Concept Formation in Design: Towards a *Loosely-Wired Brain* Model

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Abstract: This paper presents a computationally tractable view on where simple concepts come from by proposing a paradigm for the formation of concepts based on the emergence of patterns in the representation of designs. It is suggested that these patterns form the basis of concepts. These 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

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 answers to these fundamental questions by proposing a paradigm for the formation of simple concepts 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. Thus, such regularities form the grounding of concepts (although not necessarily the concepts themselves).

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.*

The loosely-wired brain model is a formalisable approach based on an analogy with one view of brain development. It assumes that the system operates within a world it can sense through its sensors. Sensors, ○ in Figure 1, sense states in the world which can be interpreted as features. A feature is a structure in a representation. Features can be either predefined or emergent. New features which are patterns based on existing sensors, emerge, ● in Figure 1. These new, emergent features are added to the system in the form of new concepts which can now be utilised in all later activity of the system. The entire process can be repeated to construct a hierarchy of dependent concepts. The emergent 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 pattern recognisors which define its potential. What it is exposed to determines what concepts can be formed. Concepts can be formed from patterns in sensed data or from patterns which include previously formed concepts. Thus, the system "wires" itself up depending on its start state and what it has been exposed to.

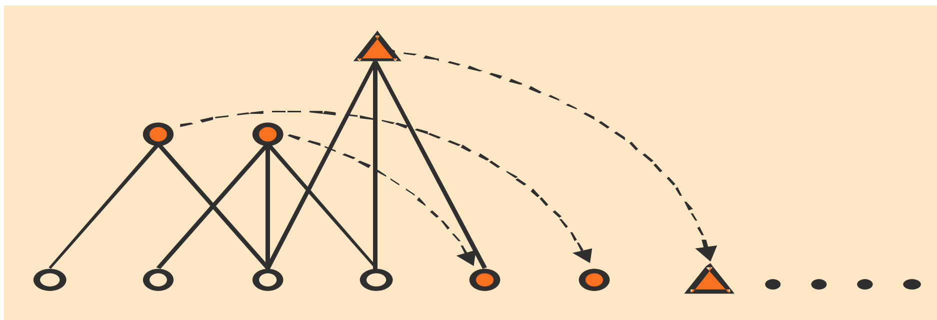

Figure 1: The original feature detectors, , are used to locate emergent regularities, , then original and newly emerged features are used to locate new emergent regularities, , which are added as new features to the system. The system recursively "wires" itself up.

The remainder of this paper takes two examples and redescribes them through this lens as concept formation systems. The first examples draw its inspiration from a modern development in genetics, namely genetic engineering. It uses genetic engineering to form the concepts which provide the foundation for the determination of style in architectural facades. The second example utilises qualitative representations of shapes to determine the foundations for the concepts which underpin the concepts associated with shape features.

2. CONCEPT FORMATION THROUGH GENETIC ENGINEERING

2.1. Representation

One approach to concept formation using the loosely-wired brain model is to use 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 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 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 concept formation is the separation of position-dependent structures from position-independent structures. The implication of the former is that the concept depends on either other concepts or a "situation" for it to apply, whilst in the latter case the concept is independent of any situation.

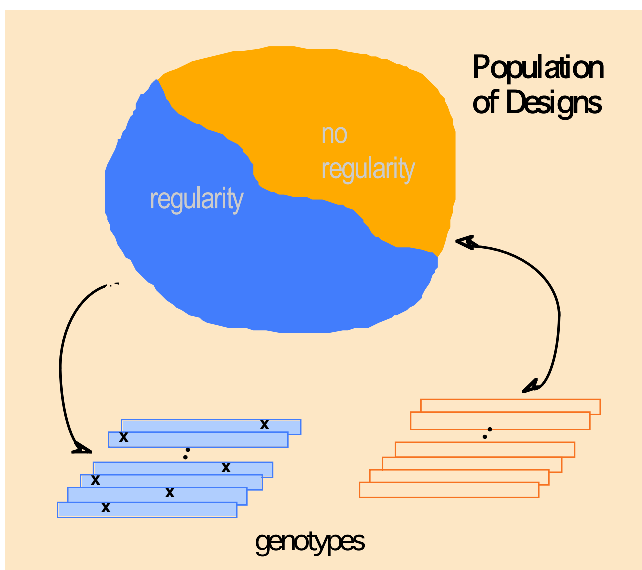

Figure 2. Genetic engineering is concerned with locating groups of genes' regularity, marked as X in the genotypes of those design which exhibit a specific behavioural regularity.

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

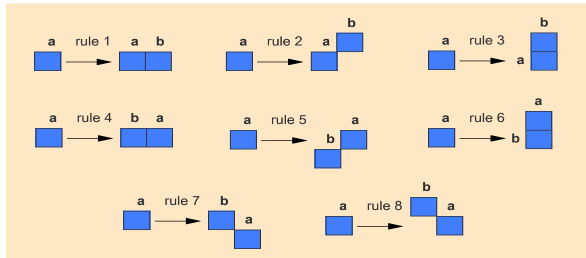

Figure 3. A set of 8 genes in the form of shape transition rules [2].

Figure 4 shows 10 designs produced from those genes. Each design is searched to determine some common regularity.

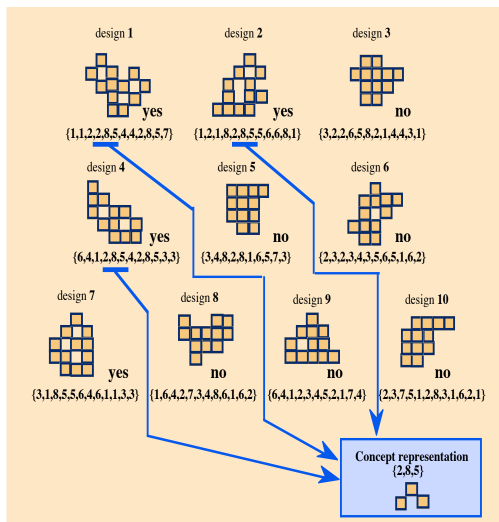

Figure 4. A set of 10 designs produced with the genes in Figure 3 and evaluated according to their regularity. Genetic engineering techniques emerge the gene group {2, 8, 5} as being the likely cause of that regularity, after [2].

From Figure 4 can be seen that a 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.

2.3. Style determination as concept formation

Style is regarded as a representation of the products' characteristics [3] or a way of doing things [4]. 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 concepts which go make up that style. The process of determining style can be modeled 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 these concepts. Figure 5 shows an outline of the structure of the process. The basic architectural elements are sensed as features in individual designs. The representation of the designs are searched for regularities which involve these features in subsets of the population of designs which appear to exhibit the style. These regularities form “simple concepts”. Simple concepts can be used to form “complex concepts”. The conjunction of complex concepts forms the style.

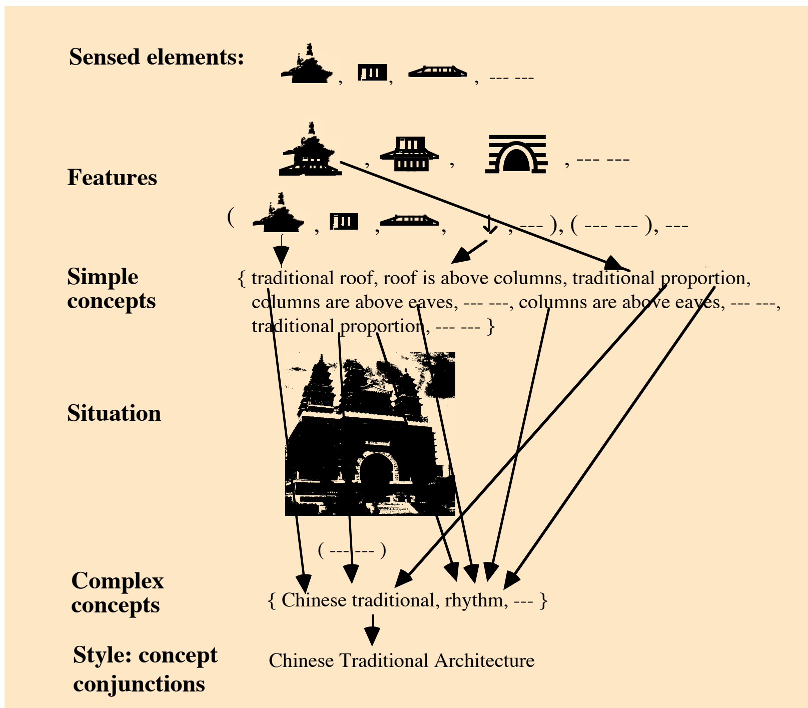

Figure 5. Emerging the hierarchical concepts of architectural style, after [5].

Figure 6 shows examples of traditional Chinese architectural facades from which 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. Examples of traditional Chinese architectural facades [6].

The complexity of a concept is a function of the number of hierarchical levels of concepts below it. Thus, 0–complexity concepts may be seen as only the features themselves. 1–complexity concepts are structures which contain only 0–complexity concepts. Thus, n–complexity concepts are structures which contain at least one (n-1)–complexity 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.

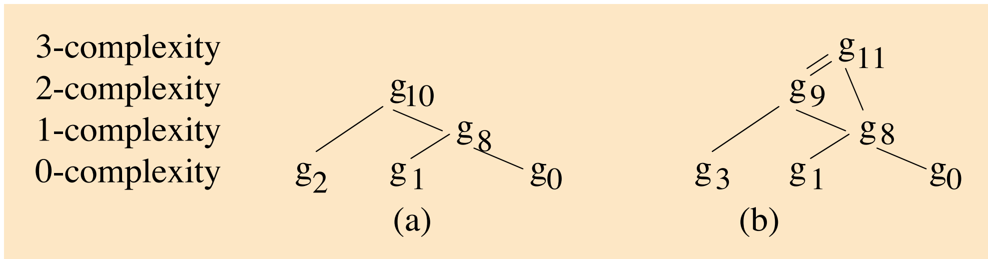

Figure 7. Derivation of concepts and their complexity [5].

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

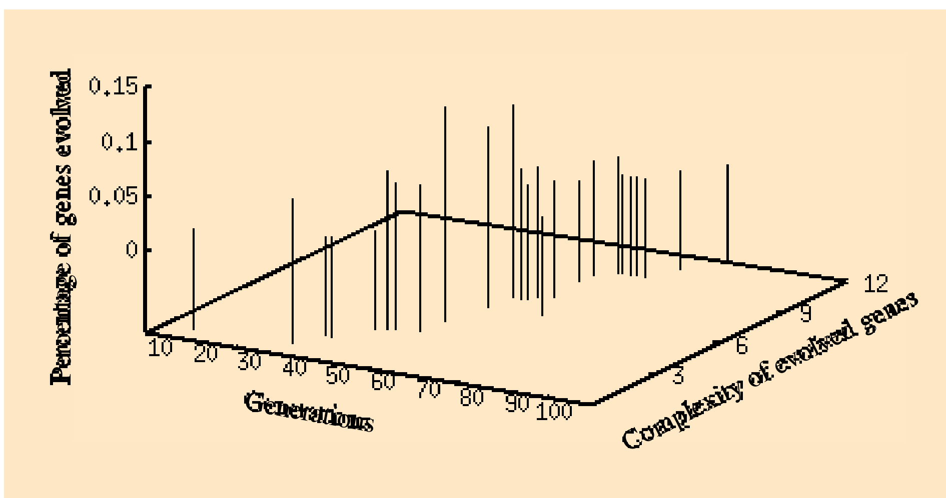

Figure 8. The complexity of concepts (in terms of evolved genes) as a function of generations of evolution of designs and their percentage of all concepts evolved [5].

As can be seen in Figure 8, the level of complexity of the concepts increases with the generations as expected. This is important to understand since it implies that concepts depend heavily on previous concepts and that high-complexity 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 concept formation through the evolution of concepts as structural regularities in genetic representations of designs. This section presents another approach also based on locating structural regularities in representations. However, the focus here is on how different concepts can be determined for what is apparently the same object through the use of multiple representations.

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 situation. 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.

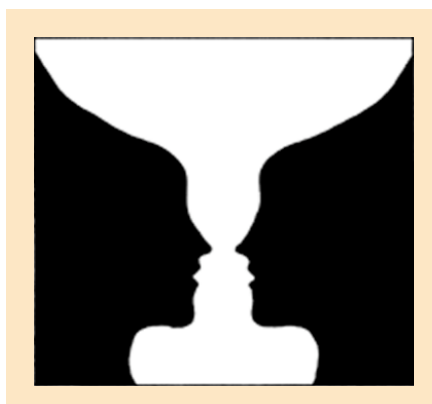

Figure 9. Is this a white vase on a black background or two black human heads in profile on a white background?

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 concepts to be formed from what looks to be a single object. This is important if those concepts are to be used later since it will not be known in advance which of the possible concepts that could be formed are likely to be useful.

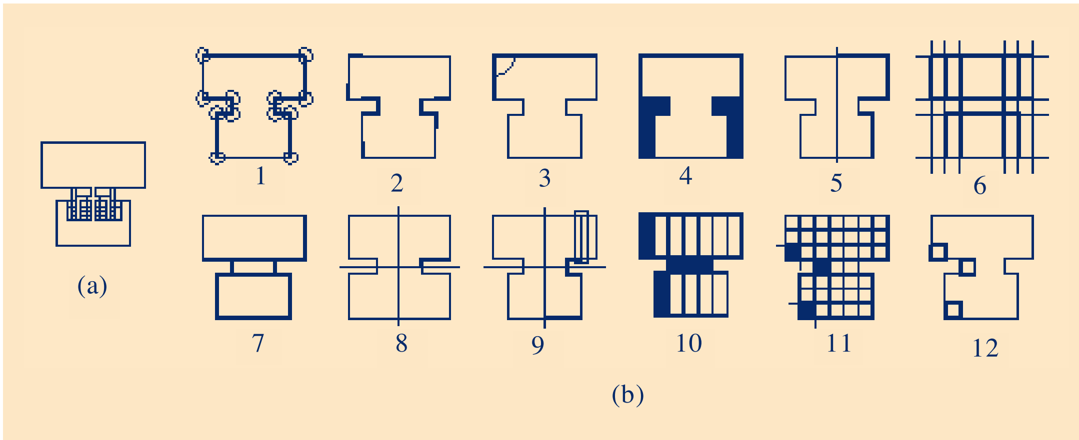

Figure 10. Representations of shape: (a) primary floor plan; (b) 1 to 12, multiple possible representations [7].

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 [8]. Qualitative codes, 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 [9].

Three basic Q-codes are employed to develop the qualitative representation of shape:

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 multiple representations derived from Q-code string representations.

- Q-code: □ = {$□_i$ | i□ {-,0,+}, □□ {A, K, L}}
- Q-sentence: □ = {$□_1$ $□_2$ ... $□_m$} where m = length(□)
- Q-word: {$□_i$ □ □ | $□_i$ = $□_j$ i=1, j□[1,m] or $□_i$ = $□_1$ ... $□_i$, |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}□ $□_i$, $□_i$ ={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.

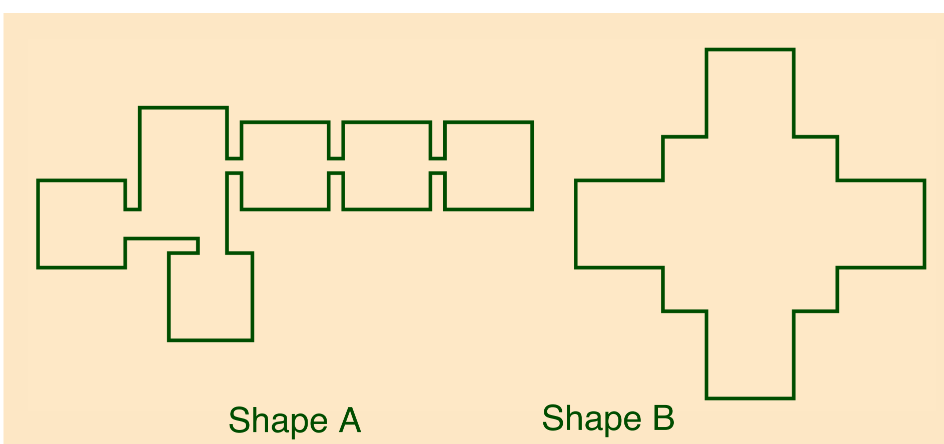

Figure 11. Two shapes used in shape concept formation [9].

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 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.

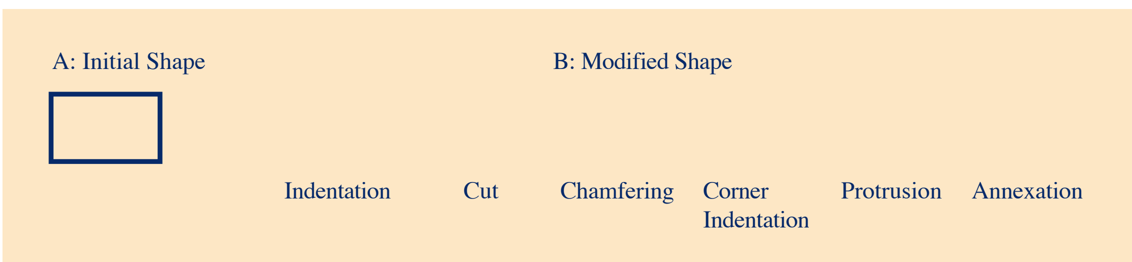

Figure 12. Shape concepts emerged from analysing Q-code regularities [9].

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 [9].

4. DISCUSSION

Commencing from a view of simple concept formation as structural regularities in representations, this paper has demonstrated two computational approaches to the emergence of concepts. Both approaches map well onto the notion of the loosely-wired brain. Each of them commences with elementary feature sensors or detectors which are used to emerge low-level concepts. These low-level concepts are then put back into the system as feature sensors or detectors so that increasingly complex concepts can be emerged using them hierarchically. Thus, as each newly emerged concept is put back into the pool of sensors the ‘brain is wired up’ with those concepts that give its world a unique character defined by the concepts it has. The way the brain wires up is a function of its starting sensors and the 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 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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