CATEGORY-SPECIFIC NAMING AND THE 'VISUAL' CHARACTERISTICS OF LINE DRAWN STIMULI

Keith R Laws[1] **and Tim M Gale**[2,3]

([1]Department of Psychology, London Guildhall University, UK; [2]Departments of Computer Science and Psychology, University of Hertfordshire, UK; [3]Queen Elizabeth Hospital, Welwyn Garden City, UK)

Abstract

It has been argued that greater intra-category structural similarity for living things may make them more difficult to recognize and name (e.g. Humphreys et al., 1988). Nevertheless, the precise meaning and quantification of 'structural similarity' remain unclear. We developed three new visual measures derived from the Snodgrass and Vanderwart (1980) corpus and examined their relationship with picture naming in a speeded presentation paradigm. The three measures were: the proportion of black pixels (PB); the degree of pixel overlap within subcategories using Euclidean Overlap (EO); and the degree of consistency in inter-pixel distribution across each picture (IPC). Within-category EO was greater for nonliving than living things, indicating less within-category visual overlap for living things. Finally, EO correlated significantly with error rates (PB and IPC did not). These findings contradict existing notions that line drawings of living things have greater visual similarity than nonliving things.

Key words: category-specific deficits, visual similarity, Euclidean Overlap, visual complexity

Introduction

One interpretation of category-specific disorders suggests that the greater intra-category structural similarity (visual overlap) of living things and the subsequent 'visual crowding' makes them more difficult to recognize and name for neurologically damaged individuals and normal subjects (Gaffan and Heywood, 1993; Humphreys et al., 1988). For example, Gaffan and Heywood (1993) found that five normal subjects made more living than nonliving errors when naming the Snodgrass and Vanderwart (1980) corpus in a rapid presentation paradigm (20 msec exposure). In a second part of the study, they trained monkeys to discriminate between pairs of pictures of living or nonliving things; and found that the monkeys took longer to learn the responses associated with living things (especially as the number of stimuli in the set increased). While normal subjects may be influenced by familiarity and name frequency, monkeys are not and so, this has been viewed as strong evidence that living things are more difficult to discriminate visually, or that they have greater within-category visual crowding than nonliving things.

In an attempt to quantify structural similarity, Humphreys et al. (1988) measured the degree of contour overlap for subcategories of item from the

Snodgrass and Vanderwart corpus of line drawings, e.g. animals, clothing[1]. This measure was derived by overlaying a grid on each item with every other item and calculating the average overlap between pictures as a function of the amount of contour in each picture (at a gross visible level). The structurally similar items were exclusively living things, while the structurally dissimilar items were nonliving things. Moreover, they showed that normal subjects are slower to name items that have greater structural similarity (i.e. living things).

Tranel et al. (1997) examined within-category shape overlap for five subcategories by measuring the number of pixels falling within the maximal shape overlap, i.e. the common sub-category silhouette. Using a mixture of the Snodgrass and Vanderwart corpus and photographs, Tranel et al. reported that the greatest shape overlap occurred for fruits/vegetables, followed by vehicles, animals and musical instruments, with tools/utensils the lowest. This only partially accords with the speculation of Gaffan and Heywood (1993) that the greater visual overlap for living things (and musical instruments) makes them harder to identify than nonliving things.

Critically, the measures developed by Humphreys et al. (1988) and Tranel et al. (1997) focussed on the common contour and common shape overlap respectively and so, do not incorporate the internal detail of items. A measure of internal detail for the Snodgrass and Vanderwart corpus was developed by Kurbat (1997) based upon the number of pixels internal to outer boundary divided by the total pixels; however, it does not incorporate the spatial arrangement of the internal detail. So, regarding line drawings, there have been some attempts to quantify the degree of structural overlap within subcategories, though each has problems. No extant measure takes account of the spatial arrangement of visual information and there has been no attempt to specify the processes underlying subject ratings of visual complexity (see Snodgrass and Vanderwart, 1980), e.g. does it reflect a high level of internal detail? The latter is a critical question because given the measures of structural overlap described earlier (e.g. Humphreys et al., 1988), visually complex items would have greater potential for high structural overlap (given that they are presumably depicted by a greater amount of line detail). Indeed, since line drawings of living things tend to have greater visual complexity (Snodgrass and Vanderwart, 1980) and greater within category contour overlap or structural similarity (Humphreys et al., 1998), these apparently subjective measures may relate more to basic visual aspects of the line drawings.

The current study focuses upon the development of three new visual measures derived from the Snodgrass and Vanderwart line drawing corpus; and examines their relationship with naming of the whole corpus by normal participants (in a speeded presentation paradigm: after Gaffan and Heywood, 1993). This corpus was chosen because the pictures have been and continue to be used in the majority of studies examining category specific effects (the authors reviewed over 50 studies between 1988-2000 and over 90% used this corpus for their main results); and because much is already known about other

---

[1] Humphreys et al. also considered the number of common parts within categories by having subjects rate the number of partonomic attributes (e.g. has legs, has wheels) for items and found more common parts for living than nonliving things (see Discussion).

characteristics of the pictures e.g. rated visual complexity, familiarity etc. The three new visual measures tap different aspects of the pictures: the proportion of black pixels per item (PB); the Euclidean Overlap (EO) between pairs of items measured as the amount of pixel overlap; and inter-pixel correlation (IPC), which is essentially a measure of the internal complexity for each picture.

As with *all* measures attempting to capture visual characteristics of the items represented (e.g. visual complexity, visual overlap), the patterns of results reflect the specific properties of the stimuli examined (here the Snodgrass and Vanderwart corpus) and do not necessarily reflect actual properties of the referent objects. Line drawings are a peculiar type of stimulus representation that may be processed in qualitatively different ways to other stimuli such as colour pictures and photographs (Biederman and Ju, 1988; Ostergaard and Davidoff, 1985; Price and Humphreys, 1989); although all may of course differ from the way in which the actual objects are processed. Nonetheless, most neuropsychological investigations of category-specific deficits have utilised the Snodgrass and Vanderwart corpus and many theories of object recognition appear to be based on findings with line drawings, so the results will have implications for the conclusions that may be drawn about factors that purportedly contribute towards emergent category effects.

The stimuli were 254 digitised pictures from the Snodgrass and Vanderwart (1980) line-drawing corpus, standardised for size such that the maximal dimension of each image fitted exactly within a 256-by-256 pixel grid (see Figure 1). The standardised images were stored in binary bitmap format such that pixels could be either white (0) or black (1).

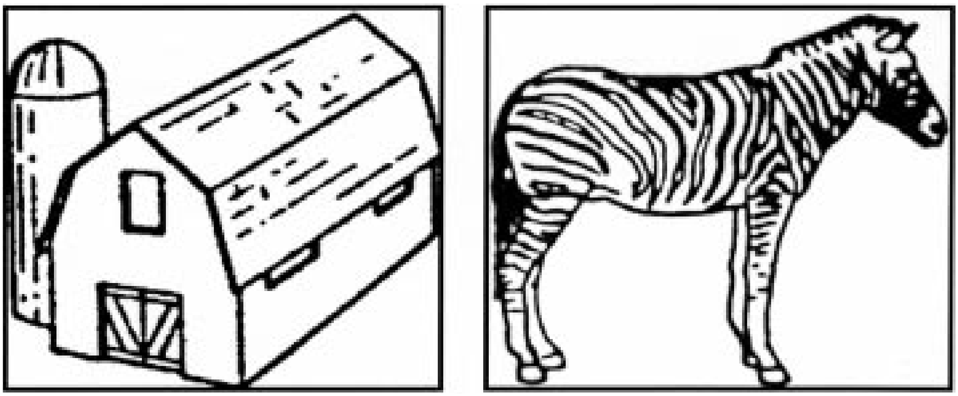

Fig. 1 – *Examples of size-standardised images. Note how the maximal dimension of each object touches the boundaries of the pixel grid.*

Measures of Visual Information

1. Proportion of Black Line (PB)

The number of black pixels (i.e. those involved in the depiction of line detail) was computed for each image and expressed as a proportion of the total number of pixels (i.e. 65,536) in each picture. This measure was termed ‘proportion black’ (PB) and was instantiated to tap an aspect of visual complexity (VC). Snodgrass and Vanderwart (1980) define VC as ‘the amount of detail or intricacy of line in the picture’, so the prediction is that pictures that are more detailed should have higher PB scores.

2. Euclidean Overlap (EO)

As a measure of complexity, PB is unrelated to the pattern (or spatial arrangement) of dark and light, and so ignores higher-level aspects of complexity reflecting the retinotopic spatial arrangement of the pictures. To examine the pixel-to-pixel spatial correspondence in pictures, we derived measures of the Euclidean Overlap for each drawing with other drawings. This measure was calculated by comparing the value of each individual pixel in turn and subtracting its value in the first picture from its value in the second. The difference is squared and summed for all pixels in the representation and the EO between the two pictures is the square root of the sum of squared differences. EO between an individual picture and all other pictures was computed to give a

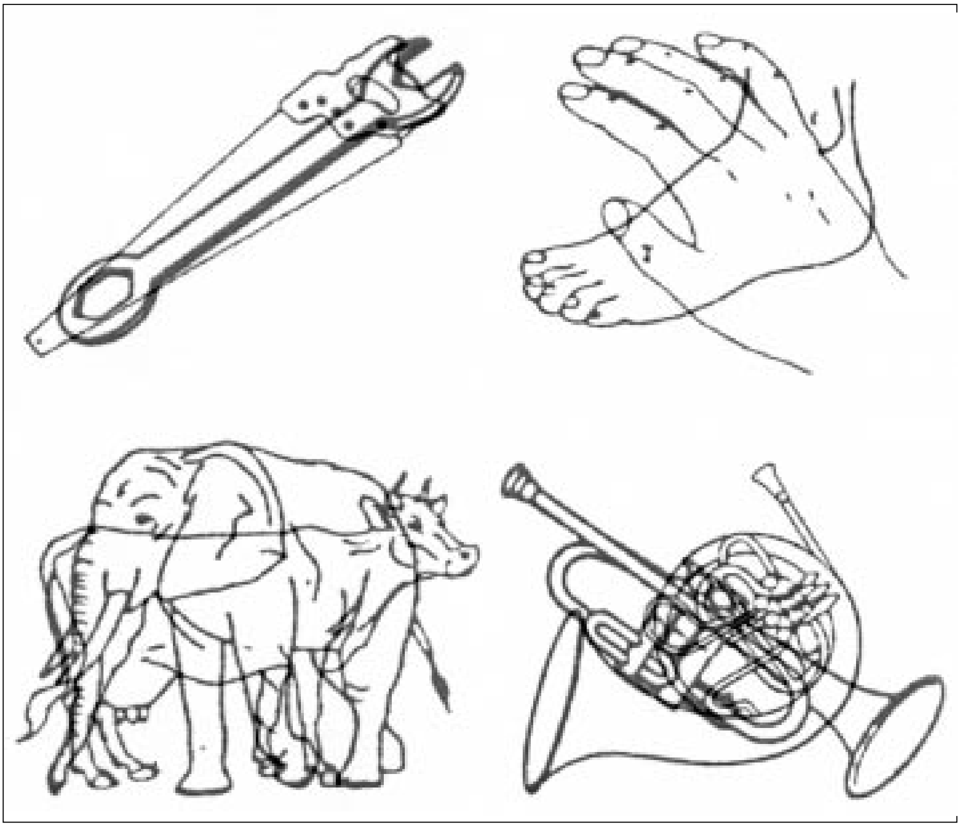

Fig. 2 – *Examples showing the range of Euclidean Overlap for pairs of figures in different subcategories.*

precise measure of the visual overlap between any two items in the corpus.

Lower scores reflect greater EO; e.g. identical pictures would have an EO of 0 and, for binary bitmaps of size n by n, the maximum EO between any two pictures is always n. EO was calculated between each individual image and every other image in the set, thereby generating a matrix of 254×254 EOs.

The mean and standard deviation EO values for each item was calculated in two ways. First, the mean and sd EO were computed between each item and its within-category associates (within-category EO) for the following categories (see Appendix for list): animals (n = 29), insects (n = 8), birds (n = 9), body-parts (n = 12), fruit (n = 11), vegetables (n = 12), furniture (n = 14), vehicles (n = 11), musical instruments (n = 10), tools (n = 9), clothing (n = 17). The second method involved calculating EO between each item and all other items in the corpus, i.e. within the whole set of 254 images.

The method of EO calculated here differs from that used by Humphreys et al. (1988), who measured the structural overlap between line drawings by (i) standardising items for size and orientation, (ii) positioning items from the same semantic category within a comparison grid; (iii) calculating the average percentage of contour overlap between each item and all its within-category associates; and so (iv) did not take into account internal detail. We decided to retain the original orientations for several reasons[2]. First, it is difficult to apply the same procedures to all categories of object. For example, it is easy to align animals so their heads point left and their tails point right; however, other categories, such as musical instruments, are less clear-cut. Second, most neuropsychological studies use the images in their standard presentation. Third, Snodgrass and Vanderwart ensured that where orientation was an issue, living (e.g. animals), and nonliving things (e.g. tools) were fairly equally distributed between left and right facing; and so, would not especially bias living or nonliving things.

3. Inter-Pixel Correlation (IPC)

A measure of average inter-pixel correlation (IPC) was computed as an additional estimate of VC. Every pixel within each image was compared with its immediate neighbours and the proportion of pixels with identical values to the central pixel was recorded. Whilst the majority of pixels were compared with 8 neighbours, those pixels at edges and corners of an image were only compared with 5 and 3 adjoining neighbours respectively. The average IPC was then computed by taking the mean IPC for all 65,536 pixels within an image.

The reason for calculating average IPC is that whilst PB may capture the amount of line detail in a picture, there are circumstances where it might give a misleading estimate of VC: a drawing with lots of black shading (e.g. a black square) might generate a high PB score yet would not be visually complex. IPC, on the other hand, looks for consistencies in black or white pixel distribution across the whole picture so images that predominantly comprise large areas of

[2] These conclusions were confirmed by the high inter-correlation between PB and EO (96% shared variance). In other words, changing the orientation of some pictures would have no more than a small impact upon within-category EO (see later).

black or white, will both generate high IPC scores. However, items that are depicted by a more random distribution of line information (e.g. highly textured items such as pineapple) should generate lower IPC scores. The prediction therefore is that IPC will correlate strongly but negatively with VC.

Picture Naming

This part of the study replicated the rapid presentation naming design of Gaffan and Heywood (1993): whereby items from the Snodgrass and Vanderwart (1980) corpus of line drawings were presented for 20 msec for naming.

Materials and Methods

Subjects

Thirty-two normal undergraduates (16 males and 16 females: mean age = 22.78 (s.d. = 6.42)) participated. All had normal or corrected-to-normal vision and none had previously seen the pictures.

Stimuli and Procedure

Two-hundred and forty-six items were drawn from the whole Snodgrass and Vanderwart (1980) corpus. Ninety-one images were classified as living things and 155 as nonliving things (n = 246). The living items included body parts; nonliving included musical instruments. Items were excluded because they are difficult to classify, including for example: natural objects such as ‘Moon’, ‘Tree’, ‘Star’ and ‘Mountain’; food items ‘Cake’, ‘Sandwich’, ‘Bread’; and people-related items such as ‘Clown’ and ‘Snowman’.

The living things had significantly greater visual complexity (3.33 vs. 2.73: $t = 5.4$, 244, $p < .001$), lower name frequency (23.32 vs. 42.05: $t = -2.0$, 226, $p = .046$) and lower familiarity (2.96 vs. 3.51: $t = -4.6$, 244, $p < .001$). The images were presented against a white background on a 30.5 cm Apple Macintosh monitor using SuperLab™ software. Each drawing was standardized for size, having a maximum horizontal and vertical extent of 7.6 cm and was viewed from a distance of 50 cm. The pictures were presented for 20 msec followed by a blank white screen until response (after Gaffan and Heywood, 1993). The order of presentation was randomised for each subject and there was no time limit for responding.

Results

Analysis across subjects revealed more living than nonliving errors [10.2 (s.d. = 4.9) vs. 6.3 (s.d. = 3.3): $t = 6.01$, d.f. = 31, $p < .001$]. Gaffan and Heywood (1993) did not present data for analysis by item; however, the greater error rate for living things [2.63 (s.d. = 4.00) vs. 1.74 (s.d. = 3.34)] over nonliving things approached significance ($t = 1.9$, 244, $p = .06$). Nevertheless, when covarying for variables (word frequency, familiarity and visual complexity), the category difference disappears ($F = 0.53$; d.f. = 1, 205; n.s.).

Proportion Black (PB)

As predicted, proportion black (PB) correlated significantly with visual complexity (VC) $r = .50$, $p < .001$. There was no difference in PB across living and nonliving categories. PB did not correlate significantly with normal errors ($r = .05$, $p = .4$), although VC did ($r = .22$, $p < .001$).

PB did not differ significantly across living and nonliving things for: (a) the whole corpus ($t = .01$, d.f. = 250, n.s.); (b) the 11 subcategories ($t = .51$, d.f. = 139, n.s.); or (c) after the removal of the two subcategories of body parts and musical instruments ($t = 2.56$, d.f. = 118, $p = .01$). Post hoc (Bonferroni) analyses of 11 subcategories revealed that musical instruments had greater PB than all other subcategories, while tools and body parts had lower PB than all other categories; no other differences were significant.

Euclidean Overlap (within Subcategories)

EO correlated significantly with: errors ($r = .21$, $p = .013$); PB ($r = .89$, $p < .001$); VC ($r = .52$, $p < .001$). Although there were different numbers of item in each subcategory EO did not correlate with subgroup size ($r = -.02$, $p > .05$).

EO did not differ significantly across living and nonliving things for: (a) all items ($t = 0.3$, d.f. = 250, n.s.); (b) items from the eleven subcategories ($t = -1.6$, d.f. = 139, n.s.); (c) however after removing body parts and musical instruments (which are known to be unusual categories within the living and nonliving domains), EO was significantly greater for nonliving than living things ($t = 3.9$, d.f. = 118, $p < .001$).

Analysis comparing between subcategories themselves revealed four homogeneous subsets i.e. that failed to differ within each grouping (using Bonferroni): (1) tools and body parts; (2) body parts, clothing, vehicles and birds; (3) clothing, vehicles and birds, animal, fruit, furniture, insects and vegetables; (4) furniture, insects, vegetables and musical instruments.

Analysis of the mean EO scores for each of the subcategories shows how they cluster into living and nonliving subcategories (see Figure 3). Moreover, this also shows how body parts cluster with nonliving things, while musical instruments cluster with living things.

Euclidean Overlap (across Every Item)

To check that the above findings did not reflect imposing some form of semantic categorisation on the items (i.e. within subcategories), EO was examined for every item against every other item in the whole corpus. In other words, do the same effects occur when every item is compared with every other item i.e. when there is no inherent stimulus categorisation at all?

Again the broad corpus of living and nonliving things did not differ significantly ($t = .01$, d.f. = 244, n.s.). EO correlated significantly with PB ($r = .98$, $p < .001$) and VC ($r = .49$, $p < .001$), but did not correlate with errors ($r = .14$, $p > .05$). Within this undefined corpus, we examined the 20 items with the smallest EO and the 20 showing the greatest EO. The 20 items with greatest visual similarity included: 7/9 tools, 7/12 body parts; the remaining items came from various categories. The items with least visual similarity included: 5/9 musical instruments, 4 visually distinctive animals (tiger, peacock, skunk, giraffe) and 5 fruits/vegetables (strawberry, grapes, celery, artichoke, onion).

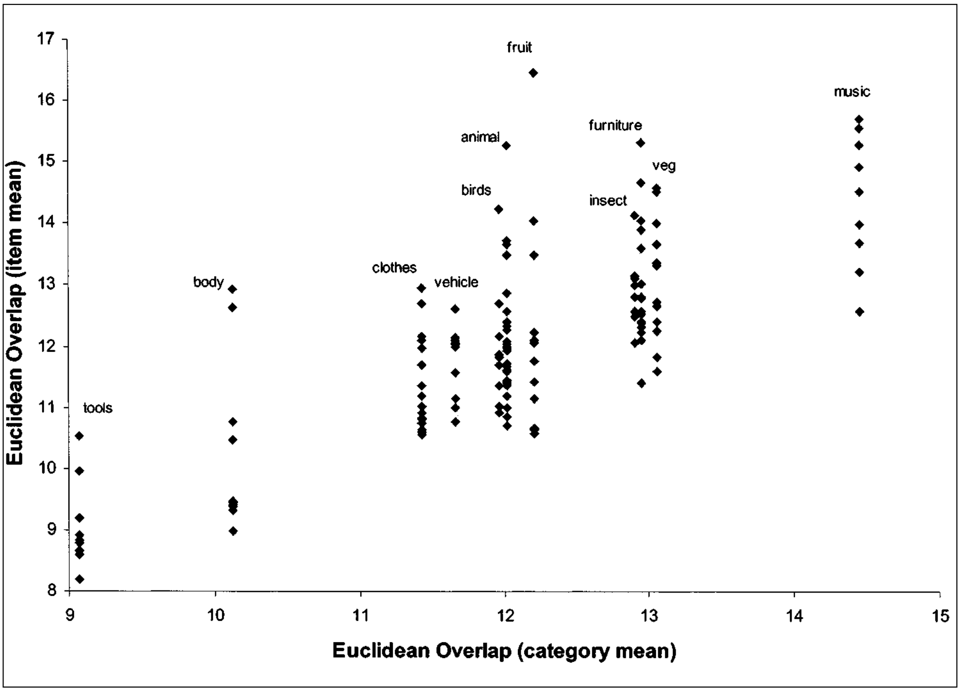

Fig. 3 – *Mean EO values for subcategories plotted against item mean EO.*

This confirms the pattern found for the within-category analysis i.e. that nonliving things tend to show greater similarity (EO) than living things.

Internal Pixel Correlation (IPC)

IPC correlated significantly with: PB ($r = -.90$, $p < .001$), EO ($r = -.89$, $p < .001$) and VC ($r = -.62$, $p < .001$), but not with errors ($r = -.06$, n.s.).

IPC did not differ significantly across living and nonliving things for: (a) all items ($t = .27$, d.f. = 250, n.s.; (b) across items in the 11 subcategories ($t = .90$, d.f. = 139, n.s.); or when body parts and musical instruments were removed ($t = -.88$, d.f. = 118, n.s.). Post hoc analyses comparing subcategories revealed that body parts and tools had greater IPC than all other subcategories; musical instruments had lower IPC than all other subcategories.

SUMMARY

The results show that PB plays a role in the appreciation of VC (sharing 25% variance) and that subjects use the VC rating scale (from Snodgrass and Vanderwart) in a way that relates to a primitive but objective measure of visual complexity i.e. amount of line. Since living and nonliving categories do not differ in PB, but do for VC, minimally, the category differences in VC are not related to the bottom-up aspects tapped by PB. Since normal error rates correlated with VC but not with PB (or IPC), it might be argued that the naming errors reflect more the top-down cognitive – rather than bottom-up – aspects of visual complexity (PB and IPC).

As predicted, IPC correlated more highly with VC than either PB or EO. In other words, IPC distinguished between those items with intricate internal detail and a low proportion of black pixels (e.g. chair, horse, yacht) and those that simply have many black pixels though low internal correlation (e.g. spectacles, ant, glove). Items with high IPC values are relatively simple shapes characterised mostly by white space (e.g., heart, hanger). These results suggest that IPC might feasibly be used when subjects make VC judgments. Third, and critically, there is no difference between non-living/living in terms of IPC (means = 0.899 and 0.900 respectively; $p = 0.85$). The fact that IPC correlates highly with VC but does not differentiate between living/non-living gives even greater support for the notion that VC is not a bottom-up measure.

The fact that EO correlated so highly with PB suggests that these measures are highly inter-dependent. This is the case within the Snodgrass and Vanderwart corpus because most pictures comprise a predominance of white space. Whilst it might be argued that white space is not relevant to the actual structure of each depicted item it must be borne in mind that, with line drawings, it is just as critical to depiction as black information. Even the most visually complex items (e.g. spool, basket) have PB scores of less than 25% and the mean PB score across all items was only 6.7% (± 3.6%). Thus, white space accounts for in excess of 90% pixels in the majority of pictures. If most pictures are characterised by white space, it follows that the main source of variance between pictures is black line information. Given that EO measures the variance in pixel distribution between two items, low EO will be obtained when the items under comparison have a greater level of black line. For this reason, PB accounts for nearly 96% of the variance in EO (across all items). However, such high inter-correlation only holds for this particular set of stimuli and cannot be extrapolated to all 'black-and-white' pictures.

As mentioned above, the three measures described here are only relevant to this set of pictures; *however*, this is true also for other 'standardised' measures such as CO, VC or any visually-based measures. So, although the *essence* of similarity between structural descriptions may not be captured by EO (or indeed any variable relating to the visual characteristics of any picture corpus), this measure does have advantages. EO is an attempt to specify exactly what is meant by visual similarity/structural overlap; it is not theory-laden; it cannot be influenced by conceptual knowledge (cf. VC, partonomic separation or perhaps CO); and moreover, EO can be applied to any other pictorial corpus

Discussion

The new measures (PB, EO and IPC) developed here provide novel and surprising information about the primary visual characteristics that affect recognition and naming for the Snodgrass and Vanderwart (1980) corpus of line drawings. Although the three measures were highly inter-correlated (positively for EO and PB, and negatively for IPC), each measured different aspects of the visual properties of the pictures: the amount of pixels (PB); the retinotopic spatial arrangement of pixels (EO); and the consistency of pixel distribution in each picture (IPC). Furthermore, contrary to existing accounts of visual similarity/crowding (Gaffan and Heywood, 1993; Humphreys et al., 1988), the measure of EO developed here indicates that nonliving things have greater within-category visual similarity than living things.

Neither PB nor IPC correlated with errors, suggesting that amount of black and/or its spatial configuration (alone) are not critical determinants of naming and identification. Nevertheless, the significant relationship for errors and within-category EO emphasises the importance of category membership (and the relations between members) for naming, i.e. prototypical items are more easily named and more errors are made to items from categories with more atypical items (e.g. musical instruments). Although within-category EO correlated with normal errors, the correlation for EO (all items) was not significant. Since category prototypicality predicts naming accuracy (but 'general typicality' does not), one interpretation of this is that subjects initially interpret depicted items within a superordinate categorical frame of reference.

Within-category EO clearly differentiated (see Figure 3) those items associated with nonliving thing disorders (all having greater EO) from those associated with living thing disorders (all having less EO). Indeed, removing body parts and musical instruments from the analysis revealed a significantly larger EO for nonliving than living things. Hence, these line drawings of living and nonliving things may be categorically separated at a low level of visual analysis[3]. Furthermore, as subcategories, body parts and musical instruments differed from all other subcategories on *all three* new visual measures; with body parts (and tools) having the simplest visual structure, but greatest overlap, while musical instruments were the most complex and showed the least overlap. The discriminability of these subcategories from all other subcategories is intriguing in the context that the measures for body parts were closer in values to those for nonliving things; while those for musical instruments were more similar to living things (indeed they were at the extreme end of the nonliving and living groups respectively). Critically therefore EO incorporates the exceptions that occur in the category-specific deficits literature, i.e. that musical instruments tend to be impaired along with living things and body parts with nonliving things. These counter-intuitive (though predictable) findings add weight to the psychological reality and potential utility of EO as a measure of structural similarity[4].

The finding that EO was greater for nonliving things challenges both the traditional idea that living things have greater visual similarity/overlap/crowding and the idea that this necessarily results in worse naming of living things for patients or normal subjects (Gaffan and Heywood, 1993; Humphreys et al., 1988). For example, Gaffan and Heywood (p.119) have suggested that "…a

---

[3] The only exception being furniture, which clustered amongst living things.

[4] This contrasts with the measure of CO developed by Humphreys et al., which identifies body parts and musical instruments together as having the least overlap. CO cannot therefore account for the clustering of impaired musical instruments with living thing disorders and body parts with nonliving things.

hammer or a saw is each visually more distinct from other objects than an antelope or a strawberry is" and so, a modality specific impairment of visual representations might explain category specific deficits (for living things). The current study shows that their 'intuitive' notion of structural similarity cannot be synonymous with the visual characteristics of the drawings themselves (at least as measured by EO or even PB and IPC). Furthermore, recent studies that have controlled across category for various artefactual variables (e.g. familiarity, name frequency, visual complexity) have consistently reported worse naming of nonliving things by normal subjects (see Laws, 2000; Laws, 1999; Laws and Neve, 1999). These studies cast doubt upon the validity of the idea that living things are more *structurally* similar (than nonliving things) and that this partly underlies category-specific disorders for living things and the naming performance of normal subjects.

Why should the results for Euclidean Overlap be the converse of those found for Contour Overlap (Humphreys et al., 1988)? One possibility centres on the notion that 'structural similarity', as measured by Humphreys et al., places greater emphasis on *cognitive* processing; by contrast, EO is a purely *visual* variable. Certainly, Humphreys and colleagues emphasize on common partonomic features and even their coarse-grained measure of Contour Overlap may more readily incorporate partonomic features (this clearly would not happen with the current pixel-based analyses). It is, however, less clear whether 'structural similarity' or 'visual crowding' (Humphreys et al., 1988; Gaffan and Heywood, 1993) refer to attributes of the stimuli themselves, the stored mental representations or both. If such measures are meant to capture *stimulus* characteristics (as EO does), then they will encounter problems. These would include, for example, the following: (i) parts with the same name may not have the same conceptual reference – for example, do a *table* and *tiger* share the commonality of having four legs? Do a *toothbrush* and *caterpillar* share the commonality of having bristles? In a purely visual sense, the answer must be yes; (ii) how does one define the type of parts that will be considered – only those parts that are visible or *also* those parts that, whilst not depicted, are conceptually part of the whole – for example, in the Snodgrass and Vanderwart corpus, *swan* does not appear to have any legs and has only one eye. Moreover, should we count more general parts like torso, trunk, body, casing, sides, front and so on? (iii) Shared parts may have no visual similarity at all – for example, the tail of a fish bears no resemblance to that of a dog; similarly the feet of a penguin and a giraffe. They also fail to capture any internal detail. Such issues do not arise with EO. Nevertheless, Humphreys et al.'s notion of structural similarity does appear to refer more to some notion of *stored representations* than characteristics of the stimuli or real-world items. Of course, our measure of stimulus similarity (EO) and some more cognitive or 'top-down' measure of representational similarity (e.g. shared part information) may both influence object recognition. Moreover, they may influence object recognition in conflicting directions: for example, top-down similarity affecting living things more greatly, while bottom-up EO has greater impact on nonliving thing recognition).

Acknowledgements. The authors would like to thank: Ray Frank and Neil Davey (Department of Computer Science, University of Hertfordshire) for writing the software to extract EO and IPC; Professor Glyn Humphreys for generously providing us with his contour overlap data; and the reviewers for their helpful and insightful comments.

References

BIEDERMAN MF and JU G. Surface versus edge-based determinants of visual recognition. *Cognitive Psychology, 20:* 38-64, 1988.

GAFFAN D and HEYWOOD CA. A spurious category-specific visual agnosia for living things in normal human and nonhuman primates. *Journal of Cognitive Neuroscience, 5:* 118-128, 1993.

HUMPHREYS GW, RIDDOCH J and QUINLAN PT. Cascade processes in picture identification. *Cognitive Neuropsychology, 5:* 67-103, 1988.

KURBAT MA. Can the recognition of living things really be selectively impaired? *Neuropsychologia, 35:* 813-827, 1997.

LAWS KR. Gender affects latencies for naming living and nonliving things. *Cortex, 35:* 729-733, 1999.

LAWS KR. Category-specific naming errors in normal subjects: the influence of evolution and experience. *Brain and Language, 75:* 123-133, 2000.

LAWS KR and NEVE C. A ‘normal’ category-specific advantage for naming living things. *Neuropsychologia, 37:* 1263-1269, 1999.

OSTERGAARD AL and DAVIDOFF JB. Some effects of colour on naming and recognition of objects. *Journal of Experimental Psychology: Learning, Memory and Cognition, 11:* 579-587, 1985.

PRICE CJ and HUMPHREYS GW. The effects of surface detail on object categorisation and naming. *Quarterly Journal of Experimental Psychology, 41A:* 797-828, 1989.

SNODGRASS JG and VANDERWART M. A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity and visual complexity. *Journal of Experimental Psychology: Human Learning and Memory, 6:* 174-215, 1980.

TRANEL D, LOGAN CG, FRANK RJ and DAMASIO AR. Explaining category-related effects in the retrieval of conceptual and lexical knowledge for concrete entities: operationalization and analysis of factors. *Neuropsychologia, 35:* 1329-1339, 1997.

Dr Keith R Laws, Department of Psychology, London Guildhall University, Calcutta House, Old Castle Street, London E1 7NT, UK. E-mail: klaws@lgu.ac.uk; Fax: +44 0870-120-5830.

(Received 10 May 2001; reviewed 15 July 2001; revised 9 August 2001; accepted 24 August 2001)

Appendix 1

PB, EO and IPC Values for Subcategory Items

Item	PB	EO	IPC	Item	PB	EO	IPC
			Animals				
Alligator	0.04	10.99	0.91	Kangaroo	0.06	11.96	0.90
Bear	0.06	11.68	0.92	Leopard	0.08	12.32	0.86
Camel	0.06	11.99	0.90	Lion	0.04	11.00	0.91
Cat	0.06	12.26	0.92	Monkey	0.05	11.42	0.91
Cow	0.05	11.36	0.90	Mouse	0.05	11.43	0.93
Deer	0.08	12.57	0.92	Pig	0.04	10.84	0.94
Dog	0.04	10.69	0.92	Rabbit	0.05	11.45	0.91
Donkey	0.06	11.73	0.90	Racoon	0.07	12.08	0.90
Elephant	0.10	13.47	0.85	Rhino	0.05	11.40	0.90
Fox	0.05	11.60	0.91	Seal	0.05	11.60	0.92
Frog	0.08	12.87	0.90	Sheep	0.05	11.18	0.91
Giraffe	0.09	13.64	0.86	Skunk	0.15	15.25	0.82
Goat	0.05	11.93	0.92	Squirrel	0.07	12.03	0.91
Gorilla	0.07	12.39	0.90	Tiger	0.11	13.71	0.83
Horse	0.06	11.92	0.89	**Mean**	**0.06**	**12.03**	**0.90**
			Birds				
Bird	0.04	11.01	0.93	Owl	0.08	12.69	0.89
Chicken	0.05	11.35	0.91	Peacock	0.12	14.21	0.77
Duck	0.05	11.70	0.92	Penguin	0.05	10.91	0.94
Eagle	0.07	11.86	0.89	Rooster	0.07	12.16	0.88
Ostrich	0.06	11.83	0.91	**Mean**	**0.07**	**11.97**	**0.89**
			Body Parts				
Arm	0.04	9.39	0.95	Leg	0.04	9.47	0.96
Ear	0.05	10.47	0.93	Lips	0.03	9.32	0.96
Eye	0.10	12.64	0.87	Nose	0.03	9.31	0.97
Finger	0.03	9.44	0.95	Thumb	0.02	8.98	0.97
Foot	0.03	9.38	0.95	Toe	0.03	9.44	0.95
Hair	0.11	12.92	0.84	**Mean**	**0.05**	**10.13**	**0.94**
Hand	0.05	10.75	0.92				
			Clothing				
Belt	0.04	10.64	0.93	Pants	0.04	10.74	0.92
Blouse	0.06	11.18	0.89	Shirt	0.07	12.11	0.88
Boot	0.07	12.16	0.91	Shoe	0.07	12.10	0.90
Cap	0.05	10.91	0.93	Skirt	0.04	10.59	0.95
Coat	0.05	11.35	0.91	Sock	0.05	10.83	0.93
Dress	0.04	10.55	0.93	Sweater	0.09	12.94	0.87
Glove	0.09	12.69	0.90	Tie	0.05	11.01	0.92
Hat	0.04	10.81	0.94	Vest	0.06	11.69	0.91
Jacket	0.06	11.98	0.88	**Mean**	**0.06**	**11.43**	**0.91**

Item	PB	EO	IPC	Item	PB	EO	IPC
			Fruit				
Apple	0.04	11.15	0.94	Peach	0.07	12.06	0.91
Banana	0.03	10.57	0.95	Pear	0.03	10.64	0.96
Cherry	0.03	10.65	0.96	Pineapple	0.10	13.48	0.82
Grapes	0.12	14.03	0.85	Strawberry	0.18	16.45	0.85
Lemon	0.06	12.10	0.93	Tomato	0.06	11.75	0.09
Orange	0.07	12.23	0.91	**Mean**	**0.07**	**12.28**	**0.83**
			Furniture				
Ashtray	0.06	12.38	0.91	Record play	0.07	12.79	0.86
Bed	0.06	12.77	0.90	Rocking	0.10	14.02	0.82
Chair	0.06	12.40	0.89	Stool	0.10	13.88	0.87
Clock	0.07	12.57	0.90	Table	0.05	12.23	0.90
Couch	0.05	12.09	0.91	Television	0.08	13.58	0.84
Desk	0.07	12.32	0.90	Vase	0.08	13.01	0.88
Dresser	0.07	12.32	0.86	**Mean**	**0.07**	**12.70**	**0.89**
Lamp	0.04	11.39	0.95				
			Insect				
Ant	0.07	12.80	0.91	Fly	0.12	14.11	0.88
Bee	0.09	12.99	0.87	Grasshopper	0.07	12.49	0.89
Beetle	0.07	12.57	0.91	Spider	0.09	13.10	0.89
Butterfly	0.08	13.14	0.84	**Mean**	**0.08**	**12.91**	**0.89**
Caterpillar	0.06	12.06	0.93				
			Musical Instrument				
Accordion	0.17	15.26	0.72	Guitar	0.07	13.67	0.89
Bell	0.10	14.89	0.85	Harp	0.10	14.50	0.82
Drum	0.12	15.68	0.86	Trumpet	0.06	13.20	0.91
Flute	0.04	12.57	0.96	Violin	0.08	13.97	0.89
French horn	0.13	15.54	0.83	**Mean**	**0.10**	**14.36**	**0.86**
			Tool				
Axe	0.03	8.60	0.96	Ruler	0.03	8.79	0.94
Chisel	0.03	8.91	0.95	Saw	0.02	8.20	0.95
Hammer	0.04	9.19	0.94	Screwdriver	0.03	8.65	0.95
Ladder	0.05	9.85	0.90	Wrench	0.03	8.84	0.95
Pliers	0.06	10.53	0.91	**Mean**	**0.04**	**9.06**	**0.94**
			Vehicle				
Airplane	0.05	11.14	0.91	Roller skate	0.07	12.04	0.88
Bike	0.07	12.09	0.85	Sled	0.04	10.75	0.91
Bus	0.08	12.13	0.83	Train	0.07	11.56	0.87
Car	0.05	10.99	0.91	Truck	0.05	10.99	0.92
Helicopter	0.07	12.00	0.87	Wagon	0.07	12.06	0.87
Motorbike	0.09	12.61	0.85	**Mean**	**0.06**	**11.67**	**0.88**

Item	PB	EO	IPC	Item	PB	EO	IPC
			Vegetable				
Artichoke	0.12	14.56	0.86	Onion	0.10	13.99	0.86
Asparagus	0.04	11.58	0.93	Peanut	0.06	12.65	0.90
Carrot	0.04	11.82	0.93	Pepper	0.07	12.71	0.90
Celery	0.12	14.49	0.82	Potato	0.05	12.39	0.93
Corn	0.08	13.30	0.86	Pumpkin	0.11	13.64	0.85
Lettuce	0.08	13.35	0.86	**Mean**	**0.08**	**13.01**	**0.89**
Mushroom	0.06	12.25	0.91				

The values for the excluded items are available from the authors on request.