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From geons to structure. A note on object representation

Emanuel Leeuwenberg, Peter Van der Helm, Rob Van Lier
Nijmegen Institute for Cognition and Information, Department of Experimental Psychology, University of Nijmegen, PO Box 9104, 6500 HE Nijmegen, The Netherlands
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Abstract. Two models of object perception are compared: recognition by components (RBC), proposed by Biederman, and structural information theory (SIT), initially proposed by Leeuwenberg. According to RBC a complex object is decomposed into predefined elementary objects, called geons. According to SIT, the decomposition is guided by regularities in the object. It is assumed that the simplest of all possible interpretations of any object is perceptually preferred. The comparison deals with two aspects of the models. One is the representation of simple objects—various definitions of object axes are considered. It is shown that the more these definitions account for object regularity and thus the more they agree with SIT, the better the object representations predict object classification. Another topic concerns assumptions underlying the models: the identification of geons is mediated by cues which are supposed to be invariant under varying viewpoints of objects. It is argued that such cues are not based on this invariance but on the regularity of actual objects. The latter conclusion is in line with SIT. An advantage of RBC, however, is that it deals with the perceptual process from stimulus to interpretation, whereas SIT merely concerns the outcome of the process, not the process itself.

1 Introduction

This paper deals with two models for visual object representation. One model is called 'recognition by components' (RBC) and was proposed by Biederman (1987). The other model is called 'structural information theory' (SIT) and was proposed by Leeuwenberg (1969, 1971) and elaborated by various researchers at the University of Nijmegen (eg Boselie and Leeuwenberg 1986; Buffart et al 1981; Collard and Buffart 1983; Mens and Leeuwenberg 1988; Van der Helm and Leeuwenberg 1986, 1991; Van Lier et al 1994; Van Tuyl 1980). In fact we have dealt with these two models in a previous paper (Leeuwenberg and Van der Helm 1991), but in a way that differs from the present one. In that previous paper, we contrasted the two models with each other. In the present paper we focus on the characteristics shared by the two models. In fact, we start from RBC and consider the changes that would transform this approach into SIT. This strategy is used with respect to two aspects of the models. The first aspect to be dealt with is the actual representation of objects as prescribed by the models (section 2). The second topic which is discussed refers to assumptions underlying the two models (section 3).

2 From axis to superstructure

The two models will not be presented fully, but only as far as relevant for comparing the two models. As mentioned above, we start from RBC. Therefore, we first indicate some features of this approach.

2.1 *Recognition by components (RBC)*

Biederman (1987) assumes that complex objects are perceived as compositions of simple objects, in a manner analogous to the way words are recognized on the basis of about forty phonemes. He distinguishes thirty-six different simple objects, called 'geons'. Each of them can be identified from their retinal projections. We will not deal with the identification process, but merely with the geon properties with respect to which geons differ from each other.

A geon is specified by an axis and a cross section. The cross section is orthogonal to the axis and may vary in three ways. The axis may only vary in one way. Thus, to specify a geon by means of a so-called geon code, four variables have to be specified, as follows.

(i) The contour of the cross section consists merely of straight line segments (S), or includes one or more circular curves (C).

(ii) The cross section is symmetrical (+) or asymmetrical (−). In fact, Biederman distinguishes three levels for this variable but, for our purpose, this binary categorization suffices.

(iii) Going along the axis, the cross section is constant (+) or varies in size. In the latter case, the cross section expands (−), or both expands and contracts (− −).

(iv) The axis is a straight line (S) or a circular curve (C).

An instance of a geon is a tube, with (C+ +S) as geon code. The first three indices refer to the cross section, being circular (C), symmetrical (+), and constant (+). The fourth index (S) refers to the straight axis of the tube. Another instance of a geon is a banana. Its geon code is (S+ − −C). The square-shaped cross section has straight line segments (S) and is symmetrical (+). The size of this cross section increases and decreases (− −). The axis is curved (C).

In our analysis of RBC we will make use of such geon codes. Obviously such codes depend on the way axes and cross sections are defined. According to Biederman, the axis primarily is the component with the 'longest extension'. In case there is no unambiguous longest component, the axis is orthogonal to the most constant and symmetrical cross section. The latter case is illustrated by means of figure 1. This figure stands for a geon. The question is how this geon can be represented in the best way. The height, width, and depth of shape in figure 1a are about equal. Therefore, three axes, *x*, *y*, and *z*, can be considered, each with a different cross section. The *x*-axis, shown in figure 1b, implies a cross section with varying proportions. It varies in both size and form. Therefore, this axis is a bad choice. The vertical *y*-axis, in figure 1c, and the horizontal *z*-axis, in figure 1d, both imply constant cross

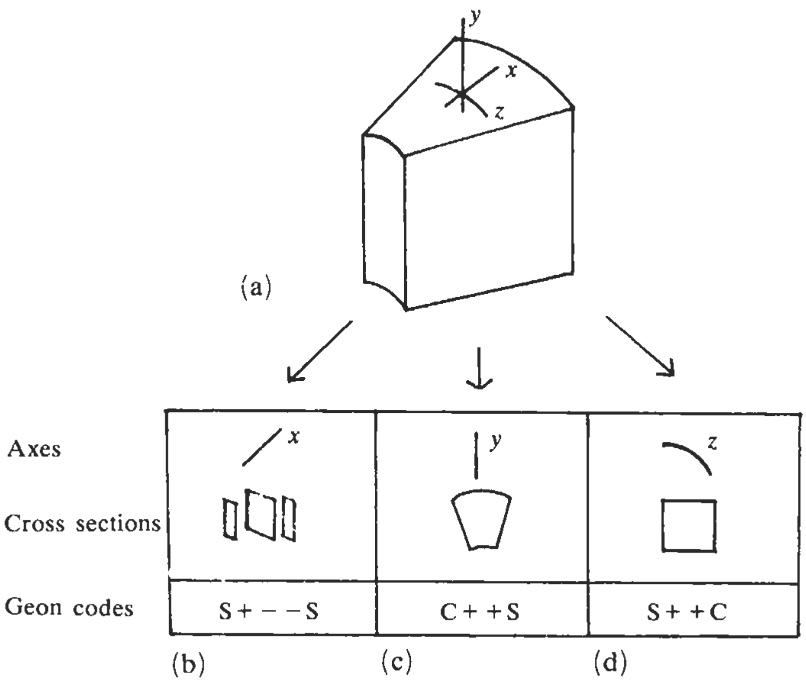

Figure 1. For the geon object in (a) three axes *x*, *y*, and *z* are possible. The cross sections of these axes are shown in (b), (c), and (d), respectively.

sections, but the cross section in figure 1c is less symmetrical than the cross-section in figure 1d. Therefore, the z-axis is the best choice.

When a geon object is simple, it is often quite clear which components are to be chosen as the axis and the cross section in its geon code. For many geon objects, however, this is not clear at all. Both metrical and structural criteria are involved in the choice of geon axes. However, the length of an axis is hardly comparable with the constancy and symmetry of a cross section. Length is a quantitative property and is called a 'metrical aspect' (MacKay 1969). Metrical identical values lead to constancies and symmetries. These regularities are qualitative properties and are called 'structural aspects' (MacKay 1969). We will demonstrate, for various concepts of axes, that the less that metrical and the more that structural aspects are involved in the definition of axes, the more it is clear what the axis means for various objects, and the better the geon codes predict object classification.

Three different concepts of axes will be considered that are consistent with the RBC rules, ie with the earlier given variables of a geon cross section and axis. We will indicate them by axis 1 to axis 3. We will see that, among them, only the third concept is consistent with SIT. In the demonstration of the axis concepts, we make use of the objects shown in figure 2 and the way these objects, being geons, were classified by sixty students. Most students (fifty-three) judged the similarity between the A and B in figure 2 as higher than the similarity between B and C. In this test, the figures were presented in different positions and orientations.

2.1.1 *RBC (axis 1).* The specification of an axis roughly agrees with the one given by Biederman (1987): the axis is primarily specified by its length. If there is no unambiguous longest length, the axis is orthogonal to the most constant and symmetrical cross section.

For A in figure 2, the axis is obvious: a semicircle. The cross section is a constant trapezoid (see cell A1, figure 2). For B the assessment of the axis is less obvious. A possible geon code is one that is similar to the one in cell A1: a semicircular axis with an extended trapezoid as constant cross section. However, according to the axis-1 specification, this geon code has to be rejected in favour of a geon code with a longer axis, namely the symmetry axis. Then, along this axis, the cross sections vary but are all symmetrical semicircles (cell B1, figure 2). Similarly for C in figure 2, the long symmetry axis has to be chosen. Along this axis, the cross sections vary but have bilateral symmetry in common (see cell C1, figure 2).

The geon codes with axis 1 do not agree well with the perceptual classification of the three objects. As indicated in figure 2, the geon codes given in A1 and B1 differ with respect to all four indices, whereas the geon codes in B1 and C1 differ only with respect to one index.

2.1.2 *RBC (axis 2).* The axis of an object is again specified by its length, but now under the condition that varying cross sections have all angles in common. This condition introduces a structural constraint, but it does not imply that varying cross sections are congruent. The constancy and symmetry of the cross section is again decisive for the axis in case there is no unambiguous longest axis.

This specification does not change the codes for A and B in figure 2 (see cells A2 and B2), but does change the code for C. According to the axis-1 code of this object, the cross sections are indeed similar but do not have all angles in common. Also, Biederman would probably prefer another code for this object, namely the one indicated in cell C2: the axis is vertical, being orthogonal to varying rectangular cross sections.

Notwithstanding the mentioned change, the geon codes with axis 2 do not agree with the perceptual classification of the objects A, B, and C in figure 2. That is, the difference between the codes in the cells A2 and B2 is still larger than the difference between the codes in B2 and C2.

2.1.3 *RBC (axis 3).* The definition of axis will now be almost the opposite of the definition given by Biederman but is still consistent with the remaining rules of RBC. Instead of length, constancy is the primary determinant of the axis: the axis is the one for which the cross section is constant. If no constant cross section is at hand, the axis agrees with the longest component, under the condition that the varying cross sections share the angular structure.

This definition changes the code for B in figure 2 into a code similar to that for A. The axis is semicircular and the cross section a constant trapezoid. The result is that the geon codes for A, B, and C in figure 2 agree with the perceptual classification of these figures. That is, the difference between the codes of cells A3 and B3 is smaller than the difference between the codes of B3 and C3.

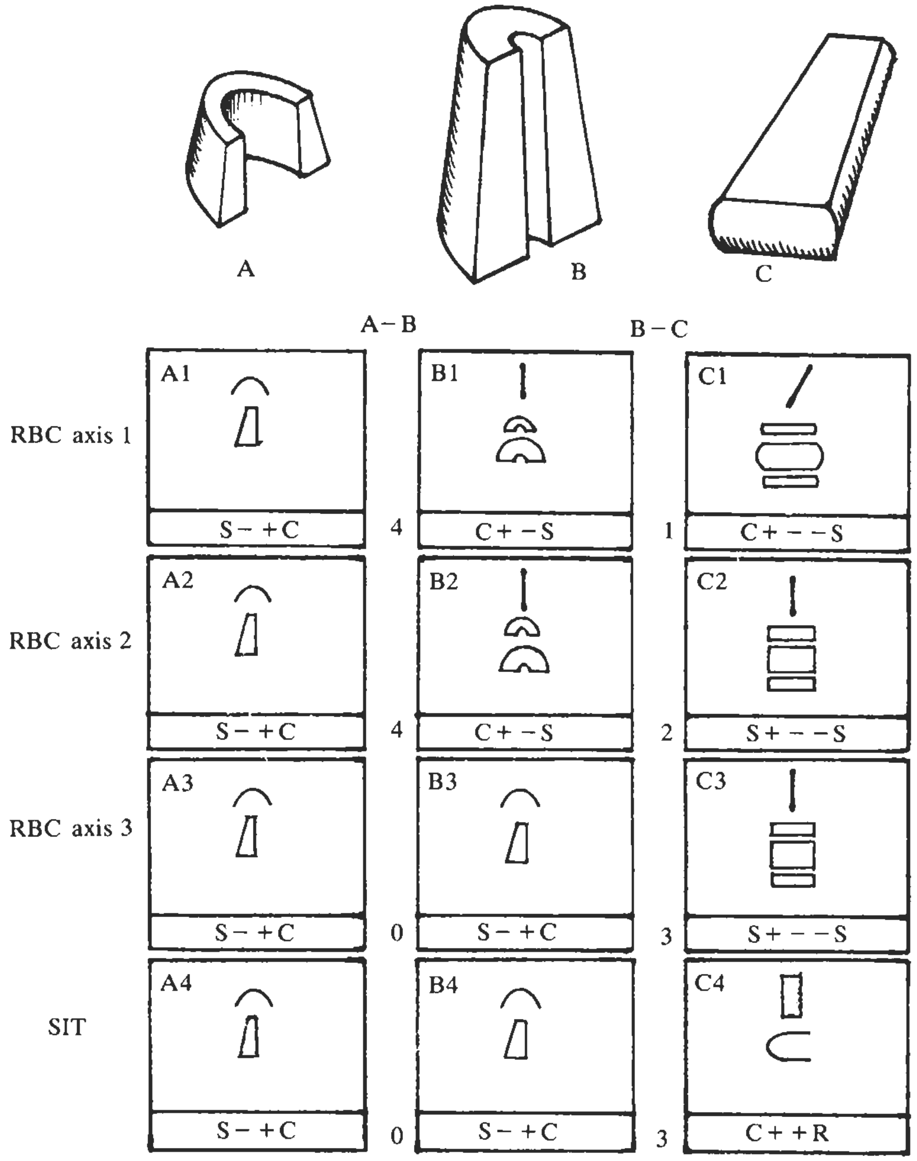

Figure 2. A, B, and C are three geon objects. These objects are represented in four ways. Three of them are compatible with RBC and one only with SIT. In the upper part of each cell, A1, ..., C4, a visualized code is presented. The top component of the visualized code refers to the axis or axis structure, and the bottom component refers to the cross section. Below the visualized code a symbolic geon code is presented. The numbers between the geon codes refer to the numbers of indices with respect to which these codes differ.

2.2 *Towards SIT*

We have shown that, going from axis 1 to axis 3, the more the definitions of axes account for regularity and constancy, the better the geon codes predict the classification of the objects in figure 2. In fact, so far only axis 3 predicts this classification well. Yet another concept of axis can be considered, which predicts this classification equally well but is inconsistent with the rules of RBC. This concept leads to a different code for C in figure 2 (see cell C4) from that of axis 3. Before we argue that this new concept accounts for even more regularity than axis 3 and stems from SIT, we will attempt to demonstrate that the code in cell C4 is more plausible than the code in cell C3. This demonstration occurs in two steps, namely by considering figures 3 and 4.

According to Biederman (axis 1, axis 2), all four geon objects in figure 3, except D, can be characterized by a circular axis and a constant trapezoidal cross section. He represents object D by a straight vertical axis and an expanding circular cross-section. However, the latter representation is, in our view, unreasonable, as object D just combines the cross section of object B and the axis of object C. According to axis 3, all four objects of figure 3 should be characterized by a circular axis and a constant trapezoidal cross section.

Object D of figure 3 is shown again in figure 4 (object A) together with a few other variants. We have just argued that this object has, according to axis 3, a circular axis. Now, as the difference between this object and C in figure 4 is equivalent to the difference between a circle and a rectangle, it is reasonable that object C has a rectangular axis. Such an axis is accepted by SIT but not by RBC. As we will argue later on, SIT allows any pattern as axis, whereas RBC only permits straight and circular line axes. Hence object C in figure 4 has, according to RBC, a vertical straight-line axis instead of a rectangular axis.

For the reason just given it is also reasonable that object D in figure 4 has a rectangular axis. Its cross section agrees with the cross section of B in figure 4. As C in figure 2 is equal to D in figure 4, C in figure 2 also has a rectangular axis (R). This is shown in cell C4 in figure 2. The codes for A and B in figure 2 are the same for RBC (axis 3) and SIT.

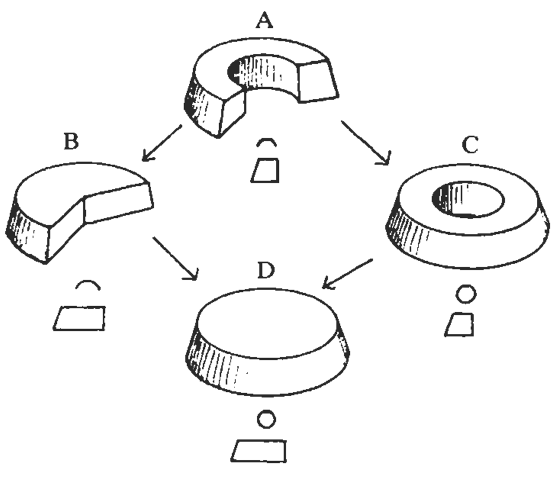

Figure 3. B has a different cross section from A, C has a different axis from A. Both differences are combined in D. Therefore it is reasoned that D has a circular axis and not a straight vertical axis.

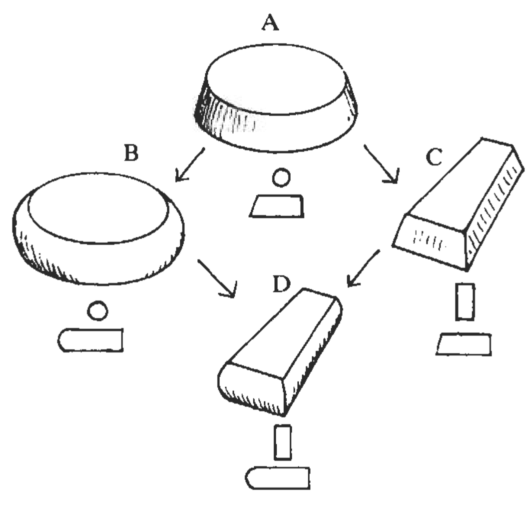

Figure 4. If A has a circular axis, B has a different cross section from A, and C has a different axis structure from A. Both differences are combined in D. Therefore it is reasoned that D has a rectangular axis structure and not a vertical straight axis.

2.3 *Structural information theory (SIT)*

The most important assumption of SIT is the minimum principle (Hochberg and McAllister 1953). This principle implies that, of all possible representations of a pattern, the 'simplest' one is perceptually preferred. The simplest pattern representation maximally accounts for constancies in a pattern. Therefore this representation is related to axis 3 and not to axis 1 or axis 2. A great difference between RBC and SIT is that RBC specifies beforehand the components (geons) of a scene, whereas according to SIT the perceptual components of a stimulus follow from the simplest representation of a stimulus. The kinds of constancies, ie regularities, that are taken into account in the representation are those that satisfy the 'accessibility' criterion, elaborated in Van der Helm and Leeuwenberg (1991).

Another assumption of SIT is that an object representation contains all the information needed to reconstruct the object. We will try to suggest a clarification of this reconstruction for the two objects shown in figure 5. We start from the axis and cross-section components in the visualized codes in A′ and B′ in figure 5. These components are supposed to be revealed by the simplest representations of these figures (Leeuwenberg and Van der Helm 1991).

The cross sections of both codes are represented by the holes in the vertical 'filters' in A″ and B″ in figure 5. These 'filters' are conceived as moving along the contours of the axes. During this motion the filters should remain orthogonal to the axis surface and orthogonal to the local orientation of the axis contour. The spaces finally selected by the moving filters will then have the shapes A and B shown in figure 5. The construction of these objects occurs in a manner analogous to the way a carpenter mills these objects from pieces of wood.

In this construction of objects, the axis and cross section play a different role. The axis determines the orientations of the cross sections, but not the other way around: the cross sections do not determine the orientations of the axes. For this reason, we replace the term axis by 'superstructure' and the term 'cross section' by

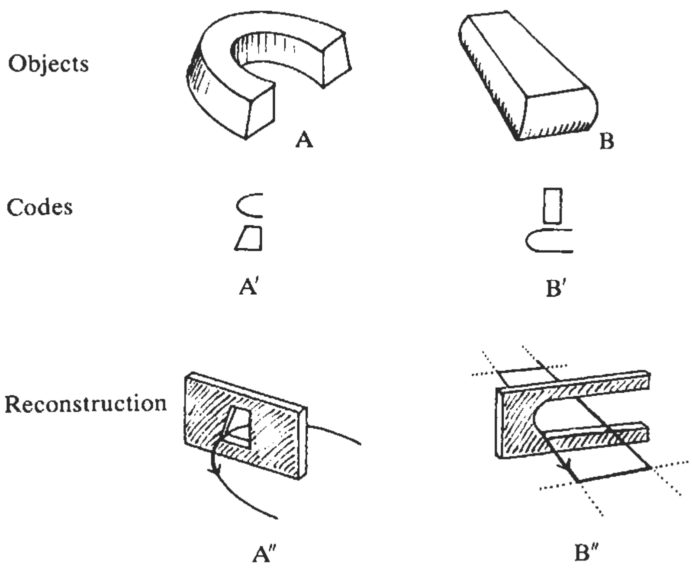

Figure 5. The visualized SIT codes of objects A and B are indicated by A′ and B′, respectively. The top components of the codes refer to superstructures. The bottom components refer to subordinate structures. A″ and B″ illustrate how the objects can be reconstructed from the visualized codes. The holes in the vertical 'filters' correspond with the subordinate structures. These 'filters' are conceived as moving along the horizontal superstructures—the semicircle for A and the rectangle for B. The spaces, selected by the moving filter holes, agree with the forms of A and B. The dotted lines in B″ indicate that the motion of the 'filter' ought to be slightly prolonged at the angles in order to obtain a solid object.

'subordinate structure'. The superstructure and subordinate structures are hierarchically related components of the simplest representation of a shape and supply the necessary information for the reconstruction of an object from its representation. With respect to the way simplest object representations can be specified, we were more explicit in Leeuwenberg and Van der Helm (1991).

2.4 *Summary*

By means of demonstrations we have tried to show that if not only structural but also metrical criteria are involved in defining axes, the specification of axes for certain objects is rather unclear and arbitrary. Both kinds of criteria play a role in RBC under the axis-1 and the axis-2 definitions. Another consequence is that such axes are not consistent with the perceptual classification of objects, as shown by the examples of figure 2. However, if only structural criteria are considered as decisive for the definition of axes, the axes are less arbitrary and lead to better predictions about the perceptual classification of objects. Axis 3 merely uses structural criteria and states that the axis is orthogonal to a constant cross section. However, as RBC only accepts straight-line and circular-line axes, whereas SIT, in principle, accepts any pattern as axis, RBC (axis 3) does not explain well the common and distinctive properties of the objects in figure 4, whereas SIT does. For instance, according to RBC (axis 3) the axis of object A in figure 4 is a circle and that of object C a vertical straight line, whereas the difference between both figures is equivalent to the difference between a circle and a rectangle.

According to SIT axes often coincide with superstructures. Therefore we have focused attention on axes in order to compare RBC and SIT. However, axes do not always coincide with superstructures and cross sections do not always coincide with subordinate structures. The superstructures refer to the highest hierarchical components in the simplest representations of objects. That means that superstructures determine the orientations of subordinate structures and not the other way around.

3 From invariance to regularity

In this part we will make some comments on assumptions underlying RBC and SIT. Again we start from RBC and try, from there, to assess the common and distinctive characteristics of both models.

Basic to RBC are the so-called 'nonaccidental properties' (NAPs). These are the properties of the projection of an object that remain invariant under various viewpoints or transformations of the object (Garner 1970). Because of this invariance, NAPs, such as parallelism, bilateral symmetry, and linearity, are thought to be retinal cues for three-dimensional features of objects (Rock 1983; Wagemans 1993). For instance, a straight line on the retina is probably the projection of a straight edge or of an object such as a needle. This we call the 'linearity cue'. The precise length of a retinal straight line is not a NAP but an accidental property as it is not a reliable index for the length of a straight edge or object.

According to Biederman, invariant properties give rise to retinal cues for object features. In contrast, we believe that, insofar as such cues are valid, they are not based on the invariance of properties but on their regularity (Lowe 1985). We will try to make our view plausible in several steps, with the focus on the linearity cue.

A in figure 6 represents a retinal straight line, B stands for a three-dimensional needle-like object, and C represents a three-dimensional hook-like object. Apart from the point projection, any projection of a needle is a straight line, such as A in figure 6 (we disregard the length of this line). Rotation of the needle around its length axis does not change its projection. However, this does not hold for the hook. In fact, the probability that the projection of the hook is a straight line is infinitely small.

Thus, if no objects other than the two objects in figure 6 are at hand, a retinal straight line is a reliable cue for the presence of the needle. So far, this means that the linearity cue is valid and that this validity can be based on the NAP of linearity.

A first question concerns the straight-line projection of a hook. We stated that the probability of this projection is infinitely small. Without doubt, this is true in an ontological sense, but not for perception. Any perceptual system has a restricted resolution. It is not able to distinguish slightly different lengths, nor is it able to distinguish angles that are slightly different. Therefore we assume that by perception a limited number, say L, of lengths and a limited number, say H, of angles can be distinguished. This implies that the probability, P, that a hook leads to a retinal straight-line projection, is not infinitely small, but $P = 1/H$. This is called an 'a posteriori' probability, as it deals with the transition from object to image. The a posteriori probability that a needle leads to a retinal straight line is still $P = 1$, and reflects the so-called 'linearity invariance' (Lowe 1985; Stevens 1980). However, the validity of the linearity cue depends on the reverse, namely, on the transition from image to object (Lowe 1985; Stevens 1980). The probability that a retinal straight line stems from the needle is then, according to the Bayes formula, equal to

$$P = \frac{1}{1+1/H}.$$

This implies that the linearity cue is still valid in the restricted world of figure 6, with only two objects.

Now we consider a broader, though still restricted, world. It comprises all possible needles and all possible hooks that can be distinguished from a fixed distance. It comprises no more objects and no same objects. In this world, there are L needles, as only L different lengths can be distinguished. As hooks consist of two line segments and of one angle in between, there are in the order of $L \times H \times L$ hooks. According to the Bayes formula, the probability that a retinal straight line stems from a needle is equal to

$$P = \frac{L}{L+LHL/H}.$$

This implies that a retinal straight line stems about L times more often from a hook than from a needle object. So in this world the linearity cue is completely invalid.

According to Biederman, but also in our view, the linearity cue is in fact valid (Pomerantz and Kubovy 1986). Suppose that the linearity is based purely on rotation invariance, as shown in the two-object world of figure 6. As we have said above, this implies that a retinal straight line actually stems about H times more often from a

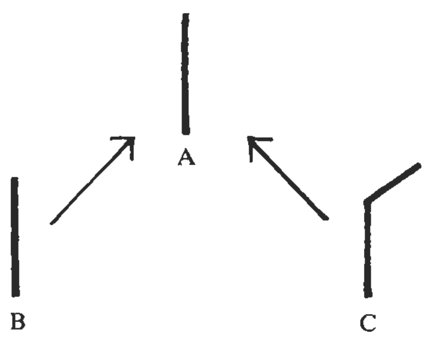

Figure 6. B and C represent three-dimensional objects. A is a possible retinal projection of B or C.

needle than from a hook. Under this supposition the previously considered world of all distinguishable needles and hooks is completely unrealistic. Instead it should comprise as many needles as hooks. As the previous world contains L needles and $L \times H \times L$ hooks, $H \times L$ times more needles should be added to it, or as many hooks should be removed from it. Without this adjustment, the linearity cue would L times more often favour the hook interpretation (see previous paragraph) instead of H times more often the needle interpretation. The adjusted world contains more regular objects than the previous world, because needles are more regular than hooks. As the contribution of regularity to the validity of the linearity cue can be quantified by $H \times L$, and the contribution of invariance by H, regularity is about L times more decisive for the linearity cue than is invariance. Hence, if a retinal straight line is interpreted as a needle and not as a hook, this is less because a needle is rotation invariant, but more because there exist many regular objects such as needles (Attneave 1982).

With respect to the contribution of invariance to the linearity cue, the contribution of regularity is, in fact, much greater than we have just estimated. All two-dimensional objects can lead to straight-line projections, not only needles and hooks (see figure 7). Each two-dimensional object, with N different line segments and $N-1$ angles, has in principle, $L^N \times H^{N-1}$ metrical variants with the same structure (Collard and Buffart 1983). Hence, for adjusting this imaginary world of all such distinguishable objects towards a world that allows a valid linearity cue, innumerably more regular objects, such as needles, have to be added to it than we have estimated before.

By means of figure 7 a qualitative relation between invariance and regularity can also be established. Only a needle (B in figure 7) leads to same projections under rotation around its length axis. All other objects (C, D, and E) are equally variant from varying viewpoints. Hence, invariance is an all-or-nothing property. This is not true for regularity. A straight line object (B) is a highly regular object, but all other objects are not equally irregular. From B to E in figure 7 the complexity increases and the regularity decreases gradually. Thus only the most regular objects give rise to invariance. So, invariance is just an accidental property of regularity and not basic to regularity.

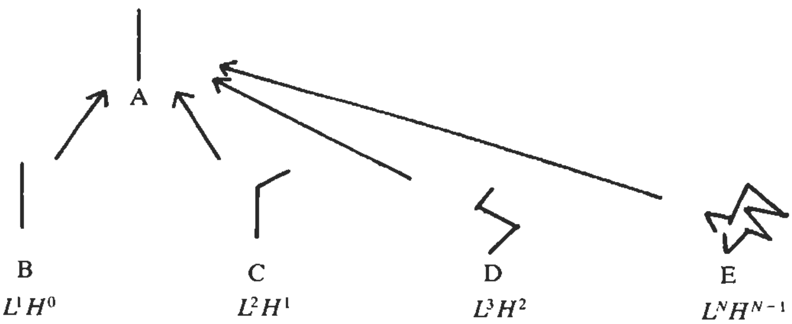

Figure 7. A is a possible projection of all two-dimensional objects (B, C, ..., E). Below each object is indicated how many different variants of that object with the same structure can be distinguished. L refers to the number of distinguishable lengths, H to the number of distinguishable angles, N to the number of line segments in the objects, and $N-1$ to the number of angles in the objects.

3.1 *Summary and conclusions*

We have argued that object regularity, not invariance, is primarily decisive for a valid linearity cue. Moreover, we have tried to show that invariance is an accidental property of regularity and not the other way around. Regularity gradually varies from low to high, whereas invariance applies only to the most regular instance on this regularity dimension. These inferences are meaningful for SIT and RBC.

According to the minimum principle the simplest, most regular interpretation of a pattern is the perceptually preferred one. However, it depends on the regularity in the real world whether the simplest interpretation is the best bet, ie veridical (Perkins 1976). It is difficult to quantify to what extent the world is regular, but our estimation is that it is, to a great extent, regular, under the plausible assumption that cues, such as the linearity cue, are at least minimally valid.

NAPs are treated as tools for the identification of geons. These NAPs are supposed to have this specific role on the basis of invariance criteria. However as we have argued, NAPs are not based on invariance but rather on regularity. That implies that a retinal straight line is not interpreted as a needle because of its invariance but because of its regularity. The latter reason is in line with the minimum principle. However, there is no reason to preserve this principle only for highly simple patterns, which accidentally reveal invariant properties, but also to use it for complex patterns, whose interpretations are equally variant under transformations, but not equally regular.

A problem for SIT is to specify the 'size of the stimulus' (Hochberg 1982) for which the minimum principle applies. For a perceiver, a stimulus is more than a sum of local parts. Almost any part can be embedded in a complex pattern, such that the interpretation of the part without context is absent in the interpretation of the whole pattern. However, we do not know to what extent context affects the interpretation of a pattern (Hochberg 1982; Kanizsa 1979; Leeuwenberg and Boselie 1988). For RBC this issue is rather irrelevant as it assumes, in advance, that the identification of a geon is mediated by cues, such as NAPs, and that a complex object is composed of elementary objects, such as geons.

4 Final remarks

A local bottom-up approach (RBC) is compared with a holistic concept of object perception (SIT). According to RBC, scenes are composed of predefined simple objects, called geons. These geons, in their turn, are specified by predefined properties of cross sections and axes. The detection of geons is mediated by viewpoint-independent object properties (NAPs), which are assumed to be invariant under object transformations. According to SIT, perception makes no use of predefined geons and predefined geon properties. Geons and these properties are just a posteriori features of simple object representations, which account for a maximum of regularities in objects. Moreover, NAPs are, according to SIT, not privileged properties that are invariant under transformations, but just accidental effects of the perceptual tendency towards simplest pattern representations.

In section 2 of this paper we considered the role of object axes in perception. According to RBC, an object axis can be straight or circular and is mainly specified by its length. We have attempted to show that these restrictions are hardly compatible with the perceptual classification of objects. This is not true for SIT. According to the latter approach an object axis can have any structure and is not determined by its length. Instead, an axis is revealed by the simplest object representation and agrees with the highest hierarchical component of this representation, namely the superstructure. Although this superstructure is not predefined by pattern-independent features, it is well defined. In contrast, the RBC definition of axis agrees with the commonsense notion of axis. This concept of axis is indeed predefined by pattern-independent features, but, in fact, not well defined.

Section 3 deals with viewpoint-independent properties. We argued that the transformation invariance of these properties is characteristic for the most regular objects, such as linear or symmetrical objects. Moreover, we showed that these properties on the retina, in principle, stem rather from irregular than from regular objects in a world that comprises all possible objects. The inference is made that, if such retinal properties are indeed taken as valid cues for regular properties of objects, this validity is based on the abundant presence of regular objects in the real world. Notice that this inference leads to a conclusion about reality on the basis of perception. This conclusion can be considered as a justification of the perceptual tendency towards simplest object representations, ie of SIT. An advantage of RBC is that it specifies the way objects are identified from their retinal projections. This is not true for SIT.

References

Attneave F, 1982 "Praegnanz and soap bubble systems: A theoretical exploration", in *Organization and Representation in Perception* Ed. J Beck (Hillsdale, NJ: Lawrence Erlbaum Associates) pp 11-29

Biederman I, 1987 "Recognition by components: A theory of human image understanding" *Psychological Review* **94** 115-147

Boselie F, Leeuwenberg E, 1986 "A test of the minimum principle requires a perceptual coding system" *Perception* **15** 331-354

Buffart H, Leeuwenberg E, Restle F, 1981 "Coding theory of visual pattern completion" *Journal of Experimental Psychology: Human Perception and Performance* **7** 241-274

Collard R, Buffart H, 1983 "Minimization of structural information: a set-theoretical approach" *Pattern Recognition* **16** 231-242

Garner W R, 1970 "Good patterns have a few alternatives" *American Scientist* **58** 34-42

Helm P Van der, Leeuwenberg E, 1986 "Avoiding explosive search in automatic selection of simplest pattern codes" *Pattern Recognition* **19** 181-191

Helm P Van der, Leeuwenberg E, 1991 "Accessibility, a criterion for regularity and hierarchy in visual pattern codes" *Journal of Mathematical Psychology* **35** 151-213

Hochberg J, 1982 "How big is a stimulus?", in *Organization and Representation in Perception* Ed. J Beck (Hillsdale, NJ: Lawrence Erlbaum Associates) pp 191-218

Hochberg J, McAllister E, 1953 "A quantitative approach to figural goodness" *Journal of Experimental Psychology* **46** 361-364

Kanizsa G, 1979 *Organization in Vision. Essay on Gestalt Perception* (New York: Praeger)

Leeuwenberg E, 1969 "Quantitative specification of information in sequential patterns" *Psychological Review* **76** 216-220

Leeuwenberg E, 1971 "A perceptual coding language for visual and auditory patterns" *American Journal of Psychology* **84** 307-349

Leeuwenberg E, Boselie F, 1988 "Against the likelihood principle in visual form perception" *Psychological Review* **95** 485-491

Leeuwenberg E, Helm P Van der, 1991 "Unity and variety in visual form" *Perception* **20** 595-622

Lier R Van, Helm P Van der, Leeuwenberg E, 1994 "Integrating global and local aspects of visual occlusion" *Perception* (in press)

Lowe D G, 1985 *Perceptual Organization and Visual Recognition* PhD thesis, Stanford Computer Science, Stanford University, Stanford, CA 94305 [also published as a book (Boston, MA: Kluwer)]

MacKay D, 1969 *Information Mechanism and Meaning* (Boston, MA: MIT Press)

Mens L, Leeuwenberg E, 1988 "Hidden figures are ever present" *Journal of Experimental Psychology: Human Perception and Performance* **14**(4) 561-571

Perkins D, 1976 "How good a bet is a good form?" *Perception* **5** 393-406

Pomerantz J, Kubovy M, 1986 "Theoretical approaches to perceptual organization", in *Handbook of Perception and Human Performance* Eds K Boff, L Kaufman, J Thomas (New York: John Wiley) pp 1-46

Rock I, 1983 *The Logic of Perception* (Cambridge, MA: Bradford)

Stevens K A, 1980 *Surface Perception by Local Analysis of Texture and Contour* PhD thesis, Technical Report 512, MIT AI Laboratory, MIT, Cambridge, MA 02139

Tuyl H Van, 1980 "Perceptual interpretation of complex line patterns" *Journal of Experimental Psychology: Human Perception and Performance* **6** 197-221

Wagemans J, 1993 "Skewed symmetry: A non-accidental property used to perceive visual forms" *Journal of Experimental Psychology: Human Perception and Performance* **19** 364-380