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Simulation of the retina : a tool for visual prostheses

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To extract high level information from natural scenes, the visual system has to cope with a wide variety of ambient lights, reflection properties of objects, spatio-temporal contexts and geometrical complexity. By pre-processing the visual information, the retina plays a key role in the functioning of the whole visual system. It is crucial to reproduce such a pre-processing in artificial devices aiming at replacing or substituting the damaged vision system by artificial means.

In this paper, we present a biologically plausible model of the retina at the cell level and its implementation as a real-time retina simulation software. It features the non-uniform sampling of the visual information by the photoreceptor cells, the non separable spatio-temporal properties of the retina, the subsequent generation of the Parvocellular and Magnocellular pathways, and the non-linear equalization of luminance and contrast at the local level. For each of these aspects, a description of the model is provided and illustrated. Their respective interest for the replacement or substitution of vision is discussed.

Keywords: retina simulation; visual prostheses; early visual system; image processing.

1. Introduction

Restoration of vision through artificial means has become a major issue involving medicine, cognitive science and engineering. [1,2,3,4] Today, more than twenty projects are engaged all over the world to design a visual implant: an electronic device which electrically stimulates the visual system of the subject to elicit perception. Other

devices called sensory substitution systems are also tested. These latest devices translate the signal from the video camera into a tactile or auditory stimulation. They also proved to give the subject meaningful perceptual abilities.[5]

Among all the issues relative to the design of visual prostheses, the question of how to process the signal before sending it to the brain has been spotted out long time ago.[6] The question here is not **how** to send the signal to the brain but **which** signal should be sent through the brain's interface. This question implies considerations with respect to the resolution of the interface, which is usually very poor compared to the one of the eye or to the camera's resolution itself. It also implies consideration with respect to the properties of the interface's target and its actual spatio-temporal response to a stimulation. Finally, it implies consideration with respect to the capacitiy of the interface in term of information transmission and number of levels that can be afforded for each stimulation points.

In the visual system, the retina holds a major role with respect to these questions. The space-variant distribution of the photoreceptors at its surface and the subsequent pyramidal wiring forming the ganglion cells reduce the number of fibers needed to transmit the signal. The spatio-temporal properties of the retinal network enhance the usability of this signal, and finally, the adaptations occurring at different levels in the retina makes the visual system able to cope with a wide variety of ambient lights levels.

Many research are now focusing on the idea to reproduce the behavior of the retina in a visual prosthesis.[7,8,9,10] They usually consider the three different aspects previously mentioned: space-variant sampling at the level of the photoreceptors, spatio-temporal behavior of the retina and adaptivity to luminance and contrast level. The aim of this article is to describe a biologically plausible model of these three aspects, to point out its main originality with respect to the other models and to present a retina simulation software that is directly derived from this model. The software's design is modular and fully configurable so that it may be adapted to different users or situations. It may constitute a new step toward a better efficiency and adaptivity of either stimulation of the visual system or sensory substitution technologies.

2. The retina : overall view

The aim of this section is to provide the reader with the information he needs to understand the subsequent proposed modelisation. Many aspects concerning the retina's physiology are still under debate. A more developed description of the retina physiology may be found in Wassle & Boycott and Rodieck.[11,12] Readers interested in a deeper insight into the modeling of the human retina may refer to Field and Chichilnisky.[13]

The human retina can be described as a pile of sheets of identical cells, the visual information being progressively transmitted from one sheet to the other while undergoing filtering and combinations.

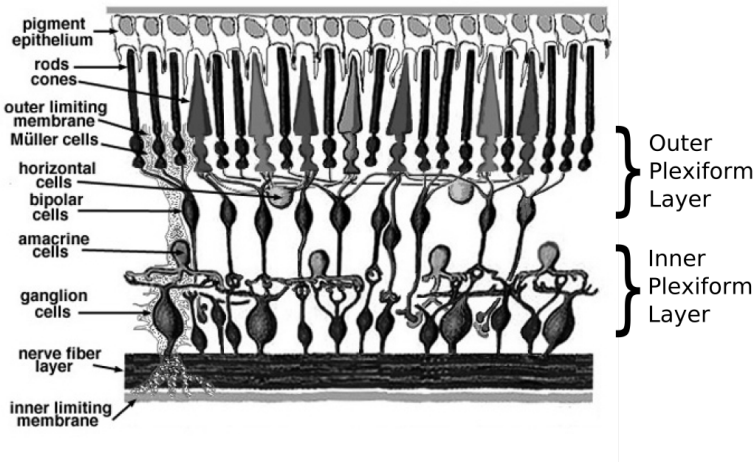

Fig. 1. Representation of the neural cells and wiring on the retina

Mainly five different sheets of cells have been described in the retina: the photoreceptor cells, the horizontal cells, the bipolar cells, the amacrine cells and, finally, the ganglion cells, which form the optic nerve (fig. 1, from webvision).[14]

Photoreceptors cells convert the incoming light into an electric potential. There are two different types of photoreceptors : cones and rods. They are respectively responsible for day and night vision. As our simulation only consider cones, we will focus on describing only their subsequent circuitry. Distribution of cones over the retina is non-uniform : it is maximal in the center of the retina, called the fovea, and then decreases with eccentricity.[15] Neighboring cones are linked altogether through gap junctions.[16]

Horizontal cells possess large dendritic arborisation and make contacts with several cones. The number of cones they contact depends on the eccentricity.[11,12] They are also linked together through Gap junctions.[16]

Bipolar cells transmit the signal from the Outer Plexiform Layer to the Inner Plexiform layer. In the Outer Plexiform Layer (OPL), Bipolar cells, Horizontal cells and cones interact in synaptic triads. There is two types of synaptic triads: invaginated and non-invaginated one. They respectively lead to the formation of bipolar ON and bipolar OFF cells. Bipolar ON cells are activated by a stimulation at the center of their receptive field, and are inhibited by a stimulation at its surrounding. Bipolar OFF cells follow the exact inverse pattern.

Ganglion cells gathered the signal from the bipolar cells in the Inner Plexiform Layer to form the optic nerve. There is three main types of ganglion cells. Midget ganglion cells make a one to one connection with bipolar cells. They project to the Parvocellular layers of the LGN, thus forming the Parvocellular pathway. Parasol ganglion cells gathered the signal from several bipolar cells. The number of bipolar

cells they connect depends on the eccentricity in the retina. Parasol Ganglion cells project to the Magnocellular layers of the retina, thus forming the Magnocellular pathway. Both Midget and Parasol cells present an ON or OFF polarity respectively related to the type of bipolar cells they connect. Finally, bi-stratified ganglion cells gathered information from both ON and OFF bipolar cells. They are believed to project to the superior colliculus.[17]

Amacrine cells uncover a population of about twenty different types of cells. They interact both with the bipolar cells and the ganglion cells in the Inner Plexiform Layer. Their role is still unclear, but it is well accepted that their overall influence is to temper the signal of the ganglion cells.[12]

In our simulation, the information in each particular sheet is represented as an image. We consider the gray level value of each pixel on an image as the response of a photoreceptor. The input picture gives rise to a series of output pictures representing the response of each cell's sheets to such stimulation, according to our knowledge about the different processes and connection that occur between them.

The retina, as every natural system, has neither regularity nor uniformity that allows its modeling without simplification. Especially, anatomy and probably functionality changes with the eccentricity. The density of the photoreceptors decreases with eccentricity. Also there are a lot of evidences that the number and type of postreceptoral cells change too.[18] It is still a debate into the biologist community to understand the different functioning of the retina along eccentricity. To overcome this problem we first propose a model of the center of the retina (the fovea) were the acuity is highest. The model is linear, regular, made of several blocks of the same type. Then we propose an extension of this model for adaptation purpose which applies local processing depending of the content of the image. Finally, we propose a model of the photoreceptor sampling that we integrate into the regular, adapted model. By that way we conciliate the irregular nature of the retina with the modeling which is simpler in the regular case.

3. The retina as a linear filter

The most extensively studied aspect of the retina is probably its spatio-temporal properties. In the visual system the retina acts as a hub which shunt the visual information into different pathways depending on its spatio-temporal content. Two main pathways can be differentiated in the optic nerve : the Parvocellular pathway which project to the Parvo cells of the Lateral Geniculate Nucleus and the Magnocellular pathway, which project onto its Magno cells. The Parvo pathway is known to have a tonic response and to convey the high spatial frequencies of the stimulus, while, conversely , the Magno Pathway is transient and conveys the low frequencies of the stimulus. This dichotomic splitting of the visual information is a base for the functioning of the whole visual system. In particular, it echoes the notion of Dorsal and Ventral pathways proposed by Goodale and Milner (1992).[19]

A very effective way to simulate the spatio-temporal properties of the retina is

to consider the analogy between a biological neuron and an electronic circuit.[20] A neuron can be described as a voltage generator with internal resistance r, and a leaky integrator (Cm and rm components) modeling the membrane characteristics (fig. 2, left).[20] This approach has been used to design analog simulation of the retina.[20,22] It can also be used to derive an analytical model of the retina as a linear filter, and to reproduce its properties for image processing.[23] Our work derives from this later approach.

3.1. *The generic retina layer*

To start with our model, we consider a two dimensional network of identical neurons interconnected to their neighbors by gap junctions. A row of such a network is represented in fig. 2 (left). Gap junctions between neuron are described as resistors (R).[24]

This structure define our basic retina layer: in first approximation, we will model each standard sheet of cell in the retina this way. Differences between the cells' properties will be further modeled as differences in the electronic capacitor and resistor values. In photoreceptors, the voltage generation results from the light conversion process (i.e. the input picture), whereas in other cells, it results from synaptic transmission (i.e. the output of the previous layers).

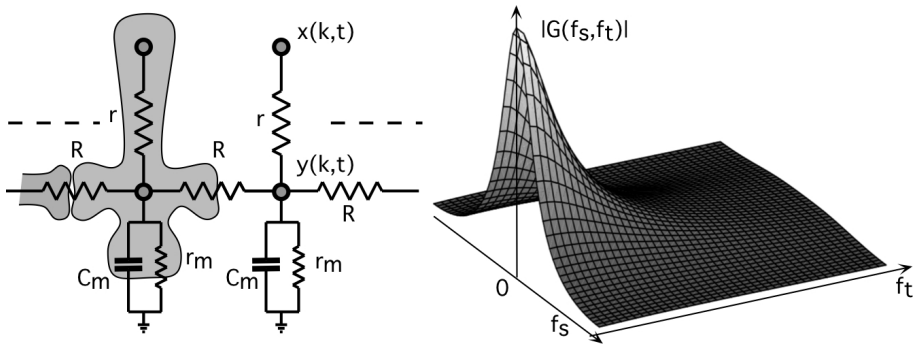

Fig. 2. Model of a generic retinal cell layer. Left : electronic model for a generic retina layer ; Right: spatio-temporal transfer function of such a layer

We can compute the transfer function of such a generic layer with respect to spatial frequency (f_s) and temporal frequency (f_t). The result is a spatio-temporal low-pass filter with non separable space and time variable (fig. 2, right).[21]

$$G(f_s, f_t) = \frac{1}{1 + \beta + 2\alpha(1 - \cos(2\pi f_s)) + j2\pi\tau f_t} \tag{1}$$

with α=r/R, β=r/rm, and τ=rCm. The spatio-temporal transfer function of

this filter depends respectively on the spatial constant α, the temporal constant τ and the overall gain parameter β which are determined by the resistors and the capacitors values in the circuit. In our simulation, each type of cell layer (photoreceptor, horizontal cells and ganglion cells) will be defined by a particular parameter set. For instance, horizontal cells are known to exhibit wider lateral connections and longer time evolution than photoreceptors, thus, they will be attributed higher α and τ values.[25]

This filter is implemented by means of a causal/ anticausal recursive filter included in a temporal loop, which reduces the computation cost to only 5 operations per pixels.[23]

3.2. *The Outer plexiform layer*

The outer plexiform layer (OPL) is the place were photoreceptors and horizontal cells joins in the synaptic triad to form the signal of the bipolar cells. The outer plexiform layer is known to be the location of the first differentiator in the retina.[26] In our simulation, the bipolar cells output is the difference between the Photoreceptors picture (a slight low pass filter on the input image) and the Horizontal cells picture (a strong low pass filter on the Photoreceptors output). The result is thus a high pass version of the input picture. The electronic model and associated transfer function of the OPL model is given in fig. 3.

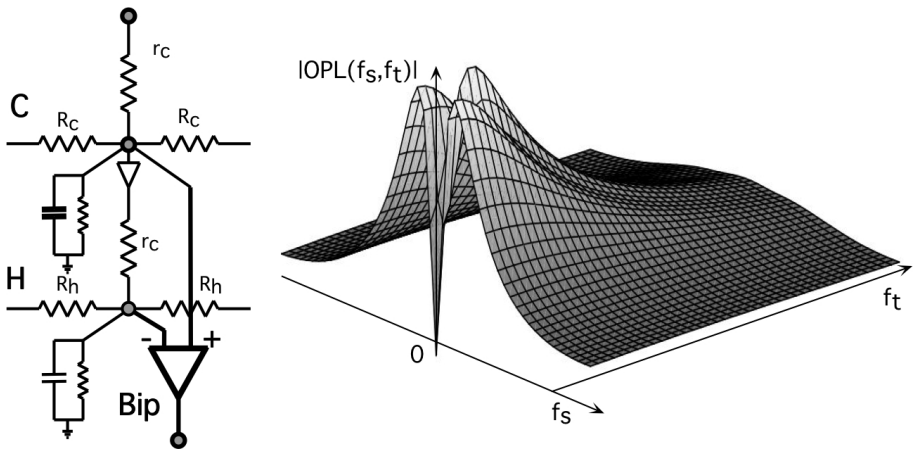

Fig. 3. Model of the Outer Plexiform Layer. Left : Electronic model of the OPL differentiator (C and H stands for cones and horizontal cells) ; Right : transfer function of the OPL

As negative and positive values cannot be coded by a single synapse, the signal is separated into two streams, one which carries the positive part of the signal and the other which carries the negative part of it. This leads to two different streams respectively sharing the ON and OFF polarity observed in bipolar cells.

3.3. *The Inner plexiform layer*

The inner plexiform layer (IPL) is the place where ganglion cells gather information from bipolar cells and interact with amacrine cells. In our simulation, we consider two types of ganglion cells: Midget ganglion cells which connect only a few bipolar cells (even only one in the fovea as known as the one to one cone to ganglion cell wiring), and Parasol ganglion cells which connect many bipolar cells.[18] In term of image processing we made the following simplification: the Parvocellular pathway is a copy of the bipolar cells image, and the Magnocellular pathway is a low-pass version of it.

In the following picture, we have drawn the temporal evolution of the spatial transfer function of the Midget ganglion cells output and the Parasol ganglion cells output for an input picture presented between time 0 and time T. As it is a simple copy of the bipolar cells output, the midget output response (fig. 4, left) is directly built from the transfer function of the OPL pictured in fig. 3 (right). This output has a tonic response to high spatial frequencies and a phasic response to low spatial frequencies, thus following the properties of the Parvocellular pathway.

The Parasol ganglion cells output is derived from the bipolar output by simply applying a spatial low pass filter (fig. 4, right). It conveys only low frequencies and presents a temporal transient behavior, thus following the properties of the Magnocellular pathway. Note that the transient behavior of the Magnocellular pathway is a direct consequence of the non-separability of space and time variable in the transfer functions: the spatial transfer function evolves with respect to time.

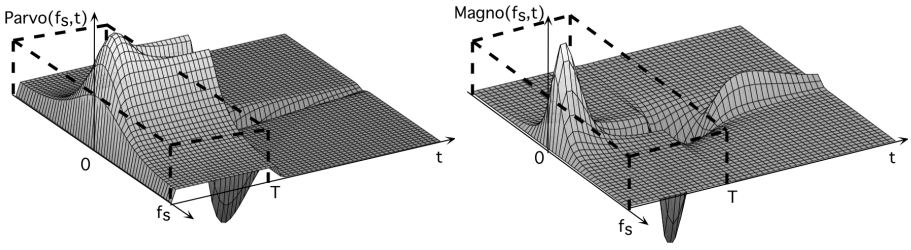

Fig. 4. Temporal evolution of the spatial transfer function of the midget and parasol ganglion cells output for a picture presented between time 0 and time T

A third output picture is obtained by summing the contribution of the ON and OFF parasol ganglion cells outputs. Such a pathway simulates bi-stratified ganglion cells. It responds whenever and wherever something happens in the visual field, and may thus be considered as providing a good saliency indicator.

Finally, A2 amacrine cells have been described that interact with the bipolar cells and enhance their transient behavior. This latter aspect has been modeled as a simple temporal high-pass filter.[23]

3.4. *Originality and interest*

The main originality of this simulation of the different pathways in the retina lies in the non-separability of space and time in the transfer functions we reproduce. This non-separability of the basic retinal filter makes it particularly suitable for processing spatio-temporal complex signal such as motion, and is the key aspect for the parallel computation of the Magno and Parvo pathways. To this day, only analog electronic devices feature, by construction, this non-separability.[9] Software simulation usually separates the temporal filtering from the spatial one which prevent them from reproducing these complex properties.

Here, this non-separability is allied to the flexibility of digital computing. In particular, the space and time constant can be easily modified, so has to be adapted to the user or to the interface's target. Moreover, as the computation of the Magno and Parvo pathway is made in parallel, it is possible to simulate both at the same time on a computer at the standard video rate.

Usually, the arguments given on the functional role of the linear filtering in the retina are the following. The linear filtering stage occurring in the OPL results in a suitable spectral whitening which compensate for the characteristic 1/f amplitude spectrum of natural visual scenes.[27] Thus, the energy in the informative frequency band is enhanced. Moreover, at the IPL level, the selective splitting of the visual information with respect to its spatio-temporal content separates the information into different pathways. These different pathways have different functions: they are respectively dedicated to details (Parvo pathway), to motion (Magno Pathway), and to saliency (Bistratified Magno Pathway). In a visual prosthesis, they could be used separately or combined to better fit the need of the user.

4. Adaptations to the local luminance and contrast conditions

In photopic conditions, luminance values in natural scenes extends to almost 6 decades, and useful signal had to be coded by neuron dynamics into only two. Adaptation is thus a necessary feature of the visual system. Such adaptations in the retina are well documented.[28] They take place at each the OPL and IPL level and are responsible respectively for luminance and contrast equalization.

4.1. *Model*

Adaptation model in the retina is known as a gain control mechanisms.[28,29] We used the Naka-Rushton equation as a model of adaptive non-linearities in both the OPL and IPL layers:

$$Y = \frac{X}{X + X0} \tag{2}$$

where X represents the input light intensity, X0 is the adaptation factor, and Y is the adapted signal. This law is approximately linear for the lowest values of

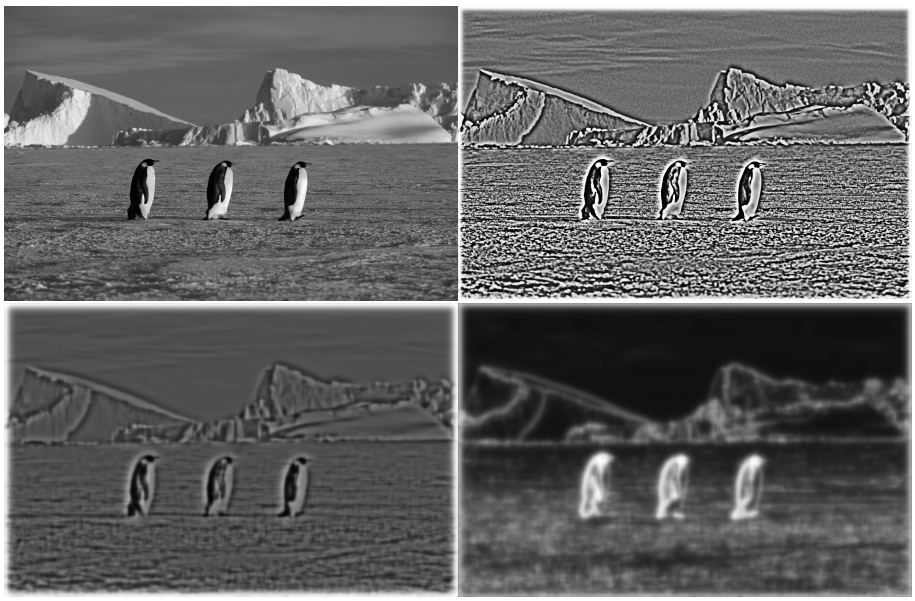

Fig. 5. Linear filtering in the retina. The input picture (top left picture) give rise to three different output. The Parvocellular output (top right) contains the high frequencies of the input, whereas the Magnocellular output (bottom left) contains the low frequency. The bistratified ganglion cells output(bottom right) may be interpretated as a saliency indicator

X. It is proportional to a logarithm for the medium one and then saturate for the highest ones (fig. 6).

The X0 parameter (the half-response stimulus) is subject to adaptation, mainly under the molecular dynamics of light transduction.[30,31] Fig. 6 illustrates the Naka-Rushton function for different values of X0. If X0 is small, the cell's output sensitivity is increased. There are several propositions to tune the adaptation parameter (X0) following the content of the scene. X0 could be determined by the average light reaching the entire field of view, which is a global adaptation factor, similar to a gamma function.[32]. In our model, conversely, X0 is a local variable attributed to each pixel and driven by a local neighborhood summation.[33] In the current simulation, OPL and IPL values of X0 are driven by the output of the horizontal cells and amacrine cells, respectively, which both form a spatio-temporal low pass version of their input signal. Thus, modulation of the light and contrast sensitivities occurs at the local level.

At the OPL level, the local Naka-Rushton law is applied to cones leading to a luminance equalization (fig. 7, middle). At the IPL level, adaptation occurs separately on ON and OFF bipolar cells. This leads to a local equalization of contrasts (fig. 7, right).

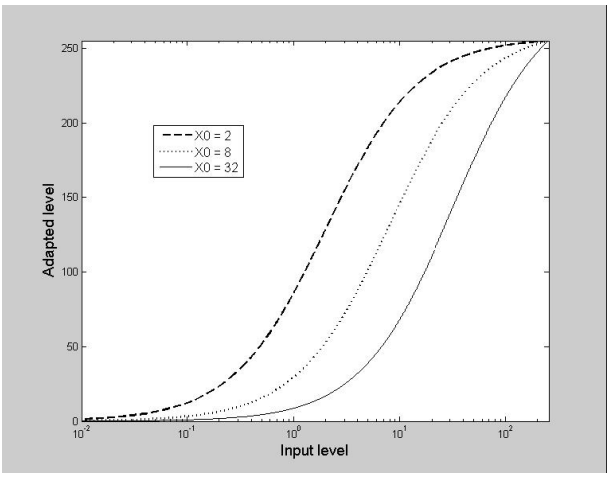

Fig. 6. The Naka-Rushton adaptation law for different values of the adaptation parameter X0. In standard model, X0 is chosen for the whole picture, while in our simulation, it has local values.

Fig. 7. Luminance and contrast adaptation in the retina. Left : input picture ; middle : luminance adapted picture ; right : luminance and contrast equalized picture

4.2. *Originality and interest*

The main originality of our simulation with respect to adaptive behavior in the retina is that the luminance and contrast equalization occur at the local level. These adaptations are illustrated on fig. 7. Numerous details appears after those pre-processings that would have remain invisible under traditional processings.

Away from the fact that it is in agreement with physiological observations [34], such adaptation mechanism is of great interest for visual prosthesis where the number of available levels of stimulation for each point is very limited. By locally adjusting the luminance and contrast level to the same baseline level, local adaptation at the IPL and OPL stage reduces the wide extent of gray levels and gray levels variation in the image.

Finally, the logarithmic behavior of the adaptation law is likely to be of interest

for visual analysis. Indeed, the light level in the image is the product of the overall illumination with the intrinseque reflexion of objects. The adaptation occurring at the cones level can thus be interpreted as a linearization of this product, facilitating the further separation between these two aspects.

5. Cone distribution and space-variant subsampling

Cones distribution at the surface of the retina is highly non uniform.[15,35] Their density is maximal at the center of the retina (the fovea) and then drastically decreases with eccentricity. This particularity is acknowledged as a means to reduce the number of visual fibers while keeping a good central resolution. Furthermore, non uniform sampling on the retina leads to a magnification of the visual information on the cortex following a roughly logarithmic law.[36]

5.1. *Model of non-uniform sampling*

To reproduce this space-variant subsampling and subsequent cortical magnification, we use the following mapping law between an image with periodic arrangement of pixel to an image which distance between pixel vary with eccentricity:

$$\rho' = \rho_{lim} \frac{\rho}{\rho + \rho_0} \tag{3}$$

where ρ is the eccentricity of the pixel of the input picture (stimulation) and ρ' is its position on the photoreceptor's output picture. This mapping is approximately linear for small excentricities and then becomes roughly logarithmic.

As sampling may induce artifacts due to aliasing, we previously apply a space variant low-pass filter to the original picture. As in the retinal filtering stage, we use a recursive spatial low-pass filter for its computational efficiency.[21]

Fig. 8. Space variant photoreceptors subsambling ; from left to right : input picture, space-variant antialising filtered picture; Photoreceptors subsampled picture

5.2. *Originality and interest*

The strong point of our model of space-variant sub-sampling of the input picture is that it follows a law similar to that observed in the visual cortex of primate, and in particular that it leads to a roughly logarithmic mapping of the visual signal for medium eccentricities.

As described by Shwartz *et al.* nerve fibers reduction may not be the only advantage conferred by such a mapping of the visual field.[36] Logarithmic mapping induces many interesting properties, in particular with respect to self motion:

- Size consistency : in peripheral vision, the size of the projection of an object is constant in a large range of viewing distance.
- Speed consistency : the speed of an approaching object do not depends on its position in the frontal plane. This aspect is particularly important for mobility and ego-motion.
- Time to contact : the speed of an object on the cortex is inversely proportional to the "Time-to-contact" with the subject.

An appropriate mapping of the visual signal may thus facilitate the relationship between the activity of the subject and the subsequent modification of the stimulation. Once again, the mapping is adjustable through the parameter ρ_0.

6. The retina simulator

In order to facilitate it's use and to enhance it's flexibility, our simulation software is designed with four basic building blocks: non-uniform sampling, spatio-temporal low pass filter, local gain control and amacrine high-pass temporal filter. Those building blocks may be wired at the user's will. The architecture of the current model of the retina is shown in fig. 9. Demonstrations of the software on videos are available at www.lis.inpg.fr/pages_perso/durette.

7. Discussion

The question of signal processing for visual prosthesis can not be sum up as reproducing at best the behavior of the retina. The field of visual prosthetics is in his infancy and the available interfaces show important limitations with respect to the actual visual system of the primate. Their resolution in particular is limited to at most a few hundred points. This raises question about the actual interest of our simulation of the retina for today's visual prosthesis. Is it always applicable? Is it relevant with respect to the efficiency of the prosthesis? Is the question of signal processing already an important matter with respect to the other challenging problems in designing a visual prosthesis? What are the pre-requisite for such a tool to be usefull?

The question of applicability is easy to answer. As image processing is applied not to the interface image but to the one coming from the video camera, it is in any

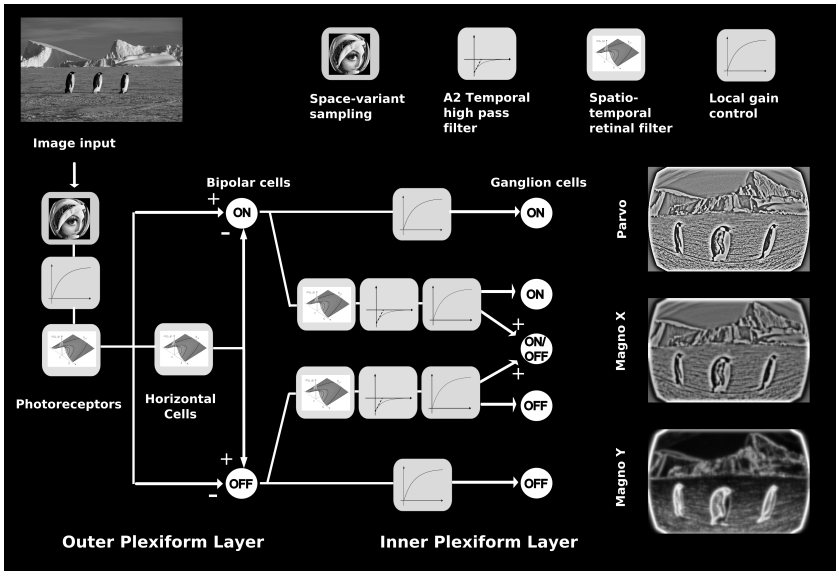

Fig. 9. The retina simulator : it is composed with four different building blocks that can be wired at the user's will. The pictured architecture correspond to the one we present in this paper.

case applicable. With respect to the question of its relevance, however, it is very difficult to make predictions. Most experimental studies on the question of pre-processing have concentrated mainly on the question of subsampling. They were conducted under simulated visual prosthesis situation.[38,39,40,41,42,43,44,45,46,47,48,49] Very simple usual pre-processing stage have also been implemented in a few prosthesis: a sobel filter in Dobelle, a Laplacian of Gaussian filter in Kajimoto, and a space variant subsampling in Capelle.[50,51,52] However, no behavioral tests were conducted. Finally, the four previously cited pre-processing devices mimicking the behavior of the retina dedicated to a visual prosthesis have, to our knowledge, not been implemented nor tested yet. For these reasons, any statement with respect to the interest of signal processing in visual prosthesis remains today as speculations. Considering the biomimetic signal processing devices, however, the argument lies in the efficiency of the visual system itself, and the whole literature acknowledge the crucial role of the retina with respect to this matter.

The question of the relative importance of signal prosthesis with respect to the other design problems remains also, to our opinion, as an open question. Minimalist devices such as the one proposed by Lenay (a sensory substitution system composed with a one and single receptor) had been able to elicit perception of distance.[53] The size of the interface may thus not be the only limiting factor. We believe that signal processing may have as much importance as the design of the interface, and that both should be considered together. The fundamental question lies not in the

interface design nor in the signal processing stage only, but rather in their hopefully relevant combination, as it is the case in the visual system.

With respect to these considerations, the pre-requisite for a signal processing device to be useful in the field of visual prosthesis today is to be as flexible as possible. It needs first to be adjustable to the wide variety of interfaces: retinal or cortical implants, auditory or tactile sensory substitution devices, etc. It needs then to be easily configurable to test the effects of its parameters on the efficiency of the prosthesis and to optimize them. With that respect, our simulation is a very practical tool to address the pre-requisite for a signal processing/ interface combination to efficiently give rise to a form of perception.

8. Conclusion

The smartest sensor we can ever find to address signal processing in visual prostheses is likely to be the retina. Observations on its neural architecture and wiring gave us the opportunity to design a software that reproduces its most significant functions at a standard video rate: non-uniform sampling of the visual information, signal splitting in different pathways with respect to its spatio-temporal content, and local equalization of luminance and contrast. We have also developed a modular and configurable architecture so that the user may manipulate it as he wishes, possibly adapting his pre-processing stage to the user or to the situation (reading, moving, ..).

We presently use this simulator in sensory substitution experiment. A Matlab version as well as a full C simulation is available for research purpose. Migration to hardware solution for embedded devices is already under consideration.

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