A Neurodynamic model of Saliency prediction in V1

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Abstract—Computations in the primary visual cortex (area V1 or striate cortex) have long been hypothesized to be responsible, among several visual processing mechanisms, of bottom-up visual attention (also named saliency). In order to validate this hypothesis, images from eye tracking datasets are processed with a biologically plausible model of V1 able to reproduce other visual processes such as brightness, chromatic induction and visual discomfort. Following Li’s neurodynamic model, we define V1’s lateral connections with a network of firing rate neurons, sensitive to visual features such as brightness, color, orientation and scale. The resulting saliency maps are generated from the model output, representing the neuronal activity of V1 projections towards brain areas involved in eye movement control. Our predictions are supported with eye tracking experimentation and results show an improvement with respect to previous models as well as consistency with human psychophysics. We propose a unified computational architecture of the primary visual cortex that models several visual processes without applying any type of training or optimization and keeping the same parametrization.

Index Terms—Saliency, dynamical, network, biological, firing rate, attention, visual cortex, DWT, V1.

I. INTRODUCTION

V

ISUAL salience can be defined as “the distinct subjective perceptual quality which makes some items in the world stand out from their neighbors and immediately grab our attention” [33]. In order to understand how visual information is predominantly selected for controlling eye movements, several studies proposed different approaches. Koch and Ullman [56] propose a computational framework in which visual features are integrated to generate a saliency map. These visual features are projected to V1 and later processed distinctively on the ventral (“what”) and dorsal (“where”) streams. These connections are projected to the superior colliculus (SC), which would generate either top-down (relevance) or bottom-up (saliency) control of eye movements by combining neuronal activity from distinct brain areas to a unique map (priority map) [23] [78]. Given these distinct levels of processing from the human visual system (HVS), a set of computational models are proposed in order to reproduce eye movement behavior. Itti et al. introduce a biologically-inspired model [34] in which low-level features are extracted using linear DoG filters, their conspicuity is calculated using center-surround differences (inspired by V1’s simple cell computations) and integrated (pooled to the SC as a master saliency map) using winner-take-all (WTA) mechanisms. Although computations of existing saliency models seem to mimic HVS mechanisms, complexity of scenes make eye-movement behavior hard to predict. Bruce & Tsotsos model [11] offered a semi-supervised mechanism to account for relevant information of the scenes in combination with the bottom-up computations of V1, predicting eye movement behavior at distinct scene contexts. Given the basis of these models, a myriad of computational models, both with artificial and biological inspiration [35] [6] [84] [64], have implemented distinct ways to predict human eye movements obtaining better performance on its predictions [63] [8] [9] [13]. Whether proposed computational eye movement prediction models precisely resemble eye-tracking data, it is questionable to consider that these predictions accurately and specifically represent saliency [10] [43].

Li’s work [43] [44] [45] [86] proposes that V1’s computations are the ones responsible of the representation of the aforementioned saliency map. Following her work, the role for the early processing of the visual features relies in V1, which projects to the SC in order to generate bottom-up saccadic eye movements [66] [67] Chapter 9 [79], mainly driven for this case by uniquely processing low-level visual features. In previous studies [59] [16] [61], we show that the proposed firing-rate neurodynamic model of V1’s intra-cortical interactions is able to reproduce brightness and color induction effects (as if V1 acted for such as a contrast enhancement mechanism) as well as visual discomfort mechanisms. We aim to use this exact model in order to compute feature conspicuity (distinctiveness between feature maps), which will alternatively represent the function of the aforementioned saliency map. In this study we will demonstrate that the computations for our model are able to reproduce eye movement behavior using eye-tracking experimentation with a trend to acquire state-of-the-art results in comparison to other saliency models as well as to be consistent with psychophysical measurements of saliency.

Reproducing other visual effects

Brightness induction refers to the changes in perceived brightness of a visual target due to the luminance of its surrounding area. From this statement, the HVS can either perceive the visual target and the surrounding area with similar/equal brightness (assimilation) or to perceive brightness differences (contrast). We can observe in Fig. 1A how two grey patches are perceived distinctively whilst being with same brightness. Similarly, the HVS perceives the chromatic properties of a visual target distinctively depending on the
chromaticities of its surrounding area. This phenomena is named chromatic induction. It appears in both “i” and “s” opponent channels (“i” for red-green and “s” for blue-yellow). This effect is observable on [Fig. 1B] where the central ring from the reference stimulus (left) appears to be “greener” (being perceived with lower “i” chromatic properties) than the central ring from the test (right), which appears to be “bluer” instead (being perceived with higher “s” chromatic properties).

These effects were reproduced previously in a multiresolution wavelet framework with BiWaM [56] and CiWaM [55] computational models. These models’ aim was to mimic V1’s simple cell mechanisms by computing center-surround differences at distinct color and luminance opponencies. Being inspired by the aforementioned models, Penacchio et al. [59] modeled an excitatory and inhibitory model of V1 as a more biologically plausible approach to solve these problems. Considering V1 physiological and neurodynamic properties of V1 cells [43] at different spatial frequencies and orientations, it is possible to reproduce psychophysical experiments of brightness [59] and chromatic induction effects.

![Fig. 1: (A) Brightness induction from the White effect [81]. (B) Chromatic induction from Monnier & Shevell’s concentric ring stimuli [48]. (C) Discomfortable image, credit by Nicholas Wade [76].](https://example.com)

Latest experiments showed that our model is also able to predict visual discomfort [61]. Specific visual patterns [Fig. 1C] are shown to cause discomfort, malaise, nausea or even migraine [60][39]. Taking into account the relative contrast energy from stimulus regions (due to its orientation, luminance, chromatic and spatial frequency distributions), we can predict whether a stimulus can cause hyperexcitability in V1, a possible cause of visual discomfort for certain images.

## II. Model Description

The model is extended from previous implementation by Pennacchio et al. [59] in Matlab and C++. Here we describe the main steps in relation to the computations done to the images: II-A. Feature Extraction | II-B. Feature Conspicuity | II-C. Feature Integration. In this section, computations in the early visual pathways will be represented in line with a stimulus example. Overall model architecture was inspired by previous work from Murray et al.’s Saliency Induction Model (SIM), also named Saliency Induction Model (SIM) [39], defining a biologically-inspired and unsupervised low-level model for saliency prediction. Although it provided a promising approach for predicting saliency maps, we aim to highlight novel computations of firing rate dynamics in accordance with physiological properties of V1 cells.

1) Color representation: Human retinal cone photoreceptors are sensitive to distinct wavelengths of the visual spectrum, corresponding to long (L), medium (M) and short (S) wavelengths. Similarly, traditional digital cameras capture light as values in the RGB color space (corresponding to Red, Green and Blue components). Retinal ganglion cells (RGC) process luminance and chromatic signals as an opponent process. This opponent process separates channels of “Red vs Green” and “Blue vs Yellow” from cone cell responses, and luminance (“Bright vs Dark”) from rod responses. Activity from these channels (R-G, B-Y and L) is then projected respectively to the lateral geniculate nucleus (LGN) as parvo-cellular (P), konio-cellular (K) and magno-cellular (M) pathways towards V1. Likewise, the CIE L*a*b* [5][42] is a color space that defines an opponent color space. We can interpret L*, a* and b* components defined in Eqs. 1,2,3 as means of representing the R-G, B-Y and L opponencies. In [Fig. 2] we illustrate an example of an image and its conversion to the Lab space, with higher activation on the “Red vs Green” opponent cells than the case of “Blue vs Yellow” and “Bright vs Dark” opponencies.

$$L = R + G + B,$$

$$a = \frac{R - G}{L},$$

$$b = \frac{R + G - 2B}{L},$$

All RGB pixel values of processed images are previously corrected with $\gamma = 1/2.2$.

![Fig. 2: Example of RGB image (left column) after converting RGB values to the Lab color space, correspondingly to color opponencies (A) “red vs green” (a*), (B) “blue vs yellow” (b*) and (C) “brightness” (L*).](https://example.com)

2) Multiscale and orientation representation: V1 cell sensitivities to distinct orientations [32] and spatial frequencies [47] are usually modeled as Gabor filters. Since Gabor transforms cannot be inverted to obtain the original image, we used the à trous algorithm, which is an undecimated discrete wavelet transform (DWT) [27][70], Chapter 6]. This decomposition allows to perform an inverse, where the basis functions remain similar to Gabor filters. We propose biologically plausible computations for extracting multiple orientations and multiscale feature representations of from V1’s receptive field (RF) hypercolumnar organization [Fig. 3]. The wavelet approximation planes $c_{s,0}$ ($s$ for scale and $\theta$ for orientation) are computed by convolving the image with the filter $h_s$.

$$c_{s,h} = c_{s-1} \otimes h_s,$$

$$c_{s,v} = c_{s-1} \otimes h^\top_s.$$
The filter \( h_s \) is obtained from \( h_{s-1} \) by doubling its size, i.e. \( h_s = \uparrow h_{s-1} \), where \( \uparrow \) means upsampling by introducing zeros between the coefficients. The filter \( (h_{s}) \) for the first scale is

\[
h_1 = \frac{1}{16} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix}
\]

This filter can be also transposed \((h'_s)\) to obtain distinct approximation orientation planes \( c_{s,h} \) and \( c_{s,v} \). From these approximation planes, we can obtain the wavelet coefficients \( \omega_{s,\theta} \) at distinct scales and orientations:

\[
\begin{align*}
\omega_{s,h} &= c_{s-1} - c_{s,h}, \\
\omega_{s,v} &= c_{s-1} - c_{s,v}, \\
\omega_{s,d} &= c_{s-1} - (c_{s,h} \odot h'_s + \omega_{s,h} + \omega_{s,v}), \\
c_s &= c_{s-1} - (\omega_{s,h} + \omega_{s,v} + \omega_{s,d}).
\end{align*}
\]

Here, \( \omega_1, \omega_v, \) and \( \omega_d \) correspond to the coefficients with “horizontal”, “vertical” and “diagonal” orientations. Initial \( c_0 = I_o \) is obtained from the CIE \( L^*a^*b^* \) components \((o = L^*, a^*, b^*)\) and \( c_n \) corresponds to the residual plane of the last wavelet component \((e.g. s = n)\). The inverse transform is obtained by integrating wavelet coefficients and residual planes:

\[
I'_o = \sum_{s=1, \beta = h,v,d} \omega_{s,\beta} + c_n,
\]

Considering that for every image, \( M \times N \) is the size of the feature map (resized to \( N \leq 128 \)), wavelet coefficient scales are defined to model the spatial frequency sensitivities \((s = 1..S)\), where \( S = \lfloor \log_2(N/8) \rfloor + 2 \).

**B. Computing V1 Dynamics: Feature Conspicuity**

Feature conspicuity from previous Murray’s SIM model is computed using center-surround feature computations (CSF) while applying a contrast sensitivity function (eCSF). Similarly, we extract low-level feature-dependent computations corresponding to the orientation sensitivities \((\theta = 0, 90, 45/135)\) of the retinotopic positions \((i)\) at distinct spatial frequencies \((s)\) for ON and OFF-center cells, but feature distinctiveness is computed with a network of excitatory-inhibitory firing rate neurons (similarly to a Spiking Neural Network), simulating V1’s lateral interactions \(\text{Fig. 4}\). Contrast enhancement or suppression emerges from lateral connections as an induction mechanism. Lateral interactions are implemented to have self-directed \((J_0)\) and monosynaptic connections \((J)\) between excitatory neurons. Inhibitory interactions have dyssynaptic connections \((W)\) through all inhibitory interneurons, defined by:

\[
\begin{align*}
J_{[is\theta,js's']}(\Delta_s) &= \lambda(\Delta_s)\cdot0.126\cdot\left(\frac{-\beta/d_s}{2(\beta/d_s)^2} - d_s/90\right), \\
W_{[is\theta,js's']}(\Delta_s) &= \lambda(\Delta_s)\cdot0.14\cdot(1 - e^{-0.4(\beta/d_s)^{1.5}})\cdot e^{-(\Delta_s/(\pi/4))^{1.5}},
\end{align*}
\]

The aforementioned connections in \(\text{Eqs. 7,8}\) are defined by a concentric toroid of radius \(\Delta_s = 15 \times 2^{s-1}\) and radial distance \(\Delta_\theta\) \(\text{respectively accounting for the distance between RF neurons from different spatial frequencies as } d_s \text{ and radial distance as } \beta\) for the projections of these receptive fields.

**Fig. 4:** Illustration of the receptive field properties of the network (A) and columnar organization of V1 excitatory and inhibitory interneurons (B). Reprinted with permission from "A Neurodynamical Model of Brightness Induction in V1", 2013, by O. Pennacchio, PLoS ONE, 8(5):e64086, p.5. Copyright 2013 by the Public Library of Science [59].

Excitatory and inhibitory membrane potentials (their derivatives) are described by

\[
\begin{align*}
\dot{x}_{is\theta} &= -\alpha_x x_{is\theta} - g_y(y_{is\theta}) \\
&- \sum_{\Delta_s, \Delta_\theta \neq 0} \Psi(\Delta_s, \Delta_\theta)g_y(y_{is\theta} + \Delta_s \theta + \Delta_\theta) + J_0 g_x(x_{is\theta}) \\
&+ \sum_{j \neq i, s', \theta'} J_{[is\theta,js's']}(\Delta_s)g_x(x_{jss'}) + I_{is\theta} + I_0, \\
\dot{y}_{is\theta} &= -\alpha_y y_{is\theta} - g_x(x_{is\theta}) \\
&+ \sum_{j \neq i, s', \theta'} W_{[is\theta,js's']}(\Delta_s)g_x(x_{jss'}) + I_c.
\end{align*}
\]

Functions \(g_x\) and \(g_y\) correspond to the activation function (implemented as piece-wise linear functions) for transforming the membrane potentials to firing rate values. The spread of the inhibitory activity within a hypercolumn is represented as \(\Psi\), and \(\alpha_x, \alpha_y\) are constants for modulating the excitatory and inhibitory potentials. The variable \(I_{is\theta}\) corresponds to the external input values of the image \(I_{is\theta} = \omega_{is\theta}\). Inhibitory top-down activity can be introduced to the model through \(I_c\), including a noise signal to stabilize the nonlinear equilibrium.
Further details of the model and its parameters are specified in [59] [Supporting Information S1]. We compute the temporal average of ON and OFF-center cells $M(x^t)$ as the model output over several oscillation cycles (being the mean of $g_t$ for a specific range of $t$, where $t$ is the membrane time, which corresponds to 10 ms) from distinct color opponencies ($o = L^a, a^b, b^s$). Distinctively from the induction cases described in [Reproducing other visual effects], we do not combine the model output $M(x^t)$ to the coefficients $\omega_i$, instead, we consider the firing rate from the model output as our predictor of feature distinctiveness, which will define our main function for our saliency map [Eq. 11]. The model output can provide detail of single neuron dynamics of firing rate, which its dynamical properties may vary across stimulus properties such as color opponency, scale and orientation.

$$\hat{S}_i = \sum_{s=1..S; o=h,d,v} M(x^t) + \sum_{s=1..S; o=h,d,v} M(x^t) + c_i,$$

(11)

C. Generating the saliency map: Feature Integration

After computing feature distinctiveness for the low-level feature maps, we need to integrate these conspicuity or distinctiveness maps in order to pool the neuronal activity to the projections of the SC as means of acquiring a unique map, which will represent our saliency map. First, we have computed the inverse transform from the DWT (IDWT) Eq. 6 for integrating the sensitivities for orientation ($\theta$) and spatial frequencies ($s$). Second, we have computed the euclidean norm ($\hat{S}$) for integrating the firing rate of the distinct color opponencies Eq. 12. Third, we have normalized the resulting map ($z(\hat{S})$) by the variance of the firing rate (Eq. 13), as stated by Li [80 Chapter 5]. Finally, we convolved the saliency map with a gaussian filter in order to simulate a smoothing caused by the deviations of $\sigma = 1$ deg given from eye tracking experimentation, recommended by LeMeur & Baccino [41].

$$\hat{S}_i = \sqrt{\hat{S}_i^a + \hat{S}_i^b + \hat{S}_i^L},$$

(12)

$$z_i(\hat{S}) = \frac{\hat{S}_i - \mu_{\hat{S}}}{\sigma_{\hat{S}}},$$

(13)

III. EXPERIMENTS

Fixations and saccades are captured using eye-tracking technology. Eye movement data is combined across all fixations from participants’ data, being represented as binary maps (called fixation maps), according to the fixation localizations in the visual space for each corresponding image, or as density distributions (alternatively named density maps) from these fixations considering eye-movement localization probabilities (Figure 6). Fixation density maps are computed accordingly from fixation maps with a gaussian filter [41].

Prediction scores are calculated using spatially-dependent metrics [15][14] which compare either fixation maps or fixation density maps to saliency map predictions from the models (AUC, CC, NSS, KL and SIM). Essentially, these metrics assign a score considering true positive (TP) values for the saliency predictions inside the locations from the fixation maps (or higher correlations with respect to density maps) and false positive (FP) values for the reverse cases. Other metrics compare saliency maps with a baseline set of other image fixation maps in order to prevent behavioral tendencies such as center biases, which are not representative data for saliency prediction. Similarly, a baseline gaussian of all images is used (InfoGain) for minimizing center biases on prediction scores.

![Figure 5: (A) Example Image. (B) Mask of salient region. (C) Predicted saliency map (GT). (D,E,F,G) Predicted saliency map given $z_i(S_i^L)$, $z_i(S_i^a)$, $z_i(S_i^b)$ and $z_i(S_i)$ respectively. (E) Results of prediction metrics from these saliency maps.](https://github.com/dberga/saliency)
| Image | GT | IKN | AIM (Ours) | SWAM (Ours) | SIM (SWAM+CS&eCSF) | NSWAM (Ours) |
|-------|----|-----|-----------|------------|-------------------|-------------|
| ![Image](image1.jpg) | ![GT](image2.jpg) | ![IKN](image3.jpg) | ![AIM](image4.jpg) | ![SWAM](image5.jpg) | ![SIM](image6.jpg) | ![NSWAM](image7.jpg) |
| ![Image](image8.jpg) | ![GT](image9.jpg) | ![IKN](image10.jpg) | ![AIM](image11.jpg) | ![SWAM](image12.jpg) | ![SIM](image13.jpg) | ![NSWAM](image14.jpg) |
| ![Image](image15.jpg) | ![GT](image16.jpg) | ![IKN](image17.jpg) | ![AIM](image18.jpg) | ![SWAM](image19.jpg) | ![SIM](image20.jpg) | ![NSWAM](image21.jpg) |
| ![Image](image22.jpg) | ![GT](image23.jpg) | ![IKN](image24.jpg) | ![AIM](image25.jpg) | ![SWAM](image26.jpg) | ![SIM](image27.jpg) | ![NSWAM](image28.jpg) |
| ![Image](image29.jpg) | ![GT](image30.jpg) | ![IKN](image31.jpg) | ![AIM](image32.jpg) | ![SWAM](image33.jpg) | ![SIM](image34.jpg) | ![NSWAM](image35.jpg) |
| ![Image](image36.jpg) | ![GT](image37.jpg) | ![IKN](image38.jpg) | ![AIM](image39.jpg) | ![SWAM](image40.jpg) | ![SIM](image41.jpg) | ![NSWAM](image42.jpg) |

Fig. 6: Examples of saliency maps from Itti et al. (IKN), Bruce & Tsotsos (AIM), Saliency WAvelet Model (SWAM), Murray et al.’s model (SIM) and our Neurodynamic model (columns 3 to 7, respectively), corresponding to images with distinct contexts (column 1). We also show the density distribution of fixations given by the eye-tracking experimentation (column 2).
corresponding to nature and synthetic images, as well as showing stable metric scores for distinct contexts (similarly as AWS and GBVS). NSWAM outperforms other biologically-inspired models (IKN, AIM, SSR, SWAM & SIM) specifically for metrics that account for center biases. These center biases are qualitatively present even for images where the salient region is conspicuous. Fig. 6, rows 8 & 9 Saliency models that compute high-level visual features are shown to perform better with real image scenes (table I). However, the image contexts that lack of high-level visual information should be more representative indicators of saliency, due to the absence of semantically or contextually-relevant visual information (nature images), or to be characterized to uniquely contain low-level features (synthetic images) presenting clear pop-out spots to direct participants fixations (which would cause lower inter-participant differences and therefore lower center biases). Although AWS and GBVS perform better on predicting fixations at distinct contexts, we remark the plausibility of our unified design for modeling distinct HVS’ functionality. NSWAM shows a new insight of applying a more biologically plausible computation of the aforementioned steps. First, they transform image values to color opponencies, found in RGC. Second, we model LGN projections to V1 simple cells using a multiresolution wavelet transform. Third, conspicuity is computed with a dynamical model of the lateral interactions of V1. Fourth, these channels are integrated to a unique map which will represent SC activity. Using a neurodynamic model with firing-rate neurons allows a more detailed understanding of the dependency of saliency on lateral connections and a potential further study in terms of single neuron dynamics using real image scenes.

### B. Psychophysical measurements

Acknowledging that the HVS processes information according to the human performance on detecting a salient object on a scene may also vary according to the visual properties of such object. With a synthetic image dataset a specific analysis of how each individual feature influences saliency can be done. In this study we will show how fixation data is predicted when varying feature contrast, concretely on parametrizing Set Size, and Brightness, Color, Size and Orientation contrast between a target salient object and the rest of distractors (feature singleton search). In this section a set of psychophysical stimuli will be displayed with its parametrization of set size or feature contrast and its sAUC in comparison to other biologically-inspired saliency models. The shuffled AUC (sAUC) is the metric we used for our psychophysical experimentation. It computes the area under ROC considering TP as fixations inside the saliency map, similarly to the AUC. However, this metric does not evaluate FP at random areas of the image but instead uses fixations inside other random images from the same dataset over several trials (10 by default). This metric gives a more accurate evaluation of predicted maps with respect human fixations but penalizing for higher model center biases (which are or can be present for distinct images in the ground truth).

### TABLE III: Results for prediction metrics with CAT2000 dataset

| Humans | OpenSaliency | DeepGazell | SAM | SalGAN | SSS | AIM | WN | SWAM (Ours) |
|--------|--------------|------------|-----|--------|-----|-----|----|-------------|
| 0.96   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.97   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.98   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.99   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |

### TABLE IV: Results for prediction metrics with SID4VAM dataset with synthetic images

| Humans | OpenSaliency | DeepGazell | SAM | SalGAN | SSS | AIM | WN | SWAM (Ours) |
|--------|--------------|------------|-----|--------|-----|-----|----|-------------|
| 0.94   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.97   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.98   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.99   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |

### TABLE I: Results for prediction metrics with Toronto dataset

| Humans | OpenSaliency | DeepGazell | SAM | SalGAN | SSS | AIM | WN | SWAM (Ours) |
|--------|--------------|------------|-----|--------|-----|-----|----|-------------|
| 0.96   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.97   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.98   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.99   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |

### TABLE II: Results for prediction metrics with KTH dataset

| Humans | OpenSaliency | DeepGazell | SAM | SalGAN | SSS | AIM | WN | SWAM (Ours) |
|--------|--------------|------------|-----|--------|-----|-----|----|-------------|
| 0.96   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.97   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.98   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.99   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |

### TABLE V: Results for prediction metrics with SWAM dataset

| Humans | OpenSaliency | DeepGazell | SAM | SalGAN | SSS | AIM | WN | SWAM (Ours) |
|--------|--------------|------------|-----|--------|-----|-----|----|-------------|
| 0.96   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.97   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.98   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |
| 0.99   | 0.621        | 0.572      | 0.604 | 0.557  | 0.611 | 0.606 | 0.584 | 0.617 |

Our results show that our model has a trend to acquire other saliency models performance, with an emphasis on outperforming previous Murray’s SIM model for the cases of KTH, CAT2000 and SID4VAM (Tables II, III and IV),
1) Brightness differences: Differences in brightness are major factors for making an object to attract attention. Thus, a bright object is less salient as luminance of other objects increase [Fig. 7]. Conversely, a dark target in a bright background will be more salient as distractors have higher luminance \[ \Delta L \] specially for stimulus with higher contrasts \[ \Delta L_{D,T} > .25 \]. Results on sAUC for NSWAM correlates with brightness contrast, for both cases of bright (\( \rho = .941, p = 1.6 \times 10^{-3} \)) and dark (\( \rho = .986, p = 4.7 \times 10^{-5} \)) background.

![Fig. 7: Array of synthetic stimuli representing distinct brightness contrasts (HSL luminance differences) from target and distractors (\( \Delta L_{D,T} \)) with (A) bright background (\( L_T = 0.5, L_B = 1, L_D = 0.5 \)) and conversely, with (B) dark background (\( L_T = 0.5, L_B = 0, L_D = 0.05 \)). Rows below A,B correspond to NSWAM’s predicted saliency maps.](image)

2) Color differences: Color changes spatial and temporal behavior of eye movements, influencing how conspicuous are specific objects on a scene [22][3]. Similarly to previous section, here we vary the chromaticity of the background, which can alter search efficiency [50][19]. In this section, we used stimuli similar to Rosenholtz’s experimentation [65], with red and blue singletons for achromatic or oversaturated backgrounds [Fig. 9] Here, chromatic contrast is defined as the HSL saturation differences \( (\Delta S_{D,T}) \) between a salient target and the rest of distractors.

![Fig. 9: Chromatic stimuli upon saturation contrast (\( \Delta S_{D,T} \)) between a red target (\( H_T = 0 \)) and an (A) unsaturated, grey background or an (B) oversaturated, red background. Other cases (C,D) present a blue target (\( H_T = 240 \)) with same background properties to (A) and (B) respectively. Rows below A-D correspond to NSWAM’s predicted saliency maps.](image)

Similarly to [Fig. 7] NSWAM has similar sAUC to SIM for all background conditions [Fig. 10,A-D]. Achromatic backgrounds contribute to salient object detection by increasing sAUC of the pop-out singleton. That effect is present for visual search results and our saliency prediction. Results comparing target search fixation maps and sAUC show distinct performance upon saturation contrast depending on background conditions. Cases which stimulus background was achromatic, distinct from the feature singleton, had higher correlation than with oversaturated background. For the cases of grey (achromatic) background, there is a correlation between sAUC results for our model and \( \Delta S_{D,T} \) with a red (\( \rho = .864, p = 1.2 \times 10^{-2} \)) and blue (\( \rho = .944, p = 1.4 \times 10^{-3} \)) target singleton. However, when background color is oversaturated red and targets are either red (\( \rho = .106, p = .82 \)) or blue (\( \rho = .483, p = .27 \)), then saturation contrast do not correlate with sAUC.
3) Size contrast: Feature distinctiveness with feature singletons have been tested by varying set size, object orientation and/or color. Here is tested how object size affects its saliency, previously tested with visual search experimentation [28][71][62]. A set of 34 symmetric objects (with a dark circle shape) are distributed randomly around the image Fig. 11, preserving equal diameter. One of the circles is defined with dissimilar size, either with higher or lower diameter with respect the rest (which are defined with a diameter of 2.5°). Performance for NSWAM’s sAUC improves with size dissimilarity. When the diameter of the dissimilar circle is higher, sAUC is higher for that particular region. For the highest scaling factor (when the dissimilar object is bigger), NSWAM has higher sAUC compared to previous biologically-inspired models (Fig. 12). Plus, there is a significant correlation between circle diameter and our model’s results of sAUC ($\rho = .955, p = 8.3 \times 10^{-4}$).

4) Orientation contrast: Using a similar setting, varying angle of objects is found to increase search efficiency when angle contrast is increased [21][53][52]. A total of 34 bars were oriented horizontally and randomly displaced around the scene (Fig. 13). The dissimilar object for this case is a bar oriented with an angle contrast with respect the rest of bars of $\Delta\Phi(1,0)=[0, 10, 20, 30, 42, 56, 90]$. Although results of sAUC show that NSWAM overperforms SIM’s saliency maps, IKN is best for capturing orientation distinctiveness (Fig. 14). In NSWAM, 3 types of orientation selective cells are modeled, corresponding to the orientation for the wavelet coefficients ($\theta = h, v, d$). A higher number of orientation selective cells would provide a higher accuracy, specially for diagonal angles (here we only provide $\theta = d$ for 45/135 combined). By modeling orientation selective cells with 2D Gabor and Log-Gabor transforms [40][24][26] it would be possible to correctly build an hypercolumnar organization with a higher number of angle sensitivities.

We have to acknowledge that for this experimentation, distractors have been set with same horizontal configuration. Specific connectivity interactions [22] between orientation dissimilarities needs to be defined in order to reproduce orientation-dependent visual illusions and conspicuousness under heterogeneous, nonlinear and categorical angle configurations (seen to be done by V2 cells [1]), which are previously known to distinctively affect visual attention [53][52][25].
5) **Visual Asymmetries**: Search asymmetries appear when searching target of type “a” is found efficiently among distractors of type “b”, but not in the opposite case (i.e. searching for ”b” among distractors of type “a”) [23,32]. Previous studies pointed out this concept when searching a circle crossed by a vertical bar among plain circles and searching a plain circle among circles crossed by a vertical bar. Using these two configurations, we filled a grid of distractors according to specific scales (Fig. 15). Scale values ($s = [1.25, 1.67, 2.08, 2.5, 3.33, 4.17, 5]$ deg) change the amount of items, with arrays of $5 \times 7, 6 \times 8, 8 \times 10, 10 \times 13, 15 \times 20$ and $20 \times 26$ objects. In Fig. 8, our model is not only more efficient than other biologically-inspired models upon dissimilar sized objects but also on detecting conspicuous objects at distinct scales, accounting for lower or larger amount of distractors. sAUC for NSWAM showed to be associated by the computations of V1. For such, we could feed our model with a selective mechanism [74] for specific low-level feature maps, enabling the possibility to perform visual search tasks. Saliency computations could be more accurately represented with a higher number of 2D Gabor/Log-Gabor filters [40,24,26] as well as the specificities of intra and inter-

Fig. 14: sAUC results for Orientation Contrast stimuli.

Fig. 15: Stimuli with distinct set sizes corresponding to search asymmetries present on a (A) salient circle crossed by a vertical bar among other circles and a (B) salient circle among other circles crossed by a vertical bar. Rows below A,B correspond to NSWAM’s predicted saliency maps.

Fig. 16: Results of sAUC upon varying scale and set size of (A) an array of circles and a salient one crossed by a vertical bar and (B) an array of circles crossed by a bar and a salient circle.

- Second, our model improves results for biologically-inspired saliency models and it is consistent with human psychophysical measurements (tested for Visual Asymmetries, Brightness, Color, Size and Orientation contrast). Adding up to the stated hypothesis, our model presents highest performance at highest contrast from feature singleton stimuli (where salient objects pop-out easily).
- Three, we remark the model plausibility by mimicking HVS physiology on its processing steps and being able to reproduce other effects such as Brightness Induction [59], Color Induction [16] and Visual Discomfort [61], efficiently working without applying any type of training or optimization and keeping the same parametrization.

Other biologically plausible alternatives that predict attention using neurodynamic modeling [43,20,17] do not provide a unified model of the visual cortex able to reproduce these distinct tasks simultaneously, and specifically, using real static or dynamic images as input. We suggest that V1 computations work as a common substrate for several tasks simultaneously. Future work of interest would consist on predicting scanpaths for real scenes in order to provide gaze-wise temporal detail for saliency prediction and saccade programming. To do so, a foveation mechanism (such as a retinal [77] or a cortical magnification transformation towards V1 retinotopy [68]) would be needed in order to process each view of the scene distinctively. Other applications of the same model would be to generate saliency maps with dynamic scenes or videos, integrating other features such as flicker or motion. In order to provide top-down computations for representing feature relevance apart from saliency, we could feed our model with a selective mechanism [24,30] for specific low-level feature maps, enabling the possibility to perform visual search tasks. Saliency computations could be more accurately represented with a higher number of 2D Gabor/Log-Gabor filters [40,24,26] as well as the specificities of intra and inter-

IV. Conclusion

In this work, we hypothesize that low-level saliency is likely to be associated by the computations of V1. For such, we proposed a neurodynamic model of V1’s lateral interactions, processing each channel separately and acquiring firing rate dynamics from real image simulations. Here we have to pinpoint three statements in agreement with our findings:

- First, our model of the lateral interactions in V1 has a trend to acquire state-of-the-art results on human eye fixations, specifically, with natural and synthetic images.
cortical interactions between simple and complex cells in a multilayer implementation of V1. Such implementation could accommodate more detailed and efficient computations of V1, projecting the excitatory recurrent dynamics from V1 (specifically from Layer 5 complex cells, also named “Meynert” cells) to SC [40][51]. Although latest hypotheses about the SC confirm that saliency is processed in the SC and not by the visual cortex, corresponding to a distinct, feature-agnostic saliency map [75][80], we claim the importance of the mechanisms of V1 to be responsible for computing distinctiveness between the stated low-level features, which might conjunctively contribute to the generation of saliency [44][55][83]. However, modeling the computations of the pathways from the RGC to the SC would be of interest for a more integrated and complete model of eye-movement prediction, seeing the roles of the distinct projections to the SC and their computations, alternatively involved in the control of eye movements.

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