Literature Review 2

Viswanath Pulle, 01690370

Primary Paper: Change Blindness Images

Secondary Paper: TO SEE OR NOT TO SEE: The Need for Attention to Perceive Changes in Scenes

The primary paper deals with the change blindness, It is an effect that is caused when we have two images that are almost identical to each other but have minute differences among them and the human eye fails to spot these subtle changes. In this paper a computational model to quantify the degree of blindness between an image pair is formulated. Using this model we can synthesize changed images with desired degrees of blindness. Lastly the proposed model is compared with state-of-the-art saliency models to show the achieved effectiveness.

The secondary paper is the basis for the primary paper which gives a detailed study of the effect of change blindness When looking at a scene, observers feel that they see its entire structure in great detail and can immediately notice any changes in it. However, when brief blank fields are placed between alternating displays of an original and a modified scene, a striking failure of perception is induced: identification of changes becomes extremely difficult, even when changes are large and made repeatedly. Identification is much faster when a verbal cue is provided, showing that poor visibility is not the cause of this difficulty. Identification is also faster for objects mentioned in brief verbal descriptions of the scene. These results support the idea that observers never form a complete, detailed representation of their surroundings. In addition, results also indicate that attention is required to perceive change, and that in the absence of localized motion signals it is guided on the basis of high-level interest.

The secondary paper proposes a flicker paradigm where an original image repeatedly alternates with a modified image, with brief blank fields placed between successive images. Differences between original and modified images can be of any size and type. This paper conducted several experiments that show the changes are chosen to be highly visible. The observer freely views the flickering display and hits a key when the change is perceived. In order to prevent guessing, the observer must then correctly report the type of change and describe the part of the scene that was changing. This paradigm allows the ISI manipulations of the brief-display techniques to be combined with the free-viewing conditions and perceptual criteria of the saccade-contingent methods and because the stimuli are available for long stretches of time and no eye movements are required, it also provides the best opportunity possible for an observer to build a representation conducive to perceiving changes in a scene.
The change blindness found with the brief-display techniques might have been caused by insufficient time to build an adequate representation of the scene, saccade-contingent change blindness might have been caused by disruptions due to eye movements. Both of these factors are eliminated in the flicker paradigm, so that if they are indeed the cause of the difficulties, perception of change should now become easy. But if attention is the key factor, a different outcome would be expected. The flicker caused by the blank fields would swamp the local motion signals due to

the image change, preventing attention from being drawn to its location. Observers would then fail to see large changes under conditions of extended free viewing, even when these changes are not synchronized to saccades. So, based off this idea, our primary authors started working on change blindness to develop a novel algorithm to measure the degree of change blindness.

In the primary paper, they describe Change blindness as a failure to notice large changes in a visual scene when there is a disruption. Such changes can take different forms, including shape changes, color changes, and object insertion, removal, or relocation. The disruption can be eye movement, a flicker or mud splash. Here an initial image is taken as an input and then a changed counterpart containing one change with a user-specified degree of blindness is generated with respect to the given input. The objective is to minimize the difference between the user desired blindness and the measured blindness of the changed image. This is an optimization problem. The input is iteratively changed by various change operators, until the objective value is optimized. The change operators supported for this modelling are insertion, deletion, replacement, relocation, scale, rotation, and color-shift.

The authors' main contribution is the development of the metric for measuring (the degree of) change blindness between an image pair, based on existing psychological findings. The procedure starts with taking an initial input image. Then certain candidate regions that are more likely to be foreground objects are empirically extracted. The input image is segmented using the novel mean shift approach, remove extremely large segments (larger than 30 percent of the whole image size) which are more likely to be background, discard tiny (smaller than 55 pixels) and long narrow segments (whose length-width-ratio is larger than 10), and group nearby segments to form larger ones based on their color properties (if the average color difference is smaller than 0.2). Next, an optional step allows users to manually refine (merge or split) the segments by drawing strokes on target segments. In the experiments authors conducted, images with simple backgrounds usually do not need user intervention. For complex images that require user intervention, the correction was done with a few strokes in seconds. The resultant disjoint segments are regarded as candidate regions, the primitives for our later change operations. Optimization is carried out as follows. Initially, a region is randomly selected from the pool of candidate regions. Then, a change operator is randomly selected and applied with a random parameter value, to synthesize a changed image I'. The blindness is then measured based on the image pair containing I and I0 . The same operator is repeatedly applied to the same region with iteratively adjusted parameter until the measured blindness converges to the desired blindness within a small tolerance or until the number of iterations exceeds a predefined limit. In the latter case, we randomly pick another combination of candidate region and change operator and try again. The whole optimization halts until a match is found or the total number of iterations reaches a predefined limit. Finally, the best changed image is obtained. As tiny changes with only a few pixel differences are hard to observe with the naked eye, they are avoided. Hence, this procedure requires that we ensure all output images to contain a large change by measuring the sum of squared pixel differences (SSD) between I and I0 .

The blindness metric B(degree of change blindness in the range [0,1]) depending on both the visual saliency S (addressing the location of the change) and the amount of change D, as follows:

$$B = \exp\left(-\max\left(\|I_k\|S(I_k),\ \|I'_k\|S(I'_k)\right) \cdot D\left(I_k, I'_k\right)\right)$$

$$D\left(I_k, I'_k\right) = \omega_c D_c\left(I_k, I'_k\right) + \omega_t D_t\left(I_k, I'_k\right) + \omega_s D_s\left(I_k, I'_k\right),$$

This method offers a semiautomatic way for synthesizing changed images with desired degrees of blindness. This is better than manual creation of change blindness images as it is ad hoc and lacks of control in difficulty levels.

Applications:

Besides the use in spot-the-difference games, our proposed metric potentially has many other applications like a metric that measures significance of changes in an image revision control system ; it can also be used as a better way to find duplicated images for an image search engine. The proposed model can also be applied in other areas of computer graphics, such as rendering acceleration, image retargeting, image tone mapping. The change blindness metric can also serve as a more perceptually aligned metric for quantifying perceptual visual differences.

Limitations:

Firstly, since the components involved in our metric, such as image saliency and image color/texture/shape differences, are mainly low-level image features, hence, it might overlook some important semantic changes which our metric cannot model. In the future, additional semantic features, such as face and symmetry information, can be potentially integrated into this metric to consider the influence of visually important semantics for example, a face semantic can be incorporated by using a saliency model that integrates a face detector.

Second is about predictability, the current exponential formulation has a lot of improvement left. This can be done by deeply analyzing experimental data, e.g., analyzing different types of changes separately. Additionally, calibrating the amount of change by considering the just noticeable difference (JND) is a possibility.

Third, this metric is a bottom up approach, a top down saliency model brings a possibility to check for better results.

Conclusion:

Change blindness is a phenomenon that happens with relation to the inability to recognize the changes in an image upon imposing a distraction. The authors of the primary paper presented the first computational model for change blindness, together with the first context-dependent saliency model which takes into account background complexity measure this factor. The authors took inspiration from the primary paper where the emphasis was how to account for all the factors that are necessary to develop the metric. It focused on changes in visual perception when an object is given focused attention and they proved that in the absence of such attention, the contents of visual memory are replaced by subsequent stimuli, and so cannot be used to make comparisons. Experiments were conducted in both research papers publishing promising results.

Since, the Change Blindness metric can be used on several applications mentioned earlier and considering the broad scope for improvement I think the authors did develop some ground breaking techniques to introduce this metric and their research is a consummate product for the computer graphics applications.

References:

Primary Paper:

L. Q. Ma, K. Xu, T. T. Wong, B. Y. Jiang and S. M. Hu, "Change Blindness Images," in IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 11, pp. 1808-1819, Nov. 2013

Secondary Paper:

To See or not to See: The Need for Attention to Perceive Changes in Scenes
Ronald A. Rensink, J. Kevin O'Regan, James J. Clark
Psychological Science
Vol 8, Issue 5, pp. 368 - 373