

Edge Detection Model Based on Involuntary Eye Movements of the Eye-Retina System

András Róka, Ádám Csapó, Barna Reskó, Péter Baranyi

Computer and Automation Research Institute,
Hungarian Academy of Sciences
E-mail: baranyi@sztaki.hu

Abstract: Traditional edge-detection algorithms in image processing typically convolute a filter operator and the input image, and then map overlapping input image regions to output signals. Convolution also serves as a basis in biologically inspired (Sobel, Laplace, Canny) algorithms. Recent results in cognitive retinal research have shown that ganglion cell receptive fields cover the mammalian retina in a mosaic arrangement, with insignificant amounts of overlap in the central fovea. This means that the biological relevance of traditional and widely adapted edge-detection algorithms with convolution-based overlapping operator architectures has been disproved. However, using traditional filters with non-overlapping operator architectures leads to considerable losses in contour information. This paper introduces a novel, tremor-based retina model and edge-detection algorithm that reconciles these differences between the physiology of the retina and the overlapping architectures used by today's widely adapted algorithms. The algorithm takes into consideration data convergence, as well as the dynamic properties of the retina, by incorporating a model of involuntary eye tremors and the impulse responses of ganglion cells. Based on the evaluation of the model, two hypotheses are formulated on the highly debated role of involuntary eye tremors: 1) The role of involuntary eye tremors has information theoretical implications 2) From an information processing point of view, the functional role of involuntary eye-movements extends to more than just the maintenance of action potentials. Involuntary eye-movements may be responsible for the compensation of information losses caused by a non-overlapping receptive field architecture. In support of these hypotheses, the article provides a detailed analysis of the model's biological relevance, along with numerical simulations and a hardware implementation.

Keywords: Image contour detection, Non-Overlapping receptive field, Artificial involuntary eye-movements

1 Introduction

The subjects of artificial vision and image processing are two of the most important areas in the development of robot technologies. Due to the overall failure of classical computational methods to provide general purpose applications in these areas, soft computing techniques and biologically inspired approaches to computation have become more and more popular in the last decade. The aim of these novel paradigms is to provide digital implementation of a variety of operations ranging from edge detection to more complex visual tasks, while guaranteeing the efficiency of biological visual systems [9,15]. In this paper we propose a novel edge-filtering method, in accordance with the latest findings in cognitive research. The paper is structured as follows: in a preliminary section we briefly present the goals of the edge-detection model. This will be followed by an overview of its biological background. Further sections treat the details of the model and discuss the hypotheses postulated based on its evaluation. Finally, test results and a hardware implementation are also presented.

2 Motivation

One thing in common between the majority of classical and biologically inspired edge detection methods used in image processing is that the output image is computed as the convolution of the input image and a filtering operator [9,7]. This has two important implications as regards the output image:

- Input and output images have the same spatial resolution.
- A given pixel value on the input image influences several pixel values on the output image.

According to findings in retinal research, the convolution-based computational philosophy is biologically inadequate. This is well demonstrated by the fact that the number of retinal cones (photoreceptors sensitive to color) is about 6 million and the number of rods (photoreceptors sensitive to light regardless of its color) is about 125 million, while at the same time the number of ganglion cells sending the visual information to the brain is only about 1.2 million. This suggests that image processing as well as massive image compression (also referred to as convergence) takes place in the retina [1,12]. In terms of image processing, the above facts also imply the following:

- Input and output images do not have the same resolution.
- The influence of a given pixel value in the input image on a given pixel value on the output image is described by a complex temporal and spatial relationship.

In this paper we propose an edge detection method that implements data convergence and several dynamic properties of ganglion cells. At the same time, the proposed algorithm is characterized by low complexity and is therefore easily implementable on hardware.

3 Biological Overview

3.1 Structure of the Retina

The retina is the first stage in the visual processing hierarchy. Besides being responsible for the detection of light intensities, the retina also carries out preprocessing tasks and filters visual information that is important in later stages of feature extraction.

The retina is composed of several types of cells: cones, rods, bipolar cells, horizontal cells, amacrine cells, and ganglion cells. All of these cells can be categorized into numerous subtypes based on their structure and functionality [5,11].

Information processing in the retina ends with a layer of ganglion cells. The axons of ganglion cells constitute the optic nerve which leads to the LGN and visual cortex, where higher-level visual processing takes place. Scientists distinguish between at least 11 kinds of ganglion cells based on the types of information they provide, as well as the way they react to stimuli (impulse response) [7].

Before providing a further description of the functionality of the retina, it is important to define the term receptive field. The state of a nerve cell is affected by every photoreceptor cell that provides it with input (either directly or indirectly). This set of cells providing input is referred to as the receptive field of the nerve cell. The structure of receptive fields can be observed from the firing patterns of cells when they are stimulated in an artificial environment.

The key information processing activity of the retina deals with the detection of light, a task which is carried out by rods and cones. These photoreceptor cells reflect the intensity of incoming light through their membrane potentials [17]. The information provided by photoreceptor cells is primarily processed by the complex structure of horizontal and bipolar cells. The co-operation of these two cell types creates the well-known center-surround receptive fields of ganglion cells [2,3,4]. The structure of center-surround receptive fields comes in two types: on-centered off-surround and off-centered on-surround receptive fields. On-centered off-surround cells are depolarized when there is light at the center of their receptive fields and less light at the periphery, while off-centered and on-surround

cells prefer more light at the periphery of their receptive field, and less at the center.

From an engineering point of view, the center-surround receptive field structure is sensitive to changes of light intensity, a property crucial for contour detection. On-centered off-surround cells are sensitive to the ‘light edge’ of a light-to-dark transition, while off-centered off-surround cells are sensitive to the ‘dark edge’ of the same transition [2,3,4].

3.2 Non-Overlapping Receptive Fields

For a long time, experiments have shown extensive overlaps between receptive fields on the retina. However, when comparing the number of axons of photoreceptor cells to the number of axons in the optic nerve, it was discovered that the 130 million axons of rods and cones are condensed into 1.2 million axons in the optic nerve. Because of this fact, it was assumed that the retina performs some kind of information compression [14].

With the evolution of experimental methods, it was possible to make a distinction between many kinds of ganglion cells. Devries and Baylor [6] were able to distinguish between 11 kinds of ganglion cells, based on their receptive fields and response characteristics. Different kinds of ganglion cells provide different kinds of information, such as contour information, intensity information, motion information, as well as information on uniformly lighted image segments. It was also shown that receptive fields of ganglion cells of the same type do not overlap in the central fovea; the center of these receptive fields are located at a distance of one diameter (Figure 1). These measurements were confirmed by Packer and Dacey [16].

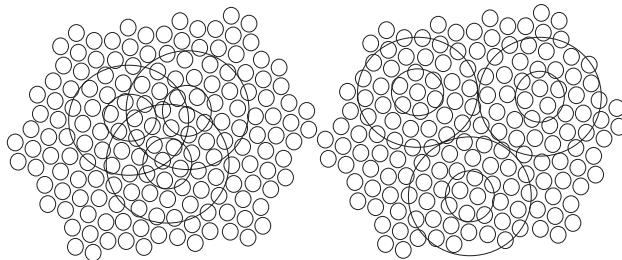


Figure 1

Contrary to the previous theory, it was shown that receptive fields of ganglion cells of the same type do not overlap in the mammalian central fovea

The scientific literature contains much contradicting data as regards the size and spatial organization of receptive fields, because the retina shows significant differences in various animal species. The model we propose takes into

consideration only the foveal areas of the mammalian retina, where the size of receptive fields is relatively small and uniform. Because of the lack of overlaps between receptive fields in the fovea, only intensity transitions that fall in the center of the receptive fields can be detected. Applying a non-overlapping architecture in today's well-known edge-detection methods leads to considerable losses in contour information. The proposed model provides a possible solution to the conflict between the continuous perception of contours and the non-overlapping receptive field architecture in the central fovea.

3.3 Involuntary Eye-Movements

The three major kinds of involuntary eye movements that occur during fixation are microsaccades, drifts and tremors (also sometimes referred to as nystagmuses) [13,10].

Of the three eye movements, later sections of this paper concentrate on tremors. 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). There is currently no conclusive evidence on the functional role of tremors, however, artificially eliminating tremors, researchers have found that vision faded away.

The model for edge-detection proposed in this paper uses non-overlapping receptive fields, but also incorporates tremors in order to achieve the effects of overlapping receptive fields through time. It will be shown that besides following the structure of human visual perception, the model accounts for the 130:1 information reduction ratio characteristic to the pathway between photoreceptor cells of the retina and ganglion cells [18].

4 The Proposed Retina-Inspired Model for Edge Detection

4.1 Filters Used for Edge Detection

The model proposed in this paper performs edge detection based on the center-surround structure of receptive fields. Despite the fact that in the retina, the size of these receptive fields increases from the fovea towards the peripheral areas, the model we propose considers only the foveal areas of the retina, where the size of receptive fields is relatively small and uniform. In the fovea, receptive fields are so small that the central area of the receptive fields consist of only one cone [16,8]. Taking into account the diameter of the photoreceptors and receptive fields

in the mammalian retina, receptive fields are represented by a 3-by-3, two-dimensional filter matrix F , which resembles the Laplace-operator (Figure 2). Each matrix value represents an input weight with which the corresponding stimulus is multiplied.

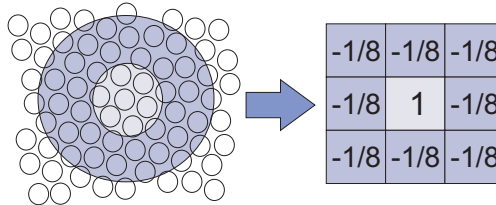


Figure 2

Receptive fields in mammalian fovea small enough to be represented by 3-by-3 pixel filter operators, as was done in many previous models

The configuration of weights depends on the concrete type of receptive field being modeled; on-centered fields have positive values in the central area, surrounded by all negative weights, while off-centered fields contain a central negative value, surrounded by all positive weights.

4.2 Non-overlapped Edge Filtering Model

If we are to accept the fact that receptive fields do not overlap in the fovea, we have to consider its implications.

The proposed model uses no overlaps between filter matrices (Figure 3). The input image is tiled using a mosaic arrangement of the filter matrix F in a non-overlapped manner. The center of each F filter is at a distance of three pixels from each of the four closest filter matrix centers. The image pixel values are multiplied by the corresponding F values and a weighted sum is calculated for each filter matrix center. The matrix composed of the filter centers provides the output matrix of the non-overlapped filtering operation. Figure 4 shows this processing structure.

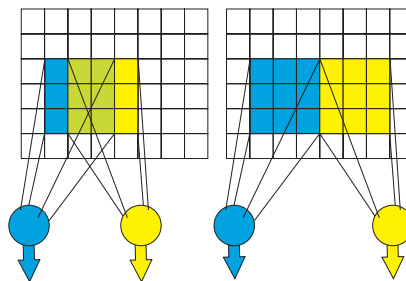


Figure 3

Overlapping and non-overlapping filtering architecture

In the model with no overlaps, it can easily occur that a change in contrast falls precisely in between two filter matrices, thus remaining undetected. Figure 5 shows an example of such information loss. Note that the output of this processing structure is identical to the 3-by-3 subsampling of the convolution of the input image with the same filter matrix F , and therefore the spatial resolution of the output is $1/9^{th}$ the spatial resolution of the output obtained using convolution. In order to make the two results comparable, the size of the input image used in convolution-based filtering is also reduced by a factor of $1/3$ along each dimension.



Figure 4

Non-overlapping processing structure. The input image is tiled using a mosaic arrangement of the filter matrix F in a non-overlapped manner.

The non-overlapped image filtering method can be formalized as follows. Let I denote the input image, F the filter mask, J and K the output images obtained using the classical convolution-based method and the non-overlapping filtering method, respectively. In classical convolution-based filtering, the output can be expressed as the convolution of I and F over a discrete 2D space:

$$J(x, y) = F \otimes I = \sum_{j=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} F(j, k) \cdot I(x - j, y - k) \quad (1)$$

The result of the non-overlapped filtering K can be obtained from the result of the overlapped filtering J , as follows:

$$K_{i,j} = J_{m-i,n-j} \quad (2)$$

where n and m indicate the size of matrix F (in the current implementation, $n = m = 3$). It can be seen from equation 2 that the number of elements in K is $m \times n$ times smaller than the number of elements in J . The model presented above takes into account the convergence between photoreceptor cells and ganglion cells, but does not incorporate temporal properties of ganglion cells, and involuntary eye-movements are also disregarded. Receptive fields were modeled using 3-by-3 matrices. It is clear that the lack of overlaps result in a deteriorated image; certain sections of line segments are blurred, or are missing altogether.

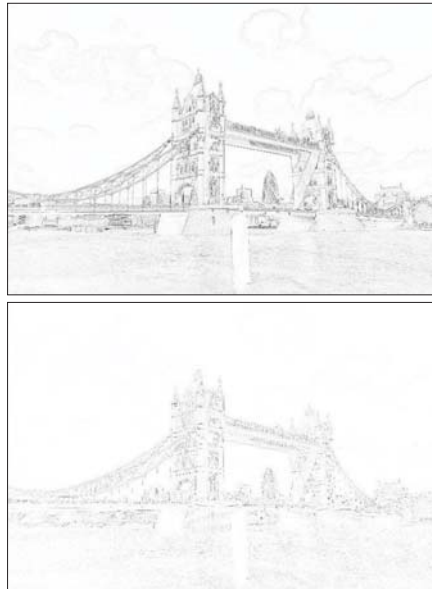


Figure 5

In the model with no overlaps in case of a change in contrast falls in between two filter matrices, thus remaining undetected, information loss occurs

4.3 Virtual Receptive Fields

The non-overlapping retina model used to generate the above images performs too poorly to be considered biologically valid. The literature does not explain how the quality of images can be guaranteed by the retina, even with the difficulties caused by this non-overlapping architecture. This section provides a possible solution to the problem.

The starting point of the model is that high-quality edge detection can be achieved only when assuming that receptive fields overlap. Taking into consideration the fact that ganglion cells of the same type do not physically overlap on the fovea, but also considering that such overlaps would otherwise be required, it is plausible to assume that the necessary overlaps are achieved through time. The large-frequency and small-amplitude involuntary eye-movements known as tremors (see section 4.5) could be capable of causing the necessary overlaps through time. Such small tremors with frequencies of 90 Hz and amplitudes of 2-3 cones are sufficient for the correction of the minor gaps between non-overlapping receptive fields, and could reveal the presence of the previously unperceived line segments. Due to tremors, the image that is projected onto the retina suffers random displacements with an amplitude of 2-3 cones. This extension of non-overlapping receptive fields covers larger parts of the scene than the receptive fields did in the

previous model, and virtual receptive fields are created through time. Such virtual fields are larger in size compared to the original receptive fields, and also show considerable overlaps. For instance, assuming a physical receptive field with a diameter of 6 cones, and tremors with an amplitude of 3 cones, the emergent virtual receptive fields will have a diameter of 12 cones and the produced overlap will be enough to perform edge filtering without any information loss.

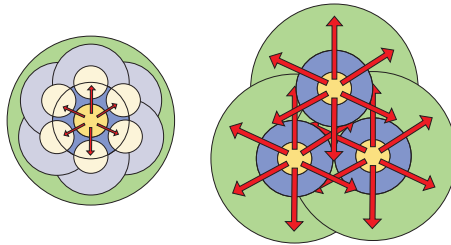


Figure 6

Due to the involuntary tremors and the impulse response of ganglion cells, virtual receptive fields are created. Virtual fields greater than real ones, and show notable overlap.

The formation of such virtual receptive fields would be impossible without taking into account the impulse responses of ganglion cells.

4.4 Temporal Model of Ganglion Cells

It is generally a common property of ganglion cells that they produce increased activity when stimulated, and that their activity decreases only gradually when the stimulus either disappears or remains stagnant. However, if stimulating effects increase, the output of ganglion cells increases even more, and finally declines to 0 (Figure 7).

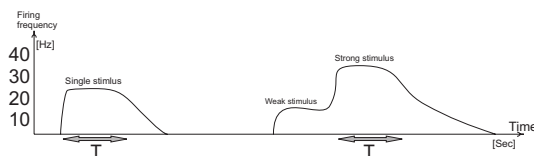


Figure 7

The general impulse response of a ganglion cell.

In the proposed model, the stochastic response properties of ganglion cells are approximated using a window function (Figure 8). This simplification is justified because it conserves the essence of the ganglion cell's functionality (in terms of its 'temporal memory' or 'time constant'), and it is also convenient because it ensures that unnecessarily complex computations are not brought into the model.

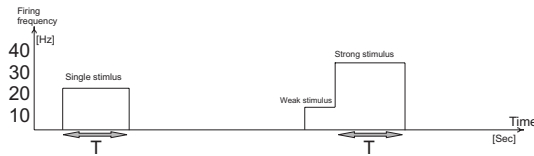


Figure 8

Modeled response of ganglion cells in time.

The proposed model calculates the sum of the inputs of ganglion cells, and holds their output for T time frames. If, during this time, their inputs are stimulated even more, then their output will increase. Otherwise, the output level will return to 0 after T time frames.

4.5 Artificial Tremors

As described above, tremors could be capable of causing the necessary overlaps between receptive fields through time. This is the reason why artificial tremors were introduced to the proposed model. Artificial tremors can be simulated by software, and can also be implemented by adding mechanical vibrations to the image sensor equipment (camera). In order to create an artificial tremor that is as similar as possible to its biological counterpart, the physical properties of tremors have to be considered.

Eye tremors have frequencies of about 90Hz, and amplitudes of about the diameter one cone. Based on this measurement data, the parameters of the artificial tremors incorporated in the non-overlapped filtering model were chosen such that:

- Amplitude: $A = 2$ pixels
- Frequency: $f = 90 \text{ frame}^{-1}$
- Direction: Random

The simulation of tremors is done by shifting the input image I in a random direction by a maximum of 2 pixels. Mechanical implementations of artificial tremors can be realized by computing the summation of the effect of two perpendicular mechanical vibrations of different frequencies.

4.6 Proposed Tremor-based Dynamic Retina Model

As described in section 4.2, the input image is tiled using a mosaic arrangement of the filter matrix F in a non-overlapped manner. This means that the sets of pixels seen by each receptive field are disjoint, and that their union covers the whole image. Each ganglion cell computes the sum of its inputs to produces its output.

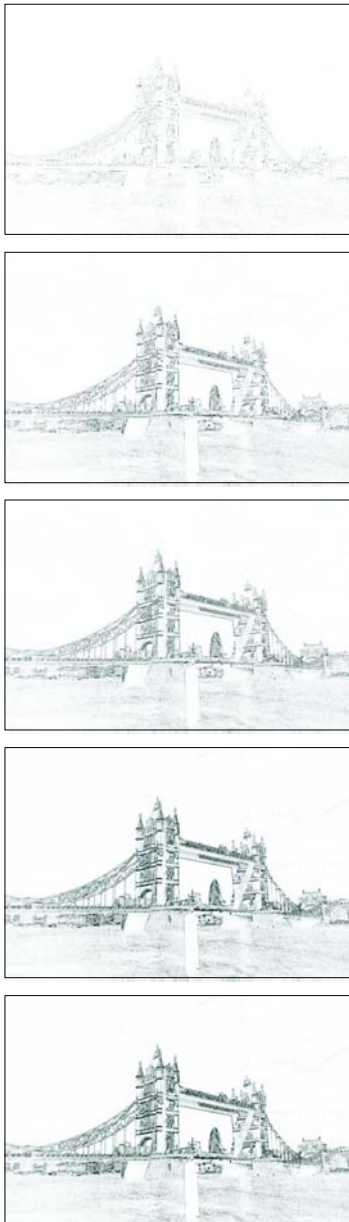


Figure 9

The obtained image using $T = 1, 5, 10, 30, 100$, from top to bottom

The difference between the non-overlapping edge filtering method (Section 4.2) and the proposed model lies in the use of artificial tremors as well as the temporal model of ganglion cells in the latter model. In the non-overlapping method, the output is a static function of the input, while in the tremor-based model, ganglion cells produce their output according to the window function described in section 4.4. Virtual receptive fields can therefore be developed through time, based on the artificial tremors. The notion of virtual receptive fields does not appear directly in the mathematical formulation of the model, but is useful in its interpretation.

At any given moment, the output of each modeled ganglion cell is determined as the maximum of the sum of its inputs within the last T time frames. From a biological point of view, the value of T is between 15 and 30 T_{tr} , where T_{tr} denotes the period time of artificial tremors. Based on simulation results, it is clear that the growth in image quality slows down as T increases. Figure 9 demonstrates the relationship between image quality and the value of T . In mathematical terms, the proposed model can be formulated as follows: Let I_s1 be the tremor-based shifted image, and F be the filter matrix. The shifted image, I_s1 , is then filtered in a non-overlapped manner using filter F , yielding K_s1 . This process is done as many times as defined by the T

time constant parameter, resulting in images K_{si} , where $i = 1..f$ and $f = T/T_{tr}$. The f images are then integrated into one image K . The integration is computed using a pixel-wise maximization:

$$\forall x, y: K(x, y) = \max_i K_{si}(x, y) \quad (3)$$

The resulting image K is one output frame of the non-overlapped filtering system. Using this approach, each output pixel aggregates edge information from its neighborhood as defined by the properties of the artificial tremor. Unlike the static (tremorless) non-overlapped case, contour information contained in the input image will not be lost, but aggregated into the output pixel. The authors were not able to find any existing theory that described such a close link between tremors and the non-overlapping receptive field architecture on the retina. According to the theory proposed here, the retina does not perform data compression (as suggested by others in the past) in order to achieve the convergence between photoreceptor cells and ganglion cells, but uses the mechanism described above. Such a mechanism allows only the most important features to be considered in each disjoint subset of the visual field.

4.7 Advantageous Properties of the Proposed Model

In the proposed model, simple implementation is coupled with fine output image quality. Through its data convergence, output images are 9 times smaller than input images (in the case of using 3-by-3 pixel filter matrices – Figure 10. For instance, a 800-by-600 input image would result in an output image with the same resolution using classical edge-detection methods 480 Kbytes). However, the tremor-based method would generate an output of only 266-by-200 pixels in the same case (53 Kbytes), and the output image still contains the necessary contour information for further image processing tasks.

In hardware implementation, from the point of view of speed rate and edge board complexity, it is important to use built-in memory if possible. The convergence of the proposed model provides an appreciable reduction of almost one order of magnitude. The output image of 53 Kbytes can easily be stored in either a PIC microcontroller, while 480 Kbytes of data generally require external memory.

5 Hardware Implementation

The tremor-based non-overlapping retina model was implemented on a Virtex II. FPGA (Figure 11). An important goal was to make the implementation independent of the type of camera used.



Figure 10

Some advantages of the proposed model are its simple implementation, fine output image quality, and its convergence of almost one order of magnitude

For this reason, the FPGA implementation receives its input from a desktop monitor, through a VGA interface. In this way, the implementation can be used both to evaluate real-time performance through a camera connected to the computer, as well as to obtain results from pre-existing video files.



Figure 11

An image of the camera, equipped with two, asymmetrically weighted vibrating motors

The camera used for the recording of input has two vibrating motors attached to it, in order to simulate tremors. In industrial applications, artificial tremors would be implemented in the reading-in method of the FPGA, but in this case mechanical vibrations were applied for the purposes of illustration. The two motors induce vibrations in a horizontal and vertical direction. Because the tremors need to be as delicate as possible, the authors decided to use a PWM remote controller to

control the motors. In this way, direct contact with the camera can be avoided, and the frequency and amplitude of tremors can be adjusted without interfering with the system's functionality.

The implementation uses the 3-by-3 F matrices presented above. This means that information can only be processed when three pixel rows are received. The first two rows modulo 3 are stored in a 2 Kbyte dual-port memory, and processing is pipelined with the reading of the third row. Although the responses of ganglion cells are calculated serially, one after the other, the final output is calculated using a pipelined arithmetic unit. The correctness of the input, as well as the commencement of calculations, is guaranteed by a control unit. The calculated output values are also stored in an internal, 53 Kbyte dual-port memory. A separate unit is used to calculate the dynamical functions of ganglion-cells based on these values. As a trade-off between biological relevance and low-complexity implementation, a moving-maximum procedure is used for these purposes. Because of the non-overlapping architecture, output images are smaller than input images. For this reason, output images are rendered to the center of the display, with a black background.

Results obtained using the hardware implementation are very similar to the software-based results seen in figure 9. The difference between the two is that the current FPGA implementation provides lower resolution, but real-time results.

6 Hypotheses

Based on recent findings in biology and the experimental results presented in this paper, the following hypotheses are postulated:

Hypothesis 1: The role of involuntary eye tremors has information theoretical implications. This hypothesis is supported by recent findings in biology, which claim that receptive fields cover the surface of the fovea in a mosaic arrangement with minimal overlaps, and also by the fact that the output of retinal edge filtering on the axons of the ganglion cell layer has a much lower resolution than the input resolution on the photoreceptor cells.

Hypothesis 2: From an information processing point of view, the functional role of involuntary eye-movements extends to more than just the maintenance of action potentials. Involuntary eye-movements may be responsible for the compensation of information losses caused by a non-overlapping receptive field architecture. This hypothesis is supported by the experimental results presented in section 4.6, which show the difference between the edge-detected images obtained by using non-overlapped filtering with and without artificial tremors. The experiments show that the application of tremors considerably enhances image quality. This can be explained by the integrative and compressive effects of tremors within a

certain locality, in contrast with the compression principle of the tremorless, non-overlapped filtering method, which completely disregards certain aspects of locality.

Conclusions

A novel, biologically inspired image filtering method was proposed. The method implements the non-overlapping mosaic arrangement of retinal receptive fields, as well as a certain kind of non-voluntary eye-motions, called tremors. The characteristics of the proposed method are different from those of convolution-based image filtering methods. In a way similar to the retina, the non-overlapped filtering implements image information compression, as a direct result of the use of non-overlapping receptive fields and artificial tremors. This has advantageous effects on the temporal and spatial requirements (execution time and memory) of a hardware implementation that needs to satisfy real-time constraints.

Based on the model, two hypotheses were formulated about the role of involuntary tremors. The first hypothesis states that convolution-based edge-detection algorithms are inadequate if our goal is to provide a biologically valid model. It is interesting to note that for the human observer, the edge-detected image using the proposed method looks more expressive than convolution-based results, which might indicate that the human vision system prefers the biologically more relevant way of producing contour images. Experimental results show that small vibrations dramatically improve the quality of edge detected images. This is generalized in the second hypothesis, which claims that a similar phenomenon may exist in the eye-retina system, which would explain the heretofore unknown role of eye tremors. The two hypotheses proposed in this paper need further support, from both biology and computational experiments.

Acknowledgements

This research was supported by the János Bolyai Postdoctoral Scholarship.

References

- [1] H. Barlow, “*Summation and inhibition of the frog’s retina*”, Journal of Physiology, 119:69–88, 1953
- [2] J. Bilotta and I. Ambrov, “*Spatial properties of goldfish ganglion cells*”, J. Gen. Physiol., 93(6):1147–1169, 1989 June
- [3] S. Brown, S. He, and R. Masland, “*Receptive Field microstructure and dendritic geometry of retinal ganglion cells*”, Neuron, 27(2):371–383, 2000 Aug.
- [4] D. Burkhardt and P. Fahey, “*Contrast enhancement and distributed encoding by bipolar cells in the retina*”, J. Neurophysiol., 80(3):1070–1081, 1998 Sept.

- [5] D. Dacey, “*Primate retina: cell types, circuits and color opponency*”, *Prog Retin Eye Res.*, 18(6):737–763, 1999 Nov.
- [6] S. Devries and D. Baylor, “*Mosaic arrangement of ganglion cell receptive fields in rabbit retina*”, *J. Neurophysiol.*, 78(4):2048–2060, 1997 Oct.
- [7] S. H. DeVries and D. A. Baylor, “*Mosaic Arrangement of Ganglion Cell Receptive Fields in Rabbit Retina*”, *The Journal of Neurophysiology*, 78(4), 1997
- [8] L. Diller, O. Packer, J. Verweij, M. McMahon, D. Williams, and D. Dacey, “*L and M cone contributions to the midget and parasol ganglion cell receptive fields of macaque monkey retina*”, *J. Neurosci.*, 24(5):1079–1088, 2004 Febr.
- [9] C. Grigorescu, N. Petkov, and M. Westenberg, “*Contour and boundary detection improved by surround suppression of texture edges*”, *Image and Vision Computing*, 22(8):609–622, 2004
- [10] Hennig and Worgotter, “*The effect of fixational eye movements on hyperacuity*”. *Computational Neuroscience*, Dept. of Psychology, University of Stirling
- [11] D. Hubel, “*Eye, Brain and Vision*”, W H Freeman, 1988
- [12] S. Kuffler, “*Discharge patterns and functional organization of mammalian retina*”, *Journal of Neurophysiology*, 16:37–68, 1953
- [13] S. Martinez-Conde, S. L. Macknik, and D. H. Hubel, “*The Role of Fixational Eye Movements in Visual Perception*”, *Nature Reviews Neuroscience*, 5(3):229–240, 2004
- [14] M. Meister, “*Multineural codes in retinal signaling*”, *Proc Natl Acad Sci USA*, 93(2):609–614, 1996 Jan.
- [15] V. Navalpakkam and L. Itti, “*An integrated model of top-down and bottom-up attention for optimal object detection*”, In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 2049–2056, 2006
- [16] O. Packer and D. Dacey, “*Receptive field structure of H1 horizontal cells in macaque monkey retina*”, *Journal of Vision*, 2(4):279–292, 2002
- [17] D. Schneeweis and J. Schnapf, “*The photovoltage of macaque cone photoreceptors: adaptation, noise, and kinetics*”, *J. Neurosci.*, 9(4):1203–1216, 1999 Febr.
- [18] R. Sekuler and R. Blake, “*Perception*”, Mc Graw Hill, 1994
- [19] J. Thiem, C. Wolff, and G. Hartmann, “*Biology-Inspired Early Vision System for a Spike Processing Neurocomputer*”, In *Biologically Motivated Computer Vision*, pp. 387–396, 2000