A neural network based model of M and P LGN cells

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Abstract— A new excitatory-inhibitory neural network model for the extended classical receptive field (ECRF) of Parvo (P), and Magno (M) cells in the lateral geniculate nucleus (LGN) is proposed. The model is based upon various well-known findings in neurophysiology, anatomy and psychophysics. The top-down linking of the proposed model to the feed-forward pathways, that is able to explain the simple, yet intriguing problem of brightness perception, may have implication in developing robust visual capturing and display systems, as well as in overall accurate representation of images as has been demonstrated in recent works.

Index Terms—receptive field; cortico-geniculate feedback; attention network; brightness induction

I. INTRODUCTION

OMPUTATIONAL models in visual perception have generally been found to pay less attention to the lateral geniculate nucleus (LGN) when compared to the V1 neurons or even the retinal ganglion cells, between which it is interposed. It is well-known that, the classical centresurround receptive field model of retinal ganglion cells proposed many years back [1] has been successfully employed to account for various brightness induction effects [2]. On the other hand, a unified explanation of many other brightness perception phenomena required the invocation of multi-scale models of cortical filtering [3-8]. In between, the role of LGN was seldom explored in addressing these issues. As we know, in any feed-forward neural network model, it is the ordered arrangement of the bottom-up inputs from lower areas that determine the selectivity of a neuron higher up. Following such a mechanism, an explanation on the orientation selectivity of cortical cells in V1 was provided in the famous works of Hubel and Wiesel [9] based on the ordered arrangement of the geniculate inputs. Early anatomical evidence regarding such ordered arrangement suggested that one of the variants of the LGN neurons known as the magnocellular (M) cells follow a pathway to layer $4C\alpha$ in V1, then to 4B and continuing up to MT or beyond, either directly or through V2. The parvocellular (P) LGN cells, in the same way, follow a different parallel path and consequently lead to a separate projection in another subregion of the layer 4 of striate cortex. These parallel pathways are maintained all through V1 and even to higher visual areas [10, 11]. Our

foremost attempt in this work would be to understand the functional mechanism of these two main classes of LGN cells, viz. M and P in terms of such a feed-forward mechanism.

These two principal visual pathways are complementary channels in various respects. For instance macaque M cells have almost no chromatic opponency, have rod inputs, possess lower spatial resolution and higher temporal resolution; P cells on the other hand are almost the opposite: have well-developed chromatic opponency, negligible Rod inputs, higher spatial resolution and lower temporal resolution [10].

However, contemporary anatomical evidences have also been raising doubts about such simple parallelism in visual pathways. They have been pointing more and more to possible vertical interactions within the V1 columns that would consequently lead to a blending of information originating in the P and M LGN cells [11, 13].

Furthermore there are enough reasons to believe that the domain of vertical interactions in the cortex, may extend further downwards in the visual system. Such a notion arises from the anatomical fact that there exists a massive projection from layer V1 of visual cortex back to the LGN, which far surpasses the forward projection both from retina to LGN and from LGN to visual cortex in terms of fiber number. As a matter of fact, this finding now remains, to date, one of the most baffling riddles in neurophysiology. Nevertheless, this goes on to show that the LGN can possibly act not merely as a relay station, it may be the first feedback station too, in the visual system. Some early data on the A-laminae cat LGN [14] may come handy in establishing such a theory. It shows that on one hand, the X pathway in cat (which is possibly homologous to the P pathway in primates) has about 9x10⁴ axons from retina to LGN, which synapse on to some 17.5x10⁴ relay cells, and similarly the Y pathway in cat, that is homologous to the M pathway in primates, has 10⁴ axons synapsing on to 12.5×10^4 relay cells. The cortico-geniculate pathway, this data shows on the other hand, contains 400 x 10⁴ axons synapsing on to the X and Y relay cells in the Alamina. This implies that the net cortical input to the LGN is as much as 40 times bigger than the retinal input, and 13 times bigger than the reciprocal LGN to cortex pathway.

Thus, in the issue of modelling the LGN, one would like to dwell upon both the bottom-up (feed-forward) as well as the top-down (feedback) aspects.

I. A NEW MODEL OF CHANNEL SELECTION IN THE LGN

It has long been shown that the geniculate cells do not differ drastically from those of ganglion cells and in fact like the retinal ganglion cells, they too possess concentrically arranged antagonistic receptive fields [16, 17], i.e. what is known as the Classical Receptive Field (CRF). Physiologists have, accordingly, proposed a Difference of Gaussian (DoG) model for the classical receptive field of both the retinal ganglion cells[1] as well as of the LGN cells [18]. In one dimension, the mathematical construct for the DoG model is:

$$DoG(\sigma_1, \sigma_2) = A_1 e^{-\frac{x^2}{2\sigma_1^2}} - A_2 e^{-\frac{x^2}{2\sigma_2^2}}$$
(1)

where, A_1 and A_2 represent the weights, while σ_1 and σ_2 represent the scales of the classical centre and the antagonistic surround respectively.

Although the DoG model was successful in explaining low-level brightness-contrast phenomena Simultaneous Brightness Contrast (SBC), there were several others especially related to brightness assimilation like the White's illusion, which could not be explained with this lateral inhibition based model [8,15,20]. On the other hand, the physiologists have also been observing that the even beyond the CRF of a ganglion or an LGN cells, there exists many cells that are capable of influencing electrophysiological property of the ganglion or retinal cell concerned [12, 21-25]. Such additional cells beyond the CRF constitute what is frequently referred to as the extended surround. It has been shown for ganglion cells [15] that three Gaussians of three different widths $\sigma 1$, $\sigma 2$ and $\sigma 3$ may, to a large extent, model the classical center, the inhibitory surround and the extended disinhibitory surround respectively. As we have already stated, since the receptive field organisation of the cells in the geniculate nucleus do not differ considerably from their retinal counterparts and because similar Extended Classical Receptive Fields (ECRF) for the Parvocellular (P) and the Magnocellular (M) cells are also reported to be present in LGN [12], we therefore propose this model for the ECRF of LGN cells:

$$ECRF(A_1, A_2, A_3, d) = A_1 e^{-\frac{r^2}{2\sigma_1^2}} - A_2 e^{-\frac{r^2}{2\sigma_2^2}} + A_3 e^{-\frac{r^2}{2\sigma_3^2}}$$
(2)

We also propose that equation (2) which model the LGN ECRF, actually represents two different spatial filters. One of these corresponds to the extended classical receptive field of the P LGN cell, while the other to the ECRF of M LGN cell. Our proposal regarding the parameters like the sampling intervals and weights for each of centre, surround and extended surrounds for these two spatial filters is listed in Table 1:

Table 1: Spatial filters for the parallel visual channels

Filter parameters	A_{l}	A_2	A_3	d
The LGN cell types				
The Parvocellular	10	0.5	0.01	0.25
LGN ECRF (P)				
The Magnocellular	10	1	0.08	0.5
LGN ECRF (M)				

Although the parameter values are inspired by previous work [15, 35], the values used here are modified so as to make task of the comparison among the two filters easier. The M channels being fed by a relatively larger number of photoreceptors, have larger weights and values of the classical inhibitory, the third Gaussian in eq. 2 (A_2 and A_3), and the spatial sampling interval (d), respectively.

We now propose our vision model based on the Reverse Hierarchy Theory (RHT) [29] which envisages that initially there occurs a completely pre-attentive and directly bottom-up vision at a glance to be followed up later by a vision with scrutiny meant for including attention-guided indirect conscious perceptual constructs. Interestingly, based on the visual latencies in various cortical areas, it has been argued [27, 28] that all such characteristics of the M pathway discussed above like faster conduction, poor chromatic selectivity etc. make it an ideal candidate for the initial vision at a glance. Our proposal here is that attentive vision involves a final choice of channel based on the initial information extracted in the visual cortex through the M pathway and subsequent feedback to LGN. Our proposal of a cortical level mediated algorithm for attentive vision, to send feedback the LGN layer, based on which the final channel selection may be implemented is as follows.

if (the initial M channel output identifies that the background around the test patches is $UNIFORM^*$)

```
{
    P channel is invoked for attentive vision, and the brightness percept is formed by P.
}
else

{
    M channel itself produces the brightness percept.
}
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*UNIFORM background means that the M channel output satisfies:

(EITHER) Condition 1[#] (OR) Condition 2[~]

*Condition 1: UNIFORMity is judged with respect to the absence of sharp intensity changes in the background (to be specified later) outside the test patch in the form of adjacent undershoots and overshoots with crossings in between, similar to that envisaged by Marr and Hildreth [19]. In other words, the vertical and horizontal line profiles of the

background above, below and on either side of the test patch do not contain contrast edges for such uniform backgrounds;

~Condition 2: UNIFORMity is judged with respect to the direction of Weber contrast across the horizontal and vertical edges of the test patch. In other words, if the Weber contrast of the test patch with its background is unidirectional (i.e. has the same sign) both across its horizontal and vertical edges, we refer to it as a high contrast surrounding or directionally uniform background for the test patch. If it is not so (i.e. Weber contrast is bi-directional, having opposite signs across the two edges), we refer to it as a low contrast surrounding or directionally non-uniform background for the test patch.

II. RESULTS AND DISCUSSION

Marr and Hildreth [19] proposed a scheme for the detection of contrast edges in the form adjacent undershoots and overshoots (or level crossings) in neural responses in cortical simple cells by a sort of AND gate connection of two nearby on- and off-centred LGN cells (substantiated later by physiologists [30, 31]). Our proposal is that the detectors in the cortex looks for such edges as crossings in the form of adjacent undershoots and overshoots in the vicinity of the test patches in the M channel filtered image. When such crossings are detectable by the initial *vision at a glance* through M, like for example as shown by the arrows in Fig.1 where the classical White's stimulus has been filtered through our proposed M channel and horizontal line profiles have

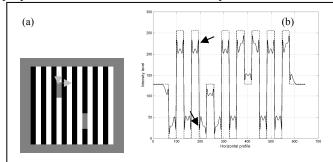


Fig 1 (a) The classical White stimulus (b) Corresponding intensity profile (a line (solid) is drawn horizontally through the test patches on the two different bars, viz. black and white) of the output image spatially filtered through the proposed ECRF of M LGN cells. Dashed line indicates actual intensity profile. The output follows the experimental observation on brightness percept, viz. assimilation in horizontal direction. The arrows indicate the adjacent undershoots and overshoots in neural responses where sharp intensity transitions occur.

been drawn through each of the test patches in the filtered image, we would say that *Condition 1* for uniformity identification, in our algorithm, is violated.

In this classical White effect, the output (Fig. 1b) for M channel filtering displays that both *Condition 1* and *Condition 2* for uniformity test is violated. The violation of *Condition 1* is evident from the adjacent sharp undershoots and overshoots around the test patches (Fig. 1b) indicating the presence of contrast edges, which can be verified by running any standard edge detector, while that of *Condition 2* is easy to see since the Weber contrasts across vertical and horizontal edges are of

opposite sign, as is evident from the two arrows in Fig. 1a, a situation that we refer to as *low contrast*. Hence M remains the preferred channel for classical White effect.

On the other hand, let us consider the classical Simultaneous brightness contrast (SBC) stimulus [26] as is evident from Fig. 2. Here both *Condition 1* and *Condition 2* are obeyed in the initial M filtered output. In Fig. 2b for example we show how a line profile in any direction around the test patch in the filtered image (like for example, the single arrow across the white region in Fig 2a), shows no discontinuity, i.e. complete absence of contrast edge which means *Condition 1* is satisfied. Similarly it is easy to see that the Weber contrast is unidirectional for the two lower arrows through the patch in Fig. 2a, so *Condition 2* for uniformity is obeyed as well. P channel therefore is the decisive winner. The output for P channel filtering explains the simultaneous brightness contrast.

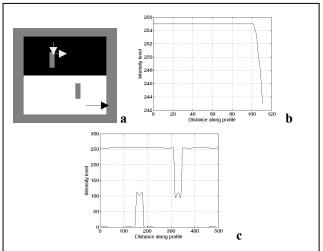


Fig. 2 (a) With further filling in, in continuity of the previous examples, emerges the classical Simultaneous brightness contrast (SBC) stimulus (b) The horizontal background profile of the M filtered image in the lower region of the test patch as marked by the bottom-most arrow, indicating the identification of uniformity in the background, i.e. satisfaction of *Condition 1*. In the same vein, as marked by the two arrows across the edges of the test patch, the Weber contrast is directionally uniform in the M filtered image, which implies satisfying *Condition 2*. P channel is therefore the decisive winner. (c) Horizontal intensity profiles through each of the two test patches of the output image spatially filtered by P channel demonstrating brightness-contrast percept as also observed in psychophysical experiments.

Now, to further investigate whether the proposed models of LGN cells can actually provide any clue to such RHT based vision at a glance and vision with scrutiny respectively, let us apply the proposed filters to a practical situation of processing real images (i.e. outside of the typical psychophysical stimuli). We find from Fig. 3, that the M channel filtering action blurs the image to some extent (Fig. 3b) while at the same time it more or less preserves the contrast-edges. The P channel, on the other hand, behaves more like a classical derivative filter. It enhances the overall contrast.







Fig. 3 (a) The egg-on-a-plate image that is often used by the image processing community. (b) The result of spatial filtering through the proposed ECRF model M LGN cells. It shows that this filter basically performs blurring but the contrast edges, though suppressed, are preserved. (c) The result of spatial filtering through the proposed ECRF model P LGN cells. It shows that this channel performs less suppression of the contrast edges and hence preserves the contrast information better compared to the M filter.

The results and explanations presented above also inspire one to envisage the cortex as a body containing several sources of multiple expertises, like several different constraints on a problem, where each expert has his own conjecture according his knowledge base. In our case, in order to make an initial gist representation of the visual scene, these may be the modules which are edge detectors and those which check for non-uniformity of intensity level (through Weber contrast) in both horizontal and vertical direction in the four immediate neighbourhoods to the objects of interest, as explained above. This means that the decisions towards gist formation are possibly arrived at through some kind of voting based on the dendritic inputs of the thalamic cells. In this respect the proposed model provides bottom-up back up to the 'blackboard' metaphor for the thalamus [32].

III. CONCLUSION

In this work, we have been able to suggest a possible mechanism by which the visual system at low-level feeds topdown information to the LGN, which is extracted in the visual cortex based on the output of an initial sensorial percept through the faster M cells, and thereby making a contextdependent final choice of channel from amongst these two. It has been shown that the perception of brightness in the region of attention is a consequence of such pathway selection. The proposed mechanism thus provides a possible explanation to many riddles in psychophysics, like for instance it explains categorically why in White effect the direction of brightness induction has no consistent correlation with the proportion of black or white border in the neighborhood of the test patches, that necessitated many Gestalt explanations like T-junction analysis coming from the psychologists. Apart from this basic goal to arrive at unified computational models for both psychophysics and neurobiology in order to understand the theory of visual perception, there is a possible potential application of the model in designing smart new generation display systems with the ability to automatically detect and correct any incoherence in the perceptible luminance of the display panels. This can be especially important in defense related or medical imaging applications where accurate perception of the luminance level can be very critical. In fact in very recent works, [33, 34] it has been elaborately demonstrated how similar non-classical receptive fields may lead to actual implementation of what has been predicted by our proposed model, viz. a bio-inspired hierarchical neural

network that can accurately represent visual images bottom-up and then facilitate top-down processing at very low processing cost. The present LGN model is a simpler as well as better alternative in terms of possible neural correlate, since the most reputed cortical ODOG model, which can explain brightness perception with some limitations [36], also suffers from the problem that there is no physiological evidence of contrast normalization that is a crucial part of the ODOG algorithm [37].

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