INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN
ICED 01 GLASGOW, AUGUST 21-23, 2001

SHAPE MATCHING AND CLUSTERING

Sungwoo Lim, Alex H B Duffy, and Byungsuk Lee

Keywords: Information classification, machine learning, taxonomies

1 Introduction

Generalising knowledge and matching patterns is a basic human trait in re-using past experiences. We often cluster (group) knowledge of similar attributes as a process of learning and or aid to manage the complexity and re-use of experiential knowledge [1, 2]. In conceptual design, an ill-defined shape may be recognised as more than one type. Resulting in shapes possibly being classified differently when different criteria are applied. This paper outlines the work being carried out to develop a new technique for shape clustering. It highlights the current methods for analysing shapes found in computer aided sketching systems, before a method is proposed that addresses shape clustering and pattern matching. Clustering for vague geometric models and multiple viewpoint support are explored.

2 Analysing Vague Shape

To pattern match and cluster vague shapes we must firstly identify the types of vagueness that may occur during geometric sketching. Then the criteria for identifying a cluster must be defined. Various methods address the problem of shape analysis as summarised in Tables 1 and 2. However, these methods consider precise shapes and are not appropriate for vague geometry. The following types of vagueness in conceptual geometric shapes cones in a variety of ways, as identified below [3].

- Vague position of a line segment – In figure 1, because the line positions are not clearly expressed, we encounter two types of vagueness. Firstly, the open/closed status of the shape type is vague. It also includes the uncertainty of whether the ends of two lines meet to form a vertex. Secondly, the size of each element (i.e. a line segment) is vague. For example, the size of the right vertical line of the sketch in figure 1 will be determined by whether the sketch represents a rectangle or polygon.

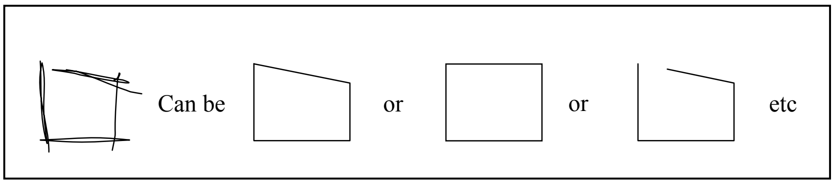


Figure 1. Vague position, size, and close/open

- Vague convex/concave vertex – Without any guidelines or contrast between light and shade, recognising a vertex as a 3D convex or concave shape from 2D sketches can be difficult. This type of vagueness occurs frequently in 2-D sketches of 3-D objects because of an optical illusion as illustrated in Figure 2.

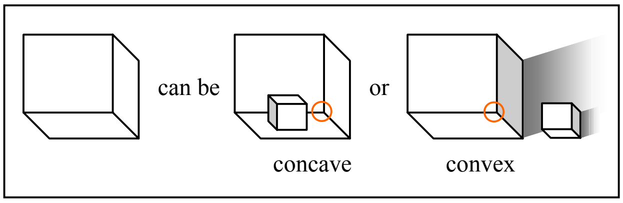


Figure 2. Vague convex/concave vertex

- Vague shape type – The type of shape of an object is often vague giving rise to more than one feasible interpretation of the shape. For example a line element may be interpreted as a straight line or as an arc and can result in different shape types as shown in Figure 3.

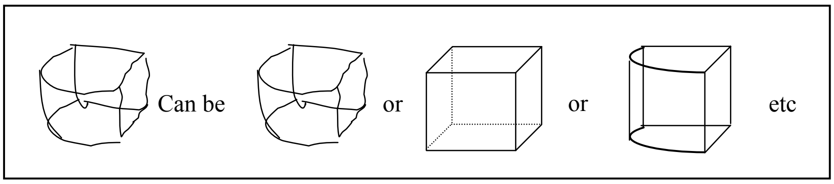


Figure 3. Vague shape type

- Vague relative spatial relation – If an ill-defined geometric object has a vague surface, the distance between this and another object is vague. Figure 4(a) shows the possible relative spatial relation whether the surfaces of the objects are vague or not. In this 2D example, the boundary of the object 'a' and 'b' are vague. Considering the minimum and maximum boundaries, the intersection status between two objects can be recognised as *vague intersection*, *intersection* and *non-intersection*. In addition, a sketch representing 3D spatial relationships can lead to some confusion. In the 3D example shown in Figure 4(b), although the object 'a' and 'b' have precise surfaces, their relative spatial relation can be recognised as three different types, as the example sketch implicates vague co-ordinates.

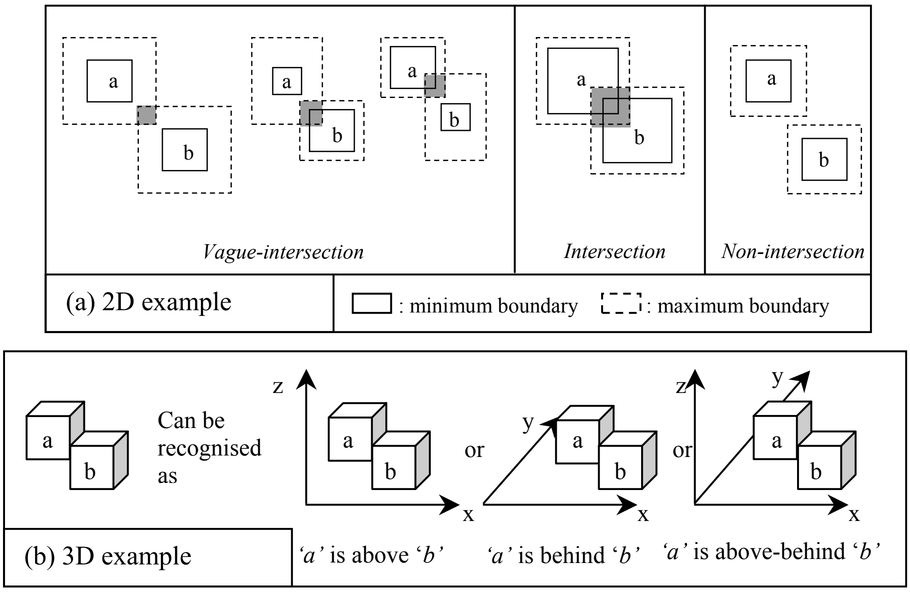


Figure 4. Vague relative spatial relation

Table 1. Shape analysis methods (summarised from [4, 5])

Shape boundary points	Boundary (external) algorithm	Shape boundary
		Fourier transforms of the boundary
	Global (internal) algorithm	Medial axis transform (MAT)
		Moment based approaches
		Shape decomposition into other primitive shapes
numeric or non-numeric Scalar transform technique		Various fourier
		Moment-based approaches
Information preservation		Allows an accurate reconstruction of a shape.

Table 2. Summary of the existing visual perception methods (summarised on the basis of [5])

Theory Classification		**Note**
Traditional	Gestalt theory	A non-computational theory of visual form.
	Gibson's theory	Concentrated around perceiving real three-dimensional objects as real objects, representations of real objects, and abstract (non-real) objects.
	Neuropsychological theory	Mostly qualitative and not computational.
	Fractal geometry	Appropriate for natural shape representation.
Modern	High curvature points	Curve partitioning.
	Lowe's system	Three-dimensional object recognition from unknown viewpoints and single two-dimensional images.
	Marr's paradigm (shape from x)	Extended as Shape from shading, contour, texture, stereo, and fractal geometry.
	Morphogenesis	A procedure for morphogenesis based on multiple levels of resolution has been developed.
	Polygonal approximation of shape	Applied as - Combination of high curvature points and line segment approximations. - Measurement methods of the curvature of 3D surfaces.
	Symmetry-Curvature theorem	For a hierarchical deformation of the object. - The inference of the shape history from a single shape. - The inference of shape evolution between two shapes.
	The principle of transversality	When two arbitrarily shaped convex objects interpenetrate each other, the meeting point is a boundary point of concave discontinuity of their tangent planes.

3 Clustering and Customised Viewpoints

Computational clustering is performed using machine learning techniques. According to Reich [1], machine learning can be considered as explanation-based learning (EBL) or similarity-based learning (SBL). Because the ill-structured nature of design often precludes formalised theories of synthesis it has been suggested that SBL is more suitable for conceptual design [1]. There are two primary classes of machine learning techniques in the SBL approach: supervised concept learning and unsupervised concept learning. Supervised requires the user to support the learning process whereas learning is automatic in unsupervised.

As Gordon [6] argued, markedly different results can be obtained when the same data set is analysed using a different clustering strategy. It is thus important to give thought to the problem of selecting criteria for clustering that are appropriate for analysing the data being investigated.

Manfaat [2] presented an approach, *Customised Viewpoint-Spatial (CV-S)*, to support the effective utilisation of spatial layout design experience by generalising past spatial layout design cases and abstracting a single case into hierarchical levels of abstractions according to the designer's needs. He argued that the layouts of a space can be hierarchically clustered into groups based on the measures of similarities between the layouts. An example of different views is shown in Figure 5.

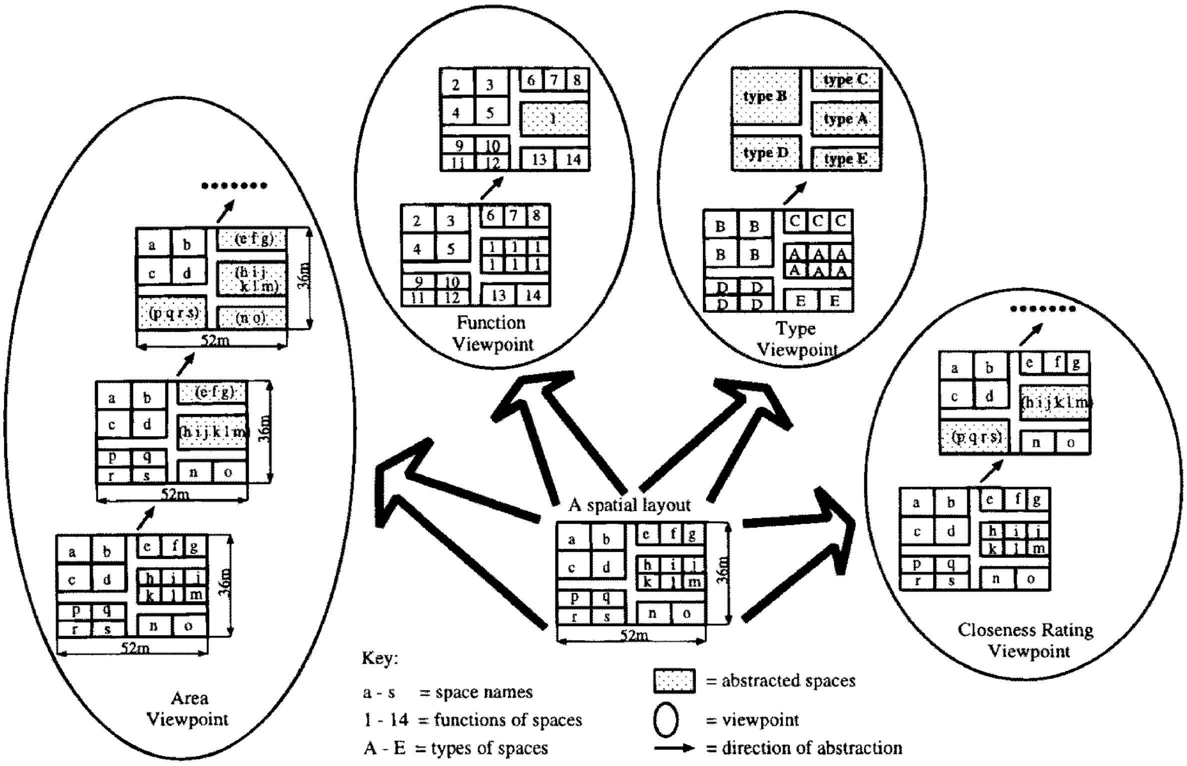


Figure 5. An illustration of abstraction of a spatial layout in four different viewpoints (adopted from [2])

Thus, pattern matching plays a key role in machine learning. It can be defined simply as the activity of matching patterns with the aim of finding similarities between them for the purpose of recognition and/or retrieval of similar patterns [7]. Patterns are matched for their similarity, grouped (clustered) together, and induction techniques used to generalise knowledge form the group members to reflect knowledge common to all in the group.

4 Multiple Clustering of Shapes

4.1 Clustering Vague Shape

A vague geometric shape can be identified by a hierarchy of shape probabilities ([3]). A child-element can be a straight line, curve, or a closed geometric shape such as a circle, rectangle, or triangle. One possible way of representing the shape vagueness of a child-element is through using probability. Consider an object in a sketch that has *n* elements (see [8]). The various possible alternative interpretations for each child-element can be represented in a hierarchical structure, with the lowest level populated by the 'primitives' of the element type.

The probability of the element being a particular geometric primitive can be obtained by mutiplying the probability of the element belonging to the appropriate group at each level leading down to the primitive in question. For example, in Figure 6, the *(n)th element* of object *A* has a 0.2016 probability to be a Closed-Polygon-Triangle derived from its probability of being a closed shape (0.64), a polygon (0.7) and a triangle (0.43), i.e. 0.64 * 0.7 * 0.45 = 0.2016.

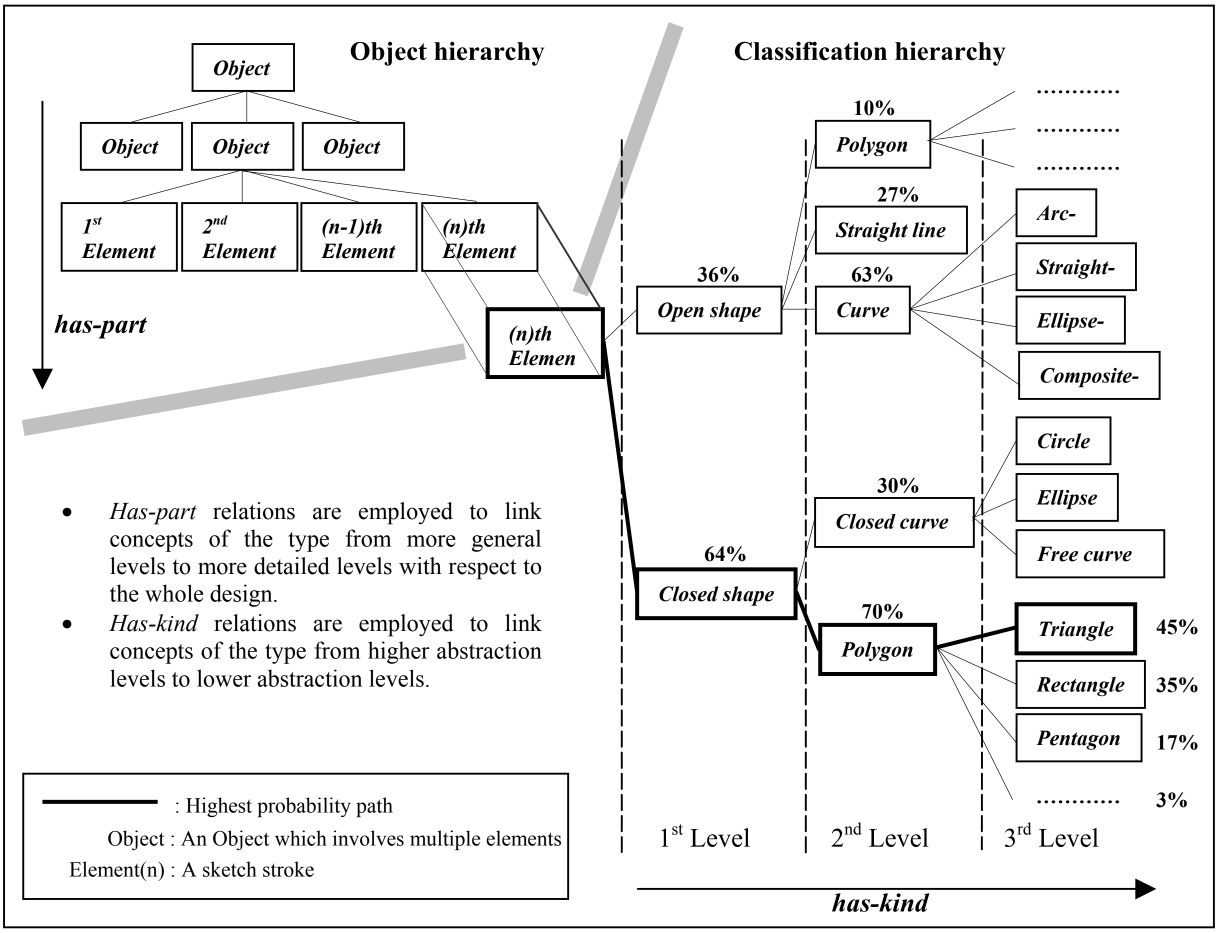


Figure 6. Hierarchical structure of vague information [3]

The hierarchical levels and the class list in each level can be changed or extended. For example, if a designer needs to analyse a sketch stroke as abstracted symbols, rather than a geometric shape element, they could change or add some levels and specific classes. Also, the level of the hierarchical structure could be extended to represent a compound object that is made from more than one object. A distinct advantage of working in this way is that the complex task of analysing the shape type is reduced to a relatively simple and manageable one through determining the probability at each level, regardless of how complicated the object, and, ultimately the whole sketch, is.

This classification hierarchy may provide clustering criteria of a vague geometric model as shown in Table 3. However, this requires further investigation.

Table 3. Classification Criteria for Clustering

Criteria		Definition	Description of Criteria
Main	Sub		
C_a		:= has child elements	Classify an object by a presence of child elements. If an object does not have any child element, the object is most likely a primitive shape.
	C_{a-1}	:= has a number of child elements	Classify an object by a number of child elements if the object has any children.
C_b		:= has sub-objects	Classify an object by a presence of sub-objects.
	C_{b-1}	:= has a number of sub-objects	Classify an object by a number of sub-objects if the object has any sub-objects.
	C_{b-2}	:= has a hierarchical depth of sub-objects	Classify by a hierarchical depth of sub-object.
C_c		:= is two-dimension	Classify two-dimensional objects.
	C_{c-1}	:= has a number of vertices	Classify an object by a number of vertices.
C_d		:= is three-dimension	Classify three-dimensional objects.
	C_{d-1}	:= has a number of surfaces	Classify an object by a number of surfaces if the object has three-dimension. A number of surfaces are analysed by the status of edges.
C_e		:= probability of a primitive.	Classify an object by the probabilities of each primitive.
	C_{e-1}	:= 1st level primitives	Classify an object by the probabilities of 1st level primitives such as “closed” and “open”.
	C_{e-2}	:= 2nd level primitives	Classify an object by the probabilities of 2nd level primitives.
	C_{e-3}	:= 3rd level primitives	Classify an object by the probabilities of 3rd level primitives.
C_f		:= has a relative spatial relationship	Classify an object by the relative spatial relationships between sub-objects.

4.2 Multiple viewpoint clustering

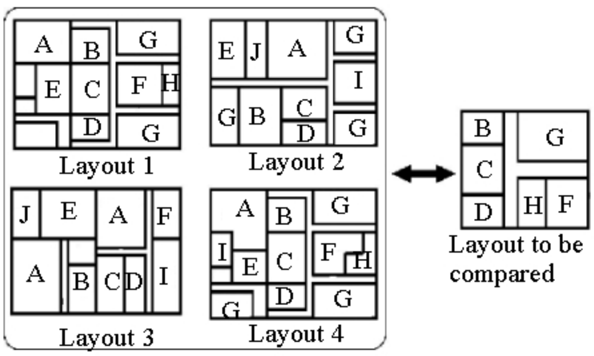
Some investigations have been conducted addressing multiple viewpoints. Howard-Jones [9] carried out an experiment in which subjects looked at a geometrical shape and generated as many interpretations of the shape as possible based on a different viewpoint. Duffy and Kerr [10] pointed out the need to support ‘Customised Viewpoints (*CV*)’. Suwa et al. [11] insisted that ‘discovering hidden features in a representation without being fixated to a single perspective of viewing’ is one of the crucial acts in creative activities.

Vague shapes may also be clustered differently depending on different viewpoints. Consider that objects *A* and *B* have various properties {A| C_a, C_b, C_c, C_d} and {B| C_a, C_e, C_f} respectively. If a designer considers that the property C_a is most important to cluster an object, then object *A* and *B* could be classified in the same cluster. In all other cases, they would be classified in a different cluster.

4.3 Shape matching

SPIDA matches topological patterns of layouts and the combined topological patterns and geometric shapes of layouts [2]. To illustrate the system’s functionality Figures 6 and 7 each show 4 past design layout (cases), the former for topological matching and the latter for combined topological and geometric shape matching. On the right of each figure are "required" layouts to be matched against the past design cases. Before proceeding the reader is invited to determine which cases best match the required layouts. You should attempt to decide the order of similarity of the layouts by determining for topological matching the cases that most reflect the required layout, where space B is adjacent to space C which is adjacent to space D, etc. For the geometric shape matching you should consider the overall shapes of the spaces and how they are related.

The results of the topological matching between each of the past design cases and the required layout are shown in Table 4. In this table, for each case, the layouts are ordered from the most to the least similar. This order is based on an analysis of corresponding spaces. If there are more than one layout case that has the same number of corresponding spaces, they have the same ranking.



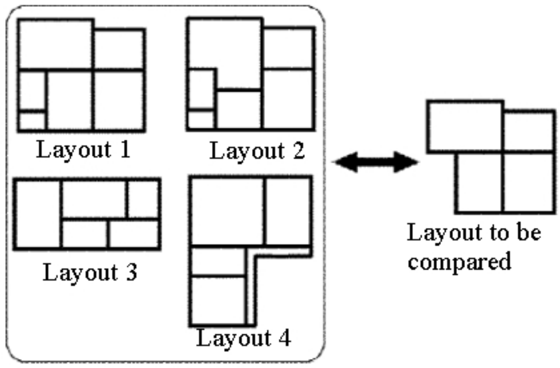


Figure 7. Topological Pattern Matching

Figure 7. Geometric Shape Matching

Table 5 shows the results of the combined topological and shape matching. In this table the cases are first ordered on the corresponding spaces and then on a shape dissimilarity measure. In this table, the layout cases are first ordered based on the corresponding spaces. They are then ordered based on a shape dissimilarity measure. The lower the measure the more similar the layout case is to the required.

Table 4. Results of Topological Pattern Matching

Ordered cases	Number of corresponding spaces
Case 1 Case 4	7
Case 3	6
Case 2	4

Table 5. Results of Geometric Shape Matching

Ordered cases	Number of corresponding spaces	Shape dissimilarity measure
1	4	0.00
2		0.47
3	3	0.23
4		0.29

Given the ability to match the layouts they then can be clustered according to their similarity measures [2].

5 Conclusion

Shape matching is a of key element in clustering geometric shapes. In this paper, we discussed about the clustering, customised viewpoints, and pattern matching regarding of shapes. Although there are various ways of representing vagueness, a hierarchical shape clustering with multiple aspects could be one way of doing this, particularly when it is desired to define the shape type of the geometric object. Work is on-going to develop the techniques presented in this paper and for a system to support the re-use of past design shape cases.

References

[1] Reich, Y. and S.J. Fenves, "The Formation and use of Abstract Concepts in Design", Concept Formation: Knowledge and Experience in Unsupervised Learning, p323-353

[2] Manfaat, D., A.H.B. Duffy, and B.S. Lee, "SPIDA: Abstracting and generalising layout design cases", Artificial Intelligence for Engineering Design, Analysis and Manufacturing (AI EDAM), 12: 1998, 141-159

[3] Lim, S., B.S. Lee, and A. Duffy, "Incremental modelling of ambiguous geometric ideas (I-MAGI)", Special Issue on Conceptual Modeling in Design Computing of the International Journal of Artificial Intelligence in Engineering, 2001. (to be published)

[4] Pavlidis, T., "A Review of Algorithms for Shape Analysis", Computer Graphics and Image Processing, 7: 1978, p243-358

[5] Loncaric, S., "A survey of shape analysis techniques", Pattern Recognition, 31(8): 1998, p983-1001

[6] Gordon, A.D., "Hierarchical Classification, in Clustering and Classification", 1996, p65-121

[7] Manfaat, D., A.H.B. Duffy, and B.S. Lee, "Review of pattern matching approaches", The knowledge Engineering Review, 11:2: 1996, p161-189

[8] Lim, S., A. Duffy, and B. Lee, "Intelligent computational sketching support for conceptual design", International Conference on Engineering Design (ICED'01), Glasgow, UK. 2001 (submitted)

[9] Howard-Jones, P.A., "The variation of ideational productivity over short timescales and the influence of an instructional strategy to defocus attention", Proceedings of Twentieth Annual Meeting of the Cognitive Science Society, 1998

[10] Duffy, A.H.B. and S.M. Kerr, "Customised Perspectives of past designs from automated group rationalisations", International Journal of Artificial Intelligence in Engineering, Special Issue on Machine Learning in Design, 8(3): 1993, p183-200

[11] Suwa, M., J. Gero, and T. Purcell, "Unexpected discoveries: How designers discover hidden features in sketches", Visual and Spatial Reasoning in Design, 1999.

S W Lim
CAD Centre, Dept. of DMEM, University of Strathclyde, James Weir building, Glasgow, Scotland, UK, G1 1XJ, UK. Tel: 44-(0)141-548-2374, Fax: 44-(0)141-552-0557, Email:sungwoo@cad.strath.ac.uk, URL:http://www.cad.strath.ac.uk/~sungwoo/Home.html