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Predicting Visual Complexity

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ABSTRACT

Inspired by the contrast between 'classical' and 'expressive' visual aesthetic design, this paper explores the 'visual complexity' of images. We wished to investigate whether the visual complexity of an image could be quantified so that it matched participants' view of complexity. An empirical study was conducted to collect data on the human view of the complexity of a set of images. The results were then related to a set of computational metrics applied to these images, so as to identify which objective metrics best encapsulate the human subjective opinion. We conclude that the subjective notion of 'complexity' is consistent both to an individual and to a group, but that it does not easily relate to the most obvious computational metrics.

Categories and Subject Descriptors

H.1.2 [**Information Systems**]: User/Machine Systems – Human information processing

General Terms

Measurement, Experimentation, Human Factors

Keywords

Image complexity, visual aesthetic, image processing, empirical results.

1. INTRODUCTION

In this paper, we consider an aspect of the aesthetics of visual interface design that has not been considered quantifiably before: that is, the 'visual complexity' of an image. If we were able to measure and combine computational features of an image so as to reliably match 'complexity' as judged by humans, then that would be the first step in being able to determining the effect (if any) of the visual complexity of images used on an interface and their effects on preference, performance or perceived usability.

This research therefore contributes to the growing area of investigating the effects of interface aesthetics, while also adding a new human perception focus to the field of image processing.

2. BACKGROUND

The focus of this paper is the objective characterization of the visual complexity of an image. We are therefore placing this research in between the "classical" and "expressive" aesthetic definitions of Lavie and Tractinsky [1]. We are concerned with the aesthetic judgments of static images that may be used, for example, as the background for an interface, or as an item on an interface, or as a clickable image on a web page. By focusing on the static images themselves (rather than webpages), we are removing any factors that might be associated with interactive features. We aim to investigate whether we can devise objective, computational measures of visual complexity – comparable to those created by Ngo for the layout of objects on an interface [2].

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3. METHOD

3.1 Objective measure of complexity

Based prior research [3,4,5], our own intuitions, pilot tests conducted as part of an associated research project [6] and considering the research that found the relationship between complexity and file size, we categorized our metrics into four types: colour, edges of objects, intensity variation, and file size. We implemented nine computational metrics (Table 1): each metric takes as input a digital image file, and produces a value.

Table 1: Computational metrics for the Visual Complexity of an image

Name	Description
Colours	Number of unique RGB colours in the image
RColours	Number of unique RGB colours, after colour reduction using similarity as determined by the CIE76 formula [7]
PColours	Number of unique RGB colours, after posterization, which limits the RGB colours to specific areas
SColours	Number of unique RGB colours, after pyramid segmentation, which arranges pixels into groups
EdgeArea	The area of the image occupied by edges, as determined by sharp changes in intensity
GrayscaleSD	Standard deviation of pixel intensities in grayscale, representing presence of objects
JPEG, PNG, GIF	Compressed file sizes

3.2 Subjective perception of complexity

A within-subjects experiment was conducted online to gather subjective rankings and ratings of visual complexity. Sixty images were used, photographs taken by the second author. A wide range of image subjects were sought, including landscapes, domestic objects and city scenes.

In the first stage, participants were shown four images in a row and asked "*Please sort the images based on how visually complex you consider them to be.*" A drag-and-drop user interface allowed the participants to easily compare and sort images. Each image was shown twice during this stage, such that each participant completed thirty four-way comparisons. A four-way comparison was chosen over two or three based on pilot studies: we wished the task to be difficult enough that participants were required to think carefully about their considerations of visual complexity.

In the second stage of the complexity experiment, participants were shown each of the sixty images individually, and were asked to rate the visual complexity of each image using a five-point Likert scale. Appropriate randomisation was used throughout.

The experiment was left to run for a two week period, during which time 54 participants completed all stages of the experiment.

3.3 Data analysis

We ensured that the ranking and rating data collected was robust enough to use by performing a graph-based within- and between-participant consistency analysis: both analyses indicated that participants were consistent in their own definition of 'complexity' and that there was a general overall definition of 'complexity' that was used by all participants [8].

We identified those images for which there was most agreement: those with a mean agreement index of over 0.849[1] (Figure 3).

Figure 3: The nine images with the highest mean agreement: the top row are 'less complex', the bottom row are 'more complex'

3.3.1 Regression analysis

The correlation between the participants' ranking of the images and their Likert ratings is 0.97 ($p<0.001$). We chose to use Likert ratings (VCL) in our analysis, as the ranking values are relative.

By looking at the pair-wise correlations between the values of all nine metrics when applied to the 60 stimuli, we eliminated those metrics for which there was a high correlation within the same type. This left us with four metrics: for colour (SColour), for edges (EdgeArea), for intensity (GreyscaleSD), and for file size (GIF): the best combination of metrics we could have chosen so as reduce the overall number of high correlations.

The best-fitting multiple regression model produced the following formula ($R^2 = 0.248$):

VCL = 1.945 + 0.013*GreyscaleSD + 0.053*SColour

3.3.2 Testing the model

We had little confidence in this model (although statistically significant), as it only explains 25% (R2=0.248) of variance in subjective ratings of visual complexity.

To see whether this model held any validity, we tested it against further, new experimental data. 28 participants underwent the same experimental process as before, with 12 new images provided by the first author. The model was used to predict the mean Likert rating for each image, and to rank the images in order of predicted visual complexity.

The correlation co-efficient between the actual and predicted Likert values was 0.257; between the actual and predicted ranks it was 0.294 (Appendix 3). Neither of these values are significant (p=0.420 and 0.354 respectively). We removed image number 5 from the analysis; as a map, it was more of a schematic than an image, and we felt that, in retrospect, its inclusion had been inappropriate (and it was an obvious outlier). Redoing the analysis without this map image produced revised correlation co-efficient of 0.450 and 0.473; again, neither of these is statistically significant (p=0.420 and 0.354 respectively).

4. DISCUSSION

This exploratory study has shown that 'visually complex' is more difficult to define computationally than subjectively. That is, while it may be easy for us to devise computational metrics that measure various aspects of an image, finding 'the right' metrics that will adequately capture the human notion of 'visual complexity' is more challenging. Despite the fact that we used obvious visual variables of colour, intensity change, and extent of edges (in addition to the variable of compressed file size), it appears that there are other less obvious image features that need to be considered.

More complex image processing algorithms for feature extraction, pattern variation, intensity fragments, level of detail of edges (as in [5]) or spatial frequency analysis might provide more useful predictor variables – even if some of these features can only be completely defined computationally, and are difficult to define or describe qualitatively. It is clear that more subtle or advanced image processing algorithms will be needed to appropriately capture the nuances of the human perception of image complexity.

5. REFERENCES

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[1] The 'agreement index' ranges from 0.5 to 1, with 1 representing complete agreement between all participants, and 0.5 representing a 50:50 split.

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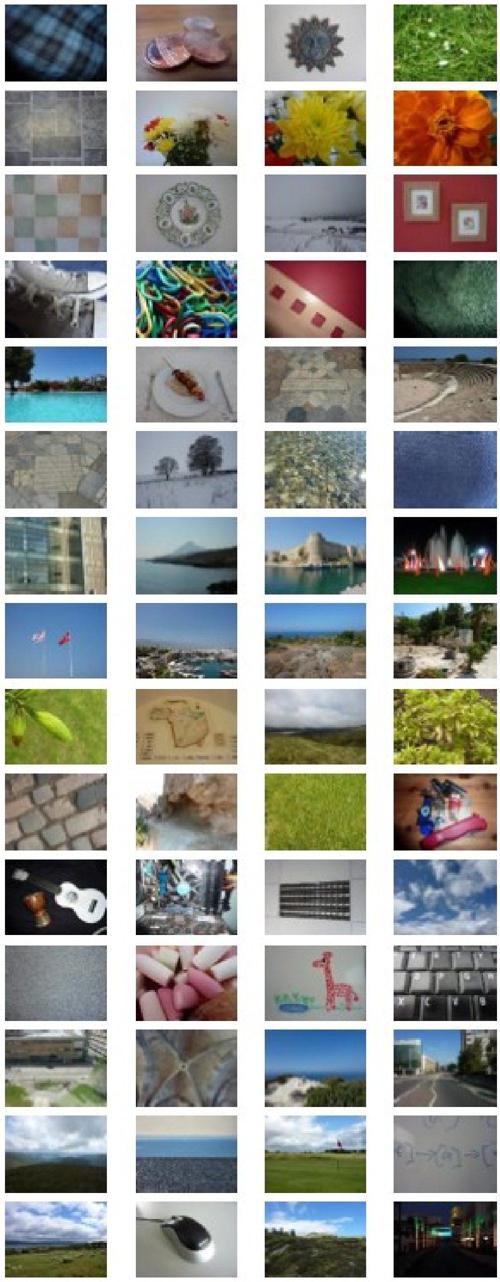
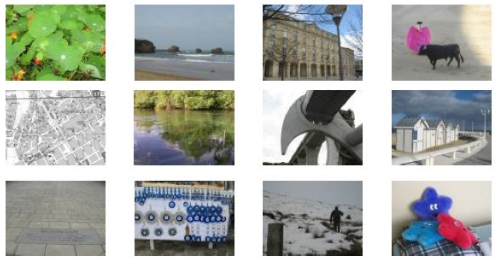
Appendix 1: Experimental Images

1-4
5-8
9-12
13-16
17-20
21-24
25-28
29-32
33-36
37-40
41-44
45-48
49-52
53-56
57-60



Appendix 2: Validation Images

1-4
5-8
9-12



Appendix 3: Validation Plots