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Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 38(0)

Authors

Kotabe, Hiroki P.
Kardan, Omid
Berman, Marc G.

Publication Date

2016

Peer reviewed

Can the High-Level Semantics of a Scene be Preserved in the Low-Level Visual Features of that Scene? A Study of Disorder and Naturalness

Hiroki P. Kotabe (hkotabe@uchicago.edu)
Omid Kardan (okardan@uchicago.edu)
Marc G. Berman (bermanm@uchicago.edu)

Department of Psychology, 5848 South University Avenue,
Chicago, IL 60637 USA

Abstract

Real-world scenes contain low-level visual features (e.g., edges, colors) and high-level semantic features (e.g., objects and places). Traditional visual perception models assume that integration of low-level visual features and segmentation of the scene must occur *before* high-level semantics are perceived. This view implies that low-level visual features of a scene alone do not carry semantic information related to that scene. Here we present evidence that suggests otherwise. We show that high-level semantics can be preserved in low-level visual features, and that different high-level semantics can be preserved in different types of low-level visual features. Specifically, the 'disorder' of a scene is preserved in edge features better than color features, whereas the converse is true for 'naturalness.' These findings suggest that semantic processing may start earlier than thought before, and integration of low-level visual features and segmentation of the scene may occur after semantic processing has begun, or in parallel.

Keywords: low-level visual features, scene semantics, semantics, scene recognition, visual perception, scene gist, visual processing

Introduction

A scene of an environment contains a lot of information that we perceive as "features," broadly construed. There are lower-level visual features such as edges and colors and higher-level semantic features such as recognizable objects, places, and descriptors (Oliva & Torralba, 2001; Rosch & Mervis, 1975). Here we focus on two specific semantic features of a scene—its level of 'disorder' and its level of 'naturalness'—due to their psychological importance (Berman, Jonides, & Kaplan, 2008; Kotabe, Kardan, & Berman, 2016; E. O. Wilson, 1984; J. Q. Wilson & Kelling, 1982). Traditional non-Gestalt visual perception models suggest that integration of low-level visual features and segmentation of the scene must occur *before* high-level semantic features are perceived (e.g., Biederman, 1987; Treisman & Gelade, 1980; Marr, 1976). This would imply that low-level visual features do not intrinsically carry information about high-level semantic features. Here we question this assumption by asking, can the low-level visual features of a scene preserve any of the high-level semantics of that scene? Furthermore, is it possible that different high-level semantics are preserved in different types of low-level visual features?

The preservation of high-level semantics in low-level visual features would be of import to theories of visual perception, posing a challenge especially to those that assume that semantic processing starts later in visual perception. First, it would suggest that semantic processing may start earlier than thought previously. Second, it would suggest that integration of low-level visual features and segmentation of the scene may occur after semantic processing has begun, or in parallel.

We know of some of work that is relevant to this idea. First, although it may seem improbable that humans can start to process semantics from information carried by low-level visual features, before objects are perceived, we note that the brain is a meaning making machine that can even find meaningful objects in white noise (Gosselin & Schyns, 2003). Furthermore, there is ample evidence that people can rapidly identify the semantic category of a scene—a remarkable feat considering the subtle comparisons one must make among the large number of scenes within a scene category (e.g., imagine the number of scenes one could consider 'natural'), not to mention the large number of scene categories. After only 20 ms of exposure to a scene, people can categorize whether the scene contains an animal or not with about 94% accuracy (Thorpe, Fize, & Marlot, 1996). This is a shorter duration than used in some subliminal priming experiments! After only 27 ms of exposure to a scene, people can recall seeing semantic features, as evidenced by a free-recall experiment (Fei-Fei, Iyer, Koch, & Perona, 2007). After only 33 ms of exposure to a scene, people can not only categorize objects in a scene (e.g., dog) but can even identify within-category kinds (e.g., a German Shepherd) above chance (Grill-Spector & Kanwisher, 2005). Even if scenes are jumbled into six parts and presented for only 50 ms, people can categorize the gist of the scenes better than chance. After 100 ms of exposure to a scene, people can perceive if an object is incompatible within the scene (Biederman, Teitelbaum, & Mezzanotte, 1983). Although we do not examine the time course of visual information processing in this study, we see this research as consistent with the idea that semantic processing starts very early in visual processing.

There is other support for our hypothesis. An electroencephalogram (EEG) experiment showed that low-level category-dependent processing can occur in less than a tenth of a second after presentation of a stimulus (Vanrullen

& Thorpe, 2001). Not only was the presentation rapid, but category-dependent brain processing started soon after exposure, consistent with low-level visual information carrying semantic information. There are studies that suggest that people can identify the semantic category of a scene in the near absence of attention (Fei-Fei, VanRullen, Koch, & Perona, 2005; Li, VanRullen, Koch, & Perona, 2002). Other research suggests that object semantics are processed prior to figure-ground segmentation (Peterson & Gibson, 1994). A patient study suggests that objects can be recognized when early visual processing is intact but recognition of object parts is impaired, consistent with low-level visual features carrying global semantic information (Davidoff & Warrington, 1999). At least one study suggests that it takes the same amount of time to detect an object as it does to categorize it (Grill-Spector & Kanwisher, 2005), which is contrary to semantic processing starting at a higher and more time-delayed level. An fMRI study also supports this idea by showing that scene categories could be decoded from activity in V1 (Walther, Caddigan, Fei-Fei, & Beck, 2009). In fact, the decoding accuracy of V1 (26%) was not that far off from the decoding accuracy of the parahippocampal place area (31%), which is known to be a key region involved in processing scene semantics. All of these studies cast doubt on traditional hierarchical models of visual perception.

Specifically concerning the preservation of semantics in low-level spatial features, Oliva and Torralba (2001) presented the spatial envelope model which proposes that the global spatial layout of a scene, defined by specific low-level visual feature configurations, carries information about the semantic category (e.g., natural vs. built) of that scene (see also Oliva & Torralba, 2006). This computational model suggests that segmentation and the processing of individual objects or regions is not necessary for classifying scenes into semantic categories.

As for the preservation of semantics in low-level color features, although some research suggests that color information is not critical for the rapid categorization of scenes (Delorme, Richard, & Fabre-Thorpe, 2000; Fei-Fei et al., 2005), other research suggests otherwise. Oliva and Schyns (2000) showed that color information helps people categorize scenes into semantic categories when the color information is diagnostic of a semantic category. Follow-up research by Goffaux et al. (2005) provided both behavioral and EEG evidence that diagnostic color information is part of the scene “gist” (Oliva, 2005) that facilitates rapid scene recognition. This is consistent with other research that suggests that prior experience benefits rapid scene understanding (Greene, Botros, Beck, & Fei-Fei, 2015). In fact, Goffaux et al. (2005) showed that atypical scene colors hinder rapid scene recognition.

Specifically concerning the preservation of semantics related with disorder and naturalness in low-level visual features, we showed that the disorder of a scene could be predicted by objective low-level visual features (Kotabe et al., 2016), and we have shown that this is also true for naturalness (Berman et al., 2014). Relatedly, Oliva and Torralba (2001) showed that naturalness could be predicted based on the principal components of power spectra which capture orientation and spatial frequency information. It is unclear, however, whether these results are possible because the disorder and naturalness of a scene systematically varies non-causally with certain low-level visual features (e.g., the low-level visual features relate with objects that convey semantics related with disorder or naturalness, rather than conveying semantics themselves) or because high-level semantics are actually preserved in low-level visual features. Here we test the latter possibility.

Notes on General Method

We sampled broadly from real-world environments by utilizing 260 colored images of environments that ranged from more urban to more natural (according to previously-collected ratings, Berman et al.; Kardan et al., 2015) and from more orderly to more disorderly (according to previously-collected ratings, Kotabe, Kardan, & Berman, 2016) (see Figure 1 for examples; all images can be downloaded here in original resolution: https://goo.gl/IKHXeC). We manipulated these scene images by extracting and scrambling their low-level edge features and their low-level color features. We had people rate these derived stimuli in terms of disorder or naturalness. Together, that gave us both disorder and naturalness ratings for the scrambled-edge stimuli, the scrambled-color stimuli, and the unaltered scene images. Data analysis was conducted on the image-level mean ratings.

Note that we did not use the rapid scene recognition paradigm for this study. Although this paradigm is useful for the study of the time course of visual information processing, it does not directly test whether low-level visual information carries high-level semantic information. It also relies on recognition instead of directly testing perception. The method we used, which involved freely rating semantic dimensions of presented scenes, directly measured the perception of these semantic dimensions. Furthermore, by taking these measurements between-subjects, we eliminated memory issues including the possibility that high-level semantics are preserved in low-level visual features only when one has previously viewed the unaltered scene (thus has memory of the scene and low-level visual features), or when one has previously viewed its low-level visual features in a scrambled stimulus (thus has memory of the low-level visual features).

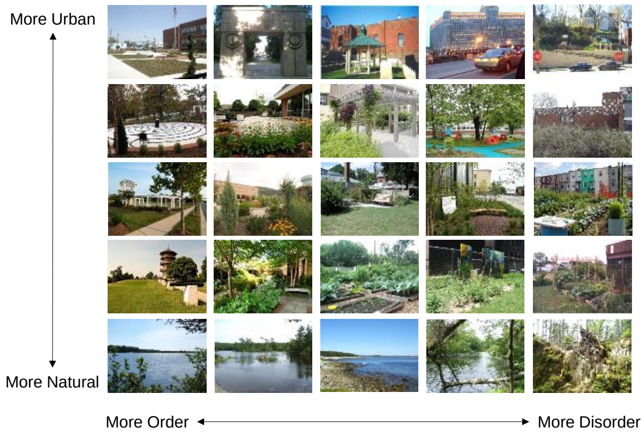

Figure 1: Sample images from our set of 260 scene images varying in naturalness and disorder.

Experiment 1: Is Disorder Preserved in Edges?

We extracted and scrambled the edges and colors of the 260 scene images. We had people rate these derived stimuli in terms of disorder. We then tested the association of these disorder ratings with the disorder ratings of the original scenes to see if disorder was preserved in the low-level visual edge or color features. Based on our previous work, which suggests that edges matter more than colors for the perception of disorder (Kotabe et al., 2016), we predicted that the disorder ratings of the scrambled-edge stimuli would correlate stronger with the disorder ratings of the original scenes than would the disorder ratings of the scrambled-color stimuli.

Method

Participants and design 191 US-based adults (108 men, 82 women, 1 other) were recruited from the online labor market Amazon Mechanical Turk (AMT) and participated in this two-condition (stimuli: scrambled edges vs. scrambled colors) between-subjects experiment.

Extracting and scrambling edges We developed a method to extract and scramble the edges of the scenes such that the average low-level edge properties (e.g., edge continuities, straight and non-straight edge ratios) would be preserved but colors and identifiable segments and objects would be removed. In this method, a matrix, called the mask matrix, was constructed to be the same size as the original images (600*800) with its elements randomly assigned between zero and one. This matrix was then convolved with a median filter sized 30*40 pixels. In this way, patches of 1s and 0s were made randomly and placed at random locations across the mask with random sizes equal to or greater than the 30*40 pixels, with half of every mask having, on average, half a surface of 1s and half a surface of 0s. Next, the edge map of the target image created as in (Berman et al., 2014; Kardan et al., 2015) was randomly rotated either 90 or 270 degrees and overlaid on the 180 degrees rotated edge map, creating a stimulus consisting of less identifiable stimuli with twice as many edges (but same straight and non-straight edge ratios) as the original image. This stimulus was then multiplied (dot product) by the mask so that half of its edges got removed at random. The resulting stimulus had, on average, the same amount of edges with similar edge types, but no identifiable segments or objects from the original image (see Figure 2b for an example).

Figure 2: (a) Example of a highly natural scene, (b) its derived scrambled-edge stimulus, and (c) its derived scrambled-color stimulus.

Extracting and scrambling colors For the scrambled-color stimuli (see Figure 2c), we randomly repositioned windows of 5*5 pixels from the image. The window size was selected so that: 1) segments and objects became non-discernible, and 2) to keep the color texture of the scene visible. For example, using a 1*1 pixel window size resulted in stimuli in which less frequent colors were so scattered that they became invisible to the eye. Using a 10*10 pixel window kept some of the segments or objects identifiable.

Procedure Participants were first given a brief introduction to the image-rating task. They were instructed, "You will be presented with a series of 50 images containing various lines (colors). We simply want you to rate each image in terms of how disorderly or orderly it looks." We intentionally did not define "disorder" or "order" because we were interested in people's natural and spontaneous definitions of disorder, which turned out to be surprisingly uniform. Participants were then randomly presented 50 of the 260 scrambled-edge stimuli (Experiment 1a) or scrambled-color stimuli (Experiment 1b) on a plain white background. The randomization scheme had two layers. First, we randomly selected 10 images from each quintile of urbanness/naturalness. Second, we presented these 50 images in random order. This ensured that each participant would view a wide sample of images from more urban to more natural. For each image, they were instructed to rate the scene in terms of disorder on a seven-point Likert-type scale ranging from "very disorderly" to "very orderly." The task would continue to the next image immediately after a rating was made. By not fixing presentation time, we would not artificially make people view the scenes for shorter or longer than they wanted to, which could have influenced their perceptions.

Results

We correlated the disorder ratings of the scrambled-edge and scrambled-color stimuli with the previously collected disorder ratings of the original scenes. Disorder ratings of the scrambled-edge stimuli significantly correlated with disorder ratings of the original scenes, $r = .38$, $p < .001$, providing first evidence that disorder was partially preserved in the low-level edge features (see Figure 3a). In contrast, disorder ratings of the scrambled-color stimuli *did not* significantly correlate with disorder ratings of the original scenes, $r = .02$, $p = .731$ (see Figure 3b), suggesting that disorder was not preserved as much in the color features. In support, the difference between these two dependent correlations was statistically significant, $t = 4.43$, $p < .001$, according to Williams' test (1959). One may note that the disorder ratings for the scrambled-color stimuli varied less ($SD = 0.52$) than the disorder ratings for the scrambled-edge stimuli ($SD = 0.90$), which may explain the small correlation of $r = .02$ insofar as reduced variance in X is related to reduced covariance between X and Y, so we conducted Thorndike Case 2 correction for range restriction setting the unrestricted *SD* of disorder ratings for the scrambled-color stimuli equal to the *SD* of disorder ratings for the scrambled-edge stimuli which increased the correlation to $r = .03$, $p = .63$, still consistent with edges preserving disorder semantics better than colors.

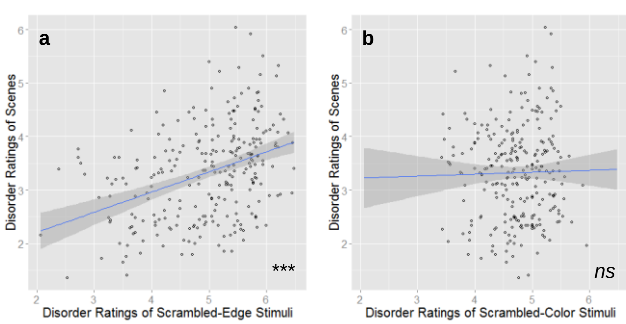

Figure 3: Results of Experiment 1. (a) Disorder ratings of scrambled-edge stimuli significantly correlated with the disorder ratings of scene images. (b) Disorder ratings of scrambled-color stimuli did not significantly correlate with the disorder ratings of scene images. Least-squares lines with 95% confidence bands shown. *** $p < .001$

Because of imperfect linearity, we also tested these associations with two nonparametric tests of association based on rank-order, Spearman's rho (ρ) and Kendall's tau-b (τ). Disorder ratings of the scrambled-edge stimuli were again significantly associated with disorder ratings of the original scenes according to both tests, $\rho = .40$, $p < .001$ and $\tau = .27$, $p < .001$, providing further evidence that disorder was partially preserved in the low-level edge features. In contrast, disorder ratings of the scrambled-color stimuli were again *not* significantly associated with disorder ratings of the original scenes according to both tests, $\rho = .02$, $p = .414$ and $\tau = .01$, $p = .758$, again suggesting that disorder was not preserved as much in the color features. In support, the difference between the two dependent ρs was statistically significant, $t = 4.58$, $p < .001$, according to Williams' test.

These results suggest that high-level semantics related to disorder at the scene-level were preserved in the low-level edge features of the scenes but not as much in the low-level color features of the scenes. This provides evidence that high-level semantics can be preserved in low-level visual features, and more specifically, that some types of low-level visual features carry certain semantic information better than others. But is it possible that different semantic information is preserved better in different low-level visual features? Specifically, is 'naturalness' better preserved in colors than in edges because colors are more diagnostic of naturalness (Oliva & Schyns, 2000)? We tested this possibility in the following experiment. We note that this would be contrary to the spatial envelope model (Oliva & Torralba, 2001) which suggests that naturalness is a perceptual dimension that is well-represented by the *spatial* structure of a scene.

Experiment 2: Is Naturalness Preserved in Colors?

We extracted and scrambled the edges and colors of the 260 scene images. We had people rate these derived stimuli in terms of naturalness. We then tested the association of these naturalness ratings with the naturalness ratings of the original scenes to see if naturalness was preserved in the low-level visual edge or color features. We predicted that the naturalness ratings of the scrambled-color stimuli would correlate stronger with the naturalness ratings of the original scenes than would the naturalness ratings of the scrambled-edge stimuli, under the assumption that colors are more diagnostic of naturalness.

Method

Participants and design 186 US-based adults (118 men, 67 women, 1 other) were recruited from AMT and participated in this two-condition (stimuli: scrambled edges vs. scrambled colors) between-subjects experiment.

Procedure The procedure was the same as in Experiment 1 except that participants rated naturalness on a seven-point Likert type scale ranging from "very urban" to "very natural."

Results

The analysis followed the same procedure as in Experiment 1. Naturalness ratings of the scrambled-color stimuli significantly correlated with naturalness ratings of the original scenes, $r = .24$, $p < .001$, providing first evidence that naturalness was partially preserved in the low-level color features (see Figure 4c). In contrast, naturalness ratings of the scrambled-edge stimuli *did not* significantly correlate with naturalness ratings of the original scenes, $r = -.06$, $p = .358$ (see Figure 4a), suggesting that naturalness was not preserved as much in the edge features. In support, the difference between these two dependent correlations was statistically significant, $t = 3.52$, $p < .001$, according to Williams' test. One may note that the naturalness ratings for the scrambled-edge stimuli varied less ($SD = 0.40$) than the disorder ratings for the scrambled-color stimuli (*SD* = 0.68), which may explain the small correlation of r = -.06, so we conducted Thorndike Case 2 correction for range restriction setting the unrestricted *SD* of naturalness ratings for the scrambled-edge stimuli equal to the *SD* of naturalness ratings for the scrambled-color stimuli which increased the correlation to r = -.10, p = .11, still consistent with colors preserving naturalness semantics better than edges.

There was an outlying clustering of scenes rated as highly natural (see Figure 4). After removing these with a cutoff of 6.5/7.0 on the naturalness scale (N = 212 remaining), the results provide even stronger support for our hypothesis. Naturalness ratings of the scrambled-color stimuli significantly correlated with naturalness ratings of the original scenes, $r = .44$, $p < .001$ (see Figure 4d). In contrast, naturalness ratings of the scrambled-edge stimuli *did not* significantly correlate with naturalness ratings of the original scenes, r = .02, p = .358 (see Figure 4b), suggesting that naturalness was not preserved as much in the edge features. In support, the difference between these two dependent correlations was statistically significant, t = 4.87, p < .001, according to Williams' test.

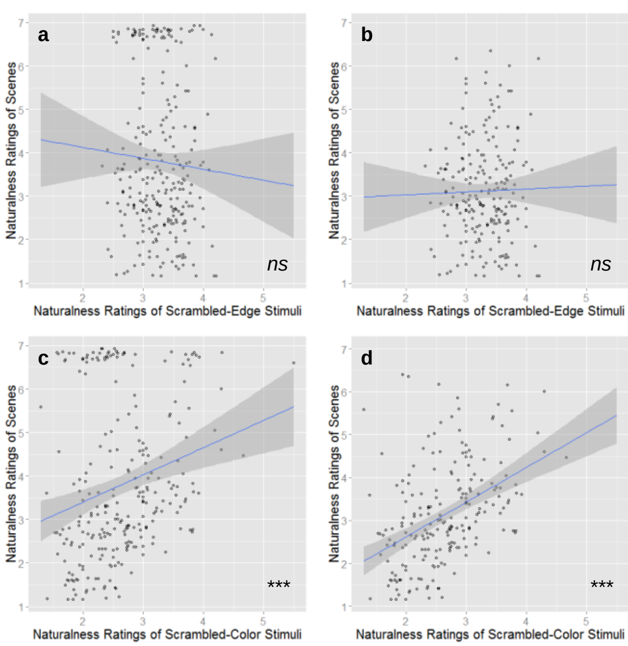

Figure 4: Results of Experiment 2 before and after removing cluster of highly natural scenes. (a-b) Naturalness ratings of scrambled-edge stimuli did not significantly correlate with the naturalness ratings of scene images; (c-d) Naturalness ratings of scrambled-color stimuli significantly correlated with the naturalness ratings of scene images. Least-squares lines with 95% CI shown. *** p < .001

Because of imperfect linearity, we also tested these associations with Spearman's rho and Kendall's tau-b. Naturalness ratings of the scrambled-color stimuli were again significantly associated with naturalness ratings of the original scenes according to both tests, before, $\rho = .29$, $p < .001$ and $\tau = .21$, $p < .001$, and after, $\rho = .48$, $p < .001$ and $\tau = .34$, $p < .001$, removing the cluster of highly natural scenes, providing further evidence that naturalness was partially preserved in the low-level color features. In contrast, naturalness ratings of the scrambled-edge stimuli were again *not* significantly associated with naturalness ratings of the original scenes according to both tests, before, $\rho = -.07$, $p = .288$ and $\tau = -.05$, $p = .287$, and after, $\rho = -.01$, $p = .851$ and $\tau = -.01$, $p = .879$, removing the cluster of highly natural scenes, again suggesting that naturalness was not preserved as much in the edge features. In support, the difference between the two dependent ρs was statistically significant before, $t = 4.27$, $p < .001$, and after, $t = 5.74$, $p < .001$, removing the highly natural scenes, according to Williams' test.

These results suggest that high-level semantics related to naturalness at the scene-level were preserved in the low-level color features of the scenes but not as much in the low-level edge features of a scene. This further supports our general hypothesis that high-level semantics can be preserved in low-level visual features. It also further supports our more specific hypothesis that some low-level visual features carry certain semantic information better than others.

Conclusion

Together, these experiments provide direct evidence that high-level semantics can be preserved in low-level visual features, and that different high-level semantics can be preserved in different types of low-level visual features. This is evidenced by our two experiments, the first showing that high-level semantics related with disorder were preserved better in low-level edge features than in low-level color features, and the second showing that high-level semantics related with naturalness were preserved better in low-level color features than in low-level edge features. This research adds to the body of literature that is starting to entertain the possibility that object perception and segmentation do *not* need to occur before identifying the semantic category of a scene.

Acknowledgments

This work was supported by a grant from the TKF Foundation and an internal grant from the University of Chicago.

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