A Non-Overlapping Receptive Field Model Based on Receptive Field Physiology

András Róka, Ádám Csapó, Péter Baranyi

Computer and Automation Research Institute, Hungarian Academy of Sciences, Budapest, Hungary
baranyi@sztaki.hu

Abstract: *Recent results in retinal research have shown that neighboring receptive fields on the mammalian retina have very little overlap. Traditional computerized edge-filtering methods, in contrast, rely greatly on the overlapping structure of artificial receptive fields. This paper presents a new edge-filtering model characterized by non-overlapping receptive fields. Artificial nystagmic eye movements are also incorporated in the model in order to achieve receptive field overlaps through time. It will be shown that these two elements combined yield results similar in quality to previous models, but also achieve a reduction in the amount of stored information, similar in proportion to the reduction discovered between the retina and the optic nerve of the human vision system.*

I INTRODUCTION

Traditional image-filtering artificial receptive fields, such as Laplace and Sobel fields, work reliably only when assuming an architecture with overlaps in receptive fields. Using edge-filtering methods widely available today without any overlap in receptive filters results in a vast number of undesirable blind spots.

Recent findings in cognitive physiology suggest that receptive fields of mammalian photoreceptor cells do not overlap [4]. The model proposed in this paper uses a non-overlapping receptive field architecture enhanced with artificial nystagmuses in order to make up for losses in information. The image is moved around randomly at a steady rate, thus an overlap is achieved between receptive fields with time. Averaging receptive field responses at given time intervals produces an effect similar to that observed when using overlapping receptive fields, but computation time and the amount of handled information is greatly reduced. The positive effects of the model can be used efficiently in real-time systems with demanding time constraints.

The paper is structured as follows: in an introductory section, an overview is given on the biological elements which served as an inspiration for this model. Further sections treat the details of the model, along with test results.

II BIOLOGICAL OVERVIEW

The three major kinds of eye movements widely accepted today are microsaccades, drifts and tremors (also referred to as nystagmuses) [7].

Microsaccades are abrupt jerks in fixation. These jerks take about 25 ms, and have amplitudes of several hundred receptive fields.

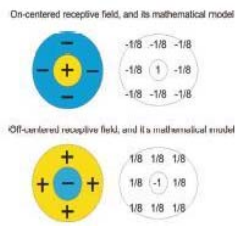


Figure 1
Mathematical model of biological receptive fields used in the model

Recent findings confirm that saccades have a key role in higher-order, cortical object recognition [3, 6].

Drifts and tremors both occur between microsaccades. Tremors are involuntary, rhythmic oscillations of the eye, that have frequencies of about 90 Hz and amplitudes of roughly the diameter of a cone on the fovea (therefore the diameter of the smallest of photoreceptor cells).

Drifts are a unidirectional wandering of the eye, and are much slower than nystagmuses, but wider in amplitudes.

The role of these three kinds of eye movements in perception is still unresolved, however, all three tend to have an importance in maintaining visual acuity [5, 2].

Artificially eliminating these movements, researchers found that vision faded away. One possible explanation for this is that ganglion cells seem to become fatigued when receiving the same stimulus over a certain amount of time.

Of the three eye movements introduced above, this paper concentrates on nystagmuses. The model for edge-detection proposed here, uses non-overlapping receptive fields, but also incorporates tremors in order to achieve the effects of overlapping receptive fields through time.

(a) Edge-detection using Sobel method

(b) Edge-detection using Sobel field but no overlaps

Figure 2
Edge-detected image using Laplace method (a) and the same image, edge-detected without overlaps in receptive fields (b)

It will be shown that besides following the structure of human visual perception, the model accounts for the 13:1 information reduction ratio characteristic to the pathway between photoreceptor cells of the retina and ganglion cells [8].

III MODEL

In order to achieve its goal, the proposed edge-filtering model uses artificial receptive fields that are structurally similar to those found on the retina. Although it uses the biological vision system as a guideline, some apparent differences can be found.

One major difference between the model and the human vision system is that while receptive fields in the model have a constant size throughout the image, the size of receptive fields on the retina gradually grows larger going from the central, foveal areas, to the peripheral areas (this is why foveal areas are said to be more sensitive to detail, while peripheral areas tend to be more sensitive to motion). This approximation is justified because the model is used for the filtering of edges in still images, not for detecting abrupt temporal changes in moving images. In this paper, 3-by-3 artificial receptive fields will be used.

3.1 Receptive Field Structure

Receptive fields are represented by two-dimensional matrices (as in many previous models), each matrix value representing a weight with which the corresponding stimulus is multiplied. The configuration of weights depends on the type of receptive field being modeled; on-center fields have positive values in the central area, surrounded by all negative weights, while off-center fields contain a central negative value, surrounded by all positive weights.

The weighting used in this model approximates an operator that calculates the second derivative of the image, and in this respect, resembles the Laplace-operator (Figure 1). Because the Laplace-operator tends to be sensitive to noise, we demonstrate the need for overlaps in receptive fields using another typical operator, the Sobel-operator. Figure 2 shows an edge-filtered image using the original Sobel method, as well as the case where receptive fields are used in a non-overlapping manner. The losses in information are clear.

In order to reconcile the differences between brain physiology research and traditional edge-filtering methods, artificial nystagmuses were introduced to the model. Such rapid oscillations are capable of achieving overlaps in receptive fields through time. Main parameters of the model include nystamgus amplitude (A) and frequency (Φ). The function yielding the edge-filtered image can be expressed as follows:

$$ED = \frac{\sum_{i=1}^{\Phi} \lambda * \text{Shift(Image, RandSeed, A)}}{\Phi}$$

where λ is the on-centered Laplace-operator shown in figure 1, and Shift is a function that translates the image both horizontally and vertically, by a random amount of pixels calculated using random seed *RandSeed*. The original image and the Laplacian are matrix convoluted Φ times, and the Φ samples are then averaged. This mulitple sampling strategy has a positive effect in noise reduction.

IV TEST RESULTS

In testing the model, optimal results were received when setting Φ to a value greater than 30, and A to a value around 5, but not more than 10. Greatly increasing Φ does not have negative effects on edge-detection (only on computing time), however, a deterioration in results can be observed when increasing A. Figures 3, 4 and 5 show results received when varying the two parameters.

The optimality of the values stated above can be confirmed by a simple, empirical evaluation method. This method states that the information (or detail) contained in an image is directly proportional to the percentage of its non-white pixels. Our assumption is that false edges are not detected by the model, because drastic increases in Φ do not imply an unbounded blackening of the image. Figure 6 shows the average percentage of black pixels in terms of Φ and A.

The choice of Φ > 30 also seems justified because the human eye is supposed to produce around 90 nystagmuses per second, thus for every

3 saccade. Intersaccadic intervals are evenly distributed, each of them take about (1000 - 3*25)/3 = 308.33 ms [7], of which the eyeballs are stable for 250 ms [1]. This implies that each intersaccadic interval should have 1/3 of of the 90 nystagmuses allotted for each second.
There is also biological support for choosing A to be between 5 and 10: tremors usually have amplitudes of the diameter of a cone on the fovea (3 in our case).

Conclusion

A novel method for edge-detection was proposed. The model used was based upon previous edge-filtering methods as well as recent discoveries in cognitive physiology.
Because of the non-overlapping receptive field architecture used, the obtained edge-filtered image is reduced in size compared to the original image. The application of 3-by-3 receptive fields reduces the original image by a ratio of 3 along each of its dimensions. The model does not take into account the fact that receptive fields on peripheral areas of the retina are larger than foveal receptive fields. An enlargement of peripheral receptive field areas in terms of pixels would approximately account for the 13:1 reduction ratio present in the human vision system.
Through test results, the sensitivity of obtained results in terms of the model's variable parameters was treated.

(a) $\phi = 10$ (b) $\phi = 30$ (c) $\phi = 50$

Figure 3
Edge-detected image received when setting A to 5 and varying the value of Φ

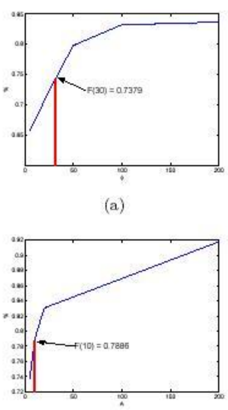
(a) $\phi = 10$ (b) $\phi = 30$ (c) $\phi = 50$

Figure 4
Edge-detected image received when setting A to 10 and varying the value of Φ

(a) $\phi = 10$ (b) $\phi = 30$ (c) $\phi = 50$

Figure 5
Edge-detected image received when setting A to 20 and varying the value of Φ

The obtained results compete with the best filtering techniques used today. Because of this and the size reduction discussed above, the model can be used efficiently in robot systems with real-time demands.



(a)

(b)

Figure 6
The percentage of non-white pixels in terms of Φ and A

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