Concept Formation in Design†

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Abstract: This paper presents a computationally tractable view on where simple design concepts come from by proposing a paradigm for the formation of design concepts based on the emergence of patterns in the representation of designs. It is suggested that these design patterns form the basis of concepts. These design patterns once learned are then added to the repertoire of known patterns so that they do not need to be learned again. This approach uses the notion called the *loosely-wired brain*. The paper elaborates this idea primarily through implemented examples drawn from the genetic engineering of evolutionary systems and the qualitative representation of shapes and their multiple representations.

Keywords: concept formation, modeling concepts, loosely-wired brain, evolutionary systems, qualitative representations

1. INTRODUCTION

Where do concepts come from? is a perennial question in designing and other intellectual domains. Do all concepts already exist and we discover them or do we make them up, ie create them? Concept formation has been the subject of study from the early days of artificial intelligence [1]. This paper presents a computationally tractable view on some potential directions for exploring these fundamental questions by proposing a paradigm for the formation of the foundation of concepts in design based on the emergence of patterns in the representation of designs. It is claimed that knowledge, in general, is based on regularities in observable phenomena. If there are no regularities then the phenomenon appears to be random and no knowledge is needed to describe it and no concepts are needed to develop the knowledge. Thus, such regularities form the grounding of concepts (although not necessarily the concepts themselves). This does not address the question of whether or how knowledge is situated and whether knowledge in humans is constructed on demand [2] rather than stored separately for later use as is implied by the approach suggested here.

This approach takes the view that the identification and elicitation of these regularities is a form of learning which requires appropriate means to identify "features" in the form of feature sensors. Once new concepts have been found they are added to the available sensors so that the same concept need never be learned afresh. This approach is founded on a notion called the *loosely-wired brain*. A richer view not only identifies and elicits these regularities, it also situates them in the context within which they were learned so that the concepts carry with them notions of their applicability derived from the situation. This applicability is then constantly modified as the concept is found to be useful in similar and related situations [3]. However, this apect is not explored further here.

The loosely-wired brain model is a formalisable approach based on an analogy with one view of brain development. It assumes that the computational system operates within a world it can sense through its sensors. As applied in designing, design-related sensors, ○ in

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Figure 1, sense design states in the design world which can be interpreted as design features. A design feature is a structure in a design representation. Design features can be either predefined or emergent [4]. *Emergence* here means that a feature was not previously represented but can now be represented because it has now been "constructed" and recognised.

New design features which are design patterns based on design existing sensors, emerge, shown as in Figure 1. These new, emergent design features are added to the design system in the form of new design-related concepts which can now be utilised in all later designing activity of the system. The entire process can be repeated to construct a hierarchy of dependent design concepts. The emergent design pattern, in Figure 1, is dependent on both the earlier emerged pattern and some original features. Thus, the system commences with a few sensors and design pattern recognisors which define its potential. What it is exposed to determines what design concepts can be formed. Design concepts can be formed from design patterns in sensed design data or from design patterns which include previously formed design concepts. Thus, the system "wires" itself up depending on its sensors, its start state and what it has been exposed to.

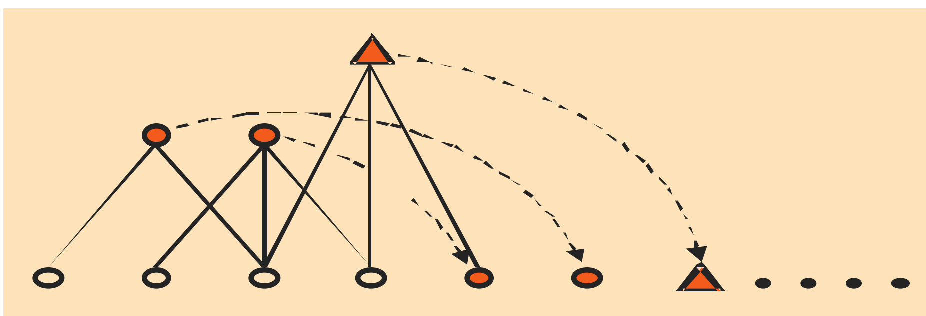

Figure 1: The original design feature detectors, , are used to locate emergent design-related regularities, , then original and newly emerged design features are used to locate new emergent design regularities, , which are added as new design features to the system. The system recursively "wires" itself up.

The remainder of this paper takes two previously described design examples and redescribes them through this lens as design concept formation systems. The first design example draw its inspiration from a modern development in genetics, namely genetic engineering. It uses genetic engineering to form the design concepts which provide the foundation for the determination of style in architectural facades. The second design example utilises qualitative representations of shapes to determine the foundations for the concepts which underpin the design concepts associated with shape features. These "concepts" are grounded in the situations the systems have been exposed to rather than being provided at the outset.

2. DESIGN CONCEPT FORMATION THROUGH GENETIC ENGINEERING

2.1. Representation

One approach to design concept formation using the loosely-wired brain model is to utilise representations of world states which are different at different levels. Thus, the representations from which concepts are derived are different to the human interpretation of those concepts. This is exemplified most clearly when the concepts themselves are derived from graphical images by humans but from symbolic representations by computational systems. This is further accentuated when using an evolutionary model since the genetic representation is fundamentally different to its expression in a design.

2.2. Evolving design concepts

The practice of genetic engineering in natural organisms involves locating genetic structures which are the likely cause of specified behaviours in the organism. This provides a direct analog with design concept formation. The behaviour of the organism is an observable regularity which maps onto a concept and the structure of the genetic material which causes that behaviour is a representation of that concept, albeit a representation which has to be expressed for the concept to appear. The practice of genetic engineering is akin to reverse engineering.

Consider Figure 2 where the population of designs is divided into two groups (it could be more). One group exhibits a specific regularity whilst the other does not. The goal is to locate a common structure in the genotypes of those designs which exhibit this regularity. Genetic engineering at this symbolic level uses pattern matching and sequence analysis techniques to locate these genetic structures. Of particular interest in this form of design concept formation is the separation of position-dependent structures from position-independent structures. The implication of the former is that the design concept depends on either other design concepts or a "situation" for it to apply, whilst in the latter case the design concept is independent of any situation.

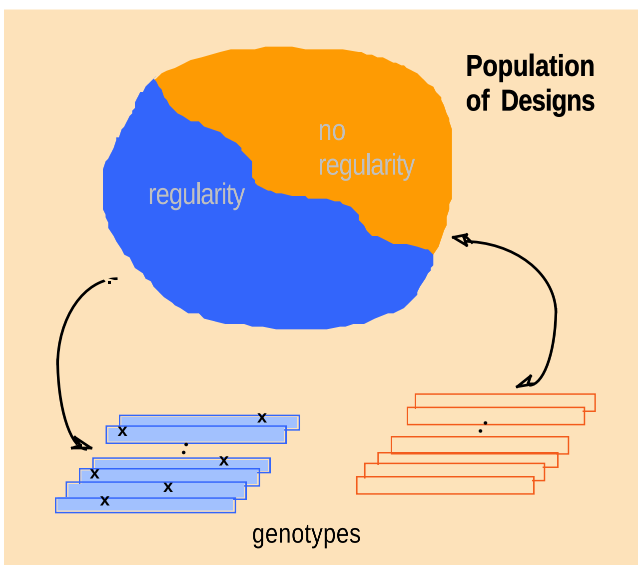

Figure 2. Genetic engineering is concerned with locating groups of genes' regularity, marked as X in the genotypes of those design which exhibit a specific behavioural regularity.

Take as an example the 8 design genes shown in Figure 3 represented in the form of state transition rules. These design genes are used to form the genotypes of designs within which a regularity is sought.

Figure 4 shows 10 designs produced from those genes. Each design is searched to determine some common regularity. From Figure 4 can be seen that a design concept has been found. There is no semantic label for that concept since such labels need to be grounded in human experience, but there is a symbolic representation and its graphical interpretation, which is appropriate for this context.

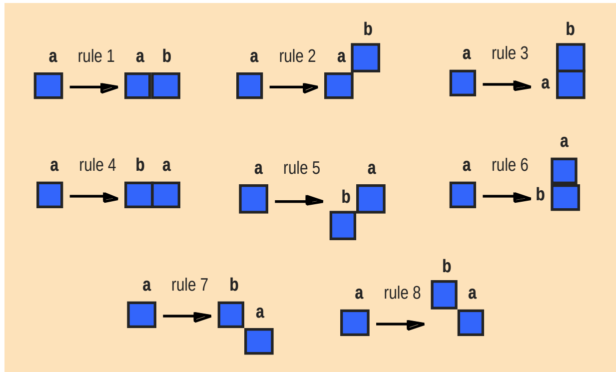

Figure 3. A set of 8 genes in the form of shape transition rules [5].

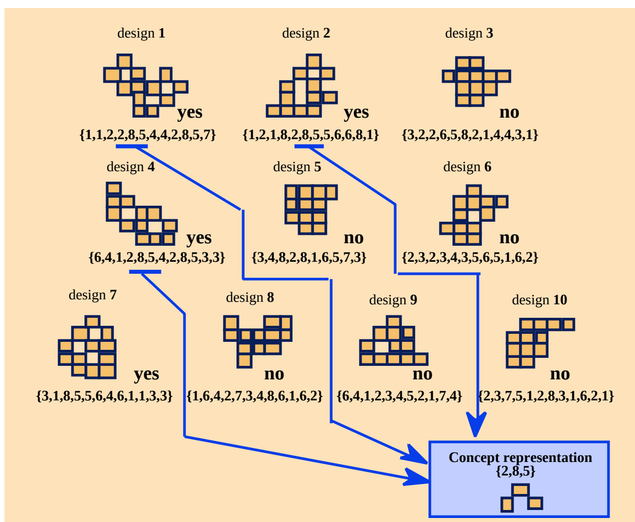

Figure 4. A set of 10 designs produced with the genes in Figure 3 and evaluated according to their regularity. Genetic engineering techniques emerge the gene group {2, 8, 5} as being the likely cause of that regularity, after [5].

2.3. Style determination as design concept formation

Style is regarded as a representation of the products' characteristics [6] or a way of doing things [7]. Style is a complex concept which has to do with seeing things in existing objects or some characterisable ways of doing things. It is associated with regularities and hence connects directly with the view of concepts presented in this paper. The determination of style thus maps onto the formation of the design concepts which go make up that design style. The process of determining design style can be modelled on the process of evolving the structures in the genetic representations of designs which exhibit regularities where those regularities, here, pertain to style. The remainder of this section presents some preliminary results from an implementation based on this view. Figure 5 shows an outline of the structure of the process. The basic architectural elements are sensed as features in individual designs. The representations of the designs are searched for regularities which involve these design features in subsets of the population of designs which appear to exhibit the style. These regularities form “simple design concepts”. Simple design concepts can be used to form “complex design concepts”. The conjunction of complex design concepts forms the style.

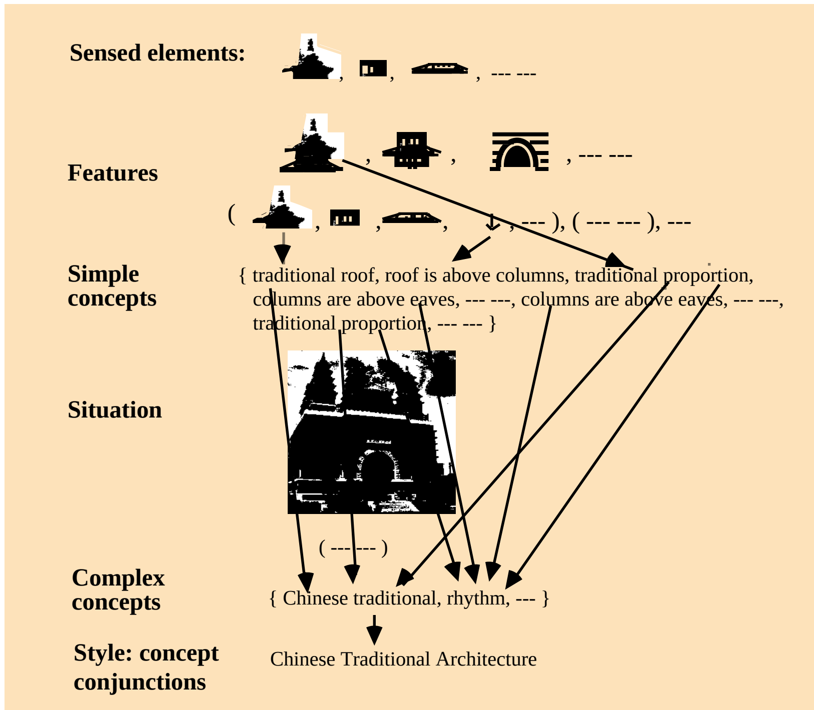

Figure 5. Emerging the hierarchical design concepts of architectural style, after [8].

Figure 6 shows examples of traditional Chinese architectural facades from which design style concepts can be derived. The basic features are coded as the genes from which the genotype is formed and the fitnesses of the resulting designs commence with feature sensors and then regularities are searched for using genetic engineering.

(a) (b) (c)

Figure 6. Three examples of traditional Chinese architectural facades [9].

The complexity of a design concept is a function of the number of hierarchical levels of design concepts below it. Thus, 0–complexity design concepts may be seen as only the design features themselves. 1–complexity design concepts are structures which contain only 0–complexity design concepts. Thus, n–complexity design concepts are structures which contain at least one (n-1)–complexity design concept within them along with other lower levels of complexity. Figure 7 shows some preliminary results from the evolution of style concepts for traditional Chinese facades; g_i is the label for an evolved gene which maps onto a design concept.

Figure 7(a) shows design concept g_{10} is made up of design concept g_8 and three design features. Design concept g_{11} is made up of design concept g_9 used twice and design concept g_8. We could imagine that in such an evolutionary system as this the evolution of design concepts would increase in complexity over time as more design concepts become available from which to build other design concepts. This is borne out in Figure 8.

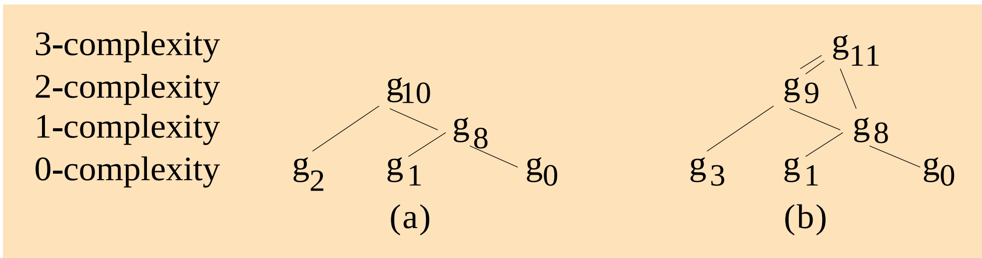

Figure 7. Derivation of design concepts and their complexity [8].

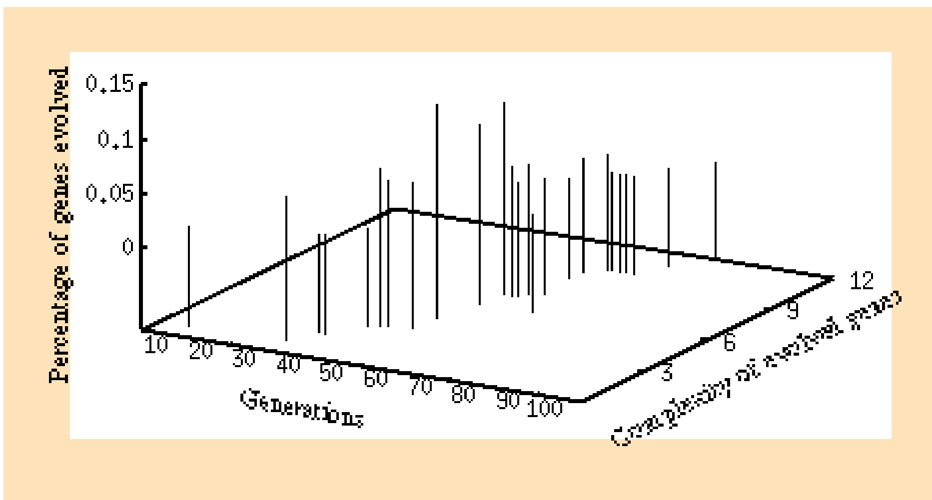

Figure 8. The complexity of design concepts (in terms of evolved genes) as a function of generations of evolution of designs and their percentage of all design concepts evolved [8].

As can be seen in Figure 8, the level of complexity of the design concepts increases with the generations as expected. This is important to understand since it implies that design concepts depend heavily on previous design concepts and that high-complexity design concepts may be far removed from the features on which they are hierarchically based.

3. CONCEPT FORMATION THROUGH MULTIPLE REPRESENTATIONS

So far this paper has presented one approach to design concept formation through the evolution of design concepts as structural regularities in genetic representations of designs. This section presents another approach also based on locating structural regularities in representations of designs. However, the focus here is on how different design concepts can be determined for what is apparently the same designed object through the use of multiple representations of that object.

3.1. Multiple representations

It appears that humans have no difficulty in using different representations for what is apparently the same object in order to achieve different goals. This fits well with the “no-function-in-structure” principle. The implication of this is that there is no unique representation for an object. This can be seen in an exaggerated form in Figure 9, an ambiguous figure. Is it a figure of a white vase on a black background or two black human heads in profile on a white background? It depends on the representation as to what is seen. This figure also brings out the notion of situatedness. If the representation is of the white vase without any background then no change in representation will bring out the black human heads. Thus, there is a nexus between the two images with one forming the situation for the other.

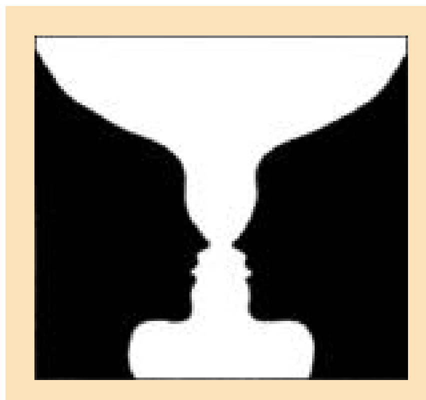

Figure 9. Is this a white vase on a black background or two black human heads in profile on a white background?

Figure 10 demonstrates multiple representations further with an example of a building plan, Figure 10(a). Figures 10(b) 1–12 illustrate different possible representations all of which produce the same building plan. In Figure 10(b) item 1 shows a node and arc representation while Figure 10(b) item 4 shows a foreground–background representation and Figure 10(b) item 6 a rectangular grid representation and Figure 10(b) item 7 a union of elements representation and so on. What makes this interesting in this context is that multiple representations provide the opportunity for multiple design concepts to be formed from what looks to be a single object. This is important if those design concepts are to be used later since it will not be known in advance which of the possible design concepts that could be formed are likely to be useful.

Thus, the representation in Figure 10(b) 5 which uses reflective symmetry allows for the emergence of other axes of reflective symmetry such as that shown in Figure 10(b) 8, whilst that in Figure 10(b) 6 which uses a tartan grid representation allows for the movement of the grid positions. Figure 10(b) 8 could not be reached from the representation in Figure 10(b) 6. We shall describe an example in further detail in the next section.

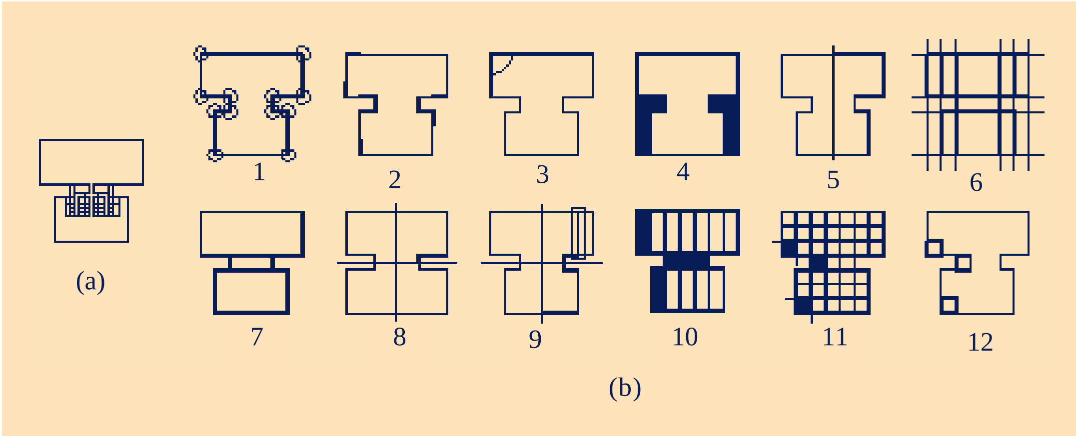

Figure 10. Representations of shape: (a) primary floor plan; (b) 1 to 12, multiple possible representations [10].

3.2. Emerging shape concepts from qualitative representations of shapes

The qualitative approach to shape representation provides an alternate approach to geometric-based representations in the sense that no accurate measurement of shape is required to model the design primitives. There have been a number of symbolic representation schemes developed for handling design primitives as shape and space. One of the most common approaches to syntactic shape description has been based on contour lines of the shape which are de-segmented using directional vectors [11]. Qualitative codes, called Q-codes, which describe attributes and changes in attributes at landmark locations are used to construct a representation. Thus, a representation becomes a string of Q-codes. A representation in this form can then be analysed for regularities which form features which map on to shape concepts. It is useful to form an analogy with language to assist in the understanding of the relationships between the Q-codes, their use in forming shape concepts and in the notion of a hierarchy of shape concepts, Table 1.

Linguistic analogy	**Reference to shape concepts**
Q-code	Simplest symbol which refers to an atomic component of a shape attribute
Q-word	Regular sequence of Q-codes which refers to a shape pattern - a shape concept
Q-phrase	Regular sequence of Q-words which shows a distinctive pattern - concepts higher in a hierarchy
Q-sentence	Aggregation of Q-codes, Q-words, and Q-phrases referring to a closed shape described by shape concepts
Q-paragraph	A group of Q-sentences where spatial relationships are described with specific connectives

Table 1. Various levels of shape concepts with their linguistic analogy, after [12].

Three basic Q-codes are employed to develop the qualitative representation of shape, these provide a set of possible multiple interpretations which can be treated separately or in various forms of union:

A: relative angle between two contiguous line segments; the value range is {-, 0, +} mapping onto angle values of less than 180^{o}, equal to 180^{o} and greater than 180^{o};

L: relative length between two contiguous line segments; the value range is {-, 0, +} mapping onto smaller than, equal to and greater than; and

K: line segment curvature; the value range is {-, 0, +} mapping onto concave, zero and convex curvatures.

Different Q-words from the same string of Q-codes produce different representations of the same shape, thus, producing multiple representations of that shape.

The following summarises the fundamental notions involved in determining shape concepts as structural regularities in multiple representations derived from Q-code string representations.

- Q-code (α): $\alpha = \{\beta_i \mid i \ \ \{-,0,+\}, \beta \ \ \{A, K, L\}\}$
- Q-sentence (σ): $\sigma = \{\alpha_1 \ \alpha_2 \ ... \ \alpha_m\}$ where m = length(σ)
- Q-word (ω): $\{\omega_i \quad \sigma \mid \omega_i = \alpha_j$ i=1, j [1,m] or $\omega_i = \alpha_1 \ ... \ \alpha_i$, |k-j|=i, i=[2,m]}
- Number of Q-code primitives: r
- Number of possible Q-words of length i: $N_W(i) = r^i$.
- A Q-word of length i occurred in Q-sentence: $P_{ij} \ \ \omega_i$, $\omega_i = \{P_{i1}, P_{i2}, P_{i3},.., P_{iN_{W(i)}}\}$
- Number of occurrences of a Q-word of length i in Q-sentence: N_O, the number of all P_{ij} for fixed i and fixed j.
- Number of kinds of Q-words of length i occurred in Q-sentence: N_K(i), the number of P_{ij} where each $N_O \geq 1$.
- Sum of all the occurrence of Q-words of length i in Q-sentence: N_A(i), the number of all P_{ij} for fixed i and variable j.

Consider the two shapes in Figure 11. Since neither has any curvature other than zero in any of the bounding line segments, only A and L Q-codes will be used. Table 2 shows their representation as A and L Q-code strings. The process of emerging shape concepts as structural regularities is applied.

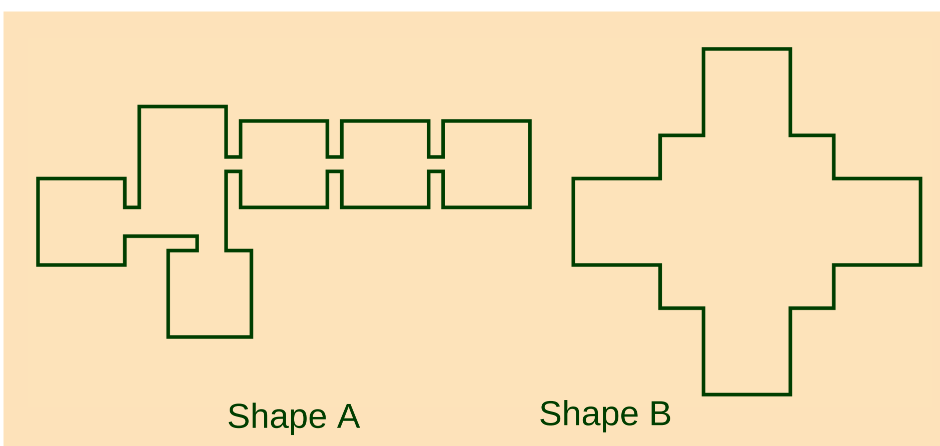

Figure 11. Two shapes used in shape concept formation [13].

Shapes	**A-code**	**L-code**
Shape A	$(A_+ A_+ A_+ A_+ A_- A_- A_- A_+ A_+ A_- A_- A_+ A_+ A_- A_- A_+ A_+ A_+ A_+ A_- A_- A_+ A_+ A_- A_- A_+ A_+ A_- A_- A_+ A_+ A_- A_- A_+ A_+ A_+ A_+ A_- A_- A_-)$	$(L_+ L_0 L_0 L_- L_+ L_- L_+ L_+ L_- L_- L_+ L_+ L_- L_- L_+ L_+ L_0 L_0 L_- L_- L_+ L_+ L_- L_- L_+ L_+ L_- L_- L_+ L_+ L_+ L_- L_+ L_+ L_0 L_0 L_- L_+ L_- L_+)$
Shape B	$(A_+ A_+ A_- A_+ A_- A_+ A_+ A_- A_+ A_- A_+ A_+ A_- A_+ A_- A_+ A_+ A_- A_+ A_-)$	$(L_0 L_0 L_- L_0 L_+ L_0 L_0 L_- L_0 L_+ L_0 L_0 L_- L_0 L_+ L_0 L_0 L_- L_0 L_+)$

Table 2. Q-code encodings of shapes in Figure 11.

An analysis of these Q-code representations for A-code strings to find regularities produces new concepts. These results indicate that a variety of shape concepts emerge, concepts for which there exist labels such as symmetry, indentation, protrusion and so on, each of which may be thought of as a feature on an initial shape. Figure 12 and Table 3 summarise some of these concepts as well as others that have been derived from the analysis of other shapes' representations. Similarly, an analysis of these Q-code representations for L-code strings to find regularities produces new concepts. Different representations produce different shape concepts.

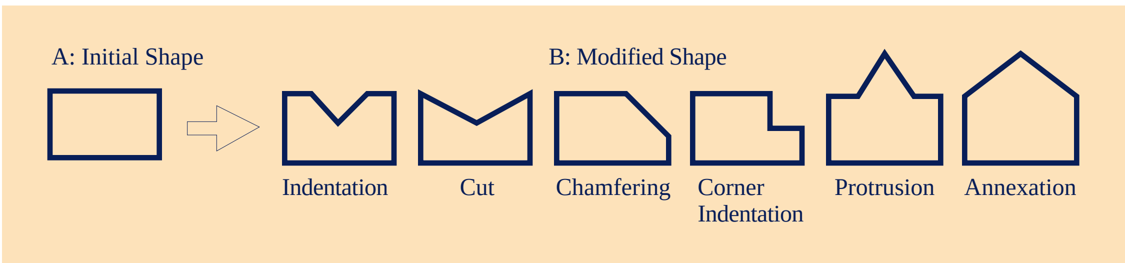

Figure 12. Shape concepts emerged from analysing Q-code regularities [13].

Class Type	Shape Concept	Difference (A, B)	Shape Concept Q-code
Indentation class	Indentation A –> B Cut A -> B Chamfering A –> B Corner-indentation A –> B	C+ C- C+ C- C+ C- C+	C+ *n* *(C-) C+ *n* *(C-) C+ C+ C+ C- C+
Protrusion class	Protrusion A –> B Annexation A –> B	C- C+ C- C+	C- *n* *(C+) C- *n* *(C+)

Table 3. Q-codes for emerged shape features, after [13].

4. DISCUSSION

Commencing from a view of simple design concept formation as structural regularities in design representations, this paper has demonstrated two computational approaches to the emergence of design concepts. Both approaches map well onto the notion of the "loosely-wired brain". Each of them commences with elementary design feature sensors or detectors which are used to emerge low-level design concepts. These low-level concepts are then put back into the system as new design feature sensors or detectors so that increasingly complex design concepts can be emerged using them hierarchically. Thus, as each newly emerged design concept is put back into the pool of sensors the 'system is wired up' with those design concepts that give its world a unique character defined by the design concepts it has. The way the system wires up is a function of its starting sensors and the design concepts it emerges, which are a function of the situations it has been exposed to. Two agents commencing with the same initial sensors and the same processes for emerging design concepts would wire up differently if they were exposed to different situations and would thus perform differently when later they were both exposed to the same situation.

The ability to understand and alter a world is a function of the concepts available to an agent. The "loosely-wired brain" model allows an agent to learn more and more about its world by learning more and more concepts. As it obtained more high-level concepts so the performance of the agent should improve.

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