Metadata of the chapter that will be visualized online

Book Title	Encyclopedia of Computer Vision	
Book Copyright - Year	2013	
Copyright Holder	Springer Science+Business Media B.V.	
Title	Geons	
Author	Degree	Prof.
	Given Name	**Sven J.**
	Particle	
	Family Name	**Dickinson**
	Suffix	
	Phone	
	Fax	
	Email	sven@cs.toronto.edu
Affiliation	Division	Department of Computer Science
	Organization	University of Toronto
	Street	6 King's College Rd.
	Postcode	M5S 3G4
	City	Toronto
	State	Ontario
	Country	Canada
Author	Degree	Prof.
	Given Name	**Irving**
	Particle	
	Family Name	**Biederman**
	Suffix	
	Phone	
	Fax	
	Email	bieder@usc.edu
Affiliation	Division	Departments of Psychology, Computer Science, and the Neuroscience Program
	Organization	University of Southern California
	Street	3641 Watt Way, Hedco Neurosciences Bldg.
	Postcode	90089-2520
	City	Los Angeles
	State	CA
	Country	USA

Corrected Proof

G

Geons

Sven J. Dickinson[1] and Irving Biederman[2]
[1]Department of Computer Science, University of Toronto, Toronto, Ontario, Canada
[2]Departments of Psychology, Computer Science, and the Neuroscience Program, University of Southern California, Los Angeles, CA, USA

Synonyms

Recognition-by-components (RBC) theory

Related Concepts

▶3-D Object Recognition from 2-D Images; ▶Generalized Cylinder; ▶Human Shape Perception; ▶Object Categorization; ▶Qualitative Shape Modeling

Definition

Geons are a set of less than 50 qualitative 2-D or 3-D part classes derived from permuting a set of four dichotomous and trichotomous properties of a generalized cylinder (GC). The values of these properties are nonaccidental in that they can be resolved from a general viewpoint, e.g., whether the axis of a cylinder is straight or curved. Geons were originally introduced by Biederman [9, 10] as the foundation for his recognition-by-components (RBC) theory for human shape perception, whereby object-centered models are represented as concatenations of geons, and object recognition from a 2-D image proceeds by matching recovered parts, typically segmented at regions of matched concavity, and their relations to object models.

Corrected Proof

Background

The concept of modeling an object as a composition of generalized cylinders dates back to Binford [18], who spawned a generation of object-recognition systems based on generalized cylinders, e.g., [20, 44, 45, 51, 54]. Generalized cylinders suffered from unbounded complexity, for arbitrarily complex functions could be used to define the axis, cross section, and sweep functions. As a result, it became popular to restrict the complexity of these functions, e.g., straight axis, constant or linear sweep, rotationally symmetric cross section, in order to facilitate their overconstrained recovery from sparse image data.

In the mid-1980s, two alternative restrictions on generalized cylinders emerged from the computer vision and human vision communities, respectively. Pentland [46] introduced the superquadric ellipsoid to the computer vision community – a 3-D, symmetry-based part representation that afforded a large degree of descriptive power with a small number of parameters. Around the same time, Biederman [9, 10] introduced geons to the human vision community as part of his recognition-by-components (RBC) theory. Like superquadric ellipsoids, geons exploited symmetry to reduce the complexity of a generalized cylinder. However, while the superquadric ellipsoid was a

K. Ikeuchi (ed.), *Encyclopedia of Computer Vision*, DOI 10.1007/978-0-387-31439-6,
© Springer Science+Business Media, LLC 2013

metric shape representation, the geon was a qualitative shape categorization. Thus, when a superquadric ellipsoid was recovered from an image, the recovered parameters defined a specific shape (a generative model), whereas when a geon was recovered from an image, it defined a symbolic part class (non-generative category) with only coarse (rather than exact) metric specification.

The appeal of the geon was twofold: (1) its properties were based on the sorts of judgments that humans are very good at, e.g., judging whether a line was straight or curved rather than estimating its exact curvature; and (2) each geon class afforded a high degree of within-class shape deformation, offering great potential for shape categorization and invariance over orientation in depth. While extensive experiments with humans and primates that lent strong support of his RBC theory, the computer vision community quickly set out to develop computational models for geon recovery from 2-D images.

Theory

Geons define a partitioning of a subspace of the generalized cylinders. Like generalized cylinders, each geon is defined by its axis function, its cross-section function, and its sweep function. Biederman noted that humans are (1) much better at distinguishing between straight and curved lines than they are at estimating curvature; (2) much better at distinguishing parallelism from nonparallel symmetry than they are at estimating the angle between two causally related lines; and (3) good at distinguishing between various types of vertices produced by a cotermination of contours, such as a fork from an arrow from a L-junction. Drawing on these properties of the human visual system, Biederman mapped the spaces of the three generalized cylinder parameters to dichotomous and trichotomous values (Fig. 1):

- *Axis shape*: the axis takes on two possible values: straight or curved.
- *Cross-section shape*: the cross-section shape takes on two possible values: straight-edged or curved-edged.
- *Sweep function*: the cross-section sweep function takes on four possible values: constant, monotonically increasing (or decreasing), monotonically increasing and then decreasing, or monotonically decreasing and then increasing.
- *Termination*: given a nonconstant sweep function, the termination of a geon could be truncated, end in a point (projects into an L-vertex), or end as a curved surface.

Originally, Biederman [10] posited cross-section symmetry as another attribute (with three possible values: rotationally symmetric, possessing an axis of reflective symmetry, or asymmetry) but that attribute was dropped as experiments showed that people assume symmetrical cross-sections, even when the cross-section is asymmetrical (as with an airplane wing).

Permuting the possible values of these four functions defines a space of $2 \times 2 \times 4 \times 3 = 48$ 3-D geons, as illustrated in Fig. 1. Adding 2D geons, e.g., circle, quadrilateral, and triangle, and subtracting the eight instances of constant sweep (2 axis shape $\times$ 2 cross-section shape $\times$ 2 point and curved terminations) when the sweep function is constant brings the total to about 50.

Related Work

Hummel et al. [37, 38] first proposed a connectionist model for recovering geons from line drawings that achieved invariance to viewpoint. In the computer vision community, Bergevin and Levine were the first to propose a computational model for geon recovery and geon-based recognition [4–8]. Dickinson et al. [27–29] introduced a hybrid object representation combining 3-D object-centered volumetric parts and 2-D viewer-centered aspects modeling the parts. While the framework was applicable to any vocabulary of volumetric parts, it was demonstrated on a qualitative shape vocabulary very similar to geons. Many geon-based frameworks followed, including probabilistic approaches [39], logic-based approaches [32], parametric geon recovery from range data [26, 48, 53], deformable contour-based approaches [47], deformable volume-based approaches [25], and active vision approaches [24, 31]. See [23] for a panel discussion on the strengths and weakness of geons and the challenges that lie ahead.

Corrected Proof

Open Problems

Geons have tremendous potential as a part representation in support of object categorization. They are qualitative and can support a high degree of within-class deformation, they (like generalized cylinders) map to the natural part structure of objects (when such elongated part structure exists), they are viewpoint-invariant 3-D parts that support object-centered 3-D models (which, in turn, better support scaling to large databases), and there is psychophysical support for them (the human is still, by far, the best example of an object categorization system). Despite these advantages, geons declined as a subject of study in the computer vision community in the late 1990s, in part due to the advent of appearance-based recognition and a general movement away from shape features.

The main reason for their decline was not necessarily a shortcoming of the representation, i.e., geons, but rather the community's inability to extract qualitative shape from real images of real objects. Except for those approaches operating on range images, the work reviewed above operated on either line drawings or uncluttered scenes containing simple, textureless objects. The key assumption made by these systems was that a salient contour in the image maps one-to-one to a salient surface discontinuity (or occluding contour) on a geon. Unfortunately, in a real scene, objects contain texture, shadows, reflectance contours, and structural "noise" (surface discontinuities that are not salient with respect to the geon class), all of which introduce unwanted contours. Moreover, images of contours (both good and bad) may be broken or noisy, requiring complex perceptual grouping and multiscale analysis to restore and capture the salient shape of the contours. Yet despite these conditions, humans and primates have absolutely no trouble distinguishing (or abstracting) those contours that mark orientation and depth discontinuities – the critical contours for geon extraction – from contours reflecting variations in surface texture, color, lighting, shadows, etc.

As discussed in Dickinson [22], the recognition community's gradual movement from shape toward appearance, coupled with the community's interest in engineering practical systems, drew attention away from basic research on shape modeling in support of object categorization. However, the community is once again realizing that over the set of exemplars belonging to an object category, shape is far more invariant than appearance. As a result, shape-based object categorization systems (mainly using contours) are beginning to reemerge, e.g., [33]. But a return to local contour-based features is not sufficient, as local shape features are still too exemplar-specific. Rather, such features must be perceptually grouped and abstracted to form more generic shape structures that offer the within-class deformation invariance required for effective categorization. Geons offer a powerful shape abstraction with great categorization potential, but only when more progress has been made on the mid-level challenges of perceptual grouping and intermediate-level shape abstraction. Some early work along these lines has started to appear [50].

Experimental Results: Computer Vision

Figure 2 illustrates three examples of geon recovery systems in the computer vision community. In Fig. 2a, the system of Bergevin and Levine [7] recovers geons from line drawings. In Fig. 2b, the system of Dickinson et al. [24] recovers geon-like volumetric parts from real images of simple objects, as does the system of Pilu and Fisher [47], as shown in Fig. 2c.

Experimental Results: Human Vision

There is now substantial neural and behavioral evidence for the representation of objects as an arrangement of geons, as specified by the recognition-by-components theory. This evidence can be summarized in terms of six independent assumptions. Any one (or several) of these assumptions can be made independent of RBC but, to date, RBC is the only theory from which all six derive.

> The representation of an object is largely edge-based – specifically, those edges specifying orientation and depth discontinuities – rather than surface-based (i.e., color, texture).

Reaction times (RTs) and error rates for naming briefly presented images of objects are as fast for line drawings as they are for full, color photography [16]. This is also true of verification in which the observer verifies whether a name ("chair"), provided prior to an

Corrected Proof

image of an object, matches the object. The equivalence in performance for identifying line drawings and photography is evident even when the objects have a diagnostic color/texture, such as a fish, fork, or banana, as opposed to objects with nondiagnostic surface properties, e.g., a chair or a lamp, which can be any color or texture.

The equivalence of photography and line drawings is also witnessed in fMRI activity where the adaptation (i.e., the reduction) of the BOLD signal that is evident with a repetition of a stimulus, fMRI-a, is the same when the images have the same format, i.e., identical photographs or line drawings, as when they have different formats, one a photograph and the other a line drawing [34]. This invariance to surface properties is also seen in the response of many single neurons in object-sensitive areas in the macaque [41]. In fMRI, the processing of surface properties, color and texture, activates different cortical areas than those activated when processing shape [21].

There are few transformations to appearance as dramatic as rendering a line drawing from a photograph yet the readily achieved invariance to this transformation poses a major challenge to appearance-based theories of object recognition.

Objects are represented by parts rather than local features, templates, or concepts.

Object priming is the facilitation that ensues as a consequence of a prior perception of an object. It can be readily evidenced by a reduction in RTs and error rates in the naming of brief, masked presentations of objects and has been documented over a 14-month period from the first to second presentation of the images. (The reduction in the magnitude of the BOLD response to a repeated stimulus, termed fMRI adaptation, is generally attributed to more efficient coding and is interpreted as a neural correlate of priming.) Almost all of this priming is visual (i.e., perceptual) rather than lexical (easier access to the name itself) in that an object with the same name but a substantially different shape, e.g., a grand piano followed by an upright piano, evidences almost no facilitation.

Studies with complementary, contour-deleted line drawings document that all the priming can be attributed to the repetition of the parts (in their appropriate relations) as opposed to local features, i.e., the specific lines and vertices in the image [14]. Thus, if every other vertex and line from each geon is deleted from one image of an object and the deleted contour composes the other member of a complementary pair, as in the two images of a flashlight on the left side of Fig. 3a (so if the two were superimposed they would comprise an intact image with no overlap of contour), the degree of priming between members of a complementary pair – which depict the same parts though with different local contours – is equal to the priming between identical images. This implies that none of the priming can be attributable to the local contours (i.e., the local lines and vertices). Presumably, the local contours are required to activate a representation of the part, but once that part (in its appropriate relations) is activated there is no contribution of the initial local image features.

Instead of deletion of local features, if the deletion is of half the parts of a complex object, as shown in Fig. 3b, then there is no visual priming between members of a complementary pair. Thus the priming is completely dependent on the overlap in the parts in the two images. These effects on behavioral priming have their exact counterpart in fMRI-a. Here, local feature complements show the same reduction in the BOLD response as when the identical images are repeated, suggesting equivalent representations, but repetition of part complements show a complete loss of adaptation thus indicating that there is no overlap in visual representations when the images are composed of different parts, even though they are of the same subordinate concept, e.g., both grand pianos [35].

Evidence against a template representation derives from studies of the priming of depth-rotated stimuli. As long as the same parts can be readily extracted in two different images of the same object, recognition or matching of a rotated object will be achieved with virtually no cost. However, if because of self-occlusion some parts disappear and other parts emerge, then priming is reduced or object matching is impaired [15].

Single cell recordings in the inferior temporal lobe (IT) of the macaque, the area generally accepted to mediate object recognition, generally fire as strongly to one or two of the parts of an object as they do to the complete object [40].

Parts are distinguished by nonaccidental properties (NAPs) and only coarsely by metric properties (MPs).

Values of various dimensions of geons can be regarded as singular or nonsingular. A singular value, such as 0 curvature (i.e., a straight contour), retains

Corrected Proof

that value as the object is rotated in depth. A nonsingular value, such as a nonzero value of curvature (i.e., a curved contour), can vary with the orientation in depth of that contour. In addition to curvature, parallelism of two contours can have a singular value of zero convergence (or divergence) or a nonzero value. Two or three contours that coterminate can be regarded as a singular value of zero separation between their terminations, forming vertices, such as Ls, arrows, or forks. This framework can define NAP differences as the difference between singular and nonsingular values as, e.g., a difference between a curved and a straight contour produced by the parallel sides of the cylinder on the left in the third row of Fig. 3c and the middle barrel. Metric differences are differences in non-singular values, such as two contours with unequal nonzero curvatures, as with the slightly curved and more curved barrels in the third row.

The aforementioned invariance to rotation in depth holds only if the objects that are to be discriminated differ in NAPs [13, 15]. Objects differing only in metric properties incur high costs when they are encountered at a different orientation in depth. At equal orientations, the discrimination of two shapes as being same or different is markedly easier if the shapes differ in NAPs than MPs [17]. Cells in the IT region of the macaque modulate (i.e., vary their firing rate) much more to a change in a NAP compared to an MP [41, 52]. Even pigeons show greater sensitivity to differences in NAPs than MPs [1]. In these comparisons of the sensitivity of NAPs and MPs, the physical differences are equated according to a model of V1 [42], the first stage of cortical shape coding.

Dimensions of generalized cylinders (GCs) are independently coded and have psychophysical and neural reality.

The set of geons is generated by combinations of the values of the independent dimensions shown in Fig. 1. (In addition, as noted previously, there can be coarse variation in the metric of these geons, such as their aspect ratio or degree of axis curvature.) Are simple object parts actually coded by independent combinations of these dimensions (vs. just being nondimensionalized variations in shape templates)? One measure of independent coding of perceptual dimensions is whether human observers can selectively attend to one dimension without any cost from variations in another, to-be-ignored, dimension. For example, the speed and accuracy of discriminating different shapes is unaffected by whether the colors of those shapes are held constant or varied. It might seem plausible that shape could be attended while ignoring a surface feature such as color. Would efficient selective attention be manifested when observers are attending to one shape dimension, say axis curvature, while ignoring variations in another shape dimension, say aspect ratio. The answer is clearly yes [43]. Moreover, a multidimensional analysis of the firing of a population of IT cells to a set of stimuli similar to that depicted in Fig. 3c shows that 95% of the variance of the spike rates can be modeled in terms of independent coding of the GC dimensions [40].

Low sensitivity for discriminating complex, irregular shapes (= texture?) compared to simple shapes but high sensitivity for distinguishing regular from irregular.

Geons are simple and regular. What about complex, highly irregular objects, such as a bush or a crumpled sweater? It would be highly unlikely that people are employing geons for the precise representation of such objects. Interestingly, the evidence is that people do not represent such variation in any detail beyond the fact that the shapes are irregular and some simple nonaccidental characterizations, e.g., whether the surfaces are round or pointed. This is also true of IT cells [2]. Essentially, objects with irregular parts are treated as texture, rather than shape.

There is a more general point to be made here. GCs (and geons) were criticized for their unwieldiness for modeling objects such as bushes. But this is confusing a graphics system, in which the goal is to achieve an exact replica of the image, with a biological recognition system designed to do basic- and subordinate-level classification in which irrelevant variation is best ignored.

Objects are represented by a structural description that specifies simple parts and relations.

Geons are the representation of the parts of an object, but objects are typically composed of more than one part. In the same manner that people are sensitive to the order of phonemes, so "rough" and "fur" have the same phonemes but in different order, people are sensitive to the arrangement of parts of an object, so they can say, e.g., that a vertical cylinder is attached end-to-middle and perpendicular to the top of a larger horizontal brick. That geons and their relations may be coded independently is documented by a

Corrected Proof

remarkable patient with a left inferior temporal lesion who had no problem distinguishing objects differing in their geons but could not distinguish objects that differed in the relations among the same geons [3]. Recent neuroimaging studies show that such relations are specified explicitly at the same cortical locus, the lateral occipital complex, that object shape is specified [36].

References

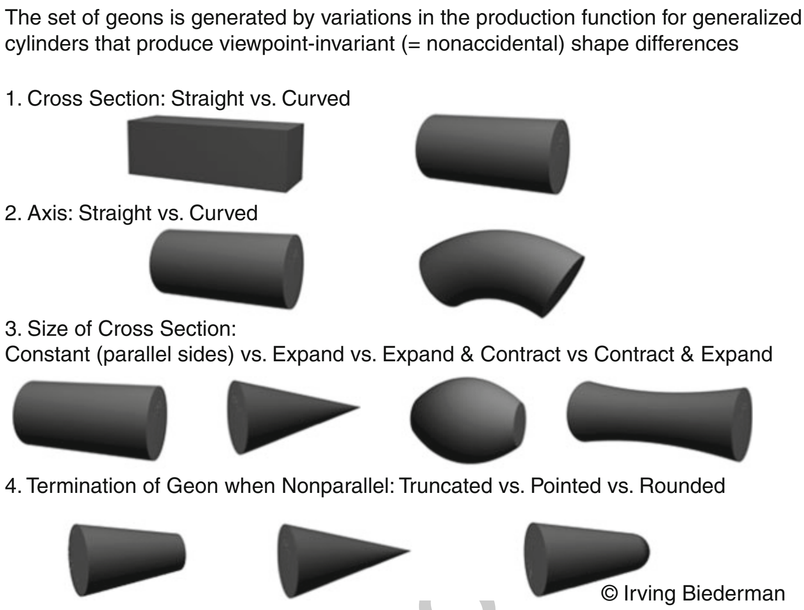
1. Lazareva OF, abd Wasserman EA, Biederman I (2008) Pigeons and humans are more sensitive to nonaccidental than to metric changes in visual objects. Behav Processes 77:199–209
2. Kayaert G, Biederman I, Vogels R (2005) Representation of regular and irregular shapes in macaque inferotemporal cortex. Cereb Cortex 15:1308–1321
3. Behrmann M, Peterson MA, Moscovitch M, Suzuki S (2006) Integrative agnosia: deficit in encoding relations between parts. J Exp Psychol Human Percept Perf 32(5):1169–1184
4. Bergevin R, Levine MD (1988) Recognition of 3-D objects in 2-D line drawings: an approach based on geons. Technical report TR-CIM-88, Center for intelligent machines, McGill University, Nov 1988
5. Bergevin R, Levine MD (1989) Generic object recognition: building coarse 3D descriptions from line drawings. In: Proceedings, IEEE workshop on interpretation of 3D scenes, Austin, pp 68–74
6. Bergevin R, Levine MD (1992) Extraction of line drawing features for object recognition. Pattern Recognit 25(3): 319–334
7. Bergevin R, Levine MD (1992) Part decomposition of objects from single view line drawings. CVGIP: Image Underst 55(1):73–83
8. Bergevin R, Levine MD (1993) Generic object recognition: building and matching coarse 3d descriptions from line drawings. IEEE Trans Pattern Anal Mach Intell 15:19–36
9. Biederman I (1985) Human image understanding: recent research and a theory. Comput Vis Graph Image Process 32:29–73
10. Biederman I (1987) Recognition-by-components: a theory of human image understanding. Psychol Rev 94:115–147
11. Biederman I (1990) Higher level vision. In: An invitation to cognitive science: visual cognition and action, vol 2. MIT, Cambridge, MA, pp 41–72
12. Biederman I (2000) Recognizing depth-rotated objects: a review of recent research and theory. Spat Vis 13:241–253
13. Biederman I, Bar M (1999) One-shot viewpoint invariance in matching novel objects. Vis Res 39:2885–2899
14. Biederman I, Cooper EE (1991) Priming contour-deleted images: evidence for intermediate representations in visual object recognition. Cognit Psychol 23:393–419
15. Biederman I, Gerhardstein PC (1993) Recognizing depth-rotated objects: evidence and conditions for 3D viewpoint invariance. J Exp Psychol Hum Percept Perform 19: 1162–1182
16. Biederman I, Ju G (1988) Surface vs. edge-based determinants of visual recognition. Cognit Psychol 20:38–64
17. Biederman, I, Yue, X, Davidoff J (2009) Representation of shape in individuals from a culture with minimal exposure to regular simple artifacts: sensitivity to nonaccidental vs. metric properties. Psychol Sci 20:1437–1442
18. Binford TO (1971) Visual perception by computer. In: Proceedings, IEEE conference on systems and control, Miami
19. Borges D, Fisher R (1997) Class-based recognition of 3d objects represented by volumetric primitives. Image Vis Comput 15(8):655–664
20. Brooks R (1983) Model-based 3-D interpretations of 2-D images. IEEE Trans Pattern Anal Mach Intell 5(2): 140–150
21. Cant JS, Goodale MA (2009) Asymmetric interference between the perception of shape and the perception of surface properties. J Vis 9(13):11–20
22. Dickinson S (2009) The evolution of object categorization and the challenge of image abstraction. In: Dickinson S, Leonardis A, Schiele B, Tarr M (eds) Object categorization: computer and human vision perspectives. Cambridge University Press, New York, pp 1–37
23. Dickinson S, Bergevin R, Biederman I, Eklundh J-O, Jain A, Munck-Fairwood R, Pentland A (1997) Panel report: the potential of geons for generic 3-D object recognition. Image Vis Comput 15(4):277–292
24. Dickinson S, Christensen H, Tsotsos J, Olofsson G (1997) Active object recognition integrating attention and viewpoint control. Comput Vis Image Underst 67(3): 239–260
25. Dickinson S, Metaxas D (1994) Integrating qualitative and quantitative shape recovery. Int J Comput Vis 13(3):1–20
26. Dickinson S, Metaxas D, Pentland A (1997) The role of model-based segmentation in the recovery of volumetric parts from range data. IEEE Trans Pattern Anal Mach Intell 19(3):259–267
27. Dickinson S, Pentland A, Rosenfeld A (1990) A representation for qualitative 3-D object recognition integrating object-centered and viewer-centered models. In: Leibovic K (ed) Vision: a convergence of disciplines. Springer, New York, pp 398–421
28. Dickinson S, Pentland A, Rosenfeld A (1992) From volumes to views: an approach to 3-D object recognition. CVGIP: Image Underst 55(2):130–154
29. Dickinson S, Pentland A, Rosenfeld A (1992) 3-D shape recovery using distributed aspect matching. IEEE Trans Pattern Anal Mach Intell 14(2):174–198
30. Du L, Munck-Fairwood R (1993) A formal definition and framework for generic object recognition. In: Proceedings, 8th Scandinavian conference on image analysis, University of Tromsø, Norway
31. Eklundh J-O, Olofsson G (1992) Geon-based recognition in an active vision system. In: ESPRIT-BRA 3038, vision as process. Springer-Verlag ESPRIT Series
32. Fairwood R (1991) Recognition of generic components using logic-program relations of image contours. Image Vis Comput 9(2):113–122

Corrected Proof

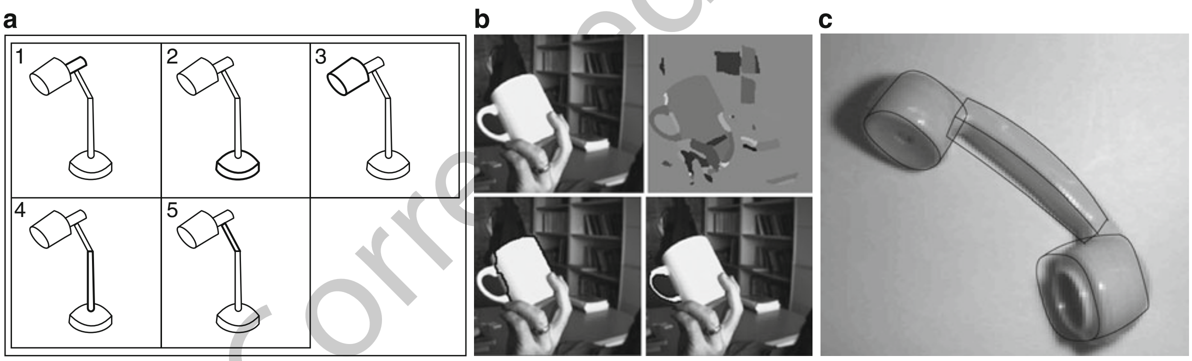
33. Ferrari V, Jurie F, Schmid C (2010) From images to shape models for object detection. Int J Comput Vis 87(3): 284–303
34. Grill-Spector K, Kourtzi Z, Kanwisher N (2001) The lateral occipital complex and its role in object recognition. Vis Res 41(10–11):1409–1422
35. Hayworth KJ, Biederman I (2006) Neural evidence for intermediate representations in object recognition. Vis Res 46:4024–4031
36. Hayworth KJ, Lescroart MD, Biederman I (2011) Visual relation encoding in anterior LOC. J Exp Psychol Human Percept Perf 37(4):1032–1050
37. Hummel JE, Biederman I (1992) Dynamic binding in a neural network for shape recognition. Psychol Rev 99: 480–517
38. Hummel JE, Biederman I, Gerhardstein P, Hilton H (1988) From edges to geons: a connectionist approach. In: Proceedings, connectionist summer school, Carnegie Mellon University, pp 462–471
39. Jacot-Descombes A, Pun T (1992) A probabilistic approach to 3-D inference of geons from a 2-D view. In: Proceedings, SPIE applications of artificial intelligence X: machine vision and robotics, Orlando pp 579–588
40. Kayaert G, Biederman I, Op de Beeck H, Vogels R (2005) Tuning for shape dimensions in macaque inferior temporal cortex. Eur J Neurosci 22:212–224
41. Kayaert G, Biederman I, Vogels R (2003) Shape tuning in macaque inferior temporal cortex. J Neurosci 23:3016–3027
42. Lades M, Vorbruggen JC, Buhmann J, Lange J, von der Malsburg C, Wurtz RP, Konen W (1993) Distortion invariant object recognition in the dynamic link architecture. IEEE Trans Comput 42:300–311
43. Lescroart MD, Biederman I, Yue X, Davidoff J (2010) A cross-cultural study of the representation of shape: sensitivity to underlying generalized-cone dimensions. Vis Cogn 18(1):50–66
44. Marr D, Nishihara H (1978) Representation and recognition of the spatial organization of three-dimensional shapes. R Soc Lond B 200:269–294
45. Nevatia R, Binford TO (1977) Description and recognition of curved objects. Artif Intell 8:77–98
46. Pentland A (1986) Perceptual organization and the representation of natural form. Artif Intell 28:293–331
47. Pilu M, Fisher RB (1996) Recognition of geons by parametric deformable contour models. In: Proceedings, European conference on computer vision, LNCS, Springer, Cambridge, UK, April 1996, pp 71–82
48. Raja N, Jain A (1992) Recognizing geons from superquadrics fitted to range data. Image Vis Comput 10(3):179–190
49. Raja N, Jain A (1994) Obtaining generic parts from range images using a multi-view representation. CVGIP: Image Underst 60(1):44–64
50. Sala P, Dickinson S (2010) Contour grouping and abstraction using simple part models. In: Proceedings, European conference on computer vision (ECCV) Crete, Greece, Sept 2010
51. Ulupinar F, Nevatia R (1993) Perception of 3-D surfaces from 2-D contours. IEEE Trans Pattern Anal Mach Intell 15:3–18
52. Vogels R, Biederman I, Bar M, Lorincz A (2001) Inferior temporal neurons show greater sensitivity to nonaccidental than metric differences. J Cogn Neurosci 13:444–453
53. Wu K, Levine MD (1997) 3-d shape approximation using parametric geons. Image Vis Comput 15(2):143–158
54. Zerroug M, Nevatia R (1996) Volumetric descriptions from a single intensity image. Int J Comput Vis 20(1/2):11–42

Corrected Proof

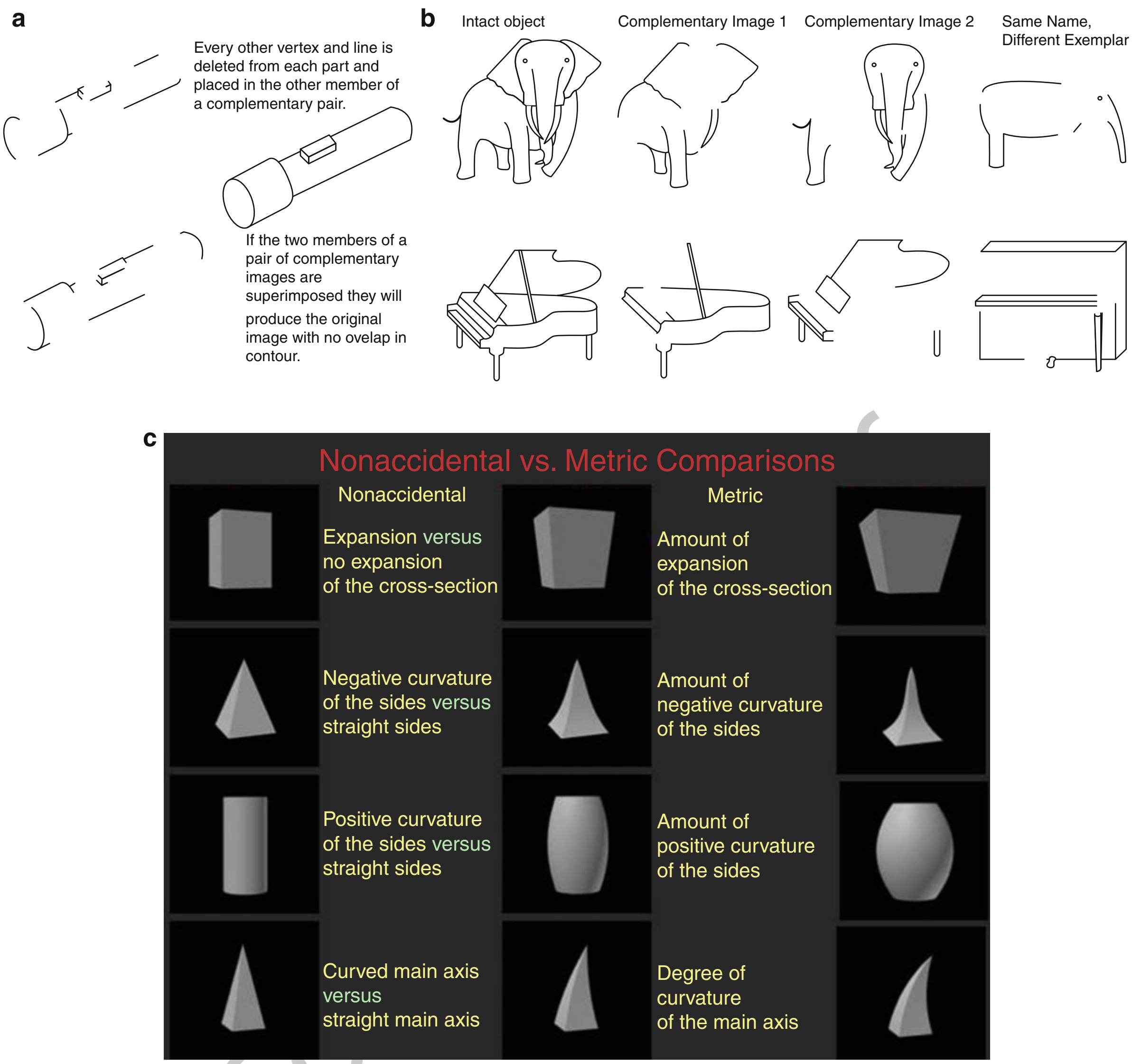
Geons, Fig. 1 The space of approximately 50 geons is defined by permuting the dichotomous and trichotomous properties of a restricted space of generalized cylinders



Corrected Proof



Geons, Fig. 2 Three examples of geon recovery in the computer vision community: (**a**) decomposing a line drawing of a lamp into its constituent geon parts (Bergevin and Levine [7]); (**b**) from a region segmentation (*upper right*) of the image of an occluded cup (*upper left*), the two recovered constituent qualitative volumetric parts (with matched contours highlighted in black) are shown in *lower left* (body cylinder) and *lower right* (handle bent cylinder) (Dickinson et al. [24]); and (**c**) decomposing a phone into its constituent geons parts (Pilu and Fisher [47])



Geons, Fig. 3 Psychophysical evidence in support of Geons: (**a**) members of a local contour-deleted complementary pair, which have the same parts but different local features, prime each other as much as they do themselves; priming is not attributable to local contours; (**b**) there is no visual priming between members of a complementary pair when they have no parts in common, as between the images of the second and third columns [14]; and (**c**) equal image differences between nonaccidental (between center and left columns) and metric properties (between center and right columns). Geons are distinguished by nonaccidental properties. Discrimination is much faster and more accurate for differences in nonaccidental than metric properties