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"NEURAL & OPTICAL CHARACTERIZATION RETINAL IMAGE IN THE HUMAN EYE BEYOND THE RESOLUTION LIMIT"

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ABSTRACT : *In a visual search to look at any object that is similar to the target so that it can be recognized and a decision made to end the search. Image processing by the eye is the example of concatentated linear filters followed by a sampling operation. The first filter is optical and is characterized by an optical point-spread function. The second filter is neural and is characterized by the neural point spread function, which is shown to be related to the receptive fields of retinal neurons. Sampling renders the internal " neural image" a discrete signal subject to the effects of aliasing. Conditions responsible for aliasing are formulated in terms of the amount of overlap of retinal samplers. Evidence of aliasing in human vision is presented along with a simulation of an aliased neural image in the peripheral visual field. In this paper, also discussed a new method for locating eye pairs based on valley field detection and measurement of fractal dimensions is proposed. Fractal dimension is an efficient representation of the texture of facial features. Possible eye candidates in an image with a complex background are identified by valley field detection.*

Keywords *- Nyquist limit, parafoveal region, central and mid-peripheral vision, neural image*

I. INTRODUCTION

Understanding the movement of the eye over images is critical for improving our ability to manage and exploit image data. Eye tracking experiments have been performed for various purposes such as understanding the human visual process and improving access to digital data.

Initial processing of visual input by the eye can be conceived as a two-stage process. The first stage is low-pass spatial filtering which occurs when the eye's optical system forms a retinal image. The second stage involves the sampling of the continuous optical image by a discrete array of retinal neurons. Although the transduction of light into neural signals is performed by the tiny photoreceptor cells of the retina, signals from many receptors are pooled by subsequent second-order retinal neurons and again by the third-order neurons which form the optic nerve. These pooling operations cause further spatial filtering of the discrete, neural representation of the visual scene.

Taken together, optical and neural spatial filtering causes each optic nerve fiber to be receptive to light over an appreciable area of the visual field.Thus, we may begin to describe the early stages of visual processing by modelling the retina as a locally homogeneous array of neurons in which each neuron samples the retinal image by summing over large, overlapping regions. The purpose of this paper is to develop such a model and then use it to assess the importance of optical and retinal processing on image coding in the human visual system.

Although the behavior of human optic-nerve fibers has never been observed experimentally, recent optical

and perceptual experiments on humans and also physiological and anatomical experiments on animal models yield a clear picture of their likely characteristics. Thus, part of the motivation for this paper was to succinctly present the main features of physiological optics and retinal architecture for the non-specialist who is interested mainly in the constraints placed on the man-machine interface by early stages of visual processing.

II.CHARACTERIZATION OF THE NEURAL IMAGE

The purpose of the next section is to introduce the concept of a neural image and to describe its primary attributes following the early stages of visual processing. Linear filter theory is used to develop a quantitative model of the neural image as a way of accounting for the effects of optical and neural spatial filtering performed by the eye and to account also for the effects of neural sampling. In section it will be shown that throughout the retina, with the exception of a central region called the fovea, the array of optic fiber neurons undersamples the retinal image. This occurs because their spatial density is well below the Nyquist limit required to faithfully represent the retinal image. Parameters of the model are estimated from recent experimental data and the results used to account perceptual aliasing in human vision.

2.1 Stages Of Signal Processing In The Eye

2.1.1 Optics

Vision begins with the formation of a light image upon the retina by the optical system of the eye as illustrated in Fig. 1. Optical imperfections and diffraction inevitably reduce image contrast in a way that may be described as low-pass spatial-filtering. If pupil diameter is less than about 2.5 mm, optical quality of the human eye for foveal vision can be nearly diffraction limited but for larger pupils, ocular aberrations limit any further improvement in retinal image quality1. Recent experiments have shown that peripheral optical quality out to 30 deg of eccentricity is about the same as in the fovea2. So, at least for central and mid-peripheral vision through a mid-sized pupil, it is not unreasonable to suppose that the optical system of the eye is a linear, shift-invariant system. Accordingly, we may calculate3 the retinal image $i(x)$ by convolution *(k)* of the point spread function *(p.s.f.)* of the eye $p(x)$ with the intensity distribution of the object $o(x)$. Thus the first stage of the visual system will be characterized by the equation,

$$i(x) = o(x) \text{ k } p(x) \qquad (1)$$

Where x is a unitless dimension in a Cartesian coordinate reference frame and is related to the visual direction e by the equation $x=\sin(\varepsilon)$.

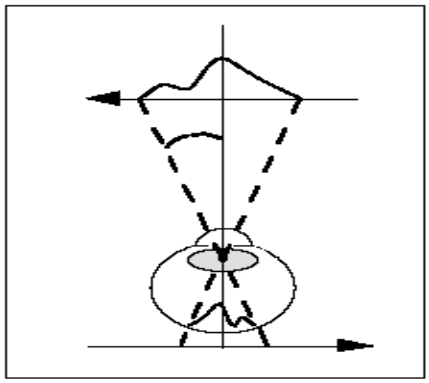

Fig. 1 A coordinate reference frame for vision.

2.1.2 Transduction

Neural processing of the retinal image begins with the transduction of light energy into corresponding

changes of membrane potential of individual photoreceptor cells. Photoreceptors are laid out in a thin sheet which varies in composition across the retina. At the very center of the foveal region, which corresponds to our central field of view, the photoreceptors are exclusively cones but in the parafoveal region rods appear and in the peripheral retina rods are far more numerous [3]. This paper will emphasize daylight vision by cones. Each cone is thought to integrate the total amount of light energy entering the cell through its own tiny aperture just a few microns in diameter. Since this entrance aperture is wholly within the body of the cone, it will not physically overlap the aperture of neighboring cones. (This is not to say that a point source of light will only stimulate only one cone at a time. In fact, the optical system of the eye will spread the image of a point source over a retinal area which may include several cones.) Based on this arrangement of the cone mosaic, we may characterize the first neural stage of the visual system as a sampling process wherein a continuous retinal image is transduced by an array of nonoverlapping samplers. The result is a discrete array of neural signals which will be called a "neural image".

2.1.3 Optic nerve output

The optic nerve in humans contains roughly one million individual fibers, each of which is an outgrowth of a third order neuron of the retina called a ganglion cell. In general, ganglion cells are functionally connected to many rods and cones by means of intermediate, second order neurons. As a result, a given ganglion cell may respond to light falling over a relatively large region of the retina called its "receptive field", with the middle of the field typically weighted most heavily. The neural connectivity underlying the receptive fields of ganglion cells is known well enough for mammals to draw a schematic wiring diagram[2] which we presume to be a reasonable blueprint for humans as well. Neighboring ganglion cells may receive input from the same cone, which implies that receptive fields of third-order neurons can overlap. In the highly specialized foveal region, however, the receptive fields of ganglion cells are about the size expected for individual cones which gives rise to the notion of essentially one-to-one connectivity of cones to ganglion cells[3].

Ganglion cells come in many varieties, but one particular class (denoted β-cells) seems to dominate throughout the primate retina. Physiological experiments on cat and monkey indicate that a β -ganglion cell responds to a linear combination of light falling on its receptive field. Accordingly, a mathematical model of a β -ganglion cell should be designed to respond by amount *r* to the light falling within its receptive field (*rf*) according to the equation.

$$r = \int_{rf} w(x) \cdot i(x)\ dx \qquad (2)$$

Where *w(x)* denotes the spatial weighting function of the receptive field. Such a model is common currency among neurophysiologists. Notice that by concentrating here upon the weighting function *w*(*x*) for the output neurons of the retina we subsume the effects of two previous stages of neural processing, namely, sampling by photoreceptors and manipulation of the cone neural image by second-order inter-neurons. Also note that for the present investigation of spatial vision it is not necessary to consider the final stage of retinal processing in which the time-continuous quantity *r* is encoded (perhaps nonlinearly) for asynchronous digital transmission along the optic nerve.

2.2 Spatial Description Of The Neural Image

The goal of this section is to build upon the framework erected above in order to give a mathematical description of what the neural image looks like as it leaves the eye *via* the optic nerve. A global analysis encompassing the whole of the visual field is too difficult to attempt here because of the complications introduced by retinal inhomogeneity between fovea and periphery. Instead, attention will be focussed on a local region where the neural architecture of the retina is relatively uniform. Accordingly, consider a homogeneous population of β -ganglion cells which are responsible for representing the retinal image in a small patch of retina as illustrated in Fig. 2. Although the visual field is two dimensional, a simpler one dimensional analysis will be sufficient for developing the main results which follow. By the assumption of homogeneity, the weighting function of each receptive field has the same form but is centered on different *x* values for different neurons. The cells need not be equally spaced for the following general results to hold.

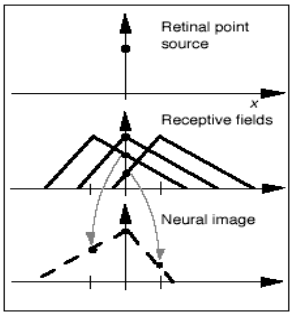

Fig. 2. Neural image for a point source of light on the retina.

If we let *xj* be the center of the receptive field of the *jth* neuron in the array, then the weighting function for that cell will be

$$w_j = w(x - x_j) \qquad (3)$$

And the corresponding response *rj* is found by combining (2) and (3) to give

$$r_j = \int_{rf} w(x - x_j) \cdot i(x)\ dx \qquad (4)$$

It is important to emphasize at this point that although the neural and light images are distinctly different entities, they share a common domain. In other words, both kinds of image are functions of *x*, the visual direction. Thus, implicit in our reasoning is that when the *jth* output neuron responds at level *rj* it is sending a message to the brain that a certain amount of light has been received from visual direction *xj*. Because of the regional specialization of the retina, the difference between visual directions of neighboring cells is small in the fovea and large in the periphery. Consequently, on a global level the neural image is spatially distorted causing the fovea to be highly magnified in comparison with the periphery. Such distortion is a prominent feature of the primate visual system which is accentuated further in higher visual centers of the brain[4]. This complication will be avoided in the present analysis by assuming local uniformity of scale.

III. FIDELITY OF THE NEURAL IMAGE

3.1 Aliasing In The Neural Image

If low-pass filtering by visual neurons is to be an effective anti-aliasing filter, then neural receptive fields must be relatively large compared to the spacing of the array. We can develop this idea quantitatively without detailed knowledge of the shape of the receptive field weighting function by employing Bracewell's equivalent bandwidth theorem[5]. This theorem, which is based on the central ordinate theorem, states that the product of equivalent width and equivalent bandwidth of a filter is unity. By definition, the equivalent width of a function is the width of the rectangle whose height is equal to the central ordinate and whose area is the same as that of the function.

In the present context, the equivalent duration of the neural filter is the equivalent diameter *dx* of the constituent receptive fields. To avoid aliasing requires that the spatial frequency bandwidth of the weighting function *w*(*x*) be less than the Nyquist limit as set by the characteristic spacing *s* of the array. If we adopt the equivalent bandwidth as a measure of the highest frequency passed to any significant extent by the filter, then by applying Bracewell's theorem we find that the requirement is for $dx > 2s$. That is to say, aliasing will be avoided if the equivalent radius of the receptive field exceeds the spacing between fields.

A similar line of reasoning can be developed for two-dimensional receptive fields. Assuming radial symmetry of the fields, Bracewell's theorem states that the product of equivalent width *dx* and equivalent bandwidth

Df is 4/∏. Since the Nyquist requirement for anti-aliasing is that *Df* <1/2*s*, this means that we need *dx*>8s/∏. In other words, aliasing will be avoided if the equivalent radius of the receptive field exceeds 4/ ∏ times the spacing between fields, a slightly more stringent requirement than found above for the one dimensional case.

3.2 Aliasing In Human Vision

Aliasing caused by neural undersampling can only occur if image frequencies beyond the Nyquist limit are present on the retina. It is technically possible to avoid low-pass filtering by the eye's optics with an interferometric visual stimulator.By using such a device it has been possible to demonstrate the existence of aliasing both foveally[6] and in the peripheral field[7]. This psychophysical evidence unequivocally shows that at least some optic nerve fibers are not protected from aliasing by neural filtering. When the eye's natural optical system is allowed to form the retinal image in the normal way, aliasing still occurs in the peripheral field but not foveally[8] as shown in Fig. 3. In the figure key, detection acuity means the highest frequency which is visible (as an alias)whereas resolution acuity means the highest frequency perceived veridically (i.e. does not alias). When compared to anatomical estimates of sampling density[9], it is evident that the lowest frequencies aliased in the periphery are well below the Nyquist rate for cones but match reasonably well the Nyquist rate of retinal ganglion cells (RGC).

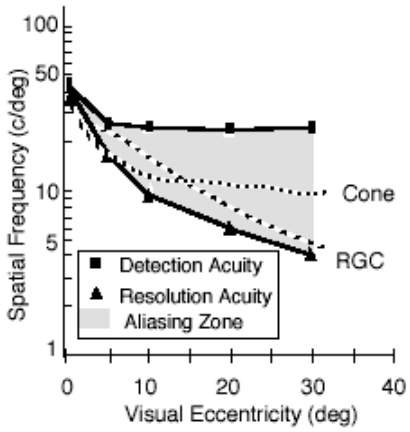

Fig.3 Aliasing spectrum in human vision

The explanation of this state of affairs is that the eye's optical system does not pass spatial frequencies beyond about 60 c/deg, which is about the Nyquist limit for the foveal population of optic nerve fibers. Thus under normal viewing conditions, the fovea is protected from aliasing because of optical, rather than neural, filtering. In the periphery, however, such high quality optics are ineffective as an anti-aliasing filter. Evidently, neural filtering also is insufficient to prevent aliasing entirely, although it may substantially reduce the magnitude of aliased signals.

IV.ESTIMATION OF FRACTAL DIMENSION

This work is supported by RGC Grant B-Q322 and the Centre for Multimedia Signal Processing, Poly U. box-counting [11],[12] can be used to estimate the fractal dimension. The box counting method is an efficient technique for estimating fractal dimensions, and it can be applied to gray-level images and binary images, as described below.

The differentlal box-counting approach[11] has been used to estimate fractal dimensions. This method counts the number of boxes that cover the image intensity surface. The surface can be considered as a 3D space in which the two coordinates *(x,y)* represent the 2D position and the third coordinate *(z)* represents the image gray-level intensity. For a given image of size *I X I,* the image is partitioned into grids of size *SXS.* The grids are numbered as *(i,j),* where $0 \leq i\ j < r$ and $r = [I/S]$. Each grid is stacked with a column of boxes of size *SXSXS'.* Suppose that the maximum gray-level intensity is G, then ***[G/S']= [I/S]***

The boxes on a grid are assigned **a** number with the box at the bottom **as** box one and the one on the top **as** *[G/S']*. If the minimum and maximum gray-levels of the image in the *(i,j)th* grid fall in the boxes numbered *k* and *1,* respectively, then

$$nr(ij) = 1 - k + 1$$

Where $r = [\ I / S\ ]$ and $0 \leq i,j < [I/S]$**.** *n,(i,j)* represent the number of boxes covering the image intensity surface over the *(i,j)th* grid, as shown in Fig. 1**.** The total number of boxes required to cover the surface **is**

$$N_r = \sum_{i,j} n_r(i,j)$$

With different grid size *S,* different values of ***r*** and *Nr* can be obtained. The fractal dimension can then be estimated from the least-square linear fit of ***log(Nr)*** against ***log(1/r).***

For binary images, only two levels exist: black and white. A black pixel represents an image point or an edge point, while a white pixel is regarded **as a** point in the background. *An* image of size *I X I* **is** divided into grids of size *S X S.* At each grid, the number of boxes, *nr(i,j),* that contain any black pixels is counted. The total number of boxes over all the grids is denoted **as**

$$N_r = \sum_{i,j} n_r(i,j)$$

Where *i j* , = 1,. . ..., *I/S* and
r = *[I/S]*. The grid size *SXS* **is** changed such that different values of ***r*** and the corresponding total box count *Nr* are obtained. Again, the fractal dimension can be estimated by using the least-square linear fit of **log *(Nr)*** against log *(1/r).*

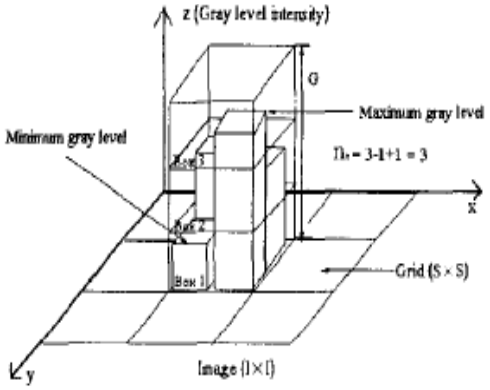

Figure **1:** Estimation of fractal dimension for **a** gray-scale image using the box-counting technique

V.VALLEY DETECTION OF THE EYES

As the iris has a relatively low gray-level intensity in a human face, a valley exists at an eye region. The valley field, *Øv,* is extracted by means of morphological operators. A possible eye candidate is identified at position *(x,y)* if the following two criteria are satisfied:

$$f(x,y) < t_i \text{ and } \Phi_v(x,y) > t_v \qquad (1)$$

Where *f(x,y)* is a facial image, and ti and tv are thresholds. A number of regions of possible eye candidates are detected, and are then reduced to **a** point by choosing the best candidate in each of the regions. Two functions,v1(x,y)and v2(x,y) are used to locate the best eye candidate in each region. The two functions are defined as follows:

$$v_1(x,y) = C_{1,1}\Phi_{1,1}(x,y) + C_{1,2}\left(\frac{f(x-2,y)+f(x+2,y)}{2} - S_{1,1}(x,y)\right)$$

$$v_2(x,y) = C_{2,1}\Phi_{2,1}(x,y) + C_{2,2}\left(\frac{f(x-3,y)+f(x+3,y)}{2} - S_{2,1}(x,y)\right) \qquad (2)$$

Where C's are weighting factors,
Øl,l(x,y) and *S1,1(x,y)* are the average valley intensity and the average gray-level intensity inside a 3x3 window, respectively, while *Ø2,l(x,y)* and *S2,1(x,y)* are the corresponding values inside a 5x5 window.

CONCLUSION

In this paper, we have proposed Image processing by the eye by linear filters followed by a sampling operation. In that the first filter is optical and is characterized by an optical point-spread function. The second filter is neural and is characterized by the neural point-spread function, which is shown to be related to the receptive fields of retinal neurons. And also we have proposed an oriented fractal dimension to accurately extract eye pairs in a complex image. Instead of searching the whole image space to determine the different scales of the eye pairs, only possible eye pairs are investigated. These possible eye pairs are identified by means of valley detection and by measuring their fractal dimensions.

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