Quantifying the Perceived Interest of Objects in Images: Effects of Size, Location, Blur, and Contrast

Vamsi Kadiyala, Srivani Pinneli, Eric C. Larson, and Damon M. Chandler
Image Coding and Analysis Lab, School of Electrical and Computer Engineering, Oklahoma State University, Stillwater, OK 74078

ABSTRACT
This paper presents the results of two psychophysical experiments designed to investigate the effects of size, location, blur, and contrast on the perceived visual interest of objects within images. In the first experiment, digital composting was used to create images containing objects (humans, animals, and non-living objects) which varied in controlled increments of size, location, blur, and contrast. Ratings of perceived interest were then measured for each object. We found that: (1) As object size increases, perceived interest increases but exhibits diminished gains for larger sizes; (2) As an object moves from the center of the image toward the image’s edge, perceived interest decreases nearly linearly with distance; (3) Blurring imposes a substantial initial decrease in perceived interest, but this drop is relatively lessened for highly blurred objects; (4) As an object’s RMS contrast is increased, perceived interest increases nearly linearly. Furthermore, these trends were quite similar for all three categories (human, animal, non-living object). To determine whether these data can predict the perceived interest of objects in real, non-composited images, a second experiment was performed in which subjects rated the visual interest of each of 562 objects in 150 images. Based on these results, an algorithm is presented which, given a segmented image, attempts to generate an object-level interest map.

1. INTRODUCTION
Images captured from the natural environment most often contain regions or objects to which a human observer’s interest is naturally drawn (regions of interest). Consider, for example, the image shown in Figure 1. For a human observer, it is quite evident that the tiger is the object of greatest interest in this image. Yet, what is about this object that make it more visually interesting (or important to the image) than the trees, plants, rock, and other objects in the scene? One logical reason is size: The tiger is larger than the trees, the plants, and the rock. Another reason is location: The tiger is located more toward the center of the image than the other objects. Other factors such as the tiger’s contrast and the extent to which the tiger is in focus compared to the landscape also certainly contribute to our impression of visual interest.

Figure 1. An image from the Berkeley Segmentation Dataset and Benchmark image database.

V.K.: E-mail: vamsi.kadiyala@okstate.edu; S.P.: E-mail: srivanp@okstate.edu; E.C.L.: E-mail: ericcl@okstate.edu;
D.M.C.: E-mail: damon.chandler@okstate.edu
Previous researchers have proposed algorithms for locating and/or quantifying regions of interest in images (e.g., Refs. 1, 2; see Ref. 3 for a review). In particular, Osberger et al. proposed an algorithm which computes an “importance map” for images based on a variety of factors such as object contrast, size, location, and shape. An image is first segmented into regions, then each factor (e.g., contrast) is measured for each region, then each measurement is converted into a relative level of interest/importance, and then the relative interests (one for each region) are combined to arrive at the overall interest map. Osberger et al. have shown that a metric of image fidelity augmented by their interest map can perform better than PSNR for fidelity assessment. However, the maps themselves were not experimentally verified; in particular, the specific relations between the measured factors (e.g., object location) and perceived interest were never psychophysically quantified. Furthermore, there remains an open question regarding the correct way to combine the per-factor measures of interest to arrive at the overall interest map.

In this paper, we examined from a psychological standpoint how various visual factors affect perceived interest. Specifically, we asked:

1. How does the perceived interest of an object change as a function of the object’s size?
2. How does the perceived interest of an object change as a function of the object’s location within the image?
3. How does the perceived interest of an object change as a function of the extent to which the object is in focus (level of blurring)?
4. How does the perceived interest of an object change as a function of the object’s contrast?
5. To what extent does object category (human vs. animal vs. other) affect perceived interest?

To answer these questions, a psychophysical experiment was performed in which subjects rated the relative interest of objects which varied in controlled increments of size, location, amount of blurring, and contrast (Experiment I). Digital compositing was used to create the stimuli, which consisted of a fixed natural-scene background onto which an image of either a human, an animal, or a non-living object was placed. This experiment was designed to yield interest-vs-size, interest-vs-location, interest-vs-blur, and interest-vs-contrast curves which relate the measurable factors (size, location, blur, and contrast) to perceived interest.

Whereas Experiment I tested the separate effects of size, location, blur, and contrast on perceived interest, typical images contain objects which vary simultaneously in all of these aspects (e.g., a large house in the foreground, and a lower-contrast, smaller house in the background which may not be in focus). To assess the utility of the results obtained in Experiment I in predicting perceived interest, a second experiment was performed in which subjects rated the relative interests of all objects in 150 images. This experiment was designed to provide insight into the extent to which combinations of these visual factors affect perceived interest.

Based on the results of these experiments, an algorithm which follows from the work of Osberger et al. is presented. The algorithm operates by using a weighted linear combination of the interest-vs-size, interest-vs-location, interest-vs-blur, and interest-vs-contrast curves from Experiment I in which the weights are derived based on a subset of the images/ratings from Experiment II. The algorithm takes as input a segmented image, and it yields a corresponding level of relative interest for each object.

This paper is organized as follows. Section 2 describes the methods and results of Experiment I. Section 3 describes the methods and results of Experiment II. The algorithm which uses these psychophysical results to predict perceived interest is presented in Section 4. General conclusions are provided in Section 5.

2. EXPERIMENT I

To investigate the effects of size, location, blur, and contrast on perceived interest, a psychophysical experiment was performed in which subjects rated the interest of various objects placed upon a common natural-scene background (Experiment I). The objects were varied in controlled increments of size, location, blur, and contrast.
2.1. Methods

2.1.1. Apparatus and Subjects

Stimuli were displayed on a high-resolution, ViewSonic VA912B 19-inch monitor. The display yielded minimum and maximum luminance of respectively, 2.7 and 207 cd/m$^2$, and an overall gamma of 2.9; luminance measurements were made by using a Minolta CS-100A photometer (Minolta Corporation, Tokyo, Japan). Stimuli were viewed binocularly through natural pupils in a darkened room at a distance of approximately 46 cm through natural pupils under D65 lighting.

Six adult subjects participated in the experiment. Three of the subjects were naive to the purpose of the experiment; the other subjects were three of the authors. Subjects ranged in age from 21 to 34 years. All subjects had either normal or corrected-to-normal acuity.

2.1.2. Stimuli

A single grayscale natural scene obtained from the van Hateren database$^4$ served as a common background for all stimuli. The original image was of size $1536 \times 1024$ pixels with 16-bit pixel values in which each pixel value was proportional to luminance in the original physical scene. This image was modified by (1) resizing the image to $1024 \times 768$ pixels; then (2) applying a point-wise power function of $f(x) = x^{1/2.9}$ (where $x$ denotes the original pixel value) such that the displayed pixels were proportional to luminance in the original physical scene; and then (3) scaling the pixel values to lie in the range $[0, 255]$.

Nine high-resolution single-object images were used as the objects of interest. Three of these objects consisted of images of humans: An image of a human male (image man), a human female (image woman), and a human child (image kid). Three of the objects contained images of animals: An image of a dog (image dog), a cat (image cat), and a turkey (image bird). Three of the objects contained images of non-living objects: An image of a fire hydrant (image hydrant), a lamp post (image lamp), and a park bench (image bench). Figure 2 depicts the single-object images used in Experiment I.

To each of the nine single-object images, the following manipulations were applied:

1. **Size**: The single-object images were resized (via bicubic interpolation) such that the number of pixels in the object were 1%, 2%, 3%, 6%, and 12% of the number of pixels in the natural-scene background. These objects were then placed within the natural-scene background at a location of 50% of the background’s half-width (256 pixels from the left-hand edge of the image) and displaced vertically so as to create a natural impression of depth.

2. **Location**: The objects were placed within the natural-scene background at leftward horizontal offsets from the center of the image of 0%, 20%, 40%, 60%, and 80% of the natural-scene’s half-width. Here, the size was held constant at 3% of the number of pixels in the natural-scene background.

3. **Blur**: The objects were blurred by using a length-15 Gaussian filter with one-dimensional impulse response $h(n) = \exp\left(-\frac{(n/7.5)^2}{2\sigma^2}\right)$, $n \in [-7, 7]$, with $\sigma$ values of 0.06, 0.08, 0.11, 0.16, and 0.22; the blurred objects were then placed within the natural-scene background. Here, the size was held constant at 3% of the number of pixels in the natural-scene background, and the location was held constant at 50% of the natural-scene’s half-width.

4. **Contrast**: The RMS contrast of the objects$^\ast$ were adjusted to values of 0.1, 0.225, 0.35, 0.475, and 0.6; the contrast-adjusted objects were then placed within the natural-scene background. Here, the size was held constant at 3% of the number of pixels in the natural-scene background, the location was held constant at 50% of the natural-scene’s half-width, and the objects were not blurred.

$^\ast$We have employed a modified RMS contrast metric computed as the RMS of local contrast measured for blocks contained within the object; see Equation (3) in Section 4.
Humans:

man  woman  kid

Animals:

dog  cat  bird

Objects:

hydrant  lamp  bench

**Figure 2.** The nine single-object images used in Experiment I. *Top row:* Images of humans. *Second row:* Images of animals. *Bottom row:* Images of non-living objects.

In addition, to serve as a fixed benchmark object, an unblurred copy of the same single-object image of size 50% and contrast 0.5 was placed at location 50% of the background’s half-width (256 pixels from the right-hand edge).

There were a total of 60 stimuli used in this experiment (9 objects × 4 factors × 5 variations per factor), a sampling of which are shown in Figure 3. The top row in Figure 3 depicts variation in size; the second row depicts variation in location; the third row depicts variation in amount of blurring; the bottom row depicts variation in contrast.

2.1.3. Procedures

Subjective ratings were measured for each set of stimuli by using a modified version of the Subjective Assessment Methodology for Video Quality (SAMVIQ) testing procedure\(^5\) applied to still images. The experiment was divided into nine sessions: One session for each of the nine single-object images (*man*, *woman*, *kid*, *dog*, *cat*, *bird*, *hydrant*, *lamp*, *bench*). Each session was further divided into four subsessions, one subsession for each factor (size, location, blur, and contrast). Each session entailed rating the fixed benchmark object (once at the beginning of the session), and rating the versions of that object which varied over the five values of the corresponding factor.

At the beginning of each session, subjects were initially shown the stimulus containing the fixed benchmark object and the version of that object at its maximum size (12%); see, e.g., the top-left image in Figure 3. Subjects were instructed to rate the visual interest of the fixed benchmark object on a scale from 0-100 where 100 corresponded to the greatest possible interest. Via keyboard input, subjects then switched between the five images and were instructed to provide for the variable object a rating of interest for the object on a scale from 0-100 where 100 corresponded to the greatest possible interest; this rating was made relative to the previous rating for the fixed benchmark object. Subjects were instructed to view all five images before reporting any ratings, and subjects were also allowed to change any previously reported ratings during the course of each subsession.
The time-course of each experimental session was not limited, however the majority of observers completed all nine experimental sessions in under 60 minutes. The order of the sessions was randomized for each subject.

2.2. Results

The raw scores for each subject on each set of five images (corresponding to a single object/factor combination) were converted to differential ratings by subtracting from each rating the rating for the corresponding fixed benchmark image. These differential ratings thus represent how an object’s perceived interest changes due to variations in size, location, blurring, or contrast.

Figure 4 depicts the results obtained from this experiment averaged across all subjects; error bars denote standard deviations of the means. The top row in Figure 4 depicts the change in perceived interest due to size. The second row in Figure 4 depicts the change in perceived interest due to location. The third row in Figure 4 depicts the change in perceived interest due to blurring. The bottom row in Figure 4 depicts the change in perceived interest due to contrast. In each graph, the horizontal axis denotes the size, location, amount of blurring, or contrast of the variable object; the vertical axis denotes the change in perceived interest.

The results of this experiment reveal that:

1. As an object’s size increases, perceived interest increases but exhibits diminished gains for larger sizes.

2. As an object moves from the center of the image toward the image’s edge, perceived interest decreases in a nearly linear fashion with distance from the center.

3. Blurring an object initially imposes a substantial decreases in perceived interest, but this drop in interest is relatively lessened for highly blurred images.
Figure 4. Change in perceived interest as a function of object factor (Experiment I). Top row: object size; second row: object location; third row: object blur; bottom row: object contrast. These data represent the average over all six subjects; error bars denote standard deviations of the means.

4. As an object’s RMS contrast is increased, perceived interest increases in a nearly linear fashion.

In addition, note that the relationship between each of the four factors and perceived interest is similar for all three categories (human, animal, non-living object), despite the fact that the objects used in this experiment were dissimilar. Although more objects need to be tested in order to make a definitive conclusion, these data suggest that, as a first approximation, it is reasonable to use average interest-vs-size, interest-vs-location, interest-vs-blur,
and interest-vs-contrast curves to attempt to predict perceived interest for all three categories.

Still, one of the shortcomings of this experiment is that it does not provide insight into the interactions between the factors. For example, if an object is both smaller and of lower contrast than its fixed benchmark counterpart, how should the interest-vs-size and interest-vs-contrast data be combined to measure the object’s perceived interest? In Section 4 we demonstrate that a weighted linear combination of the individual perceived interests can perform reasonably well at this task. The following section (Section 3) describes an experiment designed to determine the optimal weights.

3. EXPERIMENT II

To assess the utility of the results from Experiment I in predicting the perceived interest of each object in a real image (as opposed to a compositied image), it is necessary to obtain ratings for such objects. To this end, a second psychophysical experiment was performed in which subjects rated the interest of each object within actual images containing commonplace subject matter (Experiment II).

3.1. Methods

3.1.1. Apparatus and Subjects

Stimuli were displayed on a high-resolution, ViewSonic VA912B 19-inch monitor. The display yielded minimum and maximum luminance of respectively, 2.7 and 207 cd/m², and an overall gamma of 2.9; luminance measurements were made by using a Minolta CS-100A photometer (Minolta Corporation, Tokyo, Japan). Stimuli were viewed binocularly through natural pupils in a darkened room at a distance of approximately 46 cm through natural pupils under D65 lighting.

Five adult subjects participated in the experiment. Two of the subjects were naive to the purpose of the experiment; the other subjects were three of the authors. Subjects ranged in age from 21 to 34 years. All subjects had either normal or corrected-to-normal visual acuity.

3.1.2. Stimuli and Procedures

Images used in the experiment were obtained from the Berkeley Segmentation Dataset and Benchmark image database. This database was chosen because its images are accompanied by human-segmented versions (averaged over at least five subjects). One-hundred and fifty images, chosen at random from the database, were hand-segmented by the second author into 562 objects by using the database’s hand-segmented results as a reference. The images used were of size $321 \times 481$ and $481 \times 321$ with 24-bit RGB pixel values. Figure 5 depicts a subset of the images used in the experiment.

For each of the 562 objects, subjects were instructed to rate the perceived interest relative to the other objects within the image. The ratings were performed using an integer scale of 0 to 10 in which 10 corresponded to greatest interest and 0 corresponded to least interest. The time-course of each experimental session was not limited; however the majority of subjects completed the experiment in less than 60 minutes.

3.2. Results

Raw scores for each subject were converted to z-scores. The per-subject z-scores were then averaged across all subjects, and then the average z-scores were rescaled to span the range 0 to 1 for each image. Figure 6 depicts representative results obtained from this experiment in the form of perceived interest maps. In each map, brighter regions denote objects of greater perceived interest; objects shown in white received a normalized rating of 1; objects shown in black received a normalized rating of 0.

Overall, the results of Experiment II suggest that object category plays a bigger role than most other factors in determining perceived interest. For example, in image ladybug located in the middle of the top row in Figures 5 and 6, the ladybug was rated to be of greatest perceived interest, despite the fact that it is smaller and of lower RMS luminance contrast than the plant. In general, we found that subjects tended to rate objects containing human faces and/or animals to be of greatest interest. Background objects such as sky and grass were generally rated to be of least interest. The ability to determine whether an object is in the foreground vs. background is certainly an important factor for predicting perceived interest.
Figure 5. Some of the images from the Berkeley Segmentation Dataset and Benchmark database used in Experiment II.

The images and results from Experiment II were divided into two sets. Fifty of the 150 images were used as a training set for our algorithm (described next; see Section 4.3). The remaining 100 images were used as a test set to evaluate the performance of the algorithm (see Section 4.4).

4. ALGORITHM

Based on the psychophysical results, an algorithm for predicting the perceived interests of objects in images is presented. The algorithm takes as input a segmented image, and it yields a corresponding level of interest for each object. The algorithm operates by using a weighted linear combination of the results from Experiment I in which the weights are derived based on a subset of the images/ratings from Experiment II.

4.1. Step 1: Measure the Object Factors

Let $v_{size,i}$, $v_{location,i}$, $v_{blur,i}$, and $v_{contrast,i}$ denote, respectively, the size, location, amount of blur, and contrast of the $i^{th}$ object in an image. Furthermore, let $v_{foreground,i}$ denote a measure of the extent to which the object is in the foreground. These factors are measured as follows:

- **Size:** The measure of object size is given by
  \[ v_{size,i} = \frac{N_i}{N} \quad (1) \]
  where $N_i$ and $N$ denote the number of pixels in the $i^{th}$ object and the full-sized image, respectively.
Figure 6. Perceived interest maps for a sampling of the images used in Experiment II (cf Figure 5). In each map, brightness is directly proportional to perceived interest.

- **Location**: The measure of object location is given by

  \[ v_{\text{location},i} = \sqrt{\left(\frac{x_c - \text{width}}{2}\right)^2 + \left(\frac{y_c - \text{height}}{2}\right)^2} \sqrt{(\text{width})^2 + (\text{height})^2} \]  

  where \(x_c\) and \(y_c\) denote the horizontal and vertical pixel coordinates of the object’s centroid, respectively; and where \text{width} and \text{height} denote the width and height of the full-sized image, respectively.

- **Blur**: We have been unable to obtain a proper computational measure of blur. Consequently, blur was measured by-eye in this paper (the standard deviation of the Gaussian filter was estimated by the authors for all 562 objects). To maintain a valid performance analysis, results are presented with and without the blur factor.

- **Contrast**: The object’s contrast is measured by (1) dividing the object into \(B \times B\) blocks, (2) measuring the RMS contrast of each block, and then (3) combining the per-block contrasts via

  \[ v_{\text{contrast},i} = \frac{50}{M} \sqrt{\sum_{m=1}^{M} c_m^2} \]  

  where \(M\) denotes the total number of blocks in the object, and where the block size \(B\) is computed based on the object’s size via \(B = \max(4, \left\lfloor 0.05\sqrt{N} + 0.5 \right\rfloor)\). The quantity \(c_m\) denotes the RMS contrast of the
4.2. Step 2: Convert the Measured Factors into Perceived Interests

Experiment I measured five variations of size, location, blur, and contrast. In order to provide a means to interpolate between and extrapolate beyond the values tested in the experiment, the interest-vs-size, interest-vs-location, interest-vs-blur, and interest-vs-contrast curves were fitted with a sigmoidal function.

Specifically, each curve was first converted from a change in perceived interest to a relative perceived interest by adding to each result the average rating for the corresponding fixed benchmark image. These data were then averaged over all nine objects. Finally, a sigmoidal function of the form

\[ PI(v) = \max \left( 0, \frac{A_1 - A_2}{1 + e^{-\frac{v - v_0}{dv}}} + A_2 \right) \]  

was fitted to the data via a Nelder-Mead search to obtain the parameters \( A_1, A_2, v_0, \) and \( dv \) which minimized the sum-squared error between the fitted curve \( PI(v) \) and the data; \( v \) denotes one of the factors (\( v_{\text{size}}, v_{\text{location}}, v_{\text{blur}}, \) or \( v_{\text{contrast}} \)).

The resulting fits and the best-fitting parameters \( A_1, A_2, v_0, \) and \( dv \) are provided in Figure 7. Note that separate curves were fitted for each factor, thus resulting in equations for \( PI_{\text{size}}, PI_{\text{location}}, PI_{\text{blur}}, \) and \( PI_{\text{contrast}} \). Also note that because the perceived interest due to an object being in the foreground vs. background was not tested in Experiment I, we have assumed \( PI_{\text{foreground}}(v_{\text{foreground}}) = 100 \times v_{\text{foreground}} \).

4.3. Step 3: Combine the Separate Perceived Interests

To determine an overall perceived interest for each object in the image, the individual perceived interests (i.e., the perceived interest due to size, due to location, due to blurring, due to contrast, and due to an object being in the foreground) are combined.

We employ the following weighted linear sum to compute the overall perceived interest for each object:

\[ PI_{\text{total},i} = \alpha_1 PI_{\text{size}}(v_{\text{size},i}) + \alpha_2 PI_{\text{location}}(v_{\text{location},i}) + \alpha_3 PI_{\text{blur}}(v_{\text{blur},i}) + \alpha_4 PI_{\text{contrast}}(v_{\text{contrast},i}) + \alpha_5 PI_{\text{foreground}}(v_{\text{foreground},i}). \]
where the weights $\alpha_1 = 0.0015$, $\alpha_2 = 0.2805$, $\alpha_3 = 0.2321$, $\alpha_4 = 0.1703$, and $\alpha_5 = 0.1452$ were chosen to maximize the correlation between $PI_{total}$ and the subjective ratings for the 50 images in the training set from Experiment II.

After $PI_{total}$ is computed for all objects in the image, a normalization step is performed such that the object with the minimum computed perceived interest has $PI_{total} = 0$ and the object with the maximum computed perceived interest has $PI_{total} = 1$.

4.4. Algorithm Summary and Results

In summary, given a segmented image, the algorithm performs the following steps:

1. Computes each object’s factors $v_{size,i}$, $v_{location,i}$, $v_{blur,i}$, $v_{contrast,i}$, and $v_{foreground,i}$.

2. Converts the factors into perceived interests via Equation (5) or via $PI_{foreground}(v_{foreground,i}) = 100 \times v_{foreground,i}$ for $v_{foreground,i}$.

3. Computes each object’s total perceived interest via Equation (6).

4. Normalizes the total perceived interests for all objects such that the object with the minimum computed perceived interest has $PI_{total} = 0$ and the object with the maximum computed perceived interest has $PI_{total} = 1$.

Figures 8(a) and 8(b) depict scatterplots of the algorithm’s predicted perceived interests vs. human-rated perceived interests for the 100 images in the test set from Experiment II. Figure 8(a) shows results when using all factors; Figure 8(b) depicts results when excluding the blur factor. Overall, the proposed algorithm achieves a correlation coefficient of $R = 0.83$ ($R^2 = 0.68$) and $R = 0.75$ ($R^2 = 0.56$) with and without blur, respectively. As a comparison, the algorithm of Osberger et al. achieves a correlation coefficient of $R = 0.43$ ($R^2 = 0.18$) on these same images (using the same hand segmentations); see Figure 8(c).

Figure 9 depicts original images along with corresponding perceived interest maps from a sample of images from the test set of Experiment II. In each perceived interest map, greater brightness denotes greater importance. The original images are shown in the first column; the human-rated perceived interests are shown in the second column. The third and fourth columns depict, respectively, results predicted via the algorithm of Osberger et al. and via the proposed algorithm (using all factors).
5. CONCLUSIONS

In this paper, we investigated the effects of size, location, blur, and contrast on the perceived visual interest of objects in images. Two psychophysical experiments were performed, the results of which were used to develop an algorithm for predicting perceived interest.

In Experiment I, digital composting was used to create scenes containing objects which varied in controlled increments of size, location, blur, and contrast. Subjective ratings of the relative visual interests of these objects revealed that: (1) As object size increases, perceived interest increases but exhibits diminished gains for larger sizes; (2) As an object moves from the center of the image toward the image’s edge, perceived interest decreases nearly linearly with distance; (3) Blurring imposes a substantial initial decrease in perceived interest, but this drop is relatively lessened for highly blurred objects; (4) As an object’s RMS contrast is increased, perceived interest increases nearly linearly.

In Experiment II, subjective ratings of visual interest were obtained for 562 objects in 150 images. The results indicated that object category plays a bigger role than most other factors in determining perceived interest. Specifically, we found that subjects tended to rate objects containing human faces and/or animals to be

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Figure 9. Original images (first column) and perceived interest maps from the results of Experiment II (second column), from the proposed algorithm (using all factors; third column), and from the algorithm of Osberger et al.² In each perceived interest map, greater brightness denotes greater importance.
of greatest interest, and background objects such as sky and grass were generally to be of least interest, despite the fact that background objects were often larger and sometimes of greater contrast.

Based on these results, an algorithm for automatically generating an interest map from a pre-segmented image was presented. The algorithm takes as input a segmented image, and it yields a corresponding level of interest for each object. The algorithm operates by using a weighted linear combination of the results from Experiment I in which the weights were derived based on a subset of the images/ratings from Experiment II. When applied to the 100 images from the test set from Experiment II, the algorithm was found to perform well in predicting perceived interest ($R^2 = 0.68$), though a noteworthy portion of variance in the data could not be explained by the proposed algorithm. We are currently investigating the use of other visual factors (e.g., brightness, color contrast, edge strength, occlusion, and category) toward predicting perceived interest.

REFERENCES