

# Directing Attention to Onset and Offset of Image Events for Eye-Head Movement Control

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## Abstract

*This paper proposes a model that investigates a new avenue for attention control based on dynamic scenes. We have derived a computational model, based on the difference of Gaussian (DOG) model, to detect abrupt changes. On and off-DOG operators are used to detect “on” and “off” events respectively. The response of these operators is examined over various temporal window sizes so that changes at different rates can be found. The most salient “on” and “off” events are determined from the corresponding winner-take-all (WTA) network. With such a model, we explore the possibility of an attentional mechanism, in part guided by abrupt changes, for gaze control. The model has been tested with image sequences which have changes caused by brightness or motion and the results are satisfactory.*

## 1 Introduction

Recently, Yantis and several co-authors revealed from psychological experiments that the abrupt appearance of an object in the visual field draws visual attention, e.g., [7], [8]. Inspired by this novel idea of attentional capture, we derive a computational model to find abrupt changes from a sequence of images. Such a model can be used as part of an attentional mechanism for gaze control in vision systems.

## 2 The DOG model

In order to reduce the effect of noise and to let our computational model have as much biological resemblance as possible, we consider the response of applying a difference of Gaussian (DOG) operator to the raw image when finding changes in a sequence of images. Mathematically, the DOG operator is defined as

$$DOG(\vec{x}) = \alpha_c G(\vec{x}; \sigma_c) - \alpha_s G(\vec{x}; \sigma_s)$$

where  $G$  is a two-dimensional Gaussian operator at  $\vec{x}$ :

$$G(\vec{x}; \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{|\vec{x}|^2}{2\sigma^2}} \quad (1)$$

Parameters  $\sigma_c$  and  $\sigma_s$  are standard deviations for centre and surround Gaussian functions respectively. These Gaussian functions are weighted by integrated sensitivities  $\alpha_c$  (for the centre) and  $\alpha_s$  (for the surround). A detailed analysis of how the shape of the DOG operator is affected by varying the ratio  $\frac{\alpha_c}{\alpha_s}$  and  $\frac{\sigma_c}{\sigma_s}$  is given in [3]. The response,  $R(\vec{x}, t)$ , of the DOG filter to an input signal  $s(\vec{x}, t)$  at  $\vec{x}$  during time  $t$  is given by:

$$R(\vec{x}, t) = \int \int_{|\vec{w}| \leq m\sigma} DOG(\vec{w}) s(\vec{x} - \vec{w}, t) dx dy \quad (2)$$

where  $m$  is the number of standard deviations for the cutoff for Equation (1) and  $\sigma = \max(\sigma_c, \sigma_s)$ .

## 3 Extending the DOG operator to detect changes

The DOG operator introduced in Section 2 uses simple linear differences to model a centre-surround interaction. The response  $R(\vec{x}, t)$  is computed from linear differences and is analogous to a measure of contrast of events happening between centre and surround regions of the operator. When  $\sigma_c < \sigma_s$ , the centre of the operator has a positive contribution while the surround has a negative contribution. This type of DOG operator is termed the on-DOG operator and is used to detect “on” events. “On” events are defined to be situations in which the pixel intensity at the centre region increases. This may be caused by an increase of illumination or the appearance of objects in some previously blank positions. When  $\sigma_c > \sigma_s$ , the signs of the contribution of the centre and the surround are reversed. This type of DOG operator is termed the off-DOG operator and is used to detect “off” events.

“Off” events are defined to be events in which the intensity at the centre region decreases. This may be caused by a decrease of illumination or objects disappearing from some previously occupied positions. We will denote the response from on and off-DOG operators at location  $\vec{x}$  and time  $t$  by  $N(\vec{x}, t)$  and  $F(\vec{x}, t)$  respectively. In order to decide if there are any changes happening at location  $\vec{x}$ , we would have to look at how functions  $N(\vec{x}, t)$  and  $F(\vec{x}, t)$  change over the current temporal window. We will first develop a model that detects changes over two consecutive images (i.e. a temporal window of size two).

When an “on” or “off” event occurs at location  $\vec{x}$ , the response — as denoted by the function  $N(\vec{x}, t)$  and  $F(\vec{x}, t)$  respectively — should increase over time. Typically, in order to reduce the effect of noise and to ensure that the change is significant, we require the rate of increase to exceed a certain threshold, say,  $\theta_1$  and  $\theta_4$  for “on” and “off” events correspondingly. This rate can be measured by the temporal derivatives,  $\frac{\partial N}{\partial t}$  and  $\frac{\partial F}{\partial t}$ , of the functions  $N$  and  $F$ . With a temporal window of size two,  $\frac{\partial N}{\partial t}$  and  $\frac{\partial F}{\partial t}$  can be approximated by taking the first difference of response from two successive image frames. Therefore, the conditions

$$\begin{aligned} \frac{\partial N}{\partial t} &\approx N(\vec{x}, t) - N(\vec{x}, t - 1) \geq \theta_1 \text{ (for “on” events)} \\ \frac{\partial F}{\partial t} &\approx F(\vec{x}, t) - F(\vec{x}, t - 1) \geq \theta_4 \text{ (for “off” events)} \end{aligned}$$

have to be satisfied. In addition, to assure that there is change at the centre region of the operator, we have another condition:

$$\begin{aligned} \frac{\partial N_c}{\partial t} &\approx N_c(\vec{x}, t) - N_c(\vec{x}, t - 1) \geq \theta_3 \text{ (for “on” events)} \\ \frac{\partial F_c}{\partial t} &\approx F_c(\vec{x}, t) - F_c(\vec{x}, t - 1) \geq \theta_5 \text{ (for “off” events)} \end{aligned}$$

where  $N_c(\vec{x}, t)$  and  $F_c(\vec{x}, t)$  are the response from the centre region of the on and off-DOG operators respectively<sup>1</sup>. We also require that  $|N(\vec{x}, t)| \geq \theta_2$  to ensure the contrast between the centre and the surround is large enough to indicate that there is something interesting (e.g., an object) under the spatial extent of the operator for “on” events. However, this condition for minimum contrast is not required for “off” events at the current frame. When some object moves away from its original position (with the object centred at  $\vec{x}$ ), the region with  $\vec{x}$  as the centre under the current image is the background<sup>2</sup>.

<sup>1</sup>The response at the centre can be computed by  $N_c(\vec{x}, t) = \int \int_{\vec{w} \in \text{centre}} \text{DOG}(\vec{w})s(\vec{x} - \vec{w})dxdy$  and  $F_c(\vec{x}, t) = \int \int_{\vec{w} \in \text{centre}} \text{DOG}(\vec{w})s(\vec{x} - \vec{w})dxdy$ .

<sup>2</sup>A contrast is not required at the previous frame as well because an “off” event may occur at a location which is a bright uniform background in the previous frame.

## 4 Competition among scales

In order to find events of different scales, on and off-DOG operators of various scales are used. A decision process, which is performed by initiating a winner-take-all (WTA) process for each type of event, is to pick the location and scale of the most salient “on” and “off” events. Units in each WTA network represent the response from all locations and spatial scales of the corresponding event. A winner is determined from each WTA network using the updating rule described by Tsotsos [5]. But before the WTA processes are initiated, the response from different operator sizes are normalized. When the spatial extent of an operator increases, a greater area will contribute to the operator. Therefore, a mechanism has to be found to take a balance between the difference in size and response. The normalization function we use in our model is the one suggested by Culhane and Tsotsos [2]. It can be expressed as a function of  $\sigma$ :

$$W(\sigma) = \frac{\rho + 1}{\rho + \beta^{-(2m\sigma+1)}} \quad (3)$$

The parameter  $\rho$  will affect the asymptote of the function, while  $\beta$  will affect the steepness of the first part of the function. Empirically, setting  $\rho = 10$  and  $\beta = 1.3$  (as suggested by Culhane [1]) seems to yield satisfactory results for our experiments.

## 5 Extending the temporal window

We now consider a temporal window of size  $T$ , where ( $T > 2$ ). By enlarging the temporal window, our model would be looking for changes that occur at different rates as well. When the temporal window is expanded to a size  $T$ , we also have to look at how functions  $N(\vec{x}, t)$  and  $F(\vec{x}, t)$  change over  $T$  frames. The change has to be monotonic increasing and the magnitude of the overall change (when compared between the first and the last image frame) has to be significant. A simple case would be the  $T$  sampled responses all fall onto a straight line with a slope that satisfies the minimum change requirement. However, this ideal case is rarely satisfied due to noise. Instead, we must look at the change in response over time to see if it can be approximated by a straight line. For a particular location  $\vec{x}$ , this straight line will be joining the response at time  $t$  and  $t - (T - 1)$ . Empirically, all responses in between should be within a distance of  $0.2\theta_1$  (for “on” events) or  $0.2\theta_4$  (for “off” events) from this line to give a monotonic increasing response. The algorithm to detect “on” and “off” events for a general temporal window size ( $T \geq 2$ ) is given in Algorithm 1 (Figure 1).

Define *ImageResolution* to be the set of pixels composing the image (i.e. the size of the image). Scale  $\mathcal{S}$  represents a pair of values for  $\sigma_c$  and  $\sigma_s$ : for an on-DOG operator,  $\sigma_c = \mathcal{S}$  while  $\sigma_s = k\mathcal{S}$  ( $k > 1$ ); for an off-DOG operator,  $\sigma_s = \mathcal{S}$  and  $\sigma_c = k\mathcal{S}$ . Let  $\mathcal{R}_N(\vec{x}, \mathcal{S})$  and  $\mathcal{R}_F(\vec{x}, \mathcal{S})$  be the response in detecting ‘‘on’’ events and ‘‘off’’ events respectively at location  $\vec{x}$  (with respect to pixel intensity values) with operator scale  $\mathcal{S}$ . Let  $T$  be the maximum temporal window size being considered.

1. For all possible temporal window sizes  $T'$ ,  $2 \leq T' \leq T$ , do step 2 to step 12 for all possible subsequences of  $T$  consecutive images.
2. For each pixel  $\vec{x} \in \text{ImageResolution}$ , do step 3 to step 9.
3. For each scale  $\mathcal{S}$ , do step 4 to step 9.
4. Compute  $N(\vec{x}, t')$ ,  $F(\vec{x}, t')$ ,  $N_c(\vec{x}, t')$ ,  $F_c(\vec{x}, t')$  for  $t - (T' - 1) \leq t' \leq t$ .
5. Compute  $\Delta N = N(\vec{x}, t) - N(\vec{x}, t - (T' - 1))$ ,  $\Delta F = F(\vec{x}, t) - F(\vec{x}, t - (T' - 1))$ ,  $\Delta N_c = N_c(\vec{x}, t) - N_c(\vec{x}, t - (T' - 1))$ ,  $\Delta F_c = F_c(\vec{x}, t) - F_c(\vec{x}, t - (T' - 1))$ .
6. Check if the functions  $N(\vec{x}, t)$  and  $F(\vec{x}, t)$  are monotonic increasing, i.e., if  $N(\vec{x}, t')$  and  $F(\vec{x}, t')$  can be approximated by a straight line with maximum error  $0.2\theta_1$  and  $0.2\theta_4$  respectively.
7. If  $N(\vec{x}, t)$  satisfies step 6 and  $\Delta N \geq \theta_1$ ,  $|N(\vec{x}, t)| \geq \theta_2$ ,  $\Delta N_c \geq \theta_3$ , then something goes on at  $\vec{x}$  and set  $\mathcal{R}_N(\vec{x}, \mathcal{S}) = \Delta N$ . Else, set  $\mathcal{R}_N(\vec{x}, \mathcal{S}) = 0$ .
8. If  $F(\vec{x}, t)$  satisfies step 6 and  $\Delta F \geq \theta_4$ ,  $\Delta F_c \geq \theta_5$ , then something goes off at  $\vec{x}$  and set  $\mathcal{R}_F(\vec{x}, \mathcal{S}) = \Delta F$ . Else set  $\mathcal{R}_F(\vec{x}, \mathcal{S}) = 0$ .
9. Return to step 4 if have not computed all scales.
10. Normalize response from all scales using Equation (3).
11. Two WTA networks, one for ‘‘on’’ events and the other for ‘‘off’’ events, are initiated to find the location and scale of the most salient ‘‘on’’ and ‘‘off’’ events.
12. Return to step 2 if have not worked on all necessary temporal window sizes.
13. Pick the final winner for on and off-DOG operators by running WTA over the winner for each temporal window.
14. Return to step 1 for the next set of images.

Figure 1: Algorithm 1 – Algorithm for a general temporal window size  $T$  ( $T \geq 2$ )

## 6 Determining parameter values

The main parameters for the DOG operator are  $\sigma_c$ ,  $\sigma_s$ ,  $\alpha_c$  and  $\alpha_s$ . As Fleet[3] pointed out, by keeping the ratio  $\frac{\sigma_s}{\sigma_c}$  fixed and varying  $\sigma_c$  (when  $\sigma_s > \sigma_c$ ), the peak spatial frequency that the operator can detect is shifted. Moreover, the actual size of  $\sigma_c$  should be set according to the size of object or spatial frequencies that the system is required to discern. Therefore, for on-DOG operators, our model will look at a series of

operators with  $\frac{\sigma_s}{\sigma_c}$  fixed at  $k$ , with  $k > 1$ , while  $\sigma_c$  varies. For off-DOG operators, the value of  $\sigma_s$  will vary while the ratio  $\frac{\sigma_s}{\sigma_c}$  will be  $\frac{1}{k}$  (since  $\sigma_s < \sigma_c$ ).

The parameters  $\alpha_c$  and  $\alpha_s$  affect the sensitivity of the operator. By varying  $\alpha_c$  and  $\alpha_s$ , the peak at the centre of operators will be changed. We want to choose  $\alpha_c$  and  $\alpha_s$  such that the response of the operator will be low (i.e.,  $R(\vec{x}, t) = 0$ ) when it is applied to a region with uniform intensity. This will require  $\alpha_c$  and  $\alpha_s$  to satisfy the relation  $\frac{\alpha_c}{\alpha_s} = 1$ <sup>3</sup>. This relation further implies that the function  $DOG(\vec{x})$  will integrate to zero, and, therefore, cannot be of one sign.

## 7 Determining threshold values

When the DOG operator is applied to some ideal image with constant intensity  $I_c$  across the centre and constant intensity  $I_s$  for the surround, we will be able to find a closed form for the maximum possible contrast, which is also the maximum response, for both types of operators. Empirically, setting the thresholds ( $\theta_1, \theta_2, \theta_3, \theta_4$  and  $\theta_5$ ) to a certain percentage of the maximum response seems to yield a good decision criterion for choosing the appropriate threshold values.

For on-DOG operators, the value of  $R(\vec{x}, t)$  will be maximum ( $R_n^{max}$ ) when the centre has uniform maximum intensity  $I_{max}$  and the surround has minimum intensity  $I_{min}$ . These maximum and minimum values can be found by looking at a histogram formed by intensity values of pixels from current images. Conversely, the maximum value of  $R(\vec{x}, t)$  for an off-DOG operator ( $R_f^{max}$ ) is achieved when the centre has uniform intensity  $I_{min}$  and the surround has uniform intensity  $I_{max}$ . We define

$$\begin{aligned} z_n &= \sqrt{\frac{2 \log(\frac{\alpha_c}{\alpha_s} k^2)}{k^2 - 1}}, \\ s_{nc} &= -\alpha_c (e^{-\frac{(kz_n)^2}{2}} - 1) + \alpha_s (e^{-\frac{z_n^2}{2}} - 1), \\ s_{ns} &= \alpha_c (e^{-\frac{(kz_n)^2}{2}} - e^{-\frac{(km)^2}{2}}) - \alpha_s (e^{-\frac{z_n^2}{2}} - e^{-\frac{m^2}{2}}), \\ z_f &= \sqrt{\frac{2 \log(\frac{\alpha_s}{\alpha_c} k^2)}{k^2 - 1}}, \\ s_{fc} &= -\alpha_c (e^{-\frac{z_f^2}{2}} - 1) + \alpha_s (e^{-\frac{(kz_f)^2}{2}} - 1), \\ s_{fs} &= \alpha_c (e^{-\frac{z_f^2}{2}} - e^{-\frac{m^2}{2}}) - \alpha_s (e^{-\frac{(kz_f)^2}{2}} - e^{-\frac{(km)^2}{2}}). \end{aligned}$$

The maximum response for each type of operator would be  $R_n^{max} = s_{nc}I_{max} + s_{ns}I_{min}$  and  $R_f^{max} = s_{fc}I_{min} + s_{fs}I_{max}$ . Values of thresholds are set to  $\theta_1 = |p_1 R_n^{max}|$ ,  $\theta_2 = |p_2 R_n^{max}|$ ,  $\theta_3 = |p_3 \theta_1|$ ,  $\theta_4 = |p_4 R_f^{max}|$  and  $\theta_5 = |p_5 \theta_4|$ , where  $p_1, p_2, p_3, p_4$  and  $p_5$  are values between 0 and 1. Empirically, the values of  $p_1, p_2, p_3, p_4$  and  $p_5$  are set to 0.1, 0.15, 0.2, 0.1 and 0.15 respectively. Figure 2 shows how the model would behave when the values of  $p_1, p_2, p_3, p_4$  and  $p_5$  are changed.

<sup>3</sup>The derivation of this relation is described in [6].

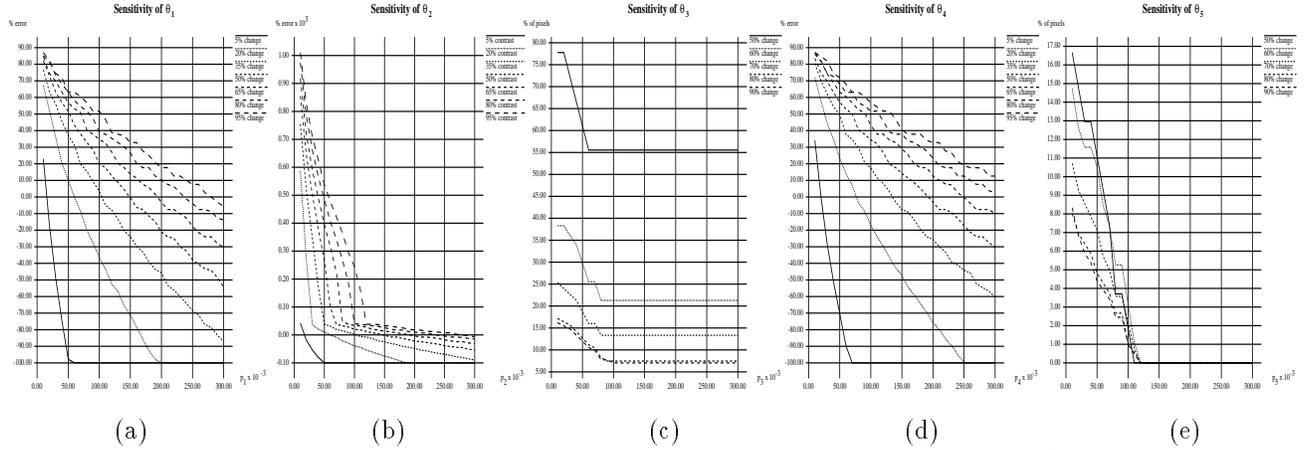


Figure 2: Sensitivity of thresholds for the on and off-DOG operators: Figures (a), (b), and (d) show the percentage errors as the value of  $p_1$ ,  $p_2$  and  $p_4$  increases respectively. Data are obtained from experiments where the change is 5%, 20%, 35%, 50%, 65%, 80% and 95% of the maximum intensity. Figures (c) and (e) show the percentage of pixels (that are marked as candidates of change) that are detected with a change at the centre as  $p_3$  and  $p_5$  increases respectively. Data are obtained from experiments where the change is 50%, 60%, 70%, 80% and 90% of the maximum intensity.

A detailed analysis of the sensitivities of the thresholds, as well as the derivation of  $z_n$ ,  $s_{nc}$ ,  $s_{ns}$ ,  $z_f$ ,  $s_{fc}$  and  $s_{fs}$  are described in [6].

## 8 Integration to an attentional model

The computational model described above can be used to direct attention to abrupt changes for eye-head movement control. The vision system will acquire  $T$  images (where  $T$  is the maximum temporal window size), and use Algorithm 1 to find locations where “on” and “off” events have occurred. The output from Algorithm 1 is treated as one of the attentional features for the input level of the processing hierarchy in Tsotsos’ inhibitory attentional beam model [5]. The most conspicuous “on” and “off” events will compete with other attention attracting image events (e.g., events that deserve attention according to some task-driven guidance) and a higher order decision process is assumed to choose the winner in this competition. If necessary, the robot will move to fixate the selected area for attention. The appropriate area will be inhibited after this shift of attention, and the input to the lowest level of the hierarchy that directs attention according to abrupt changes will be refreshed. The reason that the input has to be refreshed in our model is because changes that have occurred over a certain period of time will lose their priority for attention. Furthermore, when the attention model is directing the motion of a robot head, we have to acquire a new set of images every time the head has moved.

## 9 Implementation results

The computational model, as described by Algorithm 1 (Figure 1), has been implemented in software on Silicon Graphics 4D/380 VGX. The WTA updating process is implemented as a simple sequential search because of hardware limitations. Simulations are to run on sequences of digitized  $128 \times 128$  images in which changes are caused by brightness and motion. In the present implementation, each sequence of images is acquired in advance through a stationary monochrome CCD camera. The parameters of the model are set to  $\alpha_c = \alpha_s = 2$ ,  $k = 2.5$  and  $m = 2$ . The actual size of operators used may vary between experiments. The thresholds  $\theta_1$ ,  $\theta_2$ ,  $\theta_3$ ,  $\theta_4$  and  $\theta_5$  are set as described in Section 7. The parameters we used for the normalization function (Equation (3)) are  $\rho = 10$  and  $\beta = 1.03$ .

Figure 3 shows the result from a sequence of images in which a spotlight moves from the cylinder in the centre (an “off” event) to the block on its left (an “on” event). Six different scales for each type of operator are used to detect “on” and “off” events in this sequence under a temporal window of size two. The sizes of these operators are chosen by an intuitive approximation of the scale of events. The second and third rows in Figure 3 show which pixels are marked as candidates for “on” and “off” events respectively. The grey level of each pixel shows the magnitude of change measured at that point. The brighter the pixel, the greater the magnitude of change. Pixels at which no changes have been detected are indicated by intensity value 0 (black). From left to right, each column

shows the magnitude of change as measured by operators of increasing scale. Concentric circles indicate centre and surround regions of the winning area of each scale. The first row is the original image, with the areas for most conspicuous “on” and “off” events superimposed on Frame 2.

Figure 4 is an example in which changes are caused by motions of objects. The representation used for displaying the results is the same as in Figure 3 and we also use a temporal window of size two. By assuming that objects have pixel intensity values greater than the background, the current and previous positions of objects will be regarded as “on” and “off” events respectively. If this assumption is violated, events that register the old and new positions of objects may be reversed. The events happening in Figure 4 are: (1) the triangular block at the upper left of Frame 1 disappears in Frame 2; (2) a small rectangular block on the left moving towards the centre; (3) a rectangular block moves from the centre to the upper right; and (4) the cylindrical block from the lower right moves towards the centre. Note that not all pixels at the new position of the cylindrical block are classified as having an “on” event. It is because the new position of the cylindrical block partly overlaps with the former position of the rectangular block and both objects have roughly the same intensity level. The same effect is observed when detecting “off” events. We can also observe from this example that different events are detected from operators of different sizes.

Figure 5 demonstrates an example of simulating the model using a temporal window of size five. In this example, the luminance of blocks is decreased gradually and, therefore, all the circles in this figure are indicating “off” events. The first row is the original image, superimposed with the overall winner (from all temporal and spatial scales) of “off” events. Each column of Row 2 shows the location of the most salient change detected with the corresponding image in that column as the most current frame. Columns 2, 3, 4 and 5 show the location and scale of winning operators in detecting changes over temporal windows of sizes two, three, four and five respectively. For simplicity, only the centre of winning off-DOG operators are shown.

## 10 Discussion

There are several assumptions and limitations of the proposed model. First of all, we take for granted that there is perfect image registration from the device through which images are obtained. Second, the correspondence problem is not addressed by the model if the images are acquired from a moving sensor. Finally,

the issue of inhibition of return [4] is not addressed in our model. More experiments in the psychology area to study how receptive fields are inhibited when attention is guided by abrupt changes may help to suggest a way to deal with this problem in our model. In spite of its limitations, our computational model has several significant contributions. It investigates a new avenue that directs the attention of a machine vision system with respect to abrupt changes. Furthermore, the model can detect changes in a purely bottom-up fashion and does not require prior knowledge of the scene. With the input signal  $s(\vec{x}, t)$  representing different features, the model can be used to find changes in a visual scene with respect to different features without alteration. Specifically, the computational model can be used to compute one of the inputs at the bottom layer of the processing hierarchy in Tsotsos’ inhibitory attentional beam model, and contributes towards forming another component to the overall attention model.

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## References

- [1] Culhane, S. M., “Implementation of an Attentional Prototype for Early Vision”, Master’s Thesis, University of Toronto, 1992.
- [2] Culhane, S. M. and Tsotsos, J. K., “An Attentional Prototype for Early Vision”, *ECCV*, p. 551–560, 1992.
- [3] Fleet, D. J., “The Early Processing of Spatio-Temporal Visual Information”, Master’s Thesis, University of Toronto, 1984.
- [4] Posner, M. I. and Cohen, Y., “Components of Attention”, in *Attention and Performance X*, p. 531–556, 1984.
- [5] Tsotsos, J. K., “An Inhibitory Beam for Attentional Selection”, in *Spatial Vision for Humans and Robots*, Cambridge University Press, 1993.
- [6] Wai, W. Y. K., “A Computational Model for Detecting Image Changes”, Master’s Thesis, University of Toronto, 1994.
- [7] Yantis, S. and Jones, E., “Mechanisms of Attention Selection: Temporally Modulated Priority Tags”, *Perception and Psychophysics*, 50(2), p.166–178, 1991.
- [8] Yantis, S. and Jonides, J., “Abrupt Visual Onsets and Selective Attention: Voluntary Versus Automatic Allocation”, *Journal of Experimental Psychology: Human Perception and Performance*, Vol. 16, No. 1, p. 121–134, 1990.

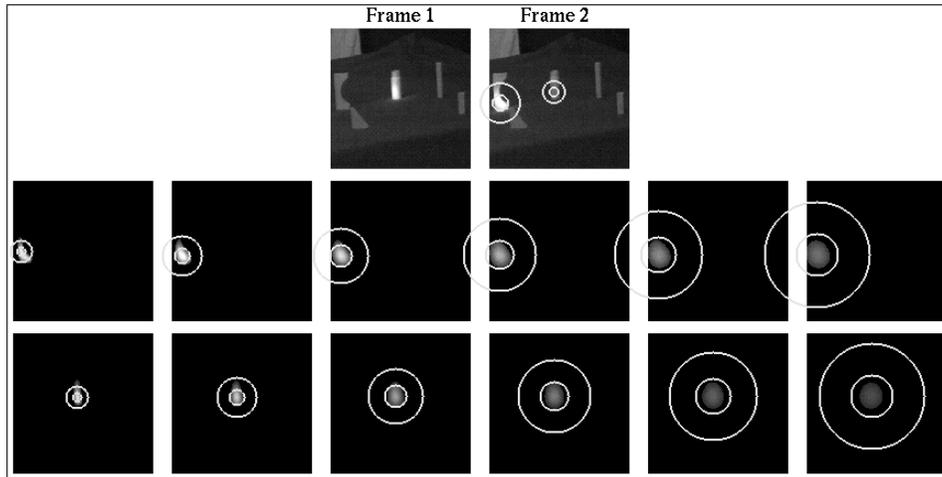


Figure 3: Example of moving a spotlight among some blocks and cylinders: The winning “on” event is the increase in luminance of the left most block; the winning “off” event is the decrease in luminance of the cylinder in the centre.

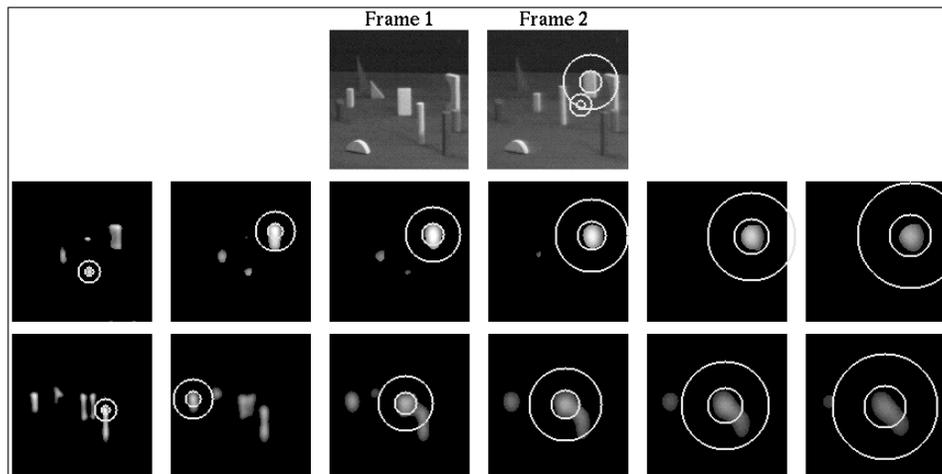


Figure 4: Example of several blocks moving among other stationary blocks: The most prominent “on” event is at the new position of the rectangular block at the upper right; the winning “off” event is at the old position of the cylindrical block.

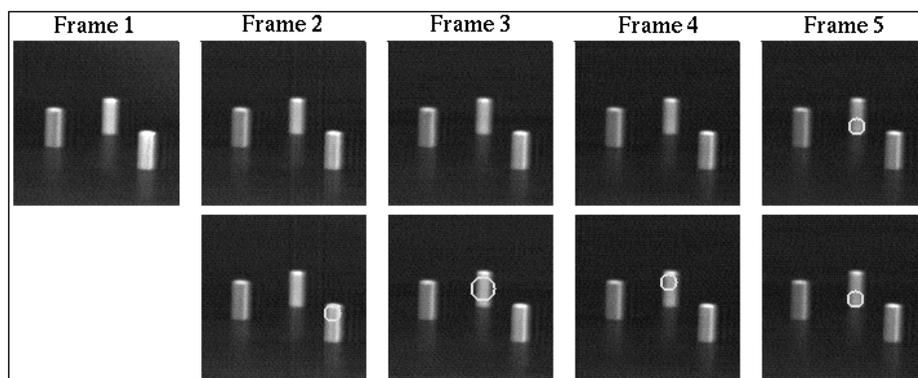


Figure 5: Example of decreasing the luminance of blocks: There are only “off” events in this example. The most conspicuous “off” event is found under a temporal window of size five. It is the decrease of luminance of the block in the middle.