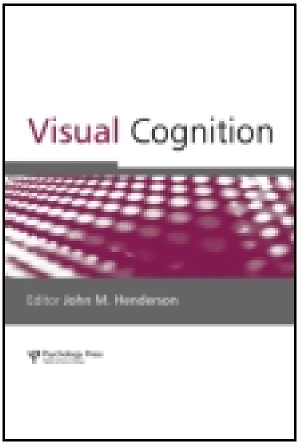

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Structural dimensions of object pictures: Organization and relation to object decision and naming

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Structural dimensions of object pictures: Organization and relation to object decision and naming

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The present paper evaluated the nature of the organization of 22 structural measures of object pictures from the Snodgrass and Vanderwart (1980) picture set (Study 1), and their contribution to object decision and to object naming latencies (Studies 2 and 3). Study 1 employed a principal components analysis and provided evidence of four underlying components: "Object parts", "internal details", "object contours", and "variability of the representation". Study 2 examined the contribution of these components to object decision and object naming and highlighted variability of the representation and internal details as the most relevant indexes of structural similarity. Study 3 investigated the interactions between these structural components and lexical frequency. Main results showed an interaction effect between variability of the representation and lexical frequency and other effects associated to internal details. Implications for the concept of structural similarity and for object recognition are discussed from a continuous and cascade processing perspective.

Keywords: Object decision; Object naming; Object recognition; Structural similarity; Structural variables.

Recognizing and naming objects are pervasive behaviours that are fundamental to human interaction and communication and that have been extensively studied in controlled situations with different visual tasks. This

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paper concerns the relevant structural dimensions of object pictures that we attend to in object decision and object naming.

Most current accounts suggest that naming a common object, or its pictorial representation, involves at least three kinds of stored representations and processing stages (e.g., Glaser, 1992; Humphreys, Riddoch, & Quinlan, 1988): A structural representation that specifies the visual shape of the object and is associated with object recognition; a semantic representation that concerns categorical, functional, and associative information about the object, linked to semantic memory; and finally a lexical form or phonological representation that corresponds to the object's name and is associated with name retrieval (some authors—e.g., Levelt, Roelofs, & Meyer, 1999—further distinguish other postsemantic representations that we will not discuss here for the sake of clarity).

Importantly, since the work of Humphreys et al. (1988), it has been considered that the processes involved at the different levels operate in a cascade and continuous manner and thus the structural dimensions and structural similarity between stimuli may influence processes subsequent to accessing this first representation level. The general idea is that the structural descriptions of all objects sharing a high proportion of common visual features will initially be activated following the presentation of a given object and this activation will be transmitted to the semantic and also the phonological level, ultimately constraining name retrieval. Moreover, the effects of variables on early and late stages of object recognition combine in an interactive rather than additive manner, consistent with object processing stages operating in a cascade and continuous manner rather than a serial discrete manner (Humphreys & Forde, 2001; Humphreys, Price, & Riddoch, 1999; Humphreys et al., 1988).

This first presemantic or structural stage is considered to involve a multiplicity of processes that also operate in an interactive manner to achieve object recognition including: The analysis of simple lower level visual elements; the grouping of these elements in simple shapes through different processes (e.g., proximity, collinearity, closure); their binding into more elaborate shape descriptions to whole objects or larger objects parts (considering the spatial relationships between shape elements); and the matching of these configurations to the structural representations stored in long-term memory (e.g., Behrmann & Kimchi, 2003; Gerlach, 2009; Humphreys et al., 1999). In the case of object naming there is a need for finer visual differentiation relative to recognition or categorization tasks (Humphreys & Forde, 2001; Humphreys et al., 1999). More specifically, there will be increased processing of visual information both involving bottom-up activation of more detailed visual knowledge and also top-down feedback in order to differentiate the activation generated by the target from that of structurally similar objects. Structural similarity effects are thus transmitted through a series of processing stages, with additional forms of information being recruited interactively to differentiate between competitors depending on the specific task requirements (Humphreys & Forde, 2001).

In this context, a crucial discussion regards which structural dimensions are relevant to the computation of structural similarity between objects and at what processing level these dimensions intervene. In fact, although two objects may be similar in various structural dimensions, it is possible that only some of these dimensions are considered when we compute their similarity. Moreover, it is possible that the relevant structural dimensions (or the type of structural similarity considered) may vary as a function of the task demands, such as object recognition or object naming. This is an ongoing discussion for which no general agreement has been reached. This stands in contrast with the contribution of lexical-semantic variables to name retrieval where there is a general agreement that especially age of acquisition (i.e., the age at which a given concept is learned) and name agreement (i.e., the degree of consensus in the names of a given picture), and secondarily the familiarity with the object (whether assessed by rating familiarity or by name written or oral word frequency) and its name length (number of syllables, phonemes, or letters) influence both naming latency and accuracy, probably intervening at a late semantic or postsemantic (lexical) stage (e.g., Almeida, Knobel, Finkbeiner, & Caramazza, 2007; Bates et al., 2003; Johnson, 1992; Johnson & Clark, 1988; Johnston & Barry, 2006; Juhasz, 2005; Snodgrass & Yuditsky, 1996).

In this debate the most widely used visual materials have been the Snodgrass and Vanderwart (1980) picture set, a corpus of 260 black and white line drawings, for which different lexical-semantic and structural dimensions have been proposed and evaluated under different tasks and experimental settings. At the structural level, these measures include ratings regarding several structural aspects of the pictures (and also their corresponding real world objects) and measures of the physical characteristics of the pictures. In the first set,[1] we can find *visual complexity* (Snodgrass & Vanderwart, 1980), corresponding to the rating of how complex the picture is in terms of its details or intricacy; *decomposability* (Lloyd-Jones & Luckhurst, 2002), corresponding to the number of judged visual parts each picture could be decomposed; *visual ambiguity* (Tranel, Logan, Frank, & Damasio, 1997), the extent to which the object class is formed by entities that are visually similar to the item but yet are distinct items; *visual familiarity* (Laws & Neve, 1999), the extent to which the subject is familiar with the item visual appearance; *image agreement* (Snodgrass & Vanderwart, 1980), the

[1] References in this section refer to the study that first proposed the measure.

extent to which the picture resembled the mental image of the item; *picture–name agreement* (Snodgrass & Vanderwart, 1980), the extent to which the picture was a good example of the items it was supposed to represent; and *within-item structural variability* (Laws & Neve, 1999) or *image variability* (Snodgrass & Vanderwart, 1980), the extent to which the items that have a given name have similar structural representations.

In the second set, various physical measures have been calculated from standardized images of the Snodgrass and Vanderwart (1980) corpus including: *Contour overlap* (Humphreys et al., 1988), the percentage of overlap of contour between a particular item and other members of its Snodgrass and Vanderwart (1980) taxonomical category; *proportion of internal details* (Kurbat, 1997), the proportion of internal pixels to the total number of pixels in the picture; *proportion of straight, concave, and convex contours, number of concavities, and curvature variability* (Kurbat, 1997), calculated from the picture contour divided by a computerized method related to creating smooth and accurate approximation of curves at coarse and fine scales; *proportion of black line* (Laws & Gale, 2002), the proportion of black pixels to the total number of pixels in the picture; *Euclidean overlap* (Laws & Gale, 2002), a measure that considers pixel-to-pixel spatial correspondence between each picture and all others from items of the same taxonomical category or from items from the whole Snodgrass and Vanderwart (1980) set; *interpixel* correlation (Laws & Gale, 2002), a measure that considers for every pixel within each picture, the proportion of immediate neighbour pixels with identical values; and *complexity* (Forsythe, Mulhern, & Sawey, 2008), a measure automatically computed on the extent to which a picture has edges (i.e., perimeter detection measure).

Prior studies have focused on the contribution of these structural dimensions to name retrieval, considering different types of naming tasks: Standard picture naming (in which pictures are presented until the participant provides a name for the picture under no timing constraints; e.g., Alario et al., 2004; Bates et al., 2003; Bonin, Chalard, Méot, & Fayol, 2002; Cuetos, Ellis, & Alvarez, 1999; Laws, Leeson, & Gale, 2002; Lloyd-Jones & Nettlemill, 2007; Snodgrass & Yuditsky, 1996), picture naming under speeded naming conditions (in which participants are asked to name the picture within a very short deadline, intended to limit the name-retrieval stage; e.g., Lloyd-Jones & Nettlemill, 2007; Vitkovitch, Humphreys, & Lloyd-Jones, 1993), picture naming with degraded stimuli (where pictures are presented for very short time and/or masked, in order to limit the visual information available for the stimuli; e.g., Laws & Gale, 2002; Laws, Leeson, & Gale, 2002; Laws & Neve, 1999), and picture naming conducted with patients presenting different visual, semantic, and/or postsemantic impairments (e.g., Humphreys et al., 1988; Turnbull & Laws, 2000).

A smaller number of studies have used this set of pictures in object decision tasks, in which participants are asked to decide if a given picture depicts a real object or not (e.g., Barbarotto, Laiacona, Macchi, & Capitani, 2002; Humphreys et al., 1988; Lloyd-Jones & Humphreys, 1997a; Magnié, Besson, Poncet, & Dolisi, 2003) and which is considered to access structural knowledge and the object recognition stage. Finally, some studies have tried to access the semantic knowledge stage using word–picture matching, where participants are asked to decide if a given picture refers to the same object of a previously presented name (e.g., Catling & Johnston, 2006; Humphreys et al., 1988; Stadhagen-Gonzalez, Damian, Pérez, Bowers, & Marín, 2009), and picture categorization, where participants have to decide if a given picture belongs to a specific category such as living or nonliving things (e.g., Laws, Gale, & Leeson, 2003; Lloyd-Jones & Humphreys, 1997b). The Snodgrass and Vanderwart picture set has also been used in several languages, including English (Barry, Morrison, & Ellis, 1997), French (Alario et al., 2004; Rossion & Pourtois, 2004), Spanish (Cuetos et al., 1999), and Japanese (Nishimoto, Miyawaki, Ueda, Une, & Takahashi, 2005). Thus, this databank is particularly well suited to investigate the nature of structural dimensions, thought to be language independent, and how they interact with higher order semantic and lexical variables, where linguistic factors play an important role.

However, despite being vastly tested, the contribution of structural variables to object recognition is still unclear, as the studies so far have not carried out a full comparison between the different dimensions (see Table 1) and have not evaluated the differential and integrated contribution of these measures to the computation of structural similarity and to object recognition and naming. First, no study has investigated how these dimensions might be related or might contribute to the different processing stages in a single experiment. Second, the discussion of structural dimensions and structural similarity has mainly focused on the categorical differences regarding these dimensions and their contribution to performance differences in category-specific impairments (e.g., Gerlach, 2009; Humphreys & Forde, 2001; Humphreys et al., 1988; Kurbat, 1997; Laws & Gale, 2002; Laws, Gale, Frank, & Davey, 2002; Laws & Hunter, 2006; Laws & Neve, 1999; Lloyd-Jones & Nettlemill, 2007; Tranel et al., 1997; Turnbull & Laws, 2000). The relationship between structural dimensions and category-specific differences in final object naming is of course important, as name retrieval at postsemantic level will ultimately be constrained by the amount of visual and semantic features that the target shares with similar items within a category. However, by restricting the debate to category-specific differences, we argue that a more general framework of the contribution of the different structural dimensions to object recognition has been lost. In particular, this approach leaves out an evaluation of the

TABLE 1
Variables (abbreviations), reference articles, and number of items

Variables	*Reference*	*Number of items*
Complexity (COMP)	Forsythe et al. (2008)	260
Proportion of concave contour coarse (CONC_C)	Kurbat (1997)	251
Proportion of concave contour fine (CONC_F)	Kurbat (1997)	251
Contour overlap (CONT_O)	Humphreys et al. (1988)	226
Proportion of convex contour coarse (CONV_C)	Kurbat (1997)	251
Proportion of convex contour fine (CONV_F)	Kurbat (1997)	251
Curvature variability coarse (CURV_C)	Kurbat (1997)	251
Curvature variability fine (CURV_F)	Kurbat (1997)	251
Decomposability (DECOMP)	Lloyd-Jones and Nettlemill (2007)	204
Euclidean overlap category (EO_CAT)	Laws and Gale (2002)	145
Euclidean overlap general (EO_GEN)	Laws and Gale (2002)	254
Image agreement (IMAG)	Snodgrass and Vanderwart (1980)	260
Proportion of internal details (INT_DET)	Kurbat (1997)	251
Interpixel correlation (IPIXCOR)	Laws and Gale (2002)	254
Number of concavities coarse (NCONC)	Kurbat (1997)	251
Number of concavities fine (NCONF)	Kurbat (1997)	251
Proportion of black line (PBLACK)	Laws and Gale (2002)	254
Proportion of straight contour coarse (STR_C)	Kurbat (1997)	251
Proportion of straight contour fine (STR_F)	Kurbat (1997)	251
Visual complexity (VCOM)	Snodgrass and Vanderwart (1980)	260
Visual Familiarity (VFAM)	Laws and Neve (1999)	251
Within-item structural variability (WSTVAR)	Turnbull and Laws (2000)	260

differential contribution of the diverse structural dimensions to the computation of structural similarity and to the various processing stages.

In the present study we wish to contribute to this evaluation from a general perspective of cascade and continuous processes in object recognition and naming (e.g., Humphreys et al., 1988) and from a perspective of a presemantic structural stage involving a multiplicity of interactive processes and different structural dimensions that may influence object recognition and name retrieval (e.g., Behrmann & Kimchi, 2003; Gerlach, 2009; Humphreys et al., 1999).

Within this framework our first goal is to evaluate how the different structural variables proposed for pictures may be related and organized in terms of larger underlying structural dimensions. A second goal is to investigate the contribution of these underlying structural dimensions to the computation of structural similarity in the context of different stages of object processing.

To address these issues, we present three studies considering the Snodgrass and Vanderwart (1980) picture set, previously published norms of the structural measures described and previously published data from object decision and standard picture naming (i.e., under no deadline conditions). In the first study we analysed the empirical interrelationships between the different structural measures and addressed their implications to the understanding of presemantic processing dimensions and structural similarity. The second study examined the contribution of the four underlying structural dimensions identified in Study 1 to structural similarity in the context of object decision and naming. Finally, the third study investigated the contribution of the four underlying structural dimensions in the context of their interaction with postsemantic variables (i.e., lexical frequency) as predicted from a perspective of cascade and continuous processing in object recognition.

STUDY 1

In the first study we evaluated how structural dimensions of line drawings may be organized, considering that such organization may reflect different levels of processing at the presemantic structural stage of object recognition. As was mentioned before, it has been proposed that this early stage involves a multiplicity of processes that operate in an interactive manner (e.g., Behrmann & Kimchi, 2003; Gerlach, 2009; Humphreys et al., 1999). Thus, different structural dimensions may tap into different processes from bottom-up activation to top-down modulation, from more local to more global visual analysis and/or from lower level to higher level visual processing.

For this purpose we conducted a principal components analysis to assess the intercorrelation among the different structural variables and to determine if the pattern of correlations could be explained by a more parsimonious set of latent dimensions associated to structural characteristics and/or processes.

Method

Variables. The study included all the structural variables previously described for which there were available norms ($n = 22$). The variables, the studies where they were taken from and the number of Snodgrass and Vanderwart (1980) items included in such studies are presented in Table 1.

Statistical analyses. We used the Statistica 7 statistical package to perform all correlational and principal component analyses. As can be seen in Table 1, there are differences in the number of items for the different variables. In some instances, the variables cannot be computed for some items (e.g., Kurbat, 1997) and in many other instances the fact that living/nonliving differences were the focus of the study led the authors to select a smaller set of items (e.g., Laws & Gale, 2002; Lloyd-Jones & Nettlemill, 2007). Particularly, Euclidean Overlap by category includes a much smaller number of items because not all of the Snodgrass and Vanderwart (1980) items were judged to belong to a coherent category (Laws & Gale, 2002). In order to maximize the number of items and, considering that the observed results were similar with or without Euclidean Overlap by category (in fact this variable is strongly correlated with Euclidean overlap general, $r = .91$, $n = 136$) we only report and discuss results for this later case (21 variables and $n = 213$).

A principal components analysis (PCA) was performed to extract the components or dimensions underlying the correlations between variables. To determine how many components should be retained we used a parallel analysis (Horn, 1965) and the SPSS statistical package (using the parallel analysis scripts developed for SPSS by O'Connor, 2000). Interpretation and labelling of each component was based on component loadings of .30 or higher, as recommended by different authors for choosing salient factor loadings (Child, 2006) and considering the components where each variable had the highest salient loadings. In order to achieve simple structure and make the pattern of loadings easy to interpret we used a standard varimax rotation.

Results and discussion

Correlations between all variables are presented in Table 2.

The four-component solution yielded by the PCA accounted for 76% of the variance and is represented in Table 3. Table 4 complements this table, illustrating the 10 items with the highest and lowest factor scores for each component (see Study 2 for details on the computation of factor scores). The first component, accounting for 29% of the variance, obtained the highest loadings from number of concavities, proportion of concave contours, curvature variability, proportion of straight contours, decomposability, and visual complexity. This component thus appears to reflect the complexity of the pictures as related to *object parts*, as concavities are part boundaries (Hoffman & Richards, 1984) and decomposability also reflects part information (Lloyd-Jones & Nettlemill, 2007). The second component (22% of the variance explained) obtained the highest loadings from Euclidean Overlap at general level, proportion of black pixel, interpixel correlation, proportion of internal details, complexity, and visual complexity. This second component appears to reflect the complexity of the pictures as related to its

TABLE 2
Correlation matrix between all variables

	COMP	*CONC_C*	*CONC_F*	*CONT_O*	*CONV_C*	*CONV_F*	*CURV_C*	*CURV_F*	*DECOMP*	*EO_GEN*	*IMAG*	*INT_DET*	*IPIXCOR*	*NCONC*	*NCONF*	*PBLACK*	*PNAM*	STR_C	*STR_F*	*VCOM*	*VFAM*
CONC_C	.28*																				
CONC_F	.27*	.94*																			
CONT_O	−.26*	.10	.02																		
CONV_C	−.11	.20*	.19*	.21*																	
CONV_F	−.13	−.09	−.11	.17	.84*																
CURV_C	.23*	.62*	.51*	.19*	.38*	.34*															
CURV_F	.28*	.66*	.59*	−.04*	−.01	−.19*	.51*														
DECOMP	.58*	.56*	.55*	−.09	−.06	−.21*	.35*	.43*													
EO_GEN	.64*	.11	.10	−.08	.17	.22*	.24*	.08	.24*												
IMAG	−.18*	−.06	−.08	−.03	.09	.02	−.11	−.15	−.23*	−.10											
INT_DET	.64*	−.19*	−.21*	−.21*	.02	.14	.07	.03	.24*	.63*	−.18*										
IPIXCOR	−.89*	−.20*	−.19*	.21*	−.05	−.06	−.26*	−.23*	−.42*	−.86*	.15	−.71*									
NCONC	.37*	.89*	.84*	.09	.10	−.14	.63*	.62*	.55*	.19*	−.09	−.16	−.27*								
NCONF	.32*	.85*	.83*	.07	.10	−.13	.53*	.67*	.51*	.15	−.11	−.16	−.24*	.93*							
PBLACK	.64*	.11	.09	−.08	.16	.20*	.24*	.10	.23*	.98*	−.11	.62*	−.88*	.19*	.15						
STR_C	−.10	−.76*	−.72*	−.20*	−.78*	−.50*	−.65*	−.41*	−.31*	−.18*	−.02	.11	.16	−.63*	−.60	−.18*	.03				
STR_F	−.08	−.59*	−.61*	−.15	−.80	−.72*	−.63*	−.25*	−.22*	−.24*	.03	.04	.18*	−.48*	−.47*	−.23*	.05	.90*			
VCOM	.67*	.54*	.52*	−.01	.05	−.12	.40*	.35*	.64*	.48*	−.23*	.43*	−.62*	.54*	.47*	.49*	−.16	−.38*	−.26*		
VFAM	−.21*	−.28*	−.27*	−.07	.02	.11	−.22*	−.20*	−.20*	−.18*	.09	−.07	.21*	−.28*	−.24*	−.22*	.35*	.17	.10	−.45*	
WSTVAR	−.01	.22*	.17	.28*	.09	0	.16	.01	−.05	.01	.42*	−.18*	.01	.21*	.17	.03	−.04	−.20*	−.12	.19*	−.39*

$N = 213$. $^*p < .01$.

TABLE 3
Component loadings of the structural variables after varimax rotation ($n = 213$)

	Component 1 Object parts	*Component 2 Internal details*	*Component 3 Object contours*	*Component 4 Variability of the representation*
COMP	.30	**.84**	−.17	−.08
CONC_C	**.95**	.03	.15	.10
CONC_F	**.92**	.02	.13	.05
CONT_O	.06	−.21	.27	**.37**
CONV_C	.07	.02	**.94**	.05
CONV_F	−.21	.08	**.94**	−.04
CURV_C	**.62**	.17	**.45**	.04
CURV_F	**.75**	.09	−.06	−.14
DECOMP	**.64**	**.38**	−.16	−.18
EO_GEN	.02	**.90**	.20	.06
IMAG	−.17	−.17	.06	**.57**
INT_DET	−.21	**.83**	.01	−.19
IPIXCOR	−.16	**−.95**	−.03	.03
NCONC	**.93**	.11	.05	.11
NCONF	**.91**	.07	.05	.05
PBLACK	.03	**.90**	.19	.08
STR_C	**−.65**	−.04	**−.71**	−.10
STR_F	**−.48**	−.08	**−.84**	−.01
VCOM	**.55**	**.63**	−.06	.14
VFAM	**−.30**	−.26	.12	**−.51**
WSTVAR	.14	−.02	.04	**.90**
Eigenvalue	6.08	4.66	3.45	1.71
Variance explained	29%	22%	16%	8%

Numbers in bold indicate loadings at or above .30.

internal details with which these variables seem to be associated (with the exception of decomposability but which has the lowest salient loading in this component). The third component explained 16% of the variance and obtained the highest loadings from proportion of convex contours and proportion of straight contours, possibly reflecting *object contours* that are not associated to object parts (with the exception of curvature variability but which has a low salient loading in this component). Finally, the fourth component (8% of the variance explained) obtained the highest loadings from within-item structural variability, image agreement, visual familiarity and contour overlap. This component appears to be related to a more top-down dimension associated with various aspects of the *variability of the representation* of a particular picture, their exemplars, or the category they belong.

Overall, this analysis reveals a major weight of more bottom-up variables (largely corresponding to the first three components and explaining 68% of

TABLE 4
The 15 top highest and lowest items for each component (in terms of factor scores)

	Component 1 Object parts	*Component 2 Internal details*	*Component 3 Object contours*	*Component 4 Variability of the representation*
Top highest items	Comb	Basket	Button	French horn
	Eye	Spool of thread	Peach	Spool of thread
	Fence	Accordion	Orange	Artichoke
	Spider	Window	Ring	Axe
	Caterpillar	Stove	Ball	Giraffe
	Ant	Peacock	Strawberry	Cigarette
	Skunk	Windmill	Tomato	Thimble
	Grasshopper	French horn	Nut	Strawberry
	Deer	Thimble	Doorknob	Harp
	Rooster	Skunk	Peanut	Wrench
	Beetle	Strawberry	Potato	Pliers
	Cow	Piano	Apple	Ostrich
	Goat	Harp	Pear	Pineapple
	Bee	Celery	Thimble	Elephant
	Horse	Bus	Football	Skunk
Top lowest items	Refrigerator	Paintbrush	House	Church
	Bowl	Banana	Knife	Sweater
	Window	Apple	Cigarette	Vase
	Book	Axe	Cigar	Hair
	Door	Nail	Church	Bottle
	Potato	Arm	Refrigerator	Boot
	Ball	Rolling pin	Ruler	Chair
	Peach	Bottle	Pen	Jacket
	Light switch	Knife	Light switch	Clock
	Glass	Baseball bat	Paintbrush	Shoe
	Football	Heart	Door	Coat
	Nut	Pear	Swing	Car
	Orange	Cherry	Baseball bat	Doll
	Thimble	Hanger	Flute	Dress
	Button	Balloon	Window	House

the observed variance) that reflect local or global aspects of the stimulus complexity and of its evaluation (i.e., object parts and internal details vs. object contours). In addition, the results also demonstrate a smaller influence of more global top-down modulation associated to the cognitive processing of the pictures and to the variability of the representations. This top-down modulation aggregates a smaller number of variables and corresponds to the fourth component identified in the PCA (explaining 8% of the observed variance).

These results show that many authors have emphasized the role of more local and bottom-up variables in object recognition and support an organization of the different structural variables proposed in the literature along two major processing dimensions—local versus global and bottom-up versus top-down. Although these results provide important information regarding the underlying nature of the organization of structural variables, they do not specify the role that these dimensions play in terms of structural similarity. We addressed this issue in Study 2.

STUDY 2

In the second study we examined the direct contribution of the four structural dimensions identified in Study 1 to structural similarity in the context of object decision and object naming. Considering the general perspective of cascade and continuous processing in object recognition (Humphreys & Forde, 2001; Humphreys et al., 1988, 1999), it is expected that structural similarity determines the time required to differentiate a target from competitors. Therefore, it should impact performance on both object decision and object naming tasks. We evaluated the contribution of the four structural dimensions to structural similarity by analysing the influence of these dimensions on object decision and naming latencies of previously published studies. Importantly, we included studies carried out in different languages as the contribution of structural dimensions should be largely language independent. However, this may not be the case for the measures that involve the subjects' judgements, with several studies showing an effect of stimulus familiarity upon visual complexity judgements (e.g., Forsythe et al., 2008) and hence the possibility of cultural differences. In contrast, other studies have shown that even when the rated structural variables correspond to a different language or a different population from the one where naming latencies are collected, the former variables still contribute to naming performance (e.g., Bates et al., 2003).

Method

Variables. The study included the four structural dimensions identified in Study 1 that were considered as possible predictors of naming performance ($n = 213$). Performance in terms of latency was analysed for one study of object decision and five studies of object naming (i.e., standard picture naming). Study selection was first made considering the availability of published articles that included a large part (or all) of the Snodgrass and Vanderwart (1980) corpus and that provided latency results by item. In addition, the final number of items, discarding items for which we did not have structural information or response time (RT) data (items for which there is low naming performance are usually discarded from latency analyses in object naming) should include more than half of the items from the original corpus. Studies' characteristics are described in Table 5, including the number of items with RT data and number of participants. In the case of the object decision study (Magnié et al., 2003), participants were additionally presented with an equal number of meaningless pictures ($n = 240$), half corresponding to chimeric objects (i.e., made up of two halves of real objects with the constraint that the global shape was unbroken) and half to nonobjects (i.e., made up by mixing up the line drawing of a real object, with the constraints that the outcome was not reminiscent of any real object and that the global shape was unbroken).

Data analysis. The values of each item on the four structural dimensions were calculated through factor scores, as given by the Statistica 7 statistical package. Considering the factor scores and latency data we computed a stepwise multiple regression for each study using the four components as the independent variables and latency as the dependent variable.

Results and discussion

The results of the multiple regressions using latencies as dependent variables and the four structural dimensions as independent variables are presented in Table 6.

As it is clear from Table 6, Component 4, the variability of the representation, and Component 2, internal details, are the main predictors of latencies across studies (although internal details is not significant in all studies). Although the variance explained by these components is modest, they stand out as consistent predictors of processing latencies, in contrast to the other two bottom-up components.

TABLE 5
Naming latency studies considered

Study	*Language (country)*	*Number of items*	*Participants*
Alario et al. (2004)	French (France)	233	46
Barry et al. (1997)	English (UK)	260	26
Bonin et al. (2002)	French (France)	207	72
Magnié et al. (2003)*	French (France)	240	28
Nishimoto et al. (2005)	Japanese (Japan)	260	120
Snodgrass and Yuditisky (1996) (Exp. 1)	English (USA)	250	84

*Object decision task. All other studies correspond to the object naming task, in which only objects from the Snodgrass and Vanderwart set were presented.

TABLE 6
Multiple regression analysis with latencies as dependent variables and the four components as independent variables; values of *R*s and beta coefficients for the independent variables in each study

	Alario et al. (2004) (n = 190)	*Barry et al. (1997) (n = 213)*	*Bonin et al. (2002) (n = 170)*	*Magnié et al. (2003) (n = 197)*	*Nishimoto et al. (2005) (n = 213)*	*Snodgrass and Yuditisky (1996) (n = 211)*
Component 1 (object parts)	−.02	−.05	−.03	.01	−.06	.05
Component 2 (internal details)	.18*	.18*	.12	.22**	.15*	.12
Component 3 (object contours)	.01	−.01	−.01	−.01	−.04	.01
Component 4 (variability of the representation)	.23**	.30**	.22**	.16**	.19**	.34**
Multiple R^2	.08	.12	.06	.07	.06	.13
F-value	4.07**	7.36**	2.43*	3.82**	3.42**	7.71**

*$p < .05$, **$p < .01$.

These results highlight internal details and variability of the representation as possible contributors to structural similarity. The relationship between level of internal details and structural similarity is straightforward, as the more internal details an object has, the higher the probability that it will be structurally similar to other objects (Laws & Gale, 2002). This is clearly illustrated by the items presented in Table 4 of Study 1. As for variability of the representation, its contribution to structural similarity is not so obvious. To better understand this relationship, it is important to consider the different variables that contribute to variability of the representation separately (see Table 3). For contour overlap, the higher the contour overlap between a target and other objects of the same category, the more structurally similar the items will be. However, this is not the case for within-structural variability and image agreement (which have the highest loadings on this component). If the exemplars of a given concept have similar structural representations (i.e., low within-structural variability) and if the particular picture that depicts it provides a good match to our mental image of the concept (i.e., high image agreement), it will be easier to assess its structural similarity to other objects, although it may not always be the case that a particular object is more similar to others. A complementary multiple regression analysis of the object decision accuracy data (also from Magnié et al., 2003) showed internal details as the only significant predictor, beta = .17, $p < .01$; multiple $R^2 = .05$. As such, it seems that this variable is critical in a task that is more related to access to structural representations. In contrast, variability of the representation was more important than internal details in the object naming studies. The differential impact of the variability of the representation on performance is consistent with the idea that naming, in comparison with object decision, requires finer visual differentiation and increased processing of visual information in terms of top-down feedback in order to differentiate the activation generated by the target from that of similar structural objects (Humphreys & Forde, 2001; Humphreys et al., 1999).

The results might show that structural dimensions directly influence object decision and naming, but the contribution of lexical-semantic variables should also be taken into account, since structural components explain only part of the variance observed in naming latencies (Table 6). Object decision studies with dementia patients suggest that this task involves not only access to structural components but also partial access to semantic representations (Chertkow, Bub, & Caplan, 1992; Hovius, Kellenbach, Graham, Hodges, & Patterson, 2003). Regarding object naming, previous standard picture naming studies have pointed to the significant role of lexical-semantic variables to naming latency (e.g., Alario et al., 2004; Barry et al., 1997; Cuetos et al., 1999; Nishimoto et al., 2005). This is consistent with the perspective of cascade and continuous processes in object recognition, which emphasizes the interactions between the different levels of processing. The potential interactions between the four structural dimensions and lexical-semantic variables are investigated in Study 3.

STUDY 3

In Study 3 we tested the potential interaction between structural and lexical-semantic dimensions. The cascade perspective considers that after the initial activation of structural descriptions, activation is transmitted continuously to subsequent semantic and lexical stages (Humphreys & Forde, 2001; Humphreys et al., 1988). As such, multiple lexical representations may be activated before the completion of the structural analysis of the stimuli and consequently structural similarity effects may interact with those of semantic and lexical variables. More specifically, the cascade model predicts that frequency effects on naming latencies are larger for pictures of structurally distinct objects than for pictures of structurally similar objects (Humphreys et al., 1988, 1999; Vitkovich et al., 1993). Moreover, as structurally distinct objects have fewer perceptual neighbours and enjoy more efficient access to stored structural descriptions, their naming times should not only be faster but should also not correlate with a measure of structure overlap. The opposite should occur for structurally similar objects (Vitkovich et al., 1993).

These hypotheses have been supported by studies in which the contour overlap measure (see Table 1) was considered as a single index of structure similarity (Humphreys et al., 1988; Humphreys et al., 1999; Vitkovich et al., 1993). However, Study 2 has identified other structural components that may more adequately represent structural similarity. Moreover, the fact that some components seem to have no direct influence on object decision or object naming latencies does not exclude the possibility that they may contribute to structural similarity by constraining the effects of subsequent semantic-lexical variables.

In the present study we evaluated the potential interaction between each of the four structural components and a measure of lexical frequency on naming latencies. For this purpose, we simulate a replication of Humphreys et al. (1998). In this study, the authors orthogonally manipulated structural similarity based on the contour overlap measure and written word frequency, and tested the effects of both variables on naming latencies. Image agreement and visual complexity were controlled for, but not the contribution of other variables or structural components, such as the ones identified in Study 1. We thus replicate the study, separately considering the potential interaction of each of the four components with lexical frequency, while controlling for the influence of the remaining three components. Analyses were carried out on the naming data from Snodgrass and Yuditsky (1996) and from Alario et al. (2004) in order to include studies in more than one language.

Method

Variables and materials. From the object naming studies analysed in Study 2 we selected those of Snodgrass and Yuditsky (1996) and Alario et al. (2004), for which we were also able to collect the written word frequency for the majority of picture names (the Kucera-Francis frequency counts for English included in the norms of Snodgrass & Vanderwart, 1980, in the first case; and the frequency counts from the French database Lexique from New, Pallier, Ferrand, & Matos, 2001, in the second case). This allowed an orthogonal manipulation of structural components and lexical frequency (which was also the measure taken by Humphreys et al., 1988). Considering these two orthogonal measures (i.e., factor scores of each structural component and written word frequency), we selected a total of 40 items for each component, half with high structural overlap and half with low structural overlap on that component. In addition, for each set, half of the items had high written name frequency and the other half had low written name frequency. There were no component differences between the high and low written name frequency items (and vice versa) and no frequency by component interactions. However, since in all four simulations there were significant differences in other components and in the number of letters between high and low written name frequency items, all subsequent analyses were performed using these dimensions as covariates.

Data analysis. To explore the hypotheses stemming from a cascade perspective, for each combination of structural component by word frequency, we analysed the effects of both variables in a 2×2 ANOVA. As such, for each study (Alario et al., 2004; Snodgrass & Yuditsky, 1996) we performed four main 2×2 ANOVAs, one for each component.

More specifically, we examined whether there was a main effect of structural similarity (i.e., faster naming times for structurally dissimilar items) and a specific interaction predicted from a cascade perspective, that is, larger frequency effects on naming latencies for structurally distinct objects than for structurally similar objects. Finally, also from a cascade perspective, we tested the predicted correlations between naming times and each structural component, which should only be significant for structurally similar items.

Results and discussion

In both studies datasets, main effects of lexical frequency were observed in a majority of manipulations but no longer remained significant when all other variables were included as covariates. Regarding the four structural components, there was only a significant effect of internal details for the Alario et al. (2004) study, $F(1, 76) = 4.85$, $MSE = 71162$, $p < .05$, and this remained significant when all other variables were entered as covariates, $F(1, 72) = 5.35$, $MSE = 80915$, $p < .05$.

Most importantly, the predicted interaction between lexical frequency and structural components was significant in both studies. Specifically, there was a significant interaction between lexical frequency and variability of the representation, $F(1, 76) = 4.57$, $MSE = 91260$, $p < .05$ for Snodgrass and Yuditsky (1996), and $F(1, 76) = 4.85$, $MSE = 80963$, $p < .05$ for Alario et al. (2004). As illustrated in Figure 1, and confirmed by planned comparisons, this interaction corresponded to the fact that the lexical frequency effect on naming latencies was significant for structurally distinct objects, $F(1, 76) = 14.28$, $MSE = 284934$, $p < .01$ for Snodgrass and Yuditsky, and $F(1, 76) = 7.11$, $MSE = 106368$, $p < .01$ for Alario et al., but not for structurally similar objects, $F(1, 76) = 0.57$, $MSE = 11357$, *ns*, for Snodgrass and Yuditsky, and $F(1, 76) = 0.30$, $MSE = 45488$, *ns*, for Alario et al. This result remained significant when other variables were entered as covariates, $F(1, 72) = 4.93$, $MSE = 96532$, $p < .05$, for Snodgrass and Yuditsky and $F(1, 72) = 5.07$, $MSE = 76969$, $p < .05$, for Alario et al.

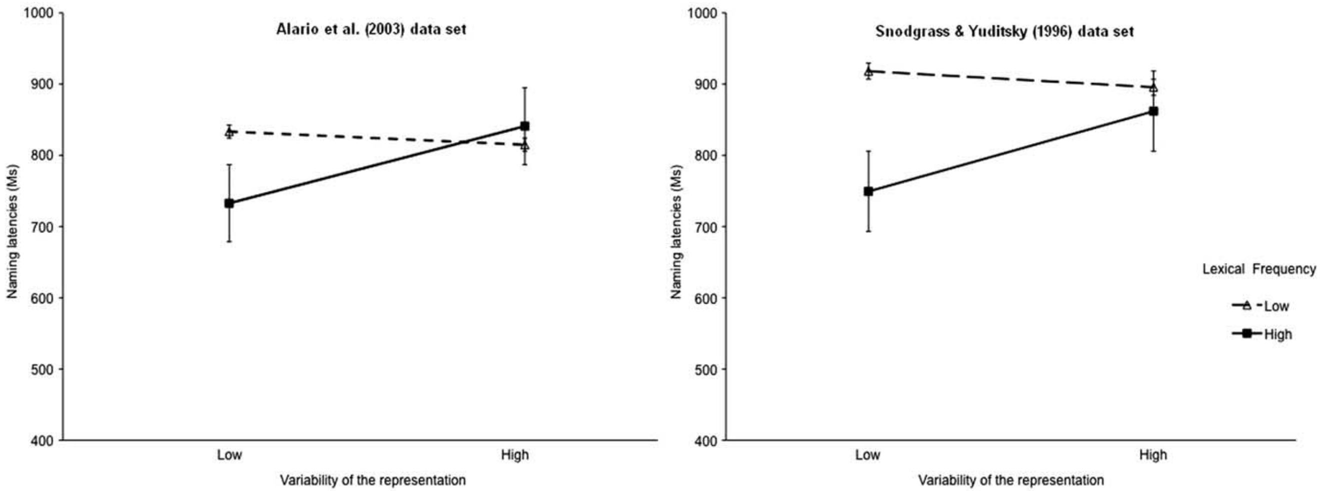

Figure 1. Picture naming latencies as a function of lexical frequency (high, low) and Component 4, variability of the representation (high, low) for the Alario et al. (2004) and for Snodgrass and Yuditsky (1996) data sets.

Regarding the hypothesized pattern of correlations, we observed a significant correlation between naming times and Component 2, internal details for the Snodgrass and Yuditsky (1996) data set. In this particular case, the correlation between structural similarity and naming latencies was significant for similar items, $r = .34$, $n = 40$, $p < .05$, but not for distinct items, $r = .18$, $n = 40$, *ns.* All other correlations were not significant.

The cascade model predicts simultaneously a main effect of structural similarity, an interaction effect of lexical frequency and structural similarity, and a correlation between the later and naming latencies. Since previous studies have used a single index of structural similarity (Humphreys et al., 1988, 1999; Vitkovich et al., 1993), it is not clear whether the different effects are driven by the same structural components. Our study points to the idea that two structural dimensions differentially modulate these effects. Variability of the representation interacted with lexical frequency, while the level of internal details showed a main effect and a correlation with naming latencies. Our results suggest a composite nature of structural similarity that may include a more bottom-up aspect, related to internal details, and a more top-down aspect related to variability of the representation. As previous studies only used a single index of structural similarity, it is possible that these two aspects were in fact conflated in their data. Further implications are considered in the General Discussion.

GENERAL DISCUSSION

In the present study we explored the nature of the organization of the different structural variables that have been proposed to characterize the presemantic processing stage of object recognition and naming. In this context, we set out to answer a set of related questions for which no satisfactory reply had yet been given in the literature. First and foremost what is the nature of the relationship between the many structural variables proposed? Also, can these variables be integrated in a more parsimonious set of underlying dimensions? Second, how do the different structural dimensions proposed impact the computation of structural similarity between objects and at what processing level do these dimensions intervene? Finally, how should the contribution of structural similarity to object recognition and naming may be accounted for under a cascade processing perspective?

To answer the first question we analysed the intercorrelation of 22 structural variables proposed by different authors for the Snodgrass and Vanderwart (1980) picture set (see Table 1) and conducted a PCA analysis to determine if the pattern of correlations could be explained by a more parsimonious set of latent dimensions. Results showed that some pairs of variables were highly interdependent in this picture set and/or measure essentially the same underlying components. More importantly, PCA analysis showed that the variables are organized in four components, three of them reflecting more bottom-up dimensions of the stimuli and one component reflecting more top-down and global processes. The first three components explain a larger part of the variance observed (68.1%) and seem to reflect the complexity of the picture as related to object parts, internal details, and object contours not associated with parts. The other component seems to tap into the variability of the representation in relation to the particular picture, and in relation to its taxonomical counterparts and exemplars.

This systematization is important to uncover the nature of the structural dimensions in object recognition and to provide a framework to interpret and evaluate both past and future research. We do not expect this framework to reflect all of the relevant dimensions and processes that occur at the presemantic stage of object recognition. One should bear in mind that this was an empirical analysis that was run on the available structural factors for a given picture set. As such, other variables may be proposed for the same picture set and other variables will have to be considered for real objects (e.g., texture, colour, three-dimensional properties, etc.). Also, the relation of these variables and/or the weight of components may change in a different picture set. For example, Laws and Gale (2002) have noted that in the standard Snodgrass and Vanderwart (1980) corpus most pictures have a predominance of white space and hence the main source of variance between pictures may be black line information. Rossion and Pourtois (2004) have used this same set and added grey-level texture and surface details and also colour. In the first case, as it is clear from their materials, texture adds more internal details to the picture, which will probably have an impact on structural similarity, as revealed by the present study. In the second case, both Rossion and Pourtois and Price and Humphreys (1989) found that colour information has a larger impact in naming objects that are structurally similar, and it will be interesting to evaluate how this relates to the different components identified in the present study.

Nevertheless, the results from Study 1 suggest an interesting organization of relevant underlying structural dimensions of object recognition: A tripartite set of more bottom-up stimulus characteristics—parts, internal details, and contours—of which the first two seem more local and the third one more global, and one more global and top-down dimension associated to the variability of stimulus in relation to their representation. This seems to be a good starting point to assess the value of these dimensions for other sets of visual stimuli and tasks, and to propose and evaluate other structural dimensions that have not yet been considered.

Regarding the second question, the importance of the different structural dimensions to structural similarity, we found a contribution of internal details and variability of the representation to naming latencies in both object decision and naming tasks. This was a small but robust and systematic effect that was found across six different studies involving different tasks, different participants, and different languages. In the case of internal details there seems to be a straightforward relation to structural similarity (i.e., the more proportion of internal details the more probable to be structurally similar to other objects) that seems relatively more important in object decision than in object naming. As for the variability of the representation, its relationship to structural similarity is more complex and seems more relevant in object naming than in object decision.

The contribution of these dimensions to structural similarity should also be assessed using more direct measures of perceived similarity, namely by collecting similarity ratings, as in Humphreys, Lamote, and Lloyd-Jones (1995). This will allow a more direct link between the two structural components (internal details and variability of the representation) and structural similarity to be established, independently of the particular set of stimuli used.

The importance of variability of the representation appears in contrast with the lesser importance that is given in the object recognition literature to top-down and global modulation as assessed by the results from Study 1. Moreover, the fact that this dimension seems to include different aspects of the variability of the representation, some of which may not be directly related to structural similarity, asks for future research on top-down and global structural variables.

The importance of this top-down dimension was also highlighted by the results of Study 3 that revealed a combined effect of lexical frequency and variability of the representation to naming latencies, whereas the manipulation of other structural dimensions failed to show this combined effect. This result is somehow contradictory from a cascade perspective. Considering the idea that earlier structural processing remains unfinished before being cascaded down for latter processing, it could be expected that the interactions with lexical frequency would include the bottom-up components. Moreover, one could even argue that the interaction observed between our top-down component and lexical frequency could simply correspond to some recurrent processing between the two levels. In addition, in the previous study by Humphreys et al. (1988), the interaction of lexical frequency was obtained with a variable (contour overlap) that also loads in this top-down component, which leads us to question some of the empirical support for a cascade and continuous processing in object recognition and naming (Humphreys & Forde, 2001; Humphreys et al., 1988, 1999). Nevertheless, results from Study 3 also showed that interactions of semantic and lexical variables with structural components also include bottom-up variables. First, in the case of internal details the predicted pattern of correlations of structural similarity to naming latencies was observed in Study 3 (although only for one of the data sets). Second, as it was mention before, the variability of the representation entertains a complex relation to structural similarity and includes different aspects that need further inquiry. In any case, the present results suggest that these interaction patterns are more complex and differentiated than what was previously considered (Humphreys et al., 1988, 1999). Moreover, the fact that the predicted main effect and pattern of correlations were obtained for a different structural component, i.e., internal details, suggests that previous studies of structural similarity may have conflated different aspects of a multidimensional concept.

We also assessed how structural components affect accuracy in an object decision task, and found an effect of internal details. It would be interesting to further explore this effect by testing the influence of the four structural components on subjects' accuracy in situations where viewing conditions are not optimal, such as naming under speeded conditions (e.g., Lloyd-Jones & Nettlemill, 2007; Vitkovitch et al., 1993) or object recognition and naming with degraded stimuli (e.g., Laws & Gale, 2002; Laws, Leeson, et al., 2002; Laws & Neve, 1999), which may differentially enhance the importance of structural processing and structural dimensions.

This may also be the case for tasks used in Study 2 applied to patients presenting different visual, semantic, and/or postsemantic impairments (e.g., Humphreys et al., 1988; Turnbull & Laws, 2000). In this situation, the dimensions identified here may be readily applicable given that the Snodgrass and Vanderwart (1980) picture set is so widely used for evaluating various neurological and developmental disabilities, of which performance on picture-naming tasks are sensitive indicators (Johnson, Paivio, & Clark, 1996).

For all these cases the present results provide a framework to investigate the contribution of structural dimensions to performance, both in terms of response latency, correct responding, and types of errors observed. This evaluation will allow a more complete test of the theoretical and practical relevance of this framework and of structural dimensions and structural similarity in general for object recognition and naming.

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