in light of the designer's task. The process may be intuitive and yet meta-cognitive as an awareness of the similarities between each diagram's features emerges on subsequent revisions of initial assessments. Further, when designers judged the similarity of two diagrams the dimensions themselves or even the number of dimensions were not known and what might have appeared intuitively to be a single dimension were in fact be a complex of several [17].

Thus, the information used to perceive information exists on a number of different visuo-spatial dimensions. There are two general criteria, which have been distinguished by Shapiro [25] as significant to the characterisation of style and are therefore considered here as essential: (i) shape elements and attributes; and (ii) spatial relationships. The approach to re-representation in a computational model plays an important role in providing cognitively plausible comparisons not only from the perspective of what and how many dimensions are represented but also how they are re-represented. Qualitative approaches to representation are a common analysis paradigm in design reasoning applications because they provide a mean to map on to feature semantics. Using such common-sense descriptors supports the identification and comparison of designs that are not only structurally or spatially close but also conceptually close, whilst not being identical.

Yet, the qualitative encoding of a design diagram using multiple spatial ontologies so as to obtain a rich variety of feature semantics is a complex re-representation problem. Due to the complexity of imputing semantics relevant to a specific domain, this approach has been less prominent in models of style.

Furthermore, an important issue not addressed in style related research in design, is the issue of the cognitive validity of spatial representation languages and their ability to capture information significant to reasoning tasks. For example, in the field of computer vision, claims that qualitative reasoning is akin to human reasoning have typically not been supported with empirical justification. Exceptions to this can be found in contributions made by Gould et al. [26] of a calculus for representing topological relations between regions and lines, and by Knauff et al. [27], who investigated the preferred Allen relation. Until recently, no such studies existed in design research to support the validity of a proposed qualitative language for re-representing visuo-spatial information and its significance in the assessment of style. In previous research we have sought to address this gap, see [17, 24]. We shall return to this issue in the first experiment in Section 5.

3. Computational Stylistics

Other chapters of this book, namely the semantic analysis of texts discussed (Chapter ?? Argamon and Koppel), and the relation of musical perception to the production of rules (Chapter ?? Koppel), both approach style via the assessment of the composition of information contained in some artefact. Whilst text and music analysis fields are more common research domains in computational stylistics, in design, there is also a growing interest in its application. Despite the lack of cognitive studies and model validation, in design a variety of computational models have been developed. Here we shall look at related models within design before presenting our own digital characterisation of style.

3.1 Previous Research in the Design Domain

A number of frameworks and models providing automated analysis of design artefacts have been developed [28, 29, 30, 31, 32, 33]. These models are typically based on a re-representation of either 2D or 3D design artefacts and some function of similarity that allows those artefacts to be compared and ordered. These models have been developed as design support systems to aid in decision making, analogy and the perception of Gestalts. Most have directly applied or adapted similarity functions from other fields of research, such as psychology and cognitive science as well as information analysis and retrieval systems. However these existing approaches are limited since comparison ultimately depends on quantifying common elements independent of a designer's task. They therefore present limitations in relation to the cognitive and contextual properties of similarity.

As a result, computational models of style have inherited an emphasis on linear analysis, which focus on distance measures that maintain a static world assumption, that is, where style is treated as unrelated to its locus of application. It is necessary to reformulate approaches to comparative by moving away from the idea of style as the outcome of a direct comparison and move towards the idea that it is a process whose outcome is reported in a post-hoc fashion.

Toward this aim, researchers have sought the benefits of artificial neural networks. Utilising artificial neural networks has many advantages in the treatment of design style as a multi-dimensional, contextually sensitive similarity measure. The underlying mathematical properties of most neural networks used in categorisation are scalar distance-based algorithms. Of these, the Self-Organising Map (SOM) is a typical representative. SOMs can be used in a variety of ways, with a number of different configurations available [34]. Whilst extensively used in other fields of research such as text and image retrieval, SOMs have not been widely utilized in design categorisation systems.

One application known to the authors is a model proposed by Colagrossi et al. [35] for categorising works of art. Colagrossi and his colleagues measured the similarity of Mondrian's Neoplasticist paintings according to a selection of features. By consolidating algebraic functions a variety of parameters were processed with only a few neurons in both the input and output of the SOM. Those parameters considered useful by the authors included line type, line weight and colour. Yet, the application of the SOM by Colagrossi does not address the many of the cognitive and contextual properties of similarity discussed in Section 2.1. This is in part due to Colagrossi's restricted application domain, i.e., distinct design corpus, lack of semantics and contextual relevancies. Under this and other existing approaches to similarity assessment in design, contextually relevant categorisations, are unable to be obtained.

SOMs as a measure of design similarity can be improved by utilising both qualitative descriptions and contextual input. On the one hand, the visuo-spatial information that can be derived from un-annotated diagrams requires rich re-representations at successive levels of abstraction [21] and neural networks are able to process multiple data sets based on qualitative re-representations. On the other hand, the designer may be an inseparable part of the assessment process and neural networks are capable of integrating query by pictorial example (QBPE), which is a common retrieval paradigm in content-based image retrieval applications [36] or via inputting relevance feedback. That is, design queries can be based on an example design diagram available either from the database itself or as a result of the designer's task. The designer classifies an example diagram as relevant or non-relevant to the current classification task, allowing selection of such styles the designer is most likely to be interested in.

QBPE and relevance feedback (RF) is commonly used in text classification and retrieval systems [37]. Yet there appears to be no model of similarity in design that integrates relevance feedback in this way. The implementation of SOM and RF presents a unique approach to computational stylistics in design. Since an analysis of style in the context of some design task may not be capable of returning the relevant style in its first response, the classification process becomes an iterative and interactive process towards the desired style and outcome. The assessment of style may therefore be treated not as a fixed and irreducible concept, but as a process, which takes place over some more-or-less open and variable dimensions of the designs being represented and compared. Under this treatment, the style of a design diagram is contextually-dependent. This view gives less explanatory force to style because it demands analysis of the design attributes whose similarity it computes in relation to context.

3.2 Our Research on Computational Stylistics

Our previous research on a computation model to analyse an artefact's design style has approached style assessment as transient, where the perceived similarities may depend on the corpus in question, the amount of *a priori* information available, the order of design comparison and, when considered in relation to a task specific context, may also depend on design objectives and requirements.

The model, called Q-SOM:RF, [18] has three main components, which are illustrated in Fig. 2, including: (i) Qualitative feature-based re-representation; (ii) Self-organising maps; and (iii) Relevance feedback (RF).

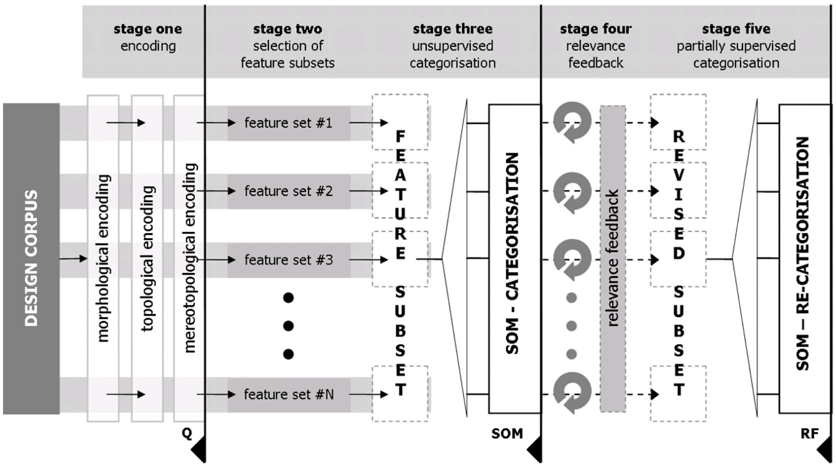


Fig. 2 Q-SOM:RF, stages of un-annotated 2D diagram categorization.

Within the three main components are five consecutive stages: (1) recognition, extraction and encoding of three different levels of spatial attributes, (2) initial feature selection of encoded spatial attributes and combination of feature lists, (3) categorisation via unsupervised learning of design diagrams based on available features, (4) positive and negative feedback processes via the observer's input, and (5) resulting weight adjustment and re-categorisation of design diagrams.

In stage one, each diagram in the design corpus is encoded using a qualitative schema capable of describing sets of higher-level semantics corresponding to three prescribed spatial ontologies. During stage two, feature sets undergo a selection process as part of input pre-processing. A feature subset is produced using either principal component analysis or manual feature selection by the observer. The third stage utilises the feature subset as input to the SOM and categorisation occurs via unsupervised learning. How distances in various feature spaces are weighted and combined to form a scalar suitable for minimization, creates an opportunity to integrate contextual dependencies in the architecture of the SOM [38, 39]. The fourth stage continues as an interactive process that moves from unsupervised categorisation to one which is guided by the observer. The final stage re-categorises diagrams which are similar to the observer's target diagram, meeting some set of target criteria, by ordering those diagrams whose distance to the target is minimal in any or all feature sets. The model is therefore capable of automatically structuring a large design corpus according to selected features or feature semantics as an iterative process, which adapts to an observer's requirements and preferences. Adaptation is based on the relevance of clusters which are judged in relation to some design task.

4. Computational Analysis

This section presents additional detail on the computational approach to style explored in this chapter. We briefly summarise the qualitative representation schema for describing a hierarchy of spatial ontologies and Self-organizing maps (SOM) as the method for design comparison. For more detail see [17] and [18, 40].

4.1 Qualitative Re-representation

Design diagrams are an explicit representation of the artifact's geometry, and it is reasonable to expect that categorization be based on 2D criterion that incorporates geometric properties which are: (i) generic – so that they have applicability over a wide spectrum of application domains, characterize as many physical dimensions of the diagram as possible including orientation, distance and topology; (ii) have both local and global support, i.e., they should be computable on shape primitives and spatial relations; (iii) provide descriptions capable of higher-level semantic mapping, (iv) are invariant over ranges of viewpoint and scale; and (v) are robust, and readily detectable by procedures that are computationally stable.

To satisfy these requirements the process of encoding follows from physicality to symbol to regularity to feature, where: (i) *Physicality* – refers to the graphic descriptions of diagrams indicating the geometric information and is the prerepresentation, upon which a process of information reduction is applied successively over three levels of abstraction; (ii) *Symbol* – refers to the unrefined symbolic encoding of graphic information, whereby spatial attributes are recognized and converted into qualitative symbol values; (iii) *Regularity* – is the syntactic matching stage in which regular or repetitious patterns of encodings are identified and grouped; where detecting characteristics relies on 'chunking' [41]; and (iv) *Feature* – involves matching pre-determined syntactic patterns with meaningful design semantics.

Fig. 3 shows an example of an encoded design diagram labelled according to the principles of physicality to symbol to regularity to feature defined within the qualitative encoding schemata. The example is a simple 2D residential plan drawing of the Farnsworth House, designed by Mies van der Rohe.

The first of four stages commences from the original representation of the design diagram is transformed in to vectorial format. After contour vectorization, three consecutive encoding stages then follow. The mapping from physicality to symbol to regularity to feature involves detecting regularities and matching features from the geometric information so that specific patterns correspond to known feature semantics [41].

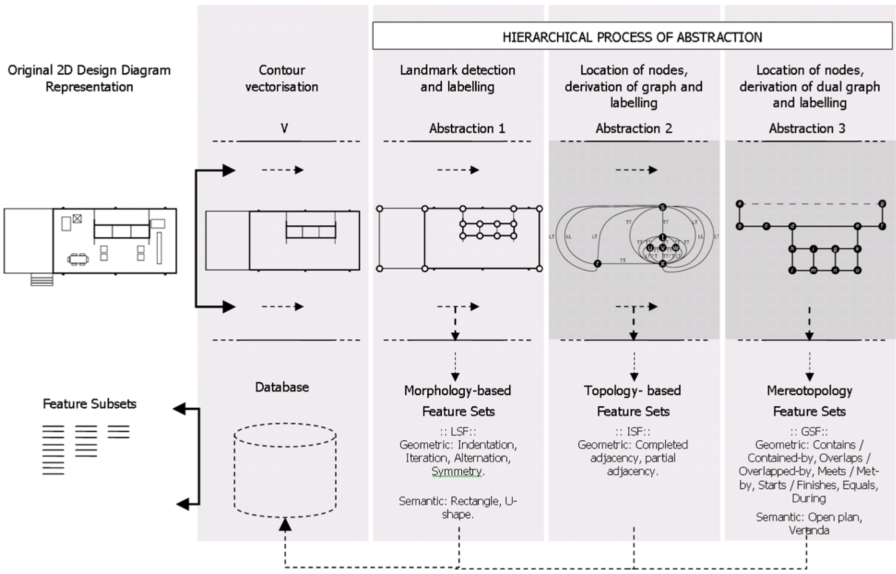


Fig. 3 Example of physical to symbol to regularity to feature mapping for the Farnsworth House by Mies van der Rohe.

This process illustrated above is summarized in the following two sections describing firstly, diagram decomposition and re-representation and secondly, abstraction and re-representation.

4.1.1 Diagram Decomposition and Re-representation

Decomposition and representation (DeREP) divides the problem into smaller more tightly constrained sub-problems by partitioning shapes into vertices and contours. To achieve this, the process eliminates the primary source of complexity by separating unrelated variables into distinct shapes. This process results in a compact and easily understandable description of the structure of the diagram.

The sequence of vertex labelling occurs as an iterative process: contour traversal, vertex detection, value assignment, contour traversal… until circuit completion (shape closure). The problem of computing all possible circuits in the diagram so that each circuit contains all vertices exactly once is achieved by finding all Hamiltonian circuits [42]. A contour cycle (i.e., closed loop) algorithm is implemented where the agent starts the cycle from each point in the diagram and visits each adjacent vertex exactly once until a closed shape is generated or until a maximum branch limit is reached. This process iterates until all possible shapes are found. Once all closed shapes are found starting from all points in the diagram, the final set is filtered to eliminate shapes containing other shapes so that the resulting set contains only the smallest shape units. The perimeter shape is then found as the sum of all of the smallest shape units. Fig. 4 shows a sample diagram and the resulting closed shapes detected.

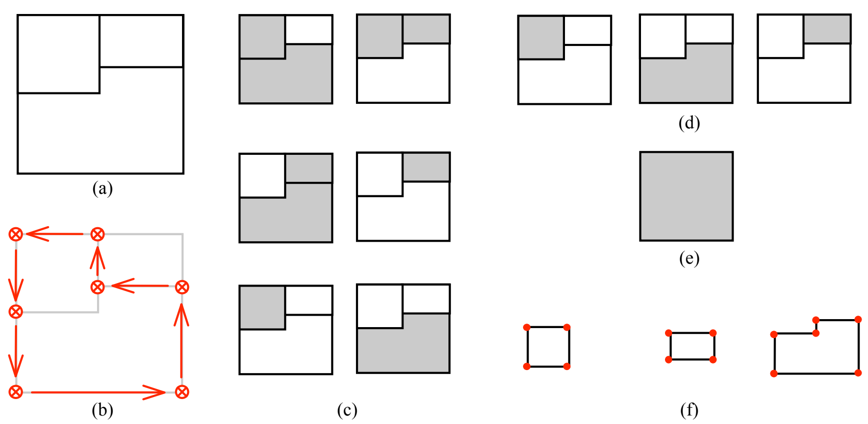


Fig. 4. (a) Original diagram, (b) Hamiltonian circuit, (c) all closed shapes found (d) smallest shape units (e) perimeter or boundary shape and (f) landmarks for labeling.

As line contours are scanned vertex by vertex, the angle and length magnitudes of the previous line segment become the landmark point for the following segment, i.e., landmarks and intervals are set each time a new contour is compared. This enables a description of shape morphology to be obtained.

Morphology Descriptors

Sign values for specifying specific qualities of isolated shape structures are based on a description of attributes encoded at a landmark vertex (intersection) where properties for line contours are divided into two separate codes. The first is a primary code and represents the relative angle of the line contour. The second is an auxiliary code and represents the relative length of the line contour. The formal definitions of primary and auxiliary codes are presented in Table 1. Also see [4].

Table 1 Definition of Qualitative Syntax for Morphology.

	ANGLE CODES	LENGTH CODES
Numeric value range	$0 \le \theta \le 2\pi$	$-\infty \le l \le \infty$
Landmark set	$\{0, \pi\}$	$\{-\infty, 0, \infty\}$
Interval set	$\{(0,\pi),(\pi,0)\}$	$\{(-\infty,0),[0,0],(0,+\infty)\}$
Q-code set	{ L , Γ }	{ L, Γ } ∧ ∨ {− ,=,+}

Where an angular change occurs, landmarks are initially set to π, separating convex and concave angles. The scanning order for each vertex is set to a counter-clockwise direction and the magnitude of the vertex is also measured in this direction. The addition of codes capturing the relative length of contours provides a description capable of distinguishing between shapes without increasing the number of primitives unnecessarily. The two primary codes L and Γ represent a vertex so that individual shapes can be described qualitatively.

Encoding results in a symbol string and a syntactic handling method employing a simple pattern recognition technique is used to group structural and identify semantic aspects of regularities. That is, patterns of symbol sequences denoting specific categories of features that are familiar in contour or identify some particular shape semantic are identified. The descriptions of simply patterns reflect basic repetitions and convexity and simple semantic labels, including: indentation, protrusion, [44], iteration, alternation and symmetry [45] are identified. From these more complex semantic mappings are then defined including primary shape types such as 'rectangle', 'square', 'L-shape', 'U-shape', 'T-shape', and 'cruciform'. Ever more complex semantics that incorporate domain specific knowledge can also be obtained which provide a description of the design concepts, for example, "chambers" and "niches".

These shape patterns are derived from low level structural primitives and describe what we shall refer to from this point as local shape features, or LSF. Features already stored in a database identify syntactic patterns and where the search and matching process examines the type and occurrence of 'chunks' and their structure as a sequence is then labelled. A systematic search for every possible pattern is necessary for the given shape or spatial description.

4.1.2 Abstraction and Re-representation

The DeREP process described above is followed by abstraction and representation (AbREP) which automates the derivation and encoding of two subsequent graph representations from the original diagram. The systematic processing of spatial relations pertaining to topological and mereotopological attributes requires the mapping from physicality to symbol to follow a similar conversion process from the graphic state to the symbolic state as implemented in the DeREP process, i.e., contour traversal, vertex detection, value assignment, contour traversal… etc. AbREP uses the array of symbols describing intersections of line contours and labelling relies on the data structures built from the previous stage.

To encode multiple line attributes, graph diagrams derived from the original contour representation are used as the means by which to parse information in a consistent manner. An 'abstract landmark', see Fig. 5, is created as an array and labelled according to a vertex's specific characteristics. This is achieved by iterating between each set of new graph vertices and traversing every pair. In this way, graphs provide a notion of hierarchy and support bottom-up development.

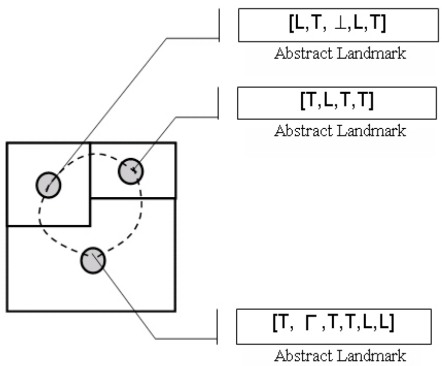


Fig. 5 Shape Encoding: abstract landmark and shape adjacency relations

There is an important aspect of the AbREP process, whereby sets of arrays describing shapes are analysed based on the relationship between each shape. At the contact of two or more shapes, specific extraction and embedding relationships relating the intersection of line contours exists [6]. Where this occurs there is a transformation in representation which extends the encoding of two line intersections to include multiple lines. This is a reduction process whereby some structural information about the shape is lost. However shape adjacencies are captured using a description of vertex arrays. Once the new arrays are derived and labelled a representation of adjacencies is captured. At this level, arrays constitute an approximate representation of the topology of shapes.

Topology Descriptors

The specification method at the level of topology builds on the previous morphological level and such that it is possible to provide a description of spatial attributes in terms of shape adjacencies and area descriptors. The symbols used to describe edges of graphs concern the disposition of physical intersections of lines which have been used to generate the polygon fields that are subsequently analysed as graphs. Edges are labelled according to the intersection type of the two vertices belonging to the line contour it crosses creating a 'dyad' symbol. In other words the pairs of syntax at the level of morphology are collapsed to create a dyad symbol.

The representation of dyad symbols reveals distinctive topological characteristics that are recognised from syntactic regularities. Once the new set is formed the area of a shape is calculated and compared to the area of the adjacent shape to obtain a description of the relative area. As a result the list of area magnitudes combined with their adjacency types is created for each abstract landmark. Formal definitions are presented in Table 2.

Table 2. Dyad symbols -qualitative syntax for topology.

	ANGLE CODES	AREA CODES
Numeric value range	$0 \le \theta \le 2\pi$	$-\infty \le l \le \infty$
Landmark set	$\{0, \pi\}$	$\{-\infty, 0, \infty\}$
Interval set	$\{[0,0],(0,\pi),[\pi,\pi],(\pi,0)\}$	$\{(-\infty,0),[0,0],(0,+\infty)\}$
Q-code set	{ L , Γ , T, ⊥, C }	{ L , Γ , T, ⊥, C } ∧ ∨ {– ,=,+}

Unlike morphological features, topological ones contain variations based on a reference frame. Using the dyad symbols in conjunction with a reference point, three types of adjacency semantics can be defined including: complete adjacency, partial adjacency and offset. These regularities identified in dyad symbols are deemed intermediary shape features, ISF, since the 'neighbourhood' of the description is based on local attributes as well as information describing topological properties. Like LSF, ISF are identified by matching an existing feature database.

Mereotopology Descriptors

The next level of abstraction describes the mereotopology of the spatial characteristics conveyed in the diagram. Mereotopology describes part, (i.e., a shape) to whole (i.e., overall plan shape) relations. The dual of the graph diagram is used to derive composite symbol values in order to describe part-whole relations. Abstracting the initial graph to its corresponding dual graph ensures that unambiguous mappings can be derived. Once all mappings have been established, the dual is used to derive feature semantics. This results in transformations that are much clearer and easier to understand while still based, by virtue of the mapping, on the original 2D representation. The second dual graph allows further derivation of spatial relationships.

By labelling the new dual-edges, 'tuple' codes derived from dyad symbols (defined at the previous level of topology) are created. For each edge of the dual graph, labels are derived from the symbol values identified at the previous level. Labelled dual edges allow regularities to be identified and feature semantics describing part-to-whole relationships between two or more shapes are identified. Since dual graphs are undirected, regularities are identified from within the tuple itself and not from a string. Formal definitions of dyads are presented in Table 3.

Table 3. Tuple symbols -qualitative syntax for mereotopology.

	ADJACENCY CODES
Numeric value range	$0 \leq \theta \leq 2\pi \wedge \vee 0 \leq \theta \leq 2\pi \wedge \vee -\infty \leq l \leq \infty$
Landmark set	$\{0, \pi\} \wedge \vee \{0, \pi\} \wedge \vee \{-\infty, 0, \infty\}$
Interval set	$\{[0,0],(0,\pi),[\pi,\pi],(\pi,0)\} \wedge \vee \{(-\infty,0),[0,0],(0,+\infty)\}$
Q-code set	$\{ \mathsf{L}, \Gamma, \mathsf{T}, \perp, \mathsf{C} \} \wedge \vee \{ \mathsf{L}, \Gamma, \mathsf{T}, \perp, \mathsf{C} \} \wedge \vee \{ >,=,< \}$

The semantic features identified at this level account more thoroughly for mereotopology. The regularities defined here are similar to Allen's thirteen interval relations for the temporal domain [46]. Mereotopological feature semantics include: meets/met-by, overlaps/overlapped-by, starts/finishes, contains/contained-by, equals and during. Allen's interval calculus has previously been extended to other visual domains [47, 48] unlike previous approaches, here it is not restricted to rectangles and although is strictly based on orthogonal shapes, is still capable of handling arbitrary multi-sided forms.

Like the features identified for morphology and topology, spatial semantics derived from visual patterns are identified and domain semantics are integrated using design concepts that map onto spatial features. Continuing with the example application of the architectural domain, spatial concepts relating to the use or behaviour of a space such as corridor, quadrangle, and courtyard are mapped to patterns detected in each tuple. Since all features are derived from higher level spatial primitives they are defined as global shape features, GSF.

The three level schema summarised here is characterised by the class aspect of handling and labelling design concepts and is useful when dealing with different design categorization scenarios. The concession of the approach is that it is essential to have a large database of concept-to-feature mappings.

4.1.3 Pre-Processing Feature Sets

Each type of feature representation identified using the DeREP and AbREP operations, i.e., morphological, topological or mereotopological, can be used to create a subsets of feature semantics. At this level of implementation the model has two approaches to pre-processing of feature sets, where dimensionality reduction can be undertaken manually by the user or by using a statistical approach.

In manual selection of feature sets, subsets can be created directly by selecting those features of interest to categorisation. These may also be based on the feature sets derived from a target diagram (if known). For example, an observer may wish to identify the style of design precedents based on certain topological relationships, such as having complete adjacency, and in conjunction with certain morphological constraints such as an external or bounding cruciform shape and containing all internal rectangular shapes.

Using the statistical approach, feature subsets can be created automatically using Correlation-based Feature Selection (CFS) [49]. CFS provides a filter based feature selection algorithm that uses correlation among features to select the best features for the given subset. CFS evaluates the worth of a set of attributes by considering the individual predictive ability of each feature along with the degree of redundancy.

4.1.4 Unsupervised Categorisation

The main advantage of using SOMs in design comparison is that they do not require target values for their outputs and learning occurs unsupervised. Since there is no absolute definition of the commonalities between design artifacts in terms of their spatial descriptions, there is no single definitive exemplar to establish reliable target outputs that can be used to train a supervised network. For this reason, SOMs using unsupervised learning are commonly used to find and construct classifiers. Hence the SOM can provide a continuous topological mapping between the feature space and the 2D mesh of neural units in the competitive layer. This is an important property since it enables the representation of a mapping, which preserves relations in the input space while at the same time performing a dimensionality reduction onto the 2D mesh.

To interpret, categorise and visualize the multi-dimensional datasets of semantic features, the SOM learns unsupervised and initially categorisation begins with a corpus of reference diagrams. The map consists of a regular “city-block” grid of neurons and categorisation follows three steps: (i) the distances between the input vector x and all reference vectors (i.e., weight vectors) are computed using a Euclidean distance measure; (ii) a winner (i.e., a neural unit for which the corresponding weight vector is at a minimum distance from the input vector) is determined; (iii) the weight vectors corresponding to the winner and the neural units in its topological neighbourhood are updated to align them towards the input vector. The SOM then attempts to represent the corpus of diagrams with optimal accuracy using the selected subset of features.

The SOM is able to learn to recognise different patterns in the input data and allocate them to appropriate ‘bins’ (styles) in the output array, each bin representing a specific pattern. Therefore if we see the output as an array of 'classification bins' (each representing a specific pattern in the input data) that are arranged in an ordered way such that near neighbours represent similar styles and distant neighbours represent different styles.

Since there does not and will not ever exist one single "correct" answer to the central issue of a definition of design style, the ability to combine the distances calculated in different feature spaces provides the critical point where relevance feedback can be incorporated. The SOM's matching process can therefore also be driven by contextual considerations, where the observer is able to determine the relative importance of distinguishing features by adjusting their weights. When contextual information is used for determining the importance of distinguishing features the correlation between the designer's requirements and the styles identified can therefore increase.

4.2.4 Relevant Styles

The correspondence between high-level design concepts and lower level physical features can often depend on the context of the observer. Consequently each design categorisation may be different due to the hidden conceptions in the relevance of diagrams and their mutual similarity. This is the rationale behind the fourth stage where if the design clusters selected by the observer map closely to each other on the SOM, then the corresponding feature performs well on the present categorisation and the relative weight of its opinion is increased. This is known as relevance feedback, or RF, and is the iterative refinement of an initial SOM categorization.

RF is provided using dynamic weight adjustments that allow the SOM to learn the optimal correspondence between the high-level concepts that the observer uses and the feature semantics automatically derived from 2D diagrams. In text and image-based research, RF is an established approach that enables contextual-dependencies to be integrated for document and image retrieval. Recently this approach has been adopted by researchers using SOMs to retrieve information from large databases [38, 39, 40].

In an analogous manner, we have aimed at integrating RF with a SOM in the design domain, by treating this process as a form of learning that moves from unsupervised learning to being partially supervised. The model tries to learn the observer's visual preferences by adjusting the feature weights accordingly. Feature weights in subsequent categorisations are adjusted using the information gathered from the observer's feedback. The observer's feedback guides the system in the following rounds of the assessment process to better approximate their present design requirements/ preferences.

The task of assigning specific weights which coincide with the observer's perception of each feature set is not feasible and therefore the initial results from the unsupervised clustering are displayed using the topographic map so that weights can be derived from user input. It is crucial that the results from the initial round are categorised in a manner such that a level of visual similarity is evident to the observer – this being the primary objective of integrating qualitative encoding. The observer is not required to explicitly specify weights for different features and instead weights can be formed implicitly from the positive and negative values assigned to a diagram or cluster of diagrams.

This process follows whereby: (i) an unsupervised SOM categorises a design corpus; (ii) the first round of results are displayed and stored to avoid the system entering a loop; (iii) the observer indicates which diagrams are to some extent relevant to the present design context and which are not and assigns positive and negative values accordingly; (iv) the adjusted weights are utilised in a re-initialised SOM and the design corpus is re-categorised; (v) the second and any subsequent round of results are displayed to the user and stored; and (vi) the process continues until the observer is satisfied.

By marking on the map, the categories the observer deems relevant, we are able to adjust each unit or node assigned a positive and negative value depending whether the observer has selected or rejected the corresponding design classification. The marking operation indicates correctly classified design clusters as positive. Diagrams are accumulated during the categorisation process into sets and weights are adjusted in succeeding iterations, moving from an unsupervised SOM to one which is partially supervised or guided.

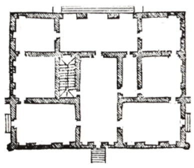
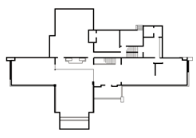
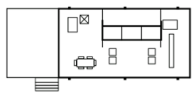
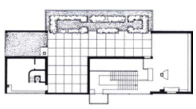
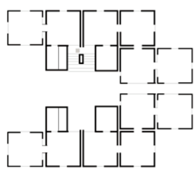
5. Experiments

Two classes of experiments were carried out to assess the cognitive plausibility and contextual sensitivity strength of our approach to computational stylistics in design. In conducting these experiments, we also aim to test the utility of the model as an aide to designers.

The first experiment tests the discriminatory power of the qualitative schema combined with the SOM's ability to categorise encoded diagrams using specific feature sets, i.e., Q-SOM without RF. The second experiment tests the complete system, i.e., Q-SOM:RF, where the relevance of categorisations is provided by an observer's feedback in the context of a design scenario. As a result we test the model's ability to handle the cognitive-contextual properties and cognitive-psychological properties of style.

The design corpus used in all experiments consists of 2D architectural design diagrams. The Exemplar diagrams from each architect and a sample of the feature sets extracted (as raw unprocessed data) are shown in Table 4.

Table 4. Exemplar diagrams based on Architect

EXEMPLAR DIAGRAM	EXEMPLAR LSF	EXEMPLAR ISF	EXEMPLAR GSF	ARCHITECT/ BLDG TYPE/ PERIOD
	Alternation, Symmetry, Square, Rectangle, Chamber, Niche	Complete Adjacency, Partial Adjacency,	Meets / Met-by, Contains / Contained-by, Overlaps / Overlapped-by, Starts / Finished-by, Corridor, Portico	Palladio Residential Public 1528 - 1580
	Indentation, Protrusion, Iteration, Alternation, Square, Rectangle, "L"-shape, "T"-shape, Niche, Stepped forward, Hearth	Complete Adjacency, Partial Adjacency, Offset	Meets / Met-by, Contains / Contained-by, Overlaps / Overlapped-by, Starts / Finished-by, Equals, Corridor, Portico	Frank Lloyd Wright Residential 1888 - 1959
	Indentation, Protrusion, Iteration, Alternation, Symmetry, Rectangle, "U"-shape	Complete Adjacency, Partial Adjacency,	Contains / Contained-by, Overlaps / Overlapped-by, Starts / Finished-by, During, Equals, Corridor, Veranda	Mies van der Rohe Residential, Public (Religious, Library, Theatre) 1912 - 1958
	Indentation, Protrusion, Iteration, Alternation, Symmetry, Square, Rectangle, "U"-shape, "L"-shape, Niche, Stepped backward.	Complete Adjacency, Partial Adjacency	Contains / Contained-by, Overlaps / Overlapped-by, Starts / Finished-by, During, Equals, Portico, Courtyard	Le Corbusier Residential, Public: (Religious) 1908 - 1965
	Indentation, Protrusion, Iteration, Alternation, Symmetry, Square, Rectangle, "U"-shape, Chamber, Locked Space, Niche, Gallery, Hearth	Complete Adjacency, Partial Adjacency, Offset	Meets / Met-by, Contains / Contained-by, Overlaps / Overlapped-by, Starts / Finished-by, Equals, Courtyard, Quadrangle	Louis Kahn Residential, Public (Religious, Library, Theatre) 1951 - 1969
	Indentation, Protrusion, Iteration, Alternation, Symmetry, Square, Rectangle, "L"-shape, Chamber, Locked Space	Complete Adjacency, Partial Adjacency, Offset	Meets / Met-by, Contains / Contained-by, Overlaps / Overlapped-by, Starts / Finished-by, Equals, Courtyard	Mario Botta Residential 1969 - 1996

The corpus tested is relatively large, totalling 131 diagrams and representing six architects, namely: Palladio, Frank Lloyd Wright, Mies van der Rohe, Le Corbusier, Louis Kahn, and Mario Botta. The two studies here undertaken use networks that have been trained using 36 diagrams, which comprise six designs randomly selected from each of the six architects.

The number of features extracted from the design corpus totalled 37,367 and there is an average of 287 features from 59 sets associated with each diagram. The characteristics of feature sets in relation to each architect are shown in Table 5.

Table 5. Characteristics of each feature set based on Architect

TYPE (ARCHITECT)	AVERAGE No. OF FEATURES	TOTAL No. OF FEATURES	No. DIAGRAMS
PALLADIO	254	3810	15
FRANK LLOYD WRIGHT	306	18360	61
MIES VAN DER ROHE	268	4288	16
LE CORBUSIER	221	1547	7
LOUIS KAHN	327	6213	19
MARIO BOTTA	243	3159	13

The level of complexity of the corpus is considered to be relatively high since although all diagrams are from a single domain, i.e., architecture, the corpus consists of designs from a number of architects and several different building typologies including small and large scale residential, as well as a variety of public buildings.

5.1 Experiment 1: Q-SOM

The first experiment is designed to assess the effectiveness of the derivation of semantic features and ascertain the benefits of dimensionality reduction in diagram categorisation. This experiment is therefore designed to test the visuo-spatial re-representations of the pictorial content of the diagram as qualitative features and feature sets. We trained, tested and evaluated networks using a variety of network topologies and different feature subsets.

5.1.1 Pre-Processing

Pre-processing of input data was undertaken using the statistical feature selection method outlined in Section 4.2., and using CFS we evaluated subsets of features by the correlation among them. In the first study we used only a re-representation of morphology (i.e., the LSF) extracted from the corpus for dimensionality reduction and eight LSF were identified as significant by CFS including: Protrusion_0, Protrusion_3, Iteration_2, Alternation_1, Symmetry, Square, Cruciform and Niche. From this point, we shall refer to all networks created using this subset as SOM_L.

In the second study, dimensionality reduction included all feature sets extracted using the DeREP and AbREP operations and in addition to the eight LSFs identified above, four GSFs: Contains/Contained_by, Overlaps/Overlapped_by, Equals, and Courtyard were evaluated as an optimal subset of attributes for clustering. Interestingly, no ISF were identified. Categorisation therefore relies on a combination of feature classes where the ratio of local to global features is 2:1. We shall refer to all networks created using this subset as SOM_{L+G}.

5.1.2 Training

For all Q-SOM experiments, two different feature vector models were constructed using the subsets identified in the previous section. In all SOM_L networks, each diagram had an average of 35 features and the final vector model contained 1239 feature instances, which created a unique feature vector for each 2D plan diagram. In SOM_{L+G} networks each diagram contains an average of 50 features and the final vector model contained 1812 feature instances comprising of feature vectors from 1,239 LSF and 573 GSF feature instances.

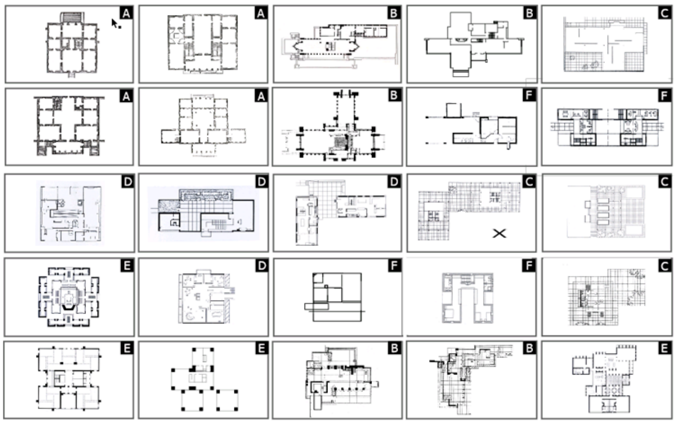
In addition to the two different feature vector models, training was also varied in terms of the topology of the network and the number of cycles, where 500, 1000 and 1500 training cycles were used. Table 6 shows the training variables for each Q-SOM.

Table 6. Characteristics of different Q-SOM networks used in diagram classification.

VECTOR MODELS		NETWORK CHARACTERISTICS	
FEATURE SUBSET	NO. INPUT NODES	TOPOLOGY	TRAINING CYCLES
SOM_L	8	3x3, 5x5, 10x10	500, 1000, 1200
SOM_{L+G}	12		

Neither SOM_L nor SOM_{L+G} utilise any other information about the diagram, i.e., the architect, building type, period, etc. Since there is no access to prior knowledge regarding the number of clusters in the data, the SOM proceeds unsupervised.

Based on a visual inspection the 5x5 $SOM_{L,}$ trained for 500 cycles, performed the best and resulted in the clusters as shown in the topographic map in Fig. 6. Results show categorisation of diagrams can be roughly linked to the architect as indicated by the map and labelled key in Fig. 6 showing each architect, where: A ≈ Palladio; B ≈ Wright, C ≈ Van Der Rohe, D ≈ Le Corbusier, E ≈ Kahn, and F ≈ Botta. A node may represent more than one diagram, but with different activation values. In some cases the node contains two architects (approximately 20%) and each label has been assigned on the basis of the dominant feature vector. Also observed from the map, the network appears to have clusters distributed separately corresponding to the same architect, including: Wright (C), Kahn (E) and Botta (F).

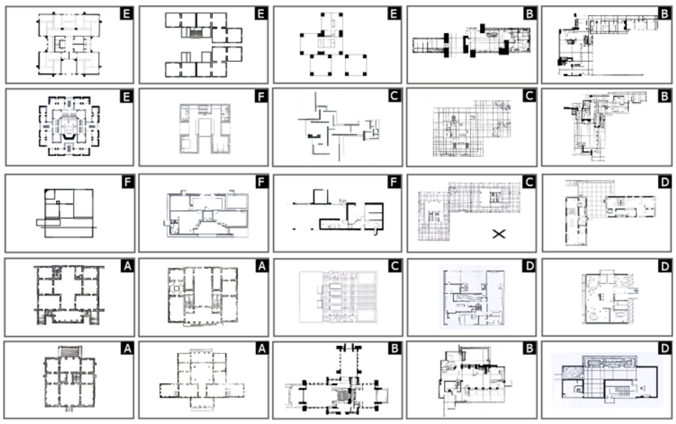


A	A	B	B	C
A	A	B	F	F
D	D	D	C	C
E	D	F	F	C
E	E	B	B	E

Palladio	A
Wright	B
Van Der Rohe	C
Le Corbusier	D
Kahn	E
Botta	F

Fig. 6. Training result: SOM_L clustering.

The 5x5 $SOM_{L+G,}$ trained for 500 cycles, also resulted in well defined clusters, as shown in Fig. 7. Like the results obtained for the 5x5 SOM_L, the results observed in the topographic map show categorisation of diagrams can be linked to the architect. The topological ordering of the diagrams in the 5x5 SOM_{L+G} shows a better result than obtained for the 5x5 SOM_L training. This is evident from the separate clusters and the distinctive change of clusters across the map, where Kahn's diagrams, E, are located in the upper left-hand corner of the map and the architect gradually changes towards the bottom-right corner to Le Corbusier, D. Although the 5x5 SOM_{L+G} also distributed two clusters for Wright's designs, B, clustering is more consistent across individual architects.



E	E	E	B	B
E	F	C	C	B
F	F	F	C	D
A	A	C	D	D
A	A	B	B	D

Palladio	A
Wright	B
Van Der Rohe	C
Le Corbusier	D
Kahn	E
Botta	F

Fig. 7. Training results: SOM_{L+G} clustering.

Significantly, in the 5x5 SOM_{L+G}, all nodes except for the node marked “x” in Fig. 7 contain input vectors from the same architect. This can also be observed from the activation weights given to each individual input vector. The SOM_L input vectors have much lower activations when compared to the SOM_{L+G} input vectors. Testing was then carried out to evaluate the clustering effectiveness of the trained networks. The objective of testing is to evaluate the success of each trained network using the two different approaches to constructing feature vectors, i.e., manual versus CFS selection.

5.1.3 Testing

The SOM_L and SOM_{L+G} networks were tested and their clustering ability was observed. As in training, the 3x3, 5x5 and 10x10 maps were all tested. To analyse the results of categorisation between the topographic maps we utilised techniques from conventional text-based categorization analysis including: Precision [50], the Jacaard or JAC method [51], and the Fowlkes-Mallows or FM method [52]. Since classification is unsupervised it is not possible to apply these evaluation methods directly as would be the case for supervised learning.

To analyse results of testing unsupervised SOMs it is necessary to utilise the most dominant label of each cluster (obtained during training) for all diagrams. For this reason, the labels (architects) identified from training are maintained so as to assign categories. The “micro-averaged” precision matrix method [50] was first used to evaluate each network and the well-established JAC and FM methods were then used to evaluate cluster quality; see [40] for further details of these evaluation methods.

The three topologies of SOM_L were tested and each network’s ability to categorise the entire design corpus was analysed. The 5x5 map was found to have the best results for all evaluation techniques measured, as shown in Table 7, with Precision and JAC results being comparable. The results of FM also show how the 5x5 map outperformed both the 3x3 and the 10x10 maps.

Table 7. Clustering ability of different map topologies trained on SOM_L Feature subsets

STUDY 1: Q-SOM	PRECISION	JAC	FM
SOM_L 3x3	0.49	0.29	0.37
SOM_L 5x5	0.62	0.38	0.45
SOM_L 10x10	0.53	0.32	0.30

Next, we tested Q-SOM_{L+G}, and again the 5x5 map has the best results for all evaluation techniques measured. As expected the 5x5 SOM_{L+G} produced better results for precision, JAC and FM than SOM_L results, shown in Table 8.

Table 8. Clustering ability of different map topologies trained on SOM_{L+G} Feature subsets

STUDY 2: Q-SOM	PRECISION	JAC	FM
SOM_{L+G} 3x3	0.61	0.46	0.42
SOM_{L+G} 5x5	0.74	0.53	0.50
SOM_{L+G} 10x10	0.60	0.46	0.39

5.1.4 Assessment of Clusters

The nature of the categories produced by the two best performing networks, i.e., 5x5 SOM_L and SOM_{L+G} are difficult to evaluate, except via visual (subjective) processes. Recently, conventional clustering techniques (e.g. K-means, EM, Hierarchical, etc.) have been used to resolve this problem. Ahmad and Vrusias [52] demonstrate the effectiveness of using conventional statistical clustering techniques, in evaluating the output of maps of unsupervised networks. Sequential clustering, i.e., first clustering using an unsupervised network and then clustering the output map, facilitates visualising clusters that are otherwise implicit in the output map.

We have used a sequential clustering method, Q-SOM followed by K-means, to examine the categories obtained. An application of K-Means clustering on the output of the 5x5 SOM_L and SOM_{L+G} maps shows how they have found data in proximate types defined by both the architect and building type. Tables 9a and 9b compare K-Means clustering of all 131 plan diagrams for both 5x5 networks.

Table 9. Distribution of plan diagrams using K-Means clustering: (a) SOM_L and (b) SOM_{L+G}, where A = Palladio Residential and Public Bldgs., B = Wright Residential Prairie Bldgs., C = Wright Residential Usonian Bldgs., D = Mies Van Der Rohe Residential Bldgs., E = Mies Van Der Rohe Public Bldgs., F = Le Corbusier Residential Bldgs., G = Le Corbusier Public Bldgs., H = Kahn Residential Bldgs., I = Kahn Public Bldgs., and J = Botta Residential Bldgs.

	CLUSTERS BY K-MEANS ON SOM_L									
Architect	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**
A	**9**							2	3	1
B	6	**19**	2		1			5		1
C		7	**14**		4					
D	1		2	**3**	1	1				1
E			1		**4**			1	2	
F				1		**3**				
G						3	**0**			
H				2		1		**8**		
I		1		1	1				**5**	
J	1			2	1	2				**7**

(a)

	CLUSTERS BY K-MEANS ON SOM_{L+G}									
Architect	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**
A	**12**				1			1		1
B	1	**25**	2		1			5		1
C		4	**19**		1		2	1		
D	1		1	**6**		1				
E					**5**			1	2	
F				1		**3**				
G				1			**2**			
H						1		**10**		
I	1		1						**7**	
J						2				**11**

(b)

The two tables show the distribution of plan diagrams where the feature vector models can be used to cluster diagrams according to an architect and their residential or public building types. Using the sequential clustering method Table 9a shows clustering of the design corpus based on the LSF subset (SOM_L) has not proven to be as defined. Diagrams associated with both architect and building type (represented using the combined LSF and GSF subset), shown in Table 9b, have generally been well clustered except for Le Corbusier's designs where no distinct clusters are distinguishable. Significantly for both SOM_L and SOM_{L+G} networks, Wright's designs are distinguished relative to two periods of Wright's work – the Prairie and Usonian houses - where clustering defines 87% of Wright's Prairie design diagrams and 84% of his Usonian.

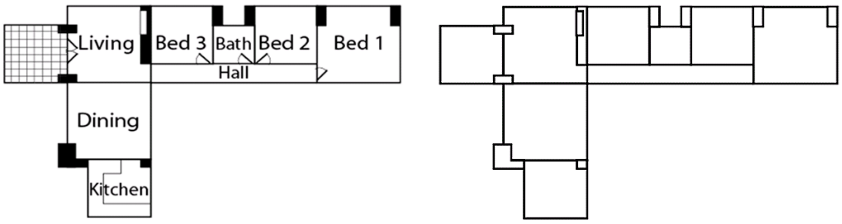
5.2 Experiment 2: Q-SOM:RF

Based on the results obtained from the 5x5 SOM_{L+G}, the final experiment trains and tests a network's ability to categorise the same corpus using the complete Q-SOM:RF model to obtain clusters which are relevant to some design context. Preprocessing is again used in dimensionality reduction to create feature vectors and categorisation proceeds as a sequential process based on manual selection of diagrams. In this experiment, categorisation is evaluated in the context of a design task where the observer (the author) has provided positive and negative values to the units of the network.

5.2.1 Design Context

A simple design task was formulated using a brief specifying the requirements of a residential plan design for a family of four. The brief specifies alterations and additions of an existing residential design to increase sleeping and living spaces, according to the following specifications of building layout: additional sleeping areas to accommodate two children; larger lounge, dining and kitchen areas; and outdoor living area.

A conceptual design sketch was then produced using the systems digital drawing interface which constrains sketching to orthogonal axis. Fig. 8a presents the design sketch produced as a result of the brief's requirements and Fig. 8b shows the sketch as interpreted by the vectorization process of the system. The sketch was encoded (all labels are ignored) and included in the design corpus with the other 131 plan diagrams.



(a) (b)

Fig. 8. Design sketch (a) original sketch of residential dwelling (b) contour vectorization

5.2.2 Pre-Processing

In this experiment, the original (raw) feature set was processed manually. Manual processing is utilised since it enables the selection of a feature subset relevant to the design task. Since it is the aim for categorisation to be grounded by the design task, the style of diagrams can be determined based on those features extracted from the design sketch shown in Fig. 8. Therefore from the 59 possible feature classes, selection of one or many feature subsets to create vector models is facilitated from the encoding of the design sketch. Salient features were identified from the local, intermediate and global shape features contained within design sketch. All features classes extracted from the design sketch are shown in Table 10.

Table 10. Reduced feature subset and user subset

FEATURES EXRACTED BY DeREP & AbREP						SUBSET			
LSF (Geometry-based)	Indentation	0	1	2	3	×	×	✓	×
	Protrusion	0	1	2	3	×	×	✓	✓
	Iteration	0	1	2	3	×	×	×	×
	Alternation	0	1	2	3	×	×	✓	×
	Symmetry	0	1	2	3	×	×	×	×
LSF (Domain-based Semantics)	Stepped forward					✓			
	Niche					✓			
ISF (Geometry-based)	Complete Adjacency					×			
	Partial Adjacency					✓			
	Offset					✓			
GSF (Geometry-based)	Contains / Contained-by					✓			
	Overlaps / Overlapped-by					×			
	Starts Finished-by					×			
GSF (Domain-based Semantics)	Corridor					✓			
	Portico					✓			
	Stepped					×			

The feature classes within the design sketch were then used to create feature vector models to classify the design corpus. A total of 31 feature classes were extracted from the design sketch, which were distributed between local, intermediate and global feature classes as: 22, 3 and 6 respectively.

Using the reduced feature subset it is possible to identify other feature subsets which may be deemed to be more salient in relation to design requirements. To demonstrate the utility of selecting a user-specific subset from the design sketch, a feature subset is shown in the final column of Table 10 (shown as ticked), where 11 feature types have been selected based on the preferences of the designer. In addition, three other feature subsets were selected, namely: (i) LSF, (ii) ISF and (iii) GSF.

Five feature vector models were then constructed consisting and network training was also varied in terms of the number of cycles, where 500, 1000 and 1500 training cycles were again used. Table 11 shows the final training variables for each of the five qualitative feature-based SOMs.

Table 11. Characteristics of the different neural network systems used in diagram classification.

VECTOR MODEL		NETWORK CHARACTERISTICS	
FEATURE SUBSET	NO. INPUT NODES	TOPOLOGY	TRAINING CYCLES
All Features	31	5x5	500, 1000, 1500
User Subset	11		
LSF	22		
ISF	3		
GSF	6		

5.2.3 Training and Testing Using Relevance Feedback

All five feature vector models were trained using the 5x5 topography. However, before testing could commence it is necessary to make explicit the targeted categories. In order to demonstrate and then evaluate the performance of the five feature vector models in conjunction with RF, a category of designs must first be defined within the corpus as the desired target/s. We selected two targets: (i) Wright's Usonian period and (ii) Kahn's residential designs. Each target contains 27 and 11 plan diagrams respectively. Each category was selected simply based on observer preferences. Neither target is necessarily more "correct" or valid than any other potential category of designs. However because Wright's Usonian and Kahn's residential designs can now be explicitly targeted by the observer using RF it is then possible to evaluate how well the system refines sequential categorisation.

Based on positive and negative feedback, each SOM tested resulted in a re-categorisation of the corpus where the iterative process continued until the observer was satisfied. The clustering of each model was produced by returning the best-scoring diagrams in each iteration step from the selections of the relevant designs among them. Results from testing the five networks show that the SOM that utilised ‘All Features’ performed the best, and provided well defined clusters. The remaining networks also resulted in well defined clusters, however the categorisations observed (on visual inspection) in these topographic maps do not, appear to be as well defined.

Formal evaluation methods used here rely on JAC and FM measures to analyse the results of each SOM’s. The first map, the ‘All Features’, returned the highest performance and the second map, the ‘User Subset’, also produced comparable results for JAC and FM measures. The performance of the remaining three maps was lower as shown in Table 12.

Table 12. Clustering ability of different feature vector models

Experiment 2: Q-SOM:RF	JAC	FM
All Features	0.53	0.50
User Subset	0.46	0.42
LSF	0.46	0.39
ISF	0.38	0.45
GSF	0.32	0.30

The result of the best performing network, the 5x5 ‘All Features’ is illustrated in Fig. 9, which was trained for a total of 1000 cycles. Results observed in the map show categorisation of diagrams can be roughly linked to two architects as indicated by the map and labelled key.

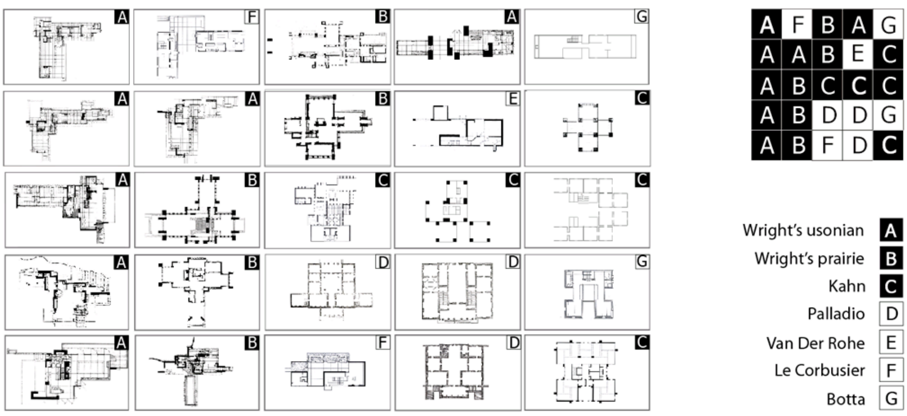


Fig. 9. Final categorization formed by ‘All Features’ for Q-SOM:RF

The labelled key in Fig. 9 indicates each architect, where: A ≈ Wright (Usonian); B ≈ Wright (Prairie) and C ≈ Kahn. Other architects whose dominant feature vectors defined some labels included: D ≈ Palladio; E ≈ Van Der Rohe, F ≈ Le-Corbusier, and G ≈ Botta. Unlike previous results shown in Section 5.2 Experiment 1, there are multiple nodes of the map that contain input vectors from different architects. Significantly, only 5% of the nodes where Wright and Kahn's diagrams are clustered contain another architect whereas the majority of the remaining nodes contain more than one architect (approximately 50%) and include some of Wright's and Kahn's diagrams.

5.2.4 Assessment of Cluster and Feature Subsets

We evaluated the performance of the networks that used the Q-SOM:RF process using a method that resembles "target testing" developed by Cox et al. [54]. Here, instead of a single target, testing evaluates the two targeted categories: Wright's Usonian and Kahn's residential designs. To obtain the performance measure τ, the targeted category *TC*, of designs defined by the user's requirements *r* is used. For each diagram in category *TC*, the total number of different clusters categorised by the network until the final category is reached is recorded. From this data, the average number of clusters formed before the final "correct" response is divided by the total number of diagrams *k*. The performance measure of the target category is then obtained as:

$$\tau = \left[\frac{\varphi(C,A)}{2}, 1 - \frac{\varphi(C,A)}{2}c\right] \tag{1}$$

where ϕ (C , A) is the *a priori* probability of the category *TC* , given by *TC* / k. In general the smaller τ , i.e., $\tau < 0.5$, the better the performance .

The results of the performance measures for all five networks are shown in Table 13. The two feature subsets containing 'All Features' and the 'User Subset' yielded better results than the LSF, ISF or GSF subsets, which can be observed in the first two rows of the table.

Table 13. Resulting τ values in the Q-SOM:RF experiment

FEATURE SUBSET	TARGET CLUSTER	
	Usonian	Kahn (Residential)
All Features	0.23	0.26
User Subset	0.29	0.31
LSF	0.36	0.33
ISF	0.54	0.62
GSF	0.39	0.43

The general trend observed from these results shows that using a larger set of features yields better results than using a smaller subset of features. Based on all performance measures we can observe that using more or all feature classes to create feature vectors yields better results than any one single feature class. Thus, a combination of all available morphological, topological and mereotopological features in conjunction with RF has resulted in the highest performance measure.

The implicit weight adjustments based on the relative importance of features contained in diagrams shows that the model is capable of categorisation using both geometric and semantic attributes contained in the corpus. This kind of automatic adaptation is desirable as it is generally not known which features would perform best in clustering the complex visuo-spatial information inherent in architectural diagrams.

The experiments demonstrate that utilising Q-SOM:RF as a system for assessing the similarity of design diagrams to distinguish style not only provides a useful method for initial unsupervised categorisation but also provides the flexibility to overcome a variety of problems resulting from context. The approach demonstrated in this experiment provides a robust method for defining the style based on a feature space that is capable of adapting to the contextual relevance of multiple spatial ontologies defined by both lower-level geometric and higher-level semantic features.

6. Discussion

In this chapter, we have investigated a conceptualization of style based on the visual and spatial perception of an artifact and tested implementations of an approach to automating the analysis of designs to identify style/s. Thus, like Stiny's Chapter in this book, our explorations look to uncover how style is defined via observation, where the derivation of style depends on seeing and the process of comparison is not fixed but is subject to adaptations according to the observer's context.

Our approach to automated analysis has therefore focused on modelling and testing (in two separate experiments) a cognitively compatible analysis and a task relevant clustering method for identify style/s significant to a designer's context. We have demonstrated how style is related to the way information is processed. and that the reporting of different design styles is as a meta-cognitive process [16] requiring explicit comparison of design information both prior and subsequent to processing by the system.

6.1 Experiments

We demonstrated and tested two systems, namely the Q-SOM and Q-SOM:RF models. The results of our experiments show that the first Q-SOM system was able to provide a mapping from the physicality of the diagram using qualitative re-representation geometric and semantic feature sets are obtained and, as a result, meaningful feature subsets can be analysed as input to the SOM; and that the second extended Q-SOM:RF system was able to effectively select from sequential and iterative processing by adjusting weights of a SOM to coincide with an observer's conceptual view of a design artifact's style. In other words, initial unsupervised clustering was adaptive in sequential clustering stages and became more relevant according to the designer's intentions.

The strength of the approach lies in its utilisation of a multi-dimensional qualitative encoding schema and its ability to simultaneously assess multiple reference design diagrams. Since an individual diagrammatic feature or even a class of features based on any one spatial dimension may not be sufficient for analysing the style of complex design diagrams the model enables the extraction of information from multiple dimensions so that the adaptation of the boundary of a style is based on a range of visuo-spatial features. In our computational experiments, the model has been shown to be capable of bridging the gap between the low-level visual features extracted from the design artefact and the high-level semantics used by designers to understand design content. The first experiment of the Q-SOM demonstrates how the approach is capable of overcoming the cognitive properties of similarity-based classification outlined in Section 2.

Furthermore the significance of features and feature subsets can be identified relative to the comparison's context via feedback. The use of target categories in the final experiment demonstrates that when contextual information is integrated to determine the relative importance of features, the correlation between the system's results and the observer's assessments increases. Significantly, this correlation can be seen to result from the detailed definition, detection and extraction of feature classes and the observer's feedback determining feature salience. In this way, the second experiment of the Q-SOM:RF model shows how the approach is capable of overcoming the contextual properties of similarity-based classification discussed in Section 2.

6.2 Future Work

In design research our approach, and specifically, the relevance feedback technique, differs from existing automated analytical systems of style. Typically existing systems have been based on simple feature-based distances measures, see for example [29, 31]. Yet, despite our model's strengths, the approach to style tested here in relation to visuo-spatial information and its cognition require further exploration in modelling an object viewpoint of style.

The promising results obtained so far require additional studies across a variety of design scenarios and where testing the interactive Q-SOM:RF system is based on multiple users with different level of design experience and knowledge. It is expected that in undertaking human-subject experiments, that the Q-SOM:RF system should perform equally well as demonstrated here when using either expert or novice designers. The performance of the model should not differ substantially between users since their individual assessments will be reflected by the model's flexibility and adaptation to feedback. However a quantitative evaluation of the Q-SOM:RF model's performance in this respect is problematic due to occurrences of an individual preference and unique perceptual biases. Subjectivity is therefore a valid part of the iterative classification processes which takes place over open and variable dimensions of the designs being compared.

Using a multiple user research programme, future studies must further test the approach so that two significant questions can be addressed:

1. Is the model superior to existing approaches? And if so, how significant is the performance improvement? The studies reported here highlight the main differences between the Q-SOM:RF model and existing models based on the re-representation of single spatial ontologies and simple metric distance measures. We have also claimed that the Q-SOM:RF model is a good estimator of the similarity among design diagrams across local, intermediate and global levels of visual and spatial information. Future studies must examine whether or not the performance of our model (under the same set of evaluation criteria) is better than the performance of existing models. Such a study should lead to the conclusion that static linear based models cannot characterize style adequately.
2. Is there a set of well-balanced features which on average, perform as well as possible? That is, are there specific subsets of features that can be used to create feature vector models and which can be inspected relative to defined design styles? The objective of this research question is investigate the idea of feature centrality in the design domain relative to the effects of context and historically defined styles, e.g., Romanesque, Classical, Gothic, etc.

6.3 Concluding Remarks

By employing qualitative modeling and a self-organizing map with a relevance feedback, the concept of similarity has been shown to be an effective grouping principle so as to enable a digital characterization of style relative to context. The important and obvious implication of our approach and investigations is that isolated features are insufficient in formulating fixed conclusions about distinctive boundaries or perimeters of design styles. Instead, causality must also be attributed to cognitive and context dependant factors that influence the perception and judgement of a feature, a diagram, a design corpus and as a result a style. Consequently, the perceptual biases of different individuals or the same individual undertaking different design task, will influence classification and thus the boundaries delineating a style may be drawn differently.

Finally, in closing it is important to note the practical value of computational stylistics in design as a tool to facilitate style related tasks during the design process, and where the benefits of such support to designers are manifold. Whilst cognitively, human observers have limited capacity to compute large amounts of visuo-spatial data, the value of automated analysis is also in part due to the capacity of individuals to discriminate and communicate what defines a style. For individuals, whilst the particular features and configurations of features is a determinant of style [55], often what makes up a style is not always easy to identify and articulate even though an observer may be able to recognize an artifact's style with little difficulty.

Using on our approach to analysis, a computational stylistics tool can provide computational support across a range of design stages – from the early planning stages, to the conceptual and schematic design stages, to the specification stages. Consequently larger and more efficient search during design precedent analysis tasks, design inspiration gathering activities, and reuse of design details can be enabled. It is possible to support such design tasks using computational stylistics since visuo-spatial information can be classified and retrieved automatically by accessing large databases of existing design artifacts, including not only 2D diagrams but also potentially 3D models. Consequently, designers would able to actively participate in the definition of existing and new styles– changing, redefining and creating their boundaries as they generate their own designs.

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