



Motion anticipation in the retina

Bruno Cessac, Selma Souihel

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Motion anticipation in the retina

Bruno Cessac, Selma Souihel

Biovision INRIA team



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In collaboration with :

Matteo Di Volo
Alain Destexhe



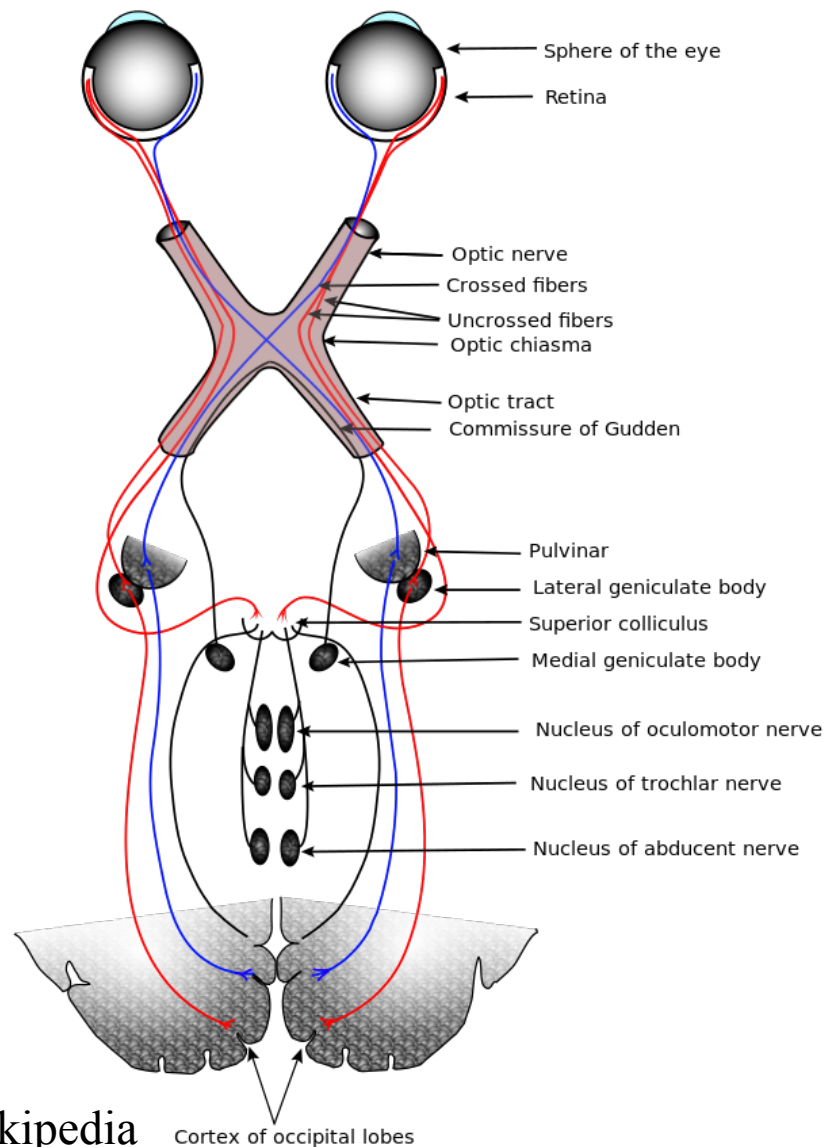
Frédéric Chavane
Sandrine Chemla



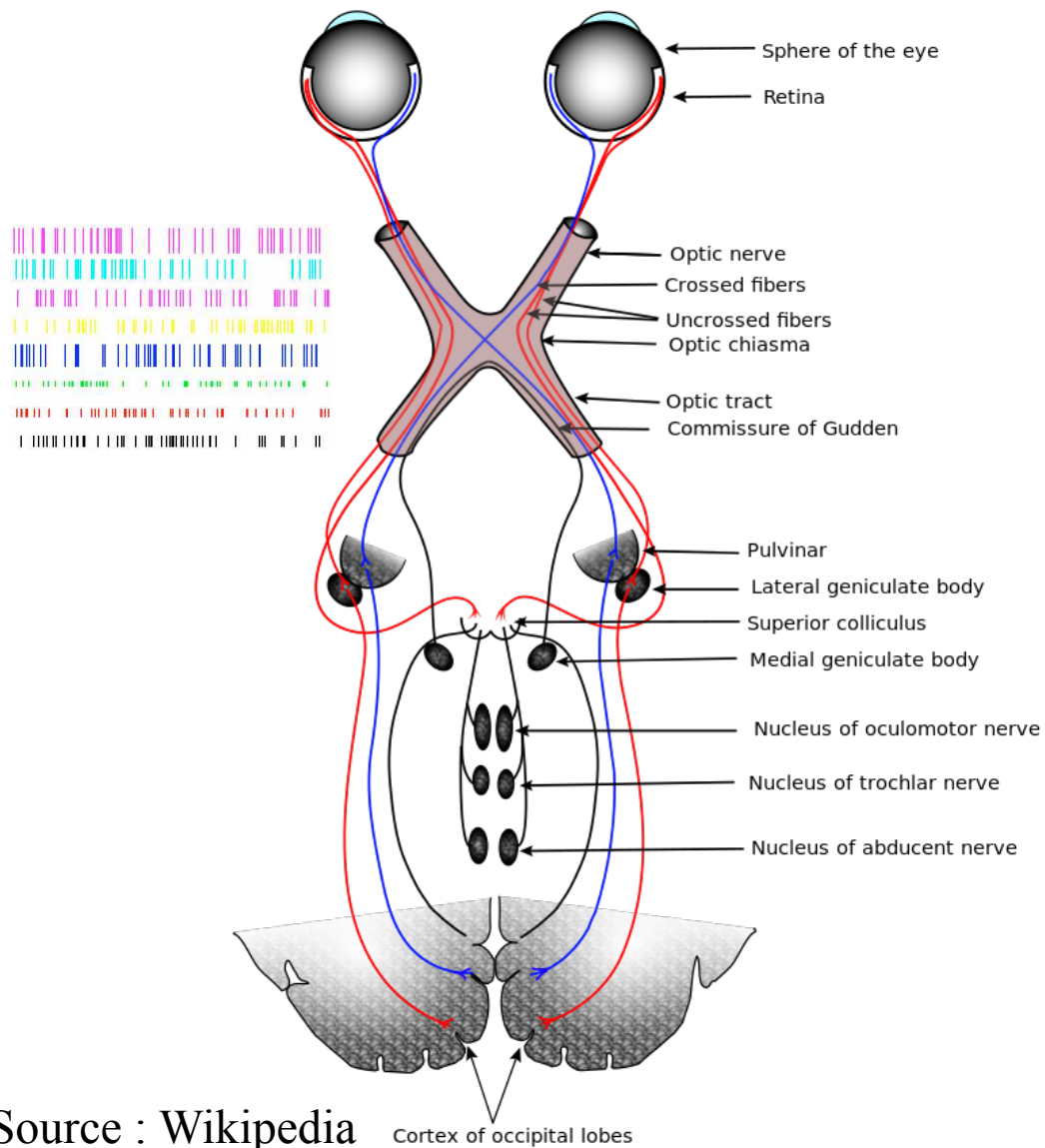
Olivier Marre



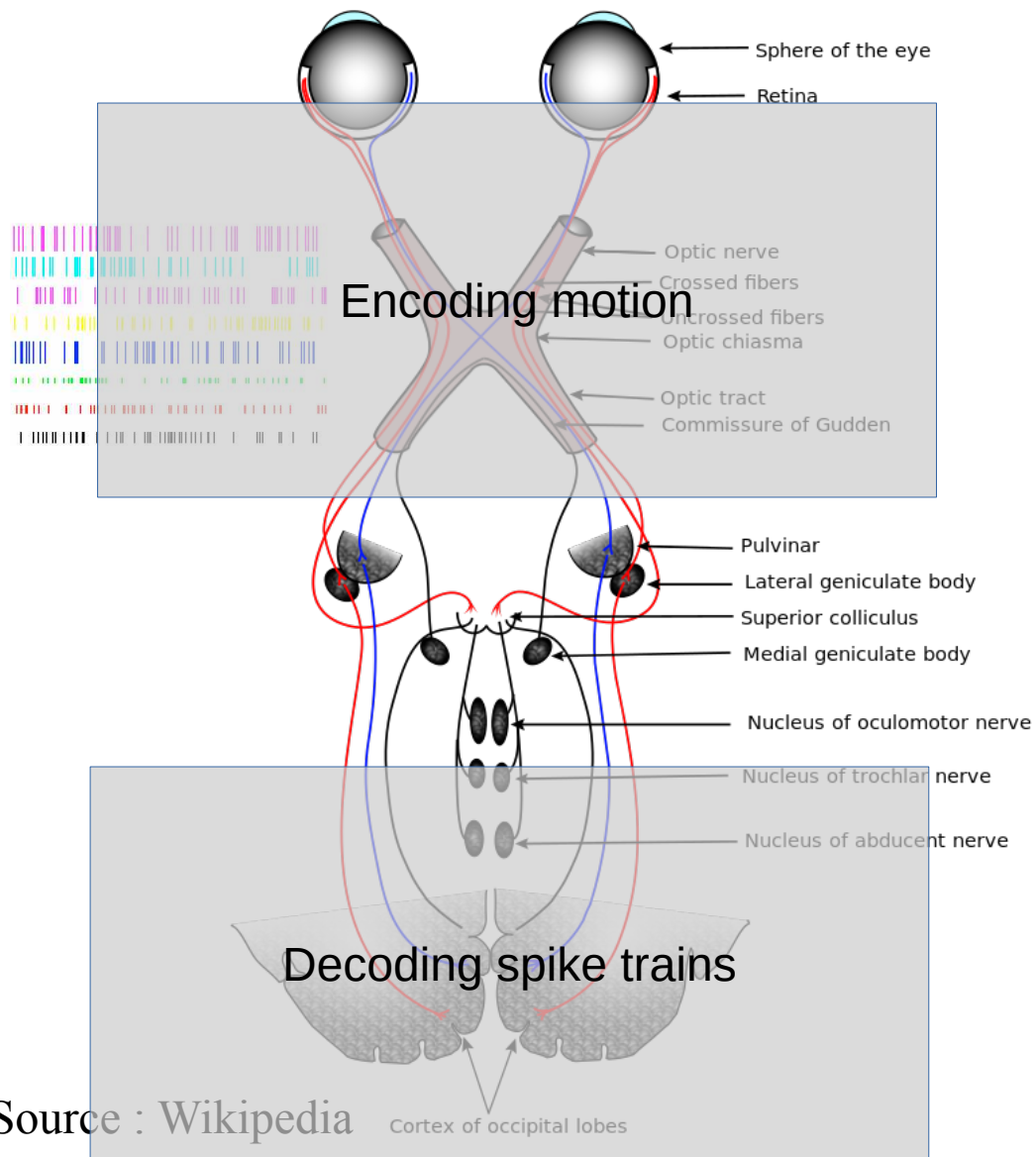
The visual flow



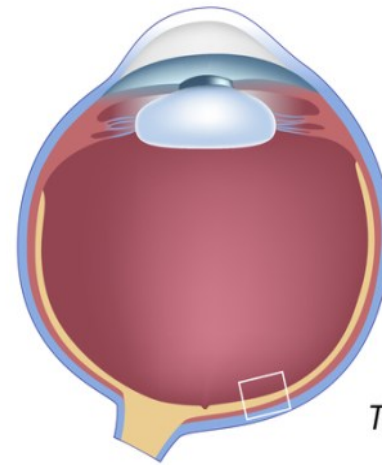
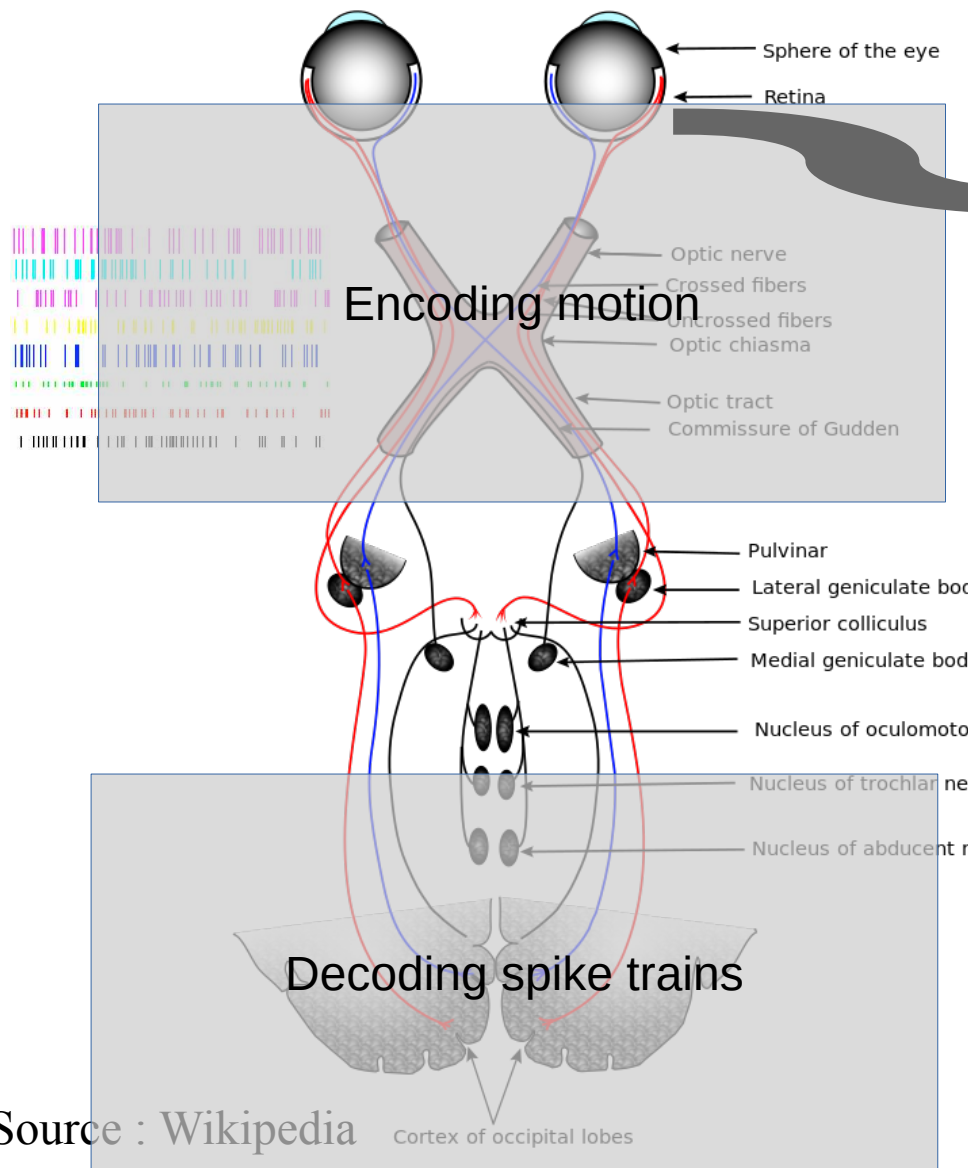
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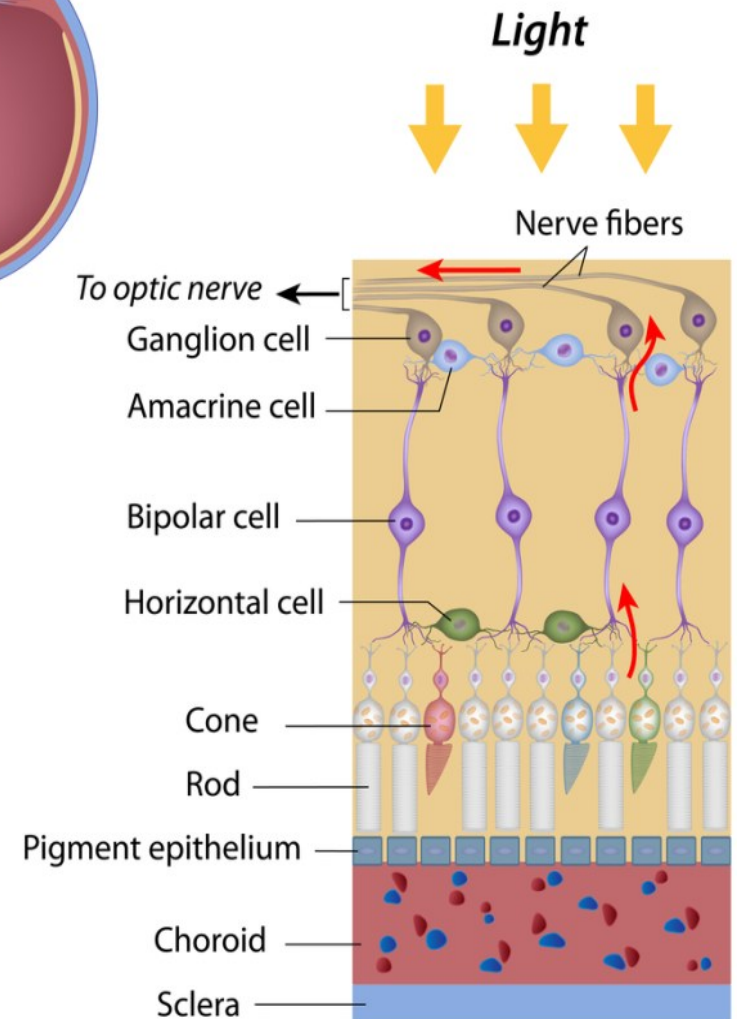
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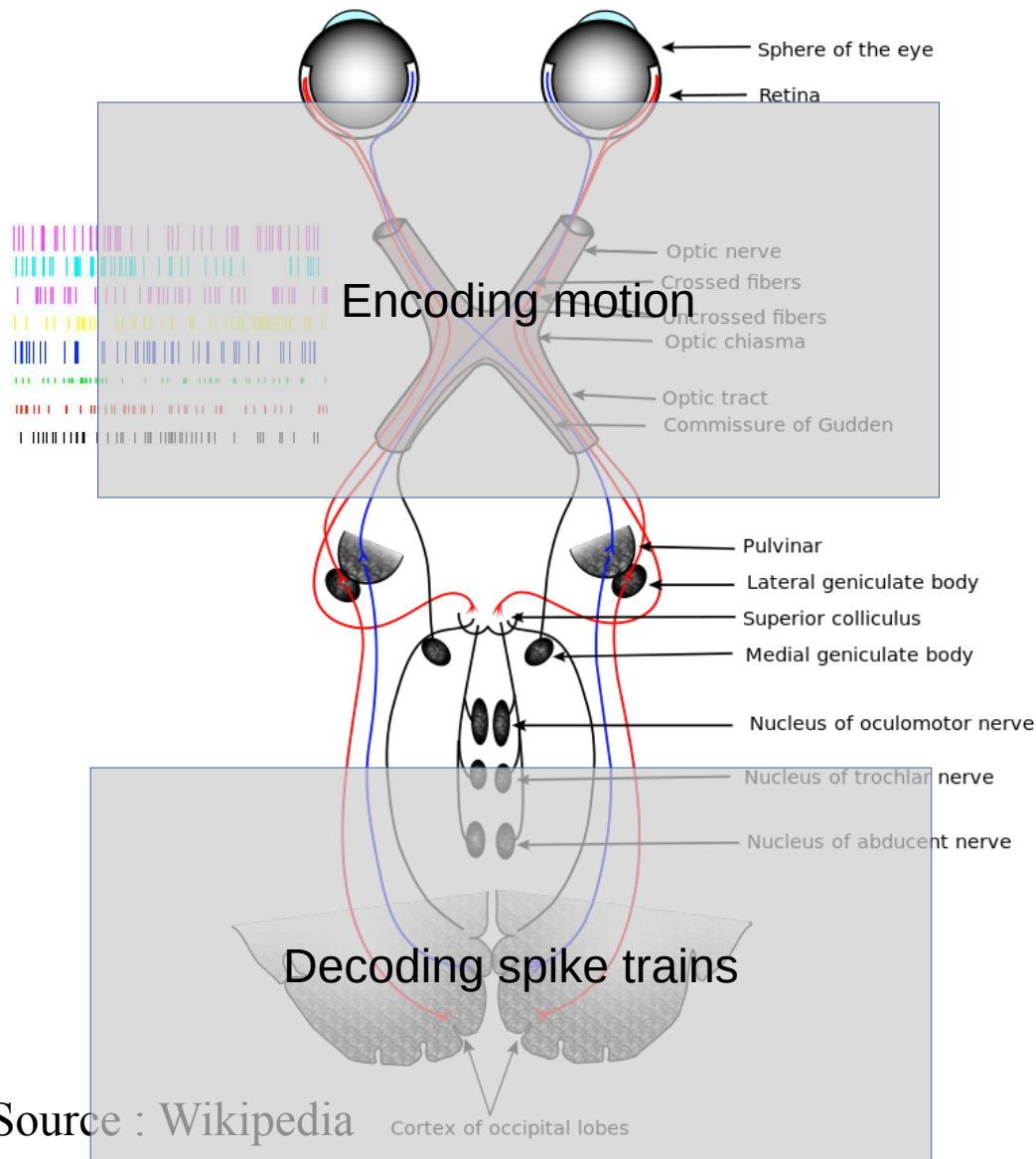
The visual flow



Structure of the Retina

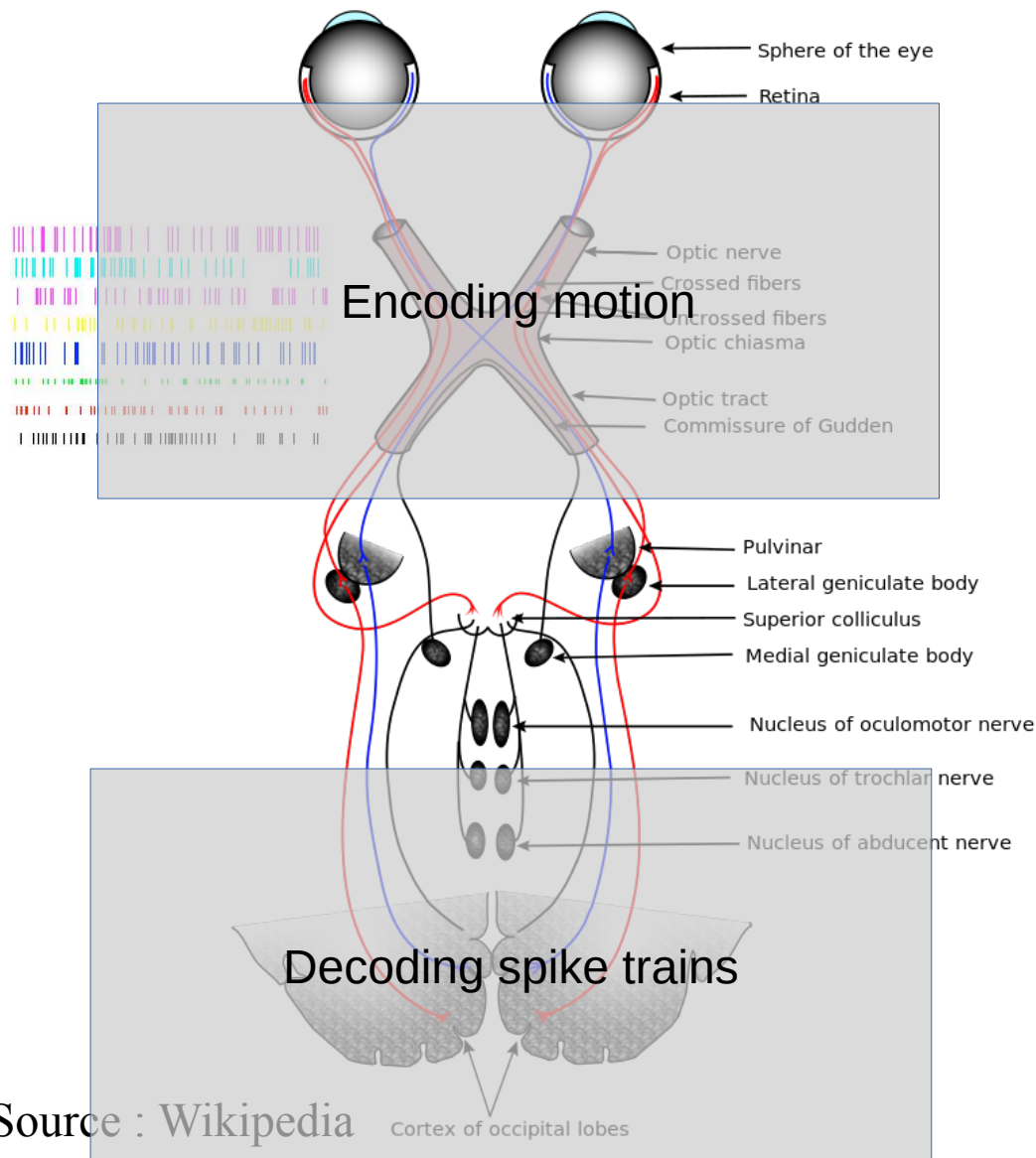


The visual flow



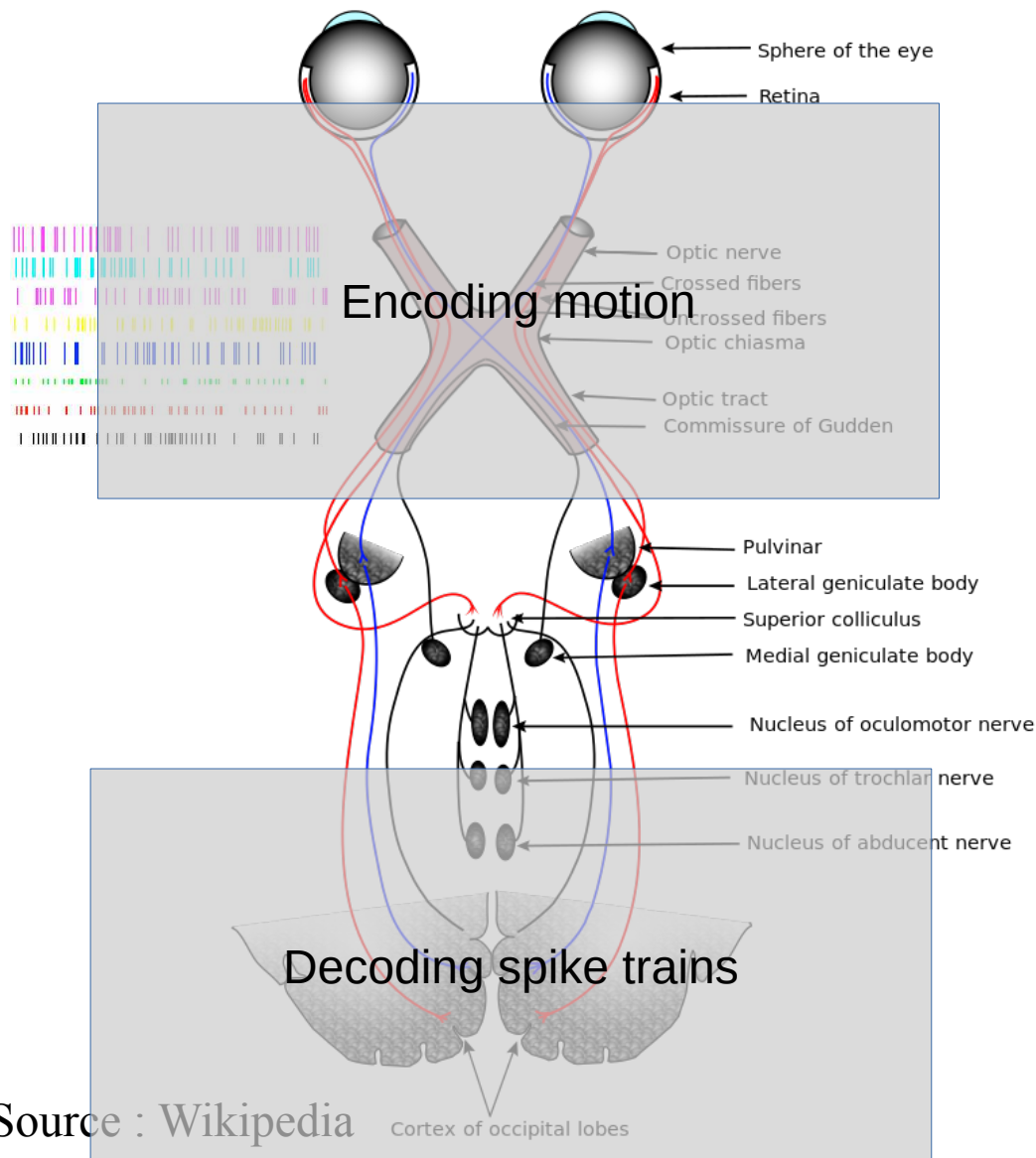
- High transduction rate : 1 photon can trigger a membrane voltage variation of ~1 mV

The visual flow



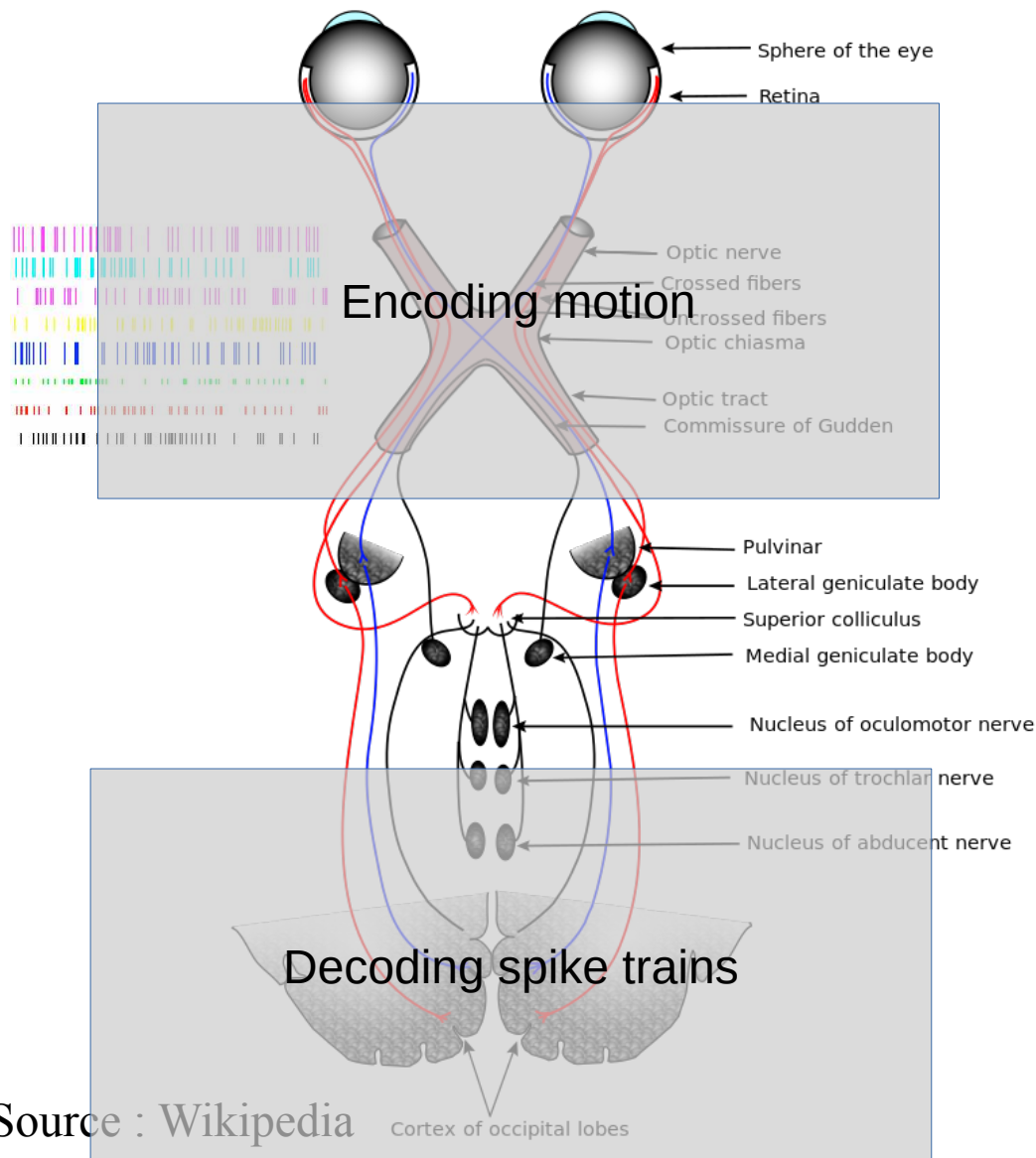
- High transduction rate : 1 photon can trigger a membrane voltage variation of ~1 mV
- Able to detect approaching motion

The visual flow



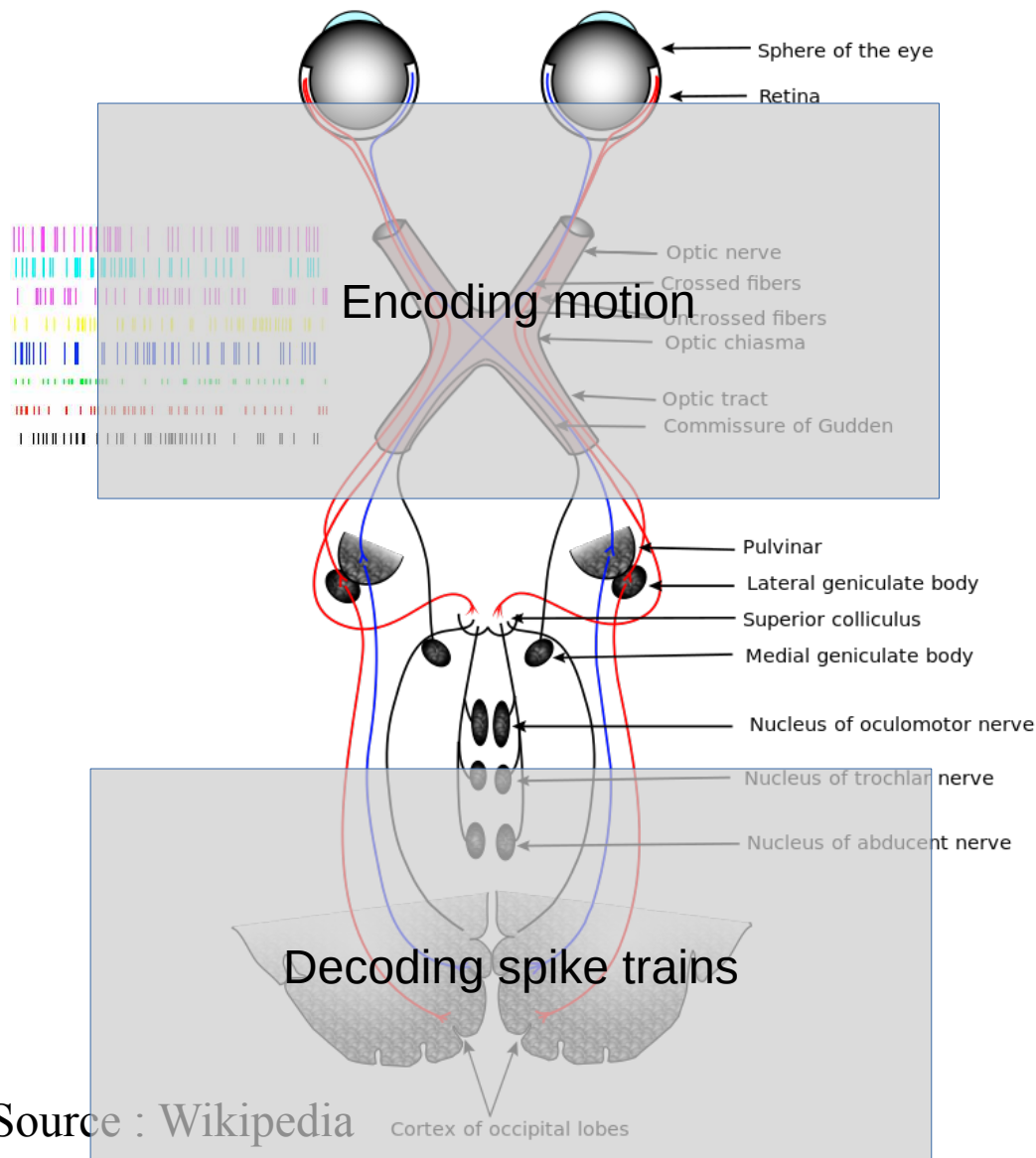
- High transduction rate : 1 photon can trigger a membrane voltage variation of ~1 mV
- Able to detect approaching motion
- Able to detect differential motion

The visual flow



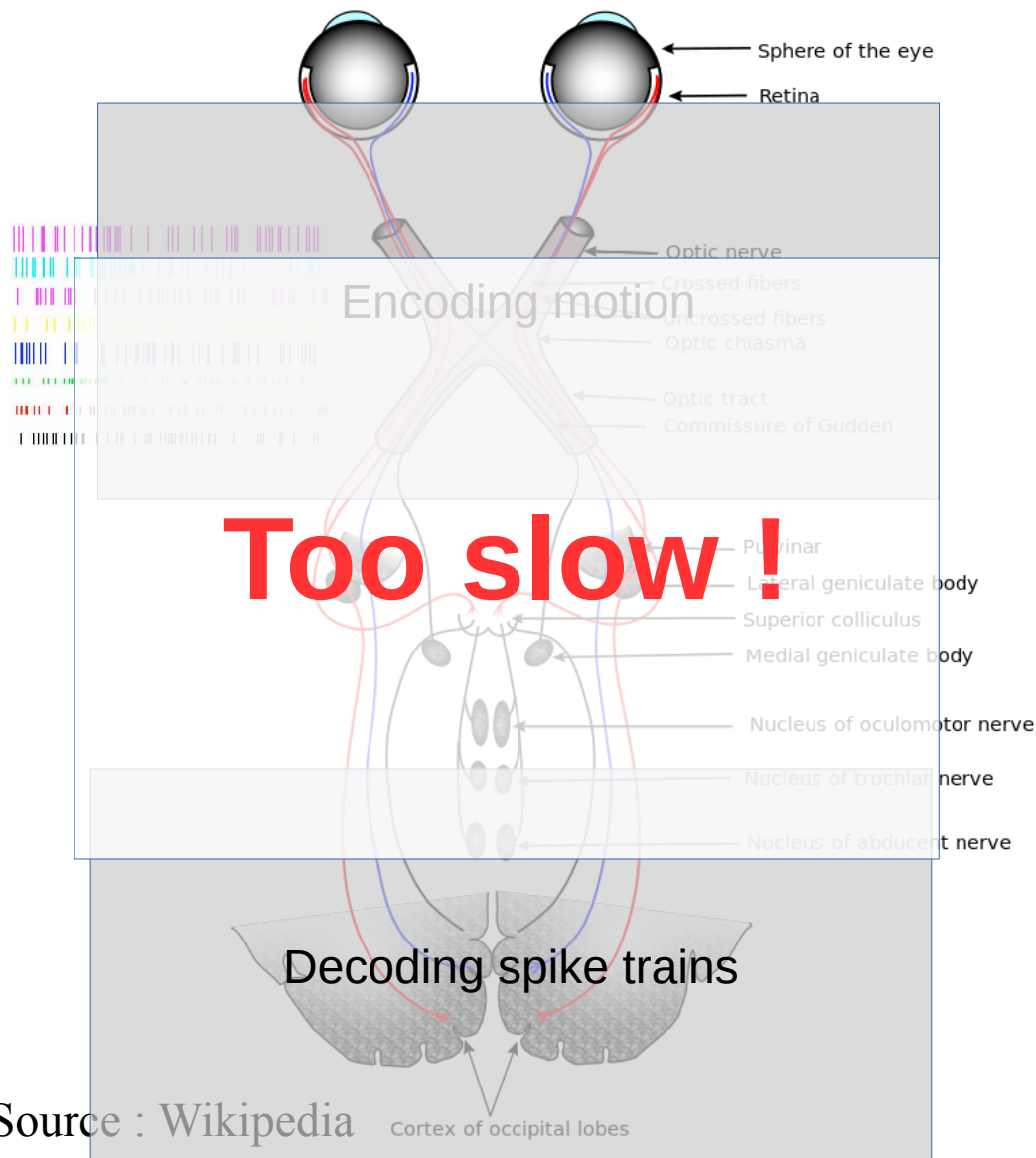
- High transduction rate : 1 photon can trigger a membrane voltage variation of ~1 mV
- Able to detect approaching motion
- Able to detect differential motion
- Sensitive to « surprise » in a visual scene

The visual flow



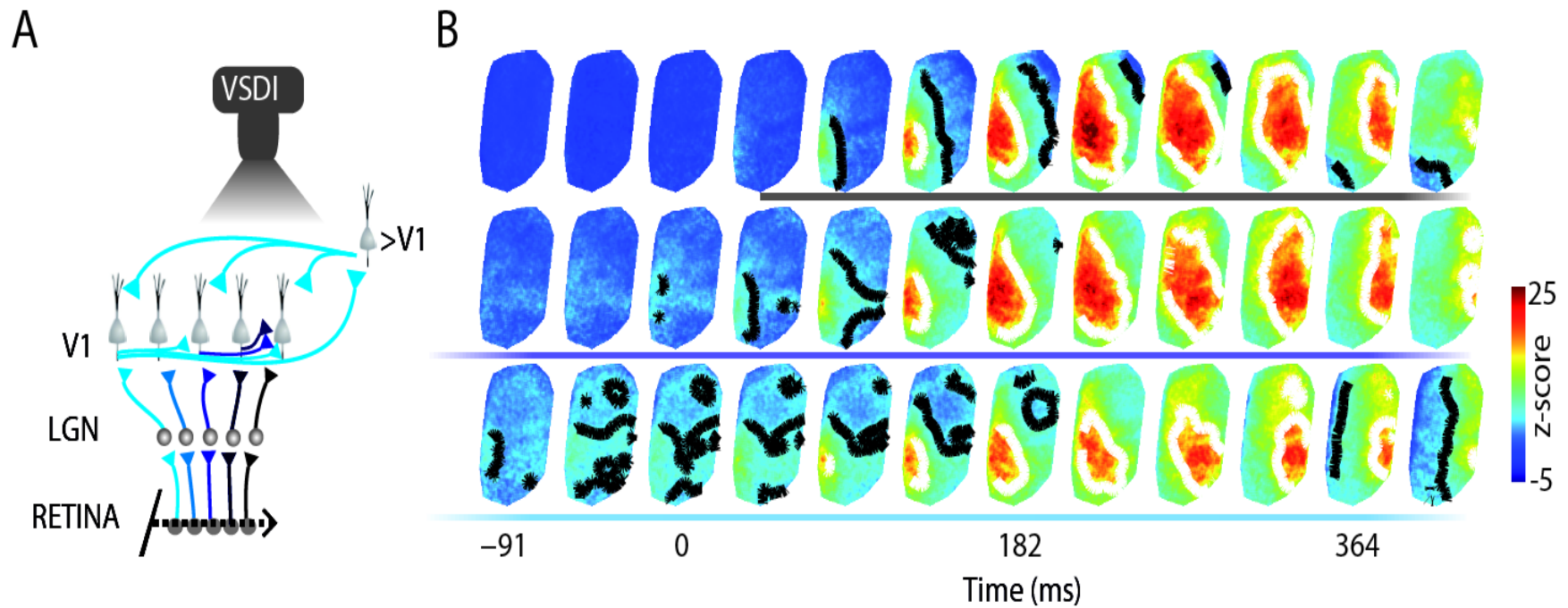
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- Able to perform motion anticipation

The visual flow



- High transduction rate : 1 photon can trigger a membrane voltage variation of ~ 1 mV
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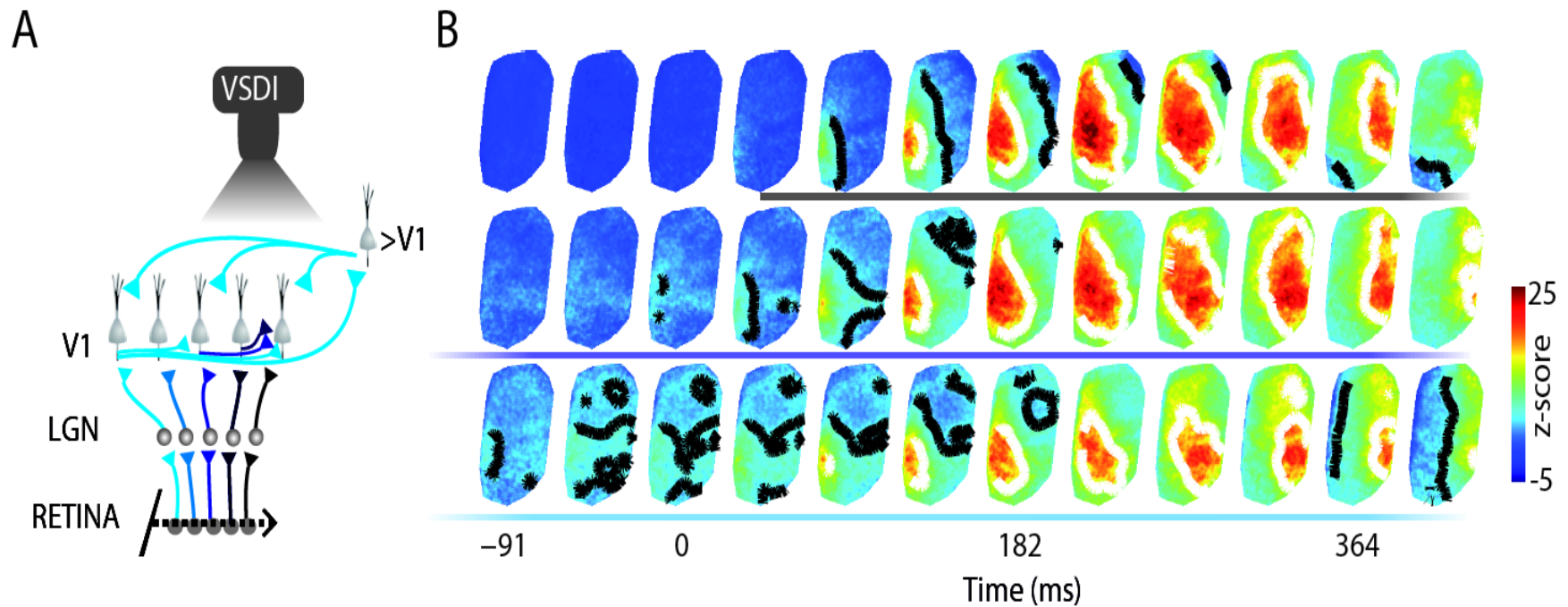
Visual Anticipation



Source : Benvenutti et al. 2015

Visual Anticipation

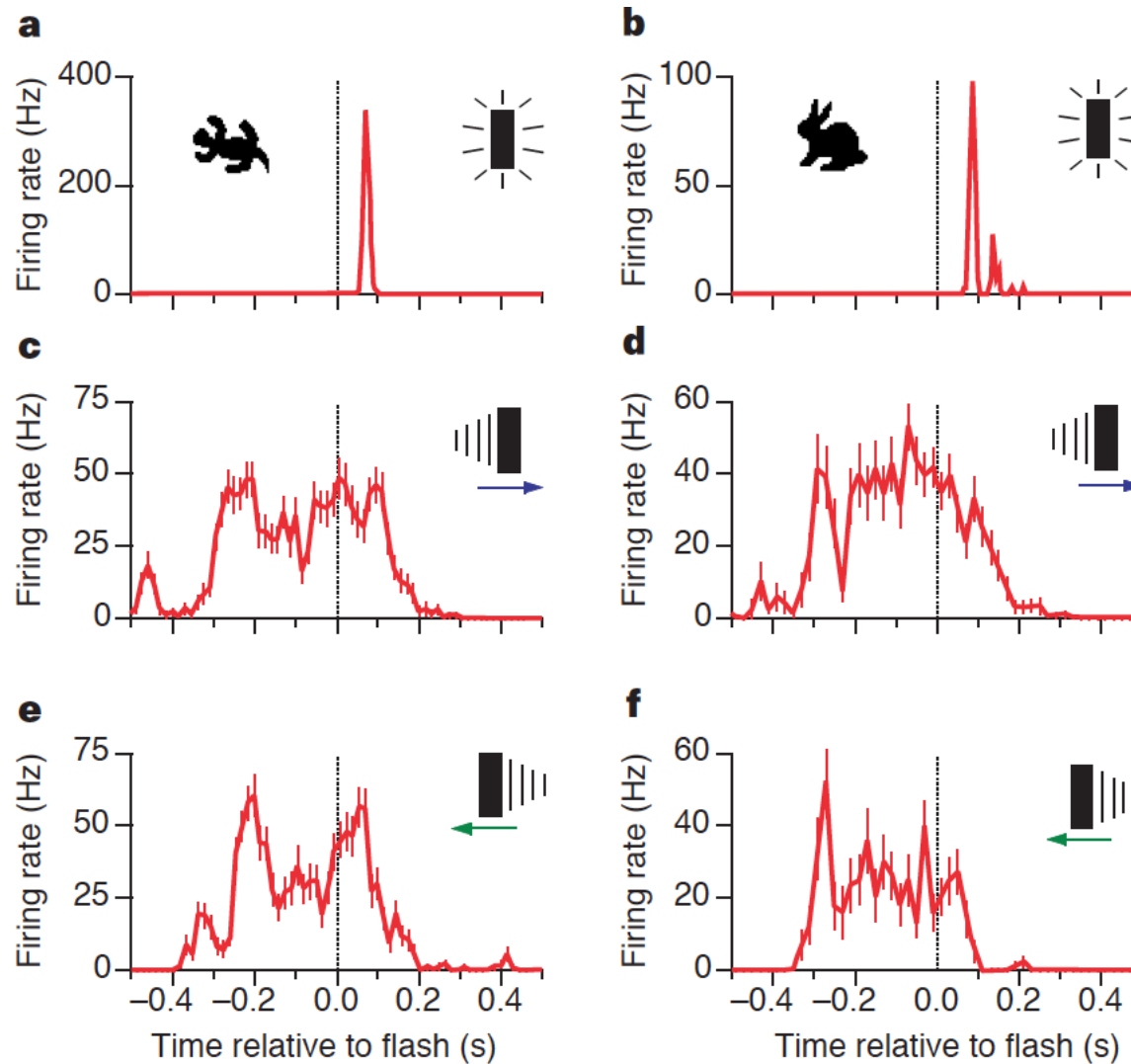
Anticipation is carried out by the primary visual cortex (V1) through an activation wave



Source : Benvenutti et al. 2015

Visual Anticipation

Anticipation also takes place in the retina



Source :
Berry et al.
1999

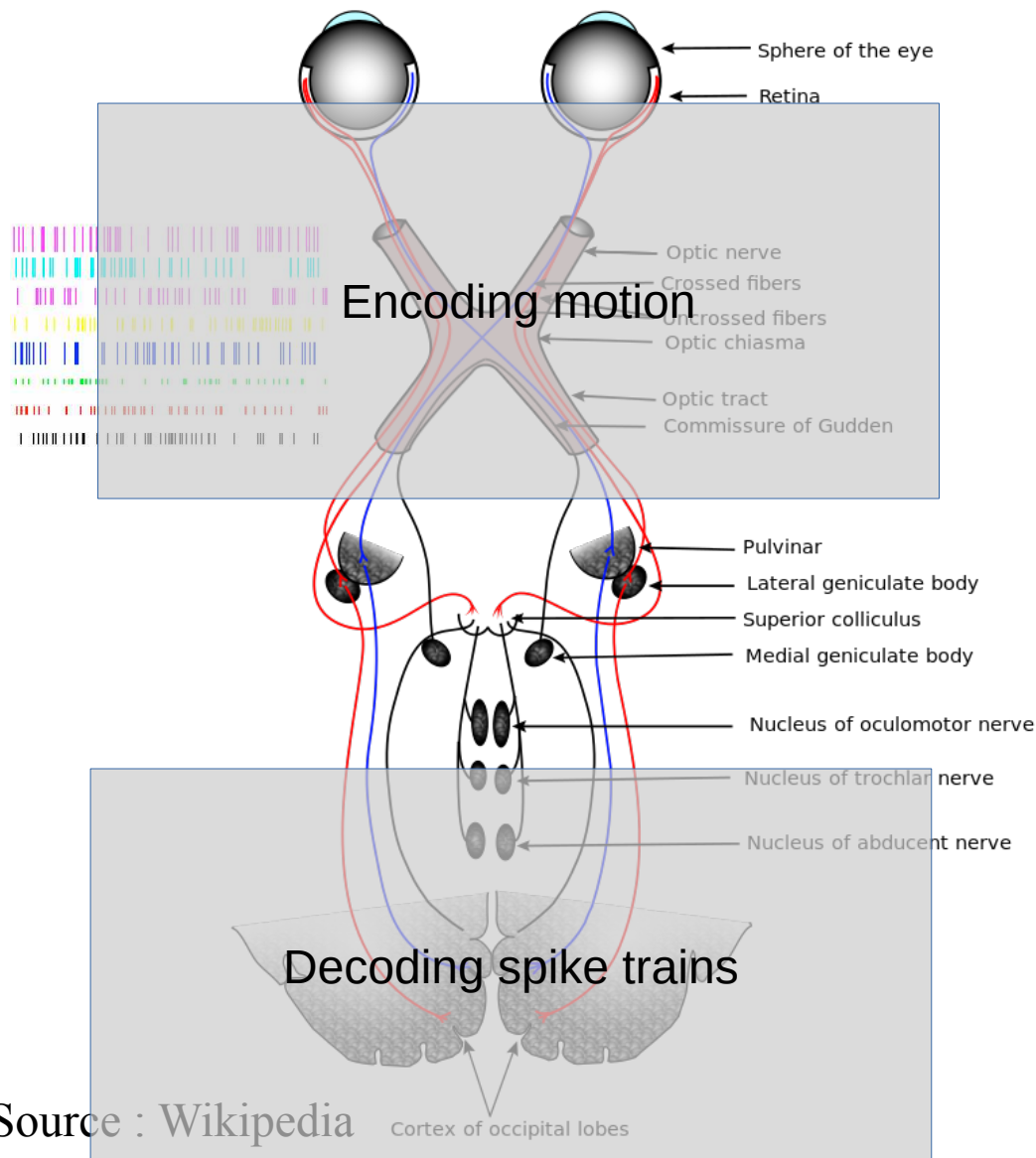
Visual Anticipation



Trajectory

What are the respective mechanisms underlying retinal and cortical anticipation?

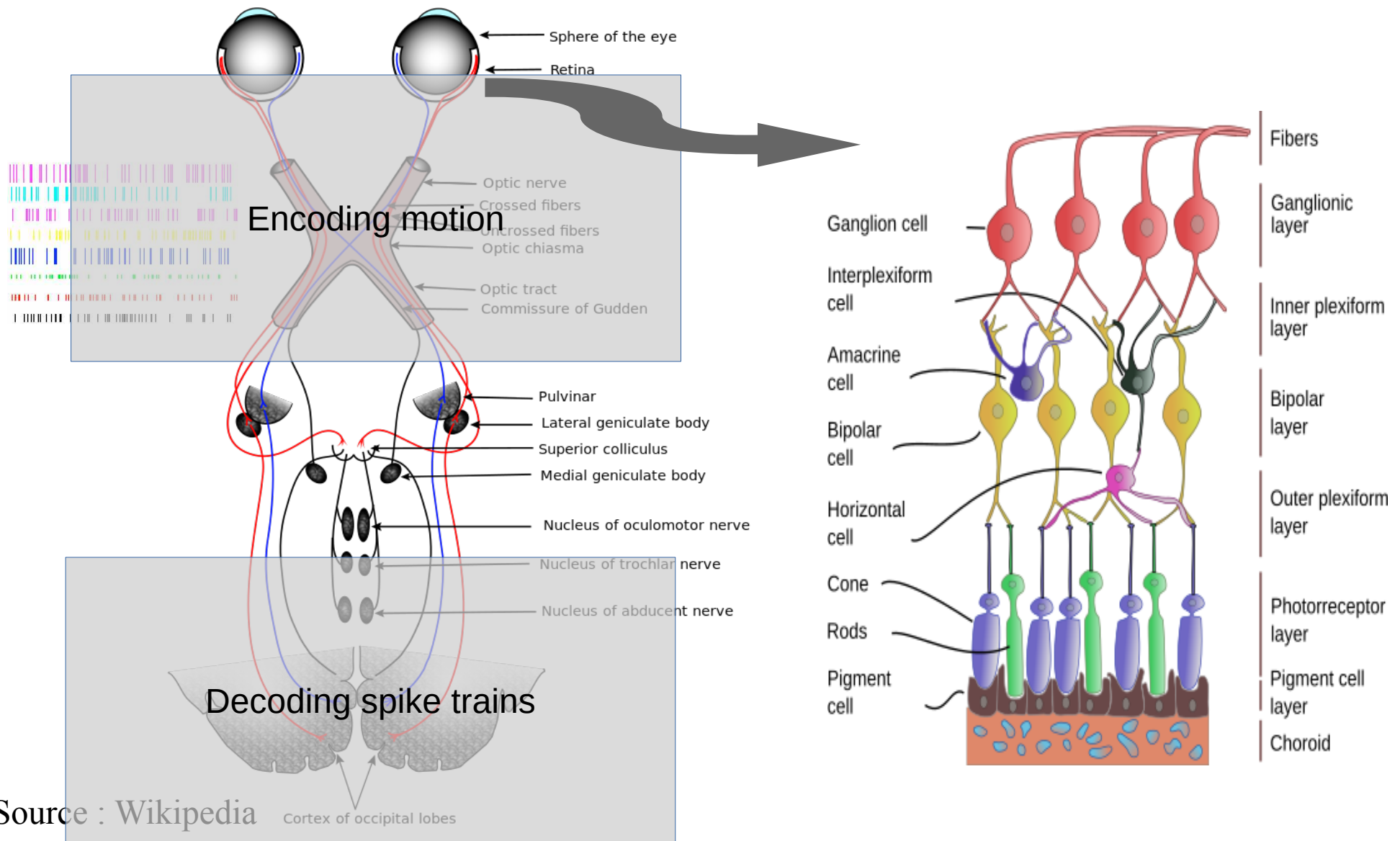
The visual flow



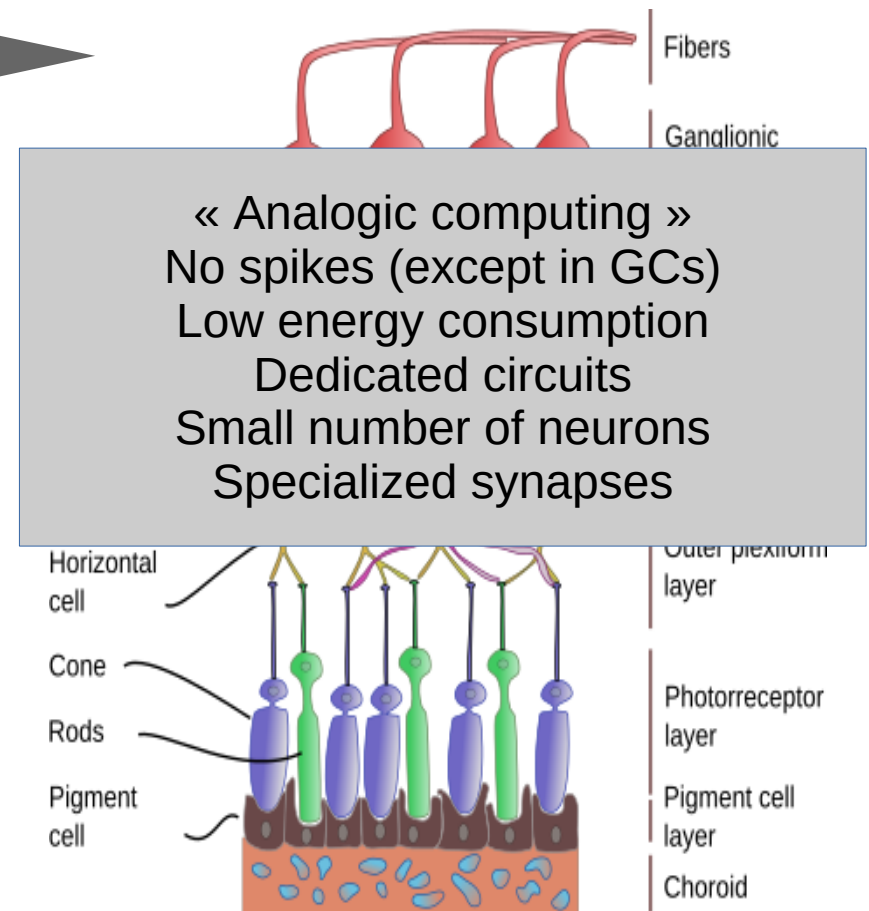
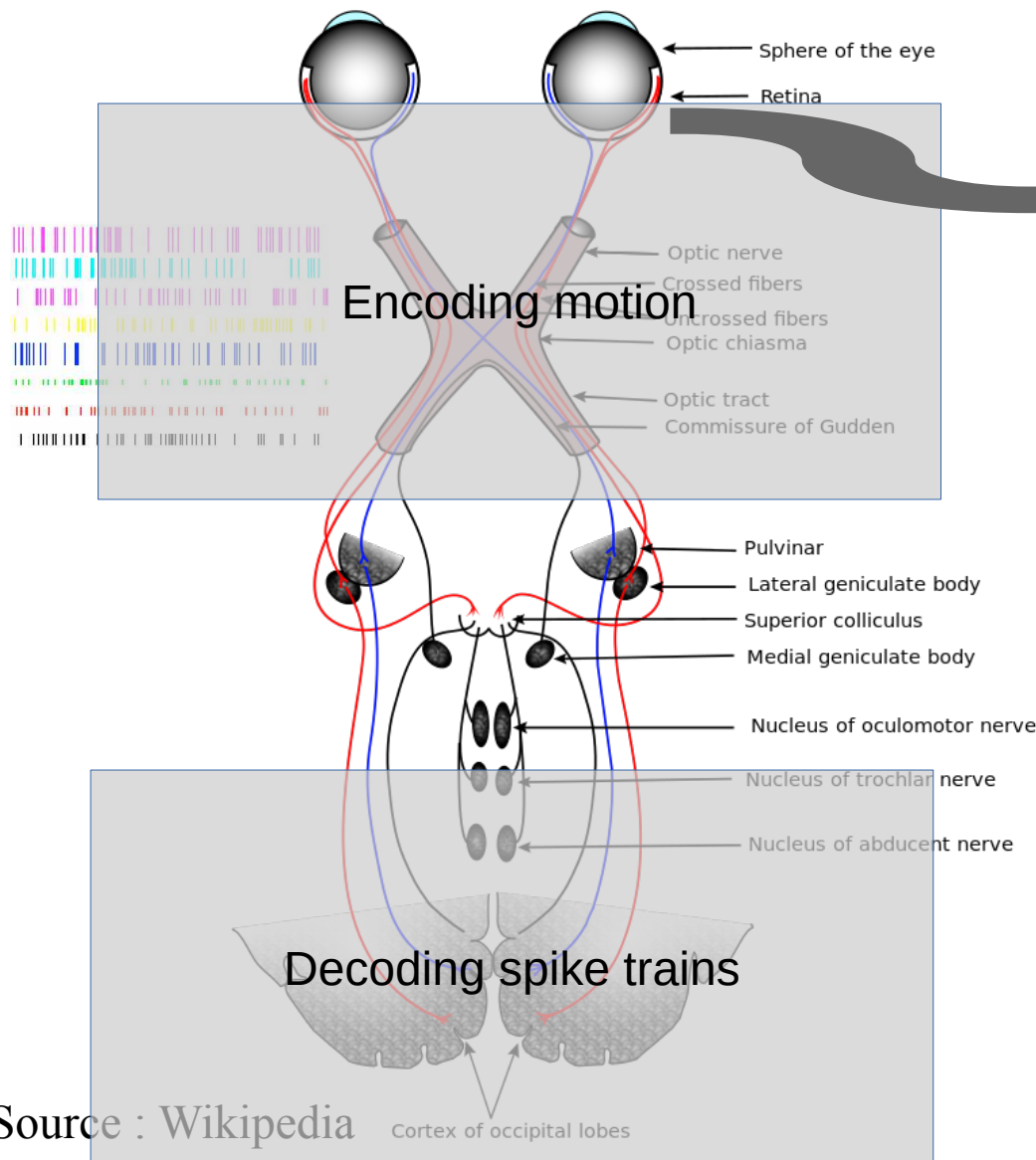
The retina is NOT a camera

- High transduction rate : 1 photon can trigger a membrane voltage variation of ~1 mV
- Able to detect approaching motion
- Able to detect differential motion
- Sensitive to « surprise » in a visual scene
- Able to perform motion anticipation

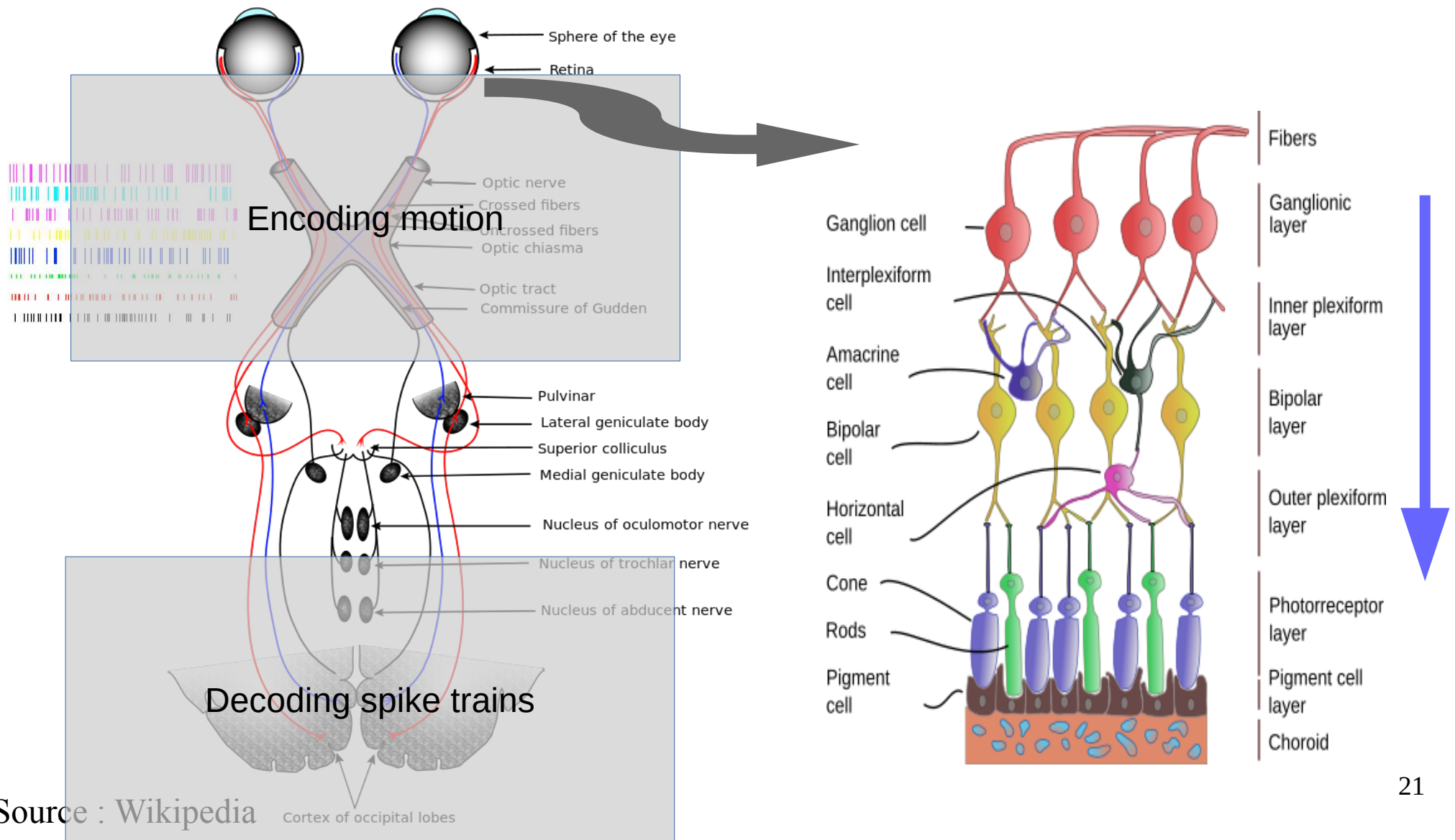
The visual flow



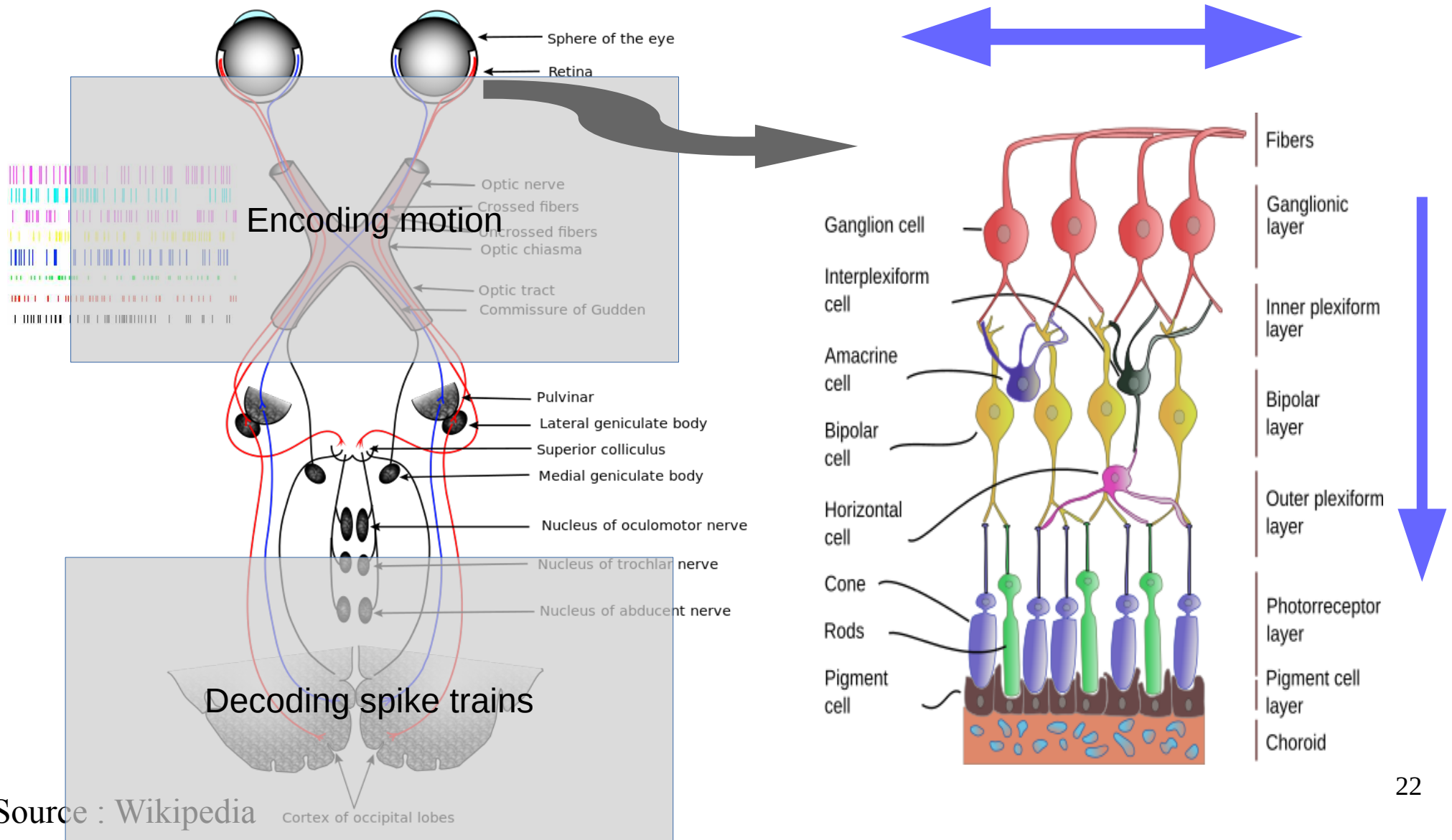
The visual flow



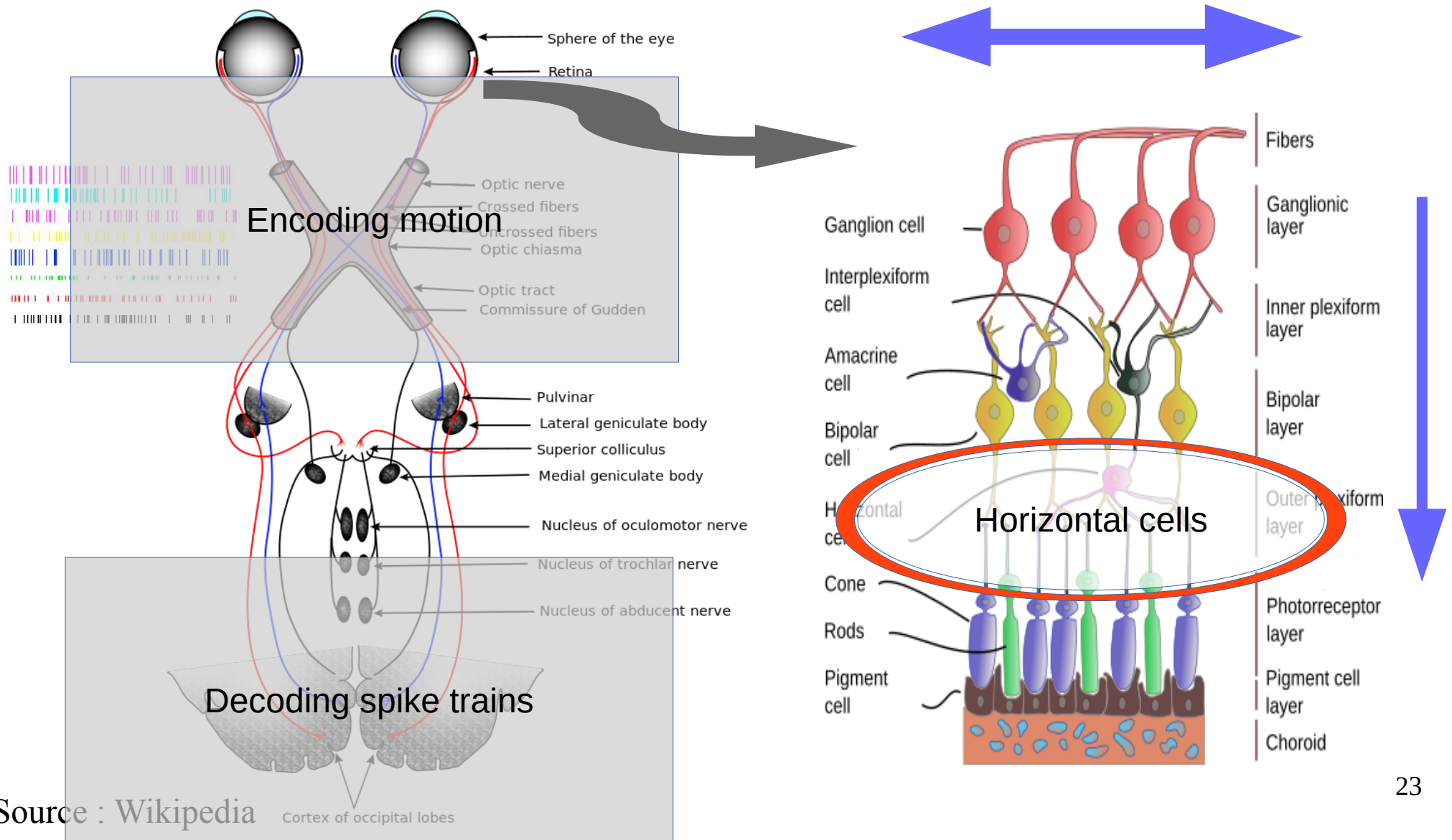
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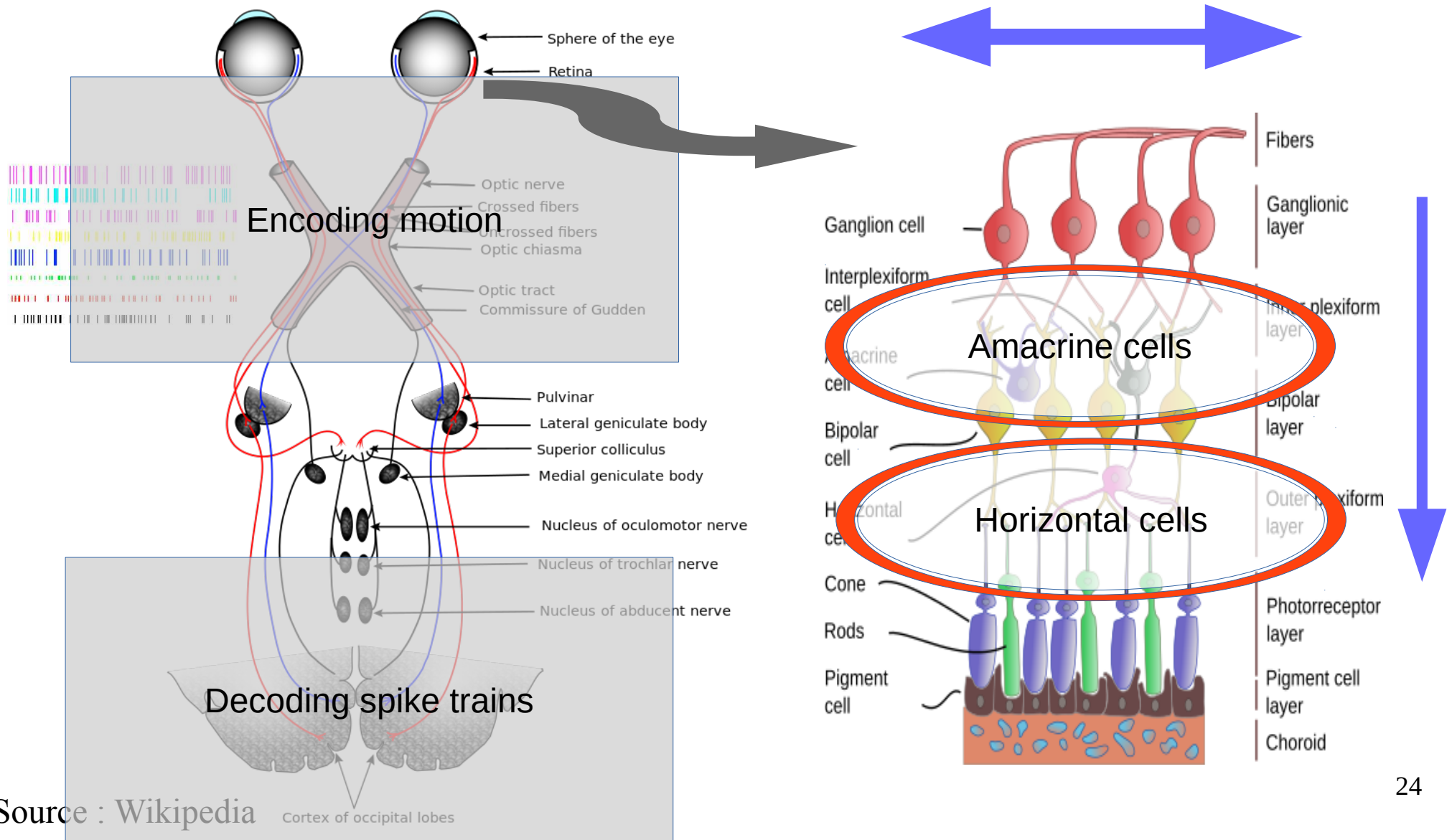
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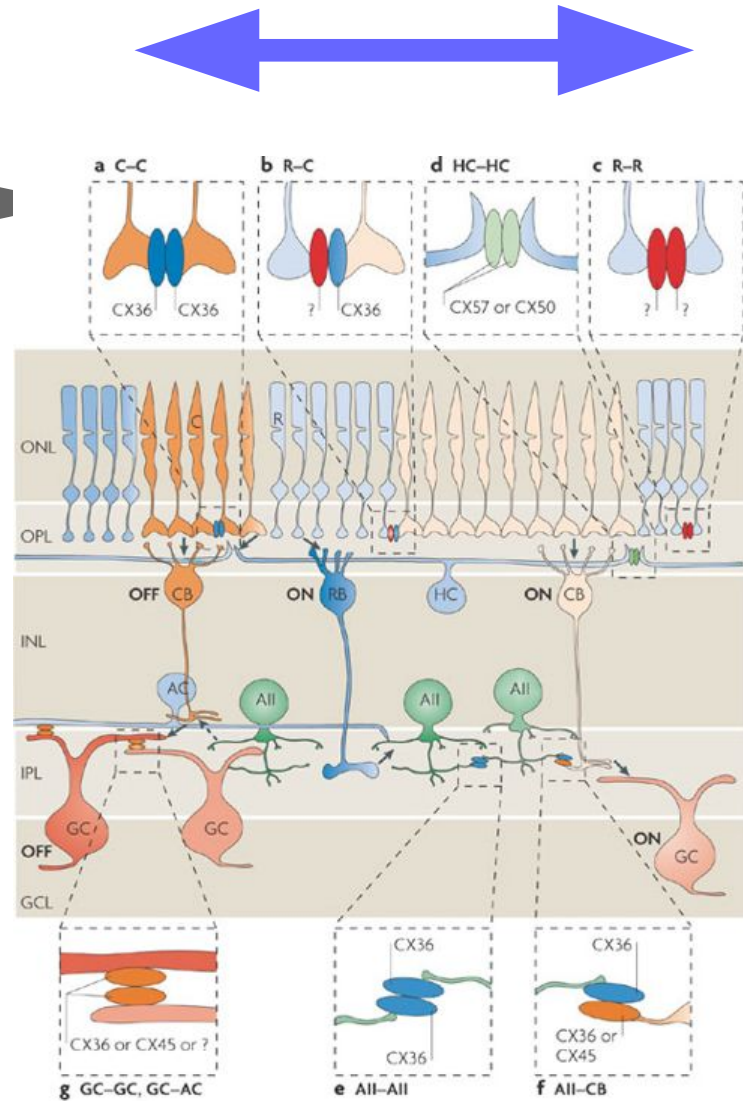
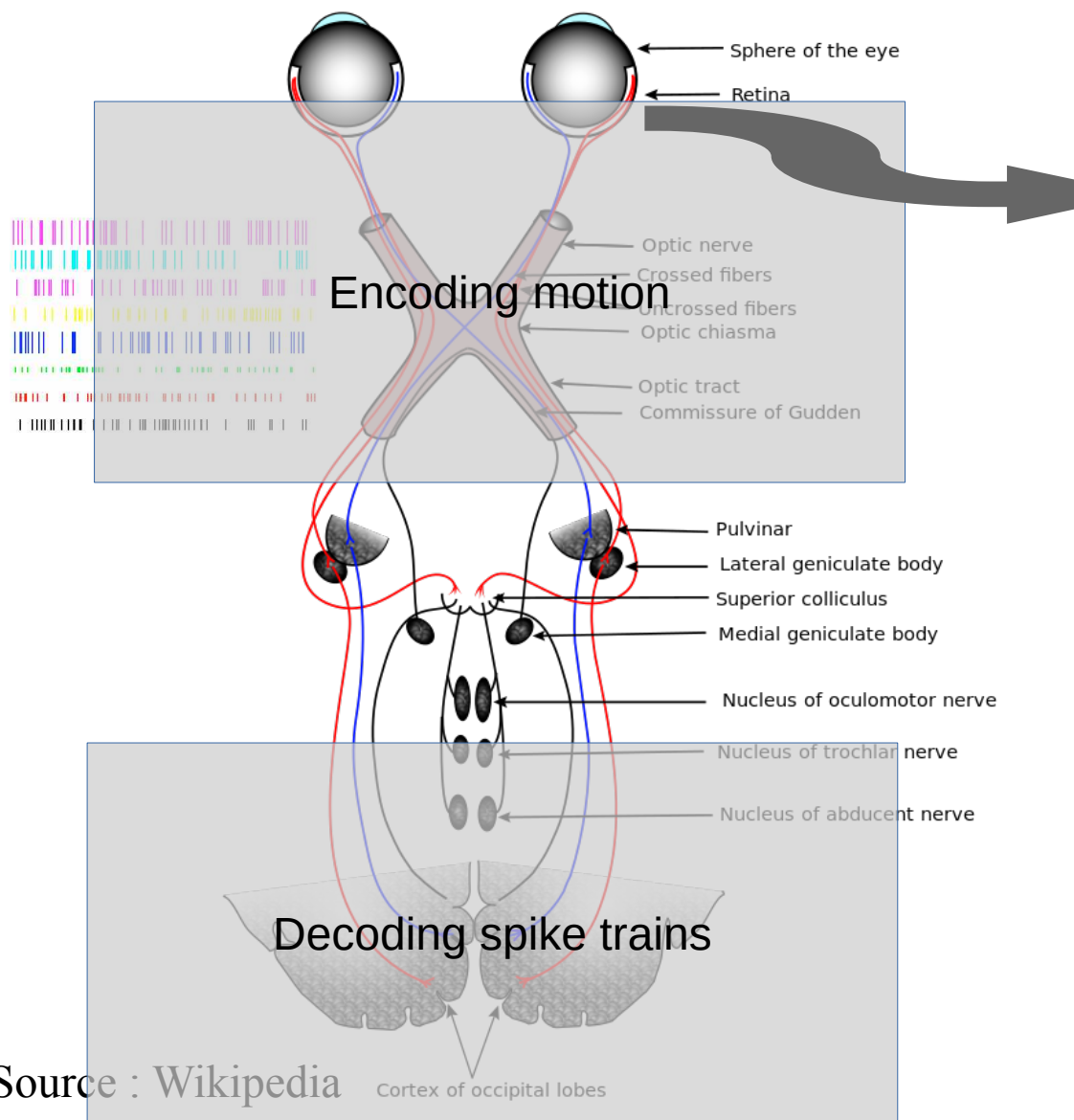
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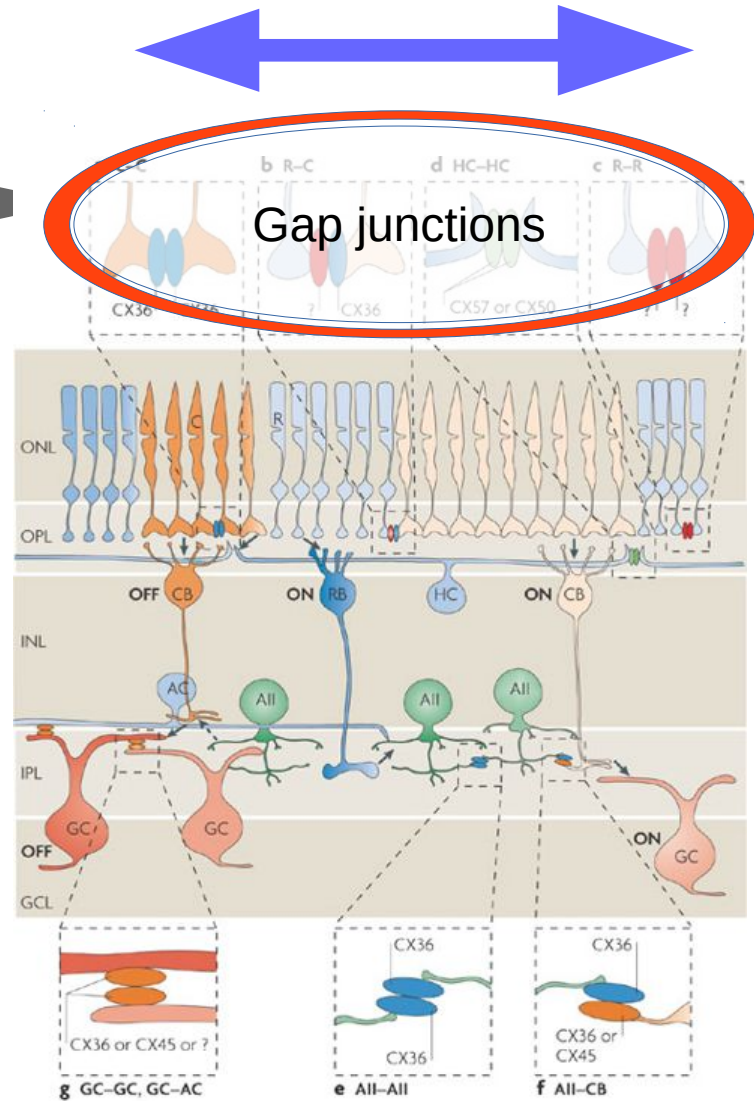
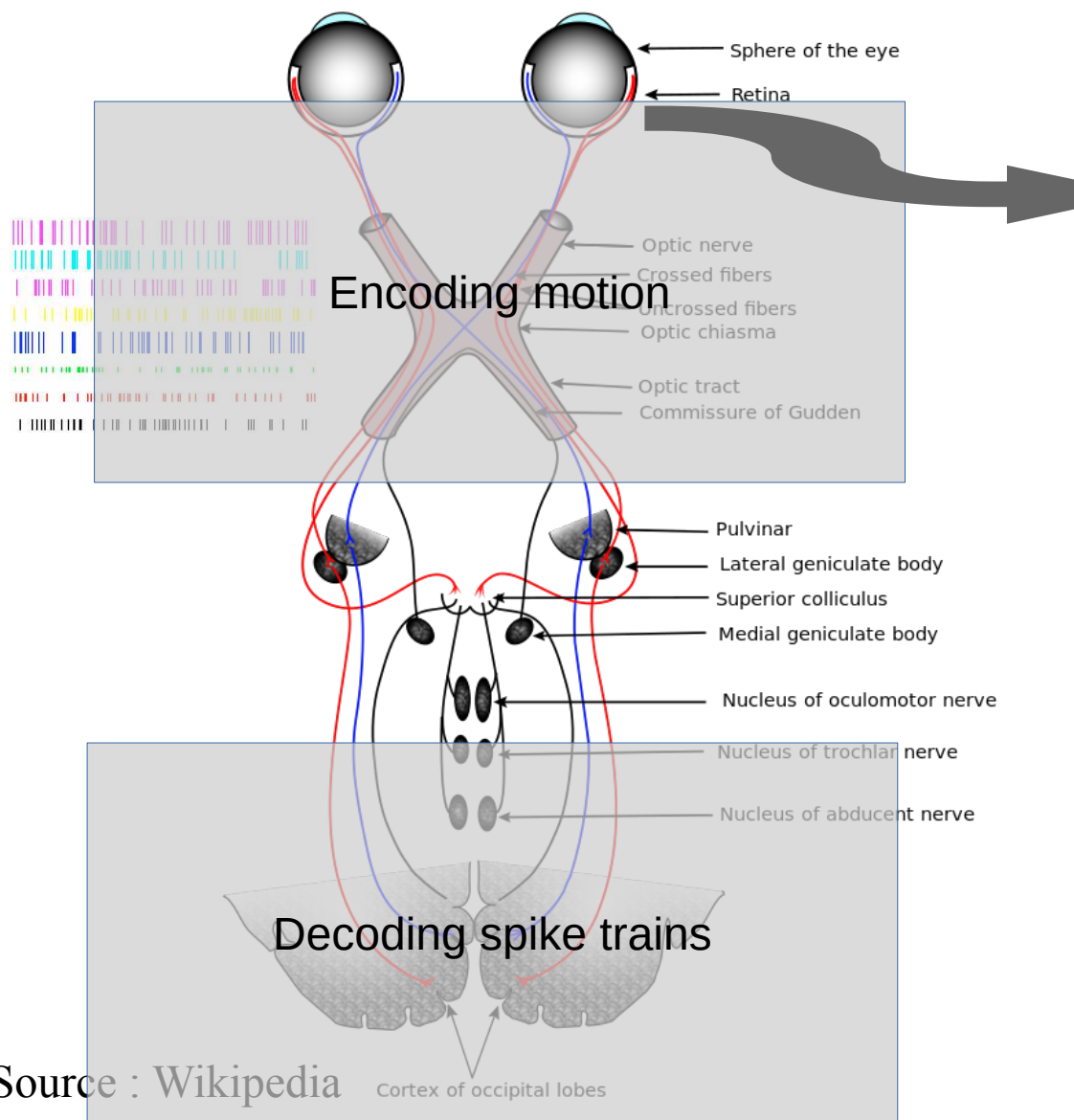
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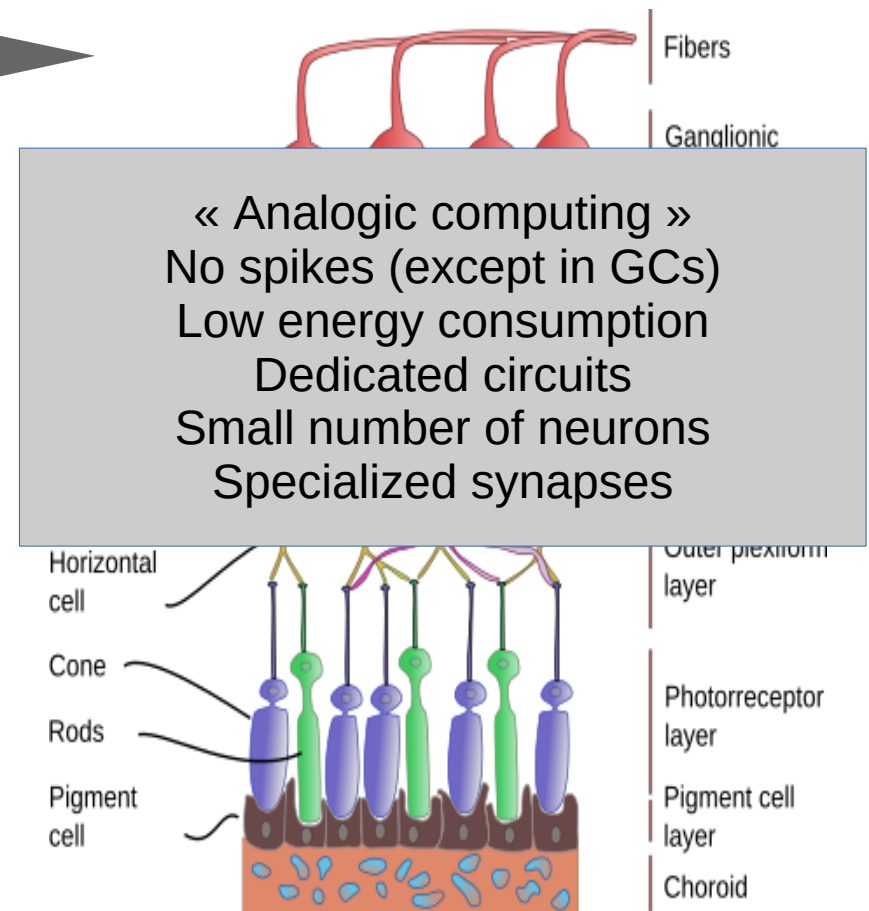
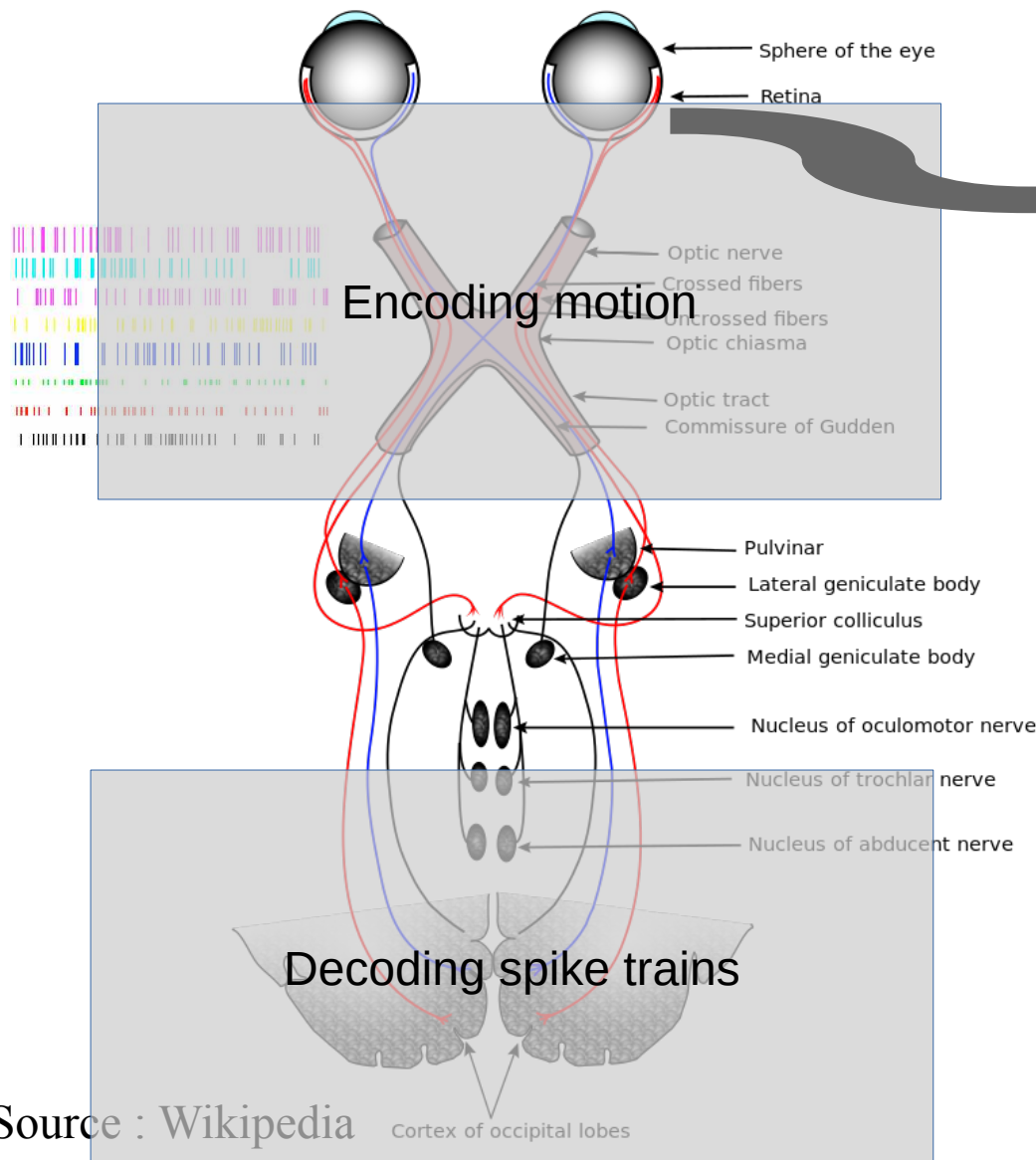
The visual flow



The visual flow

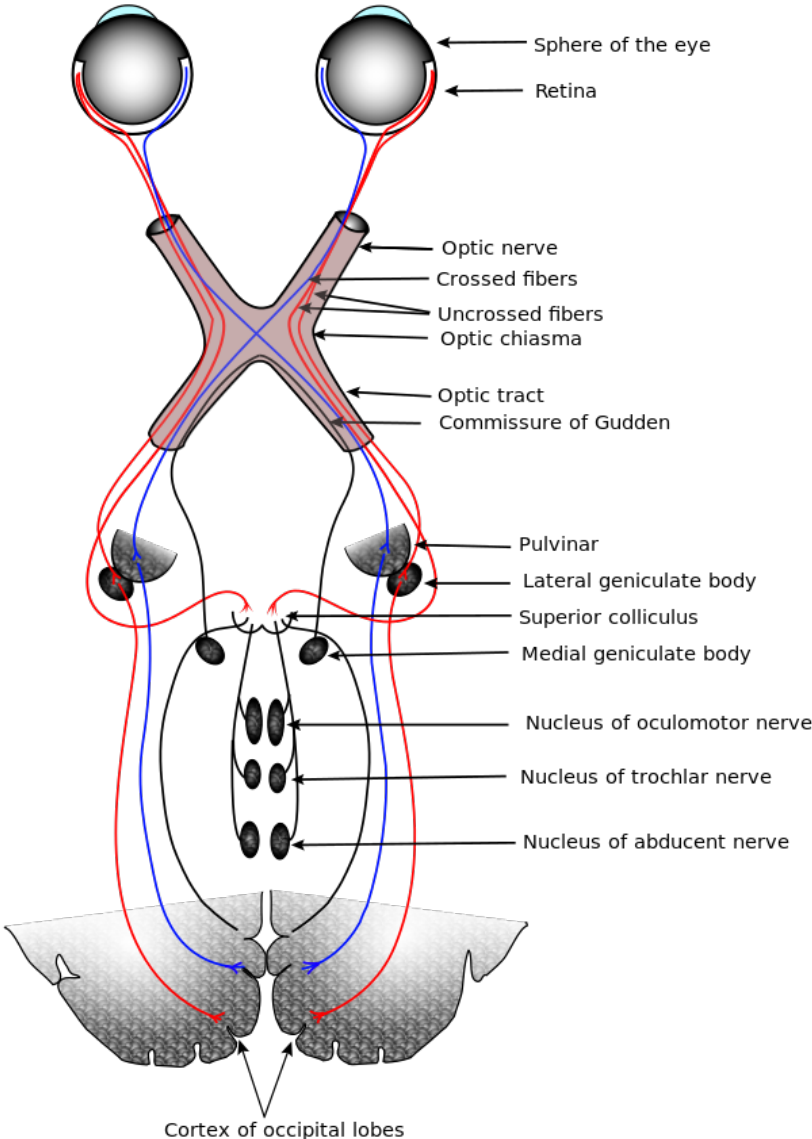


The visual flow

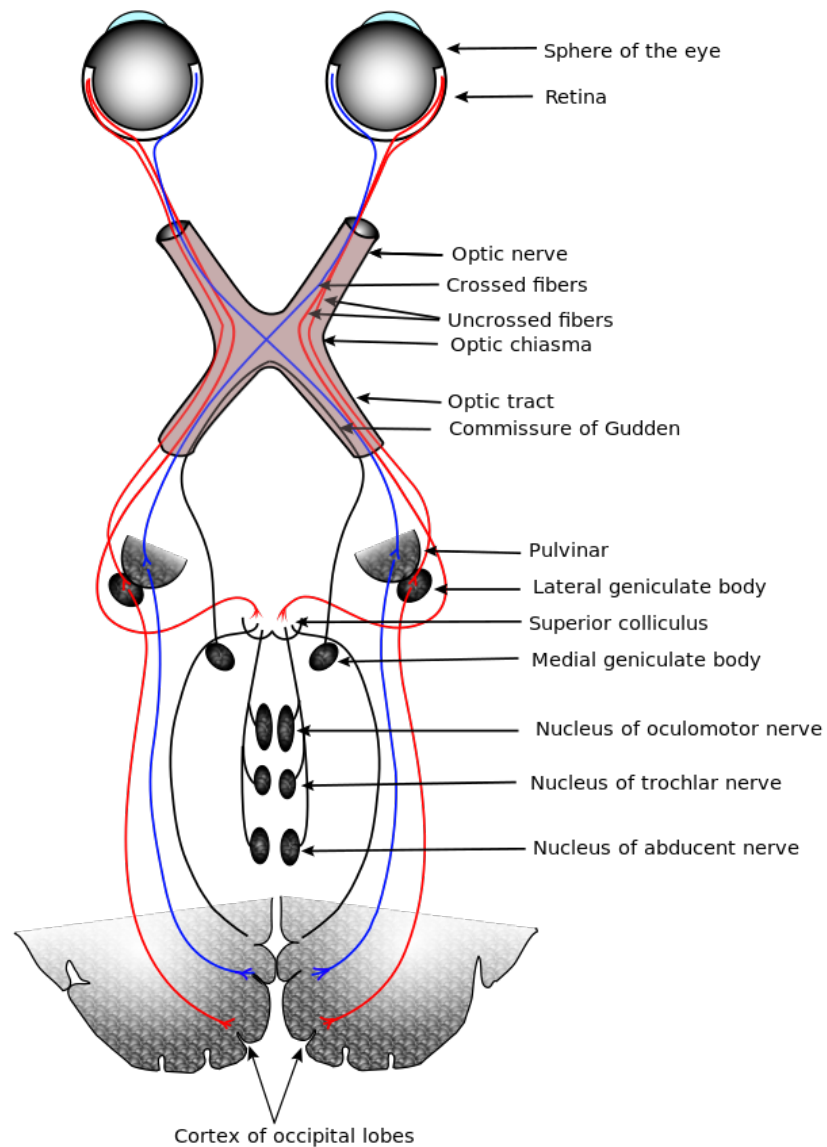


Which generic computational paradigms are at work in the retina ?

Visual Anticipation

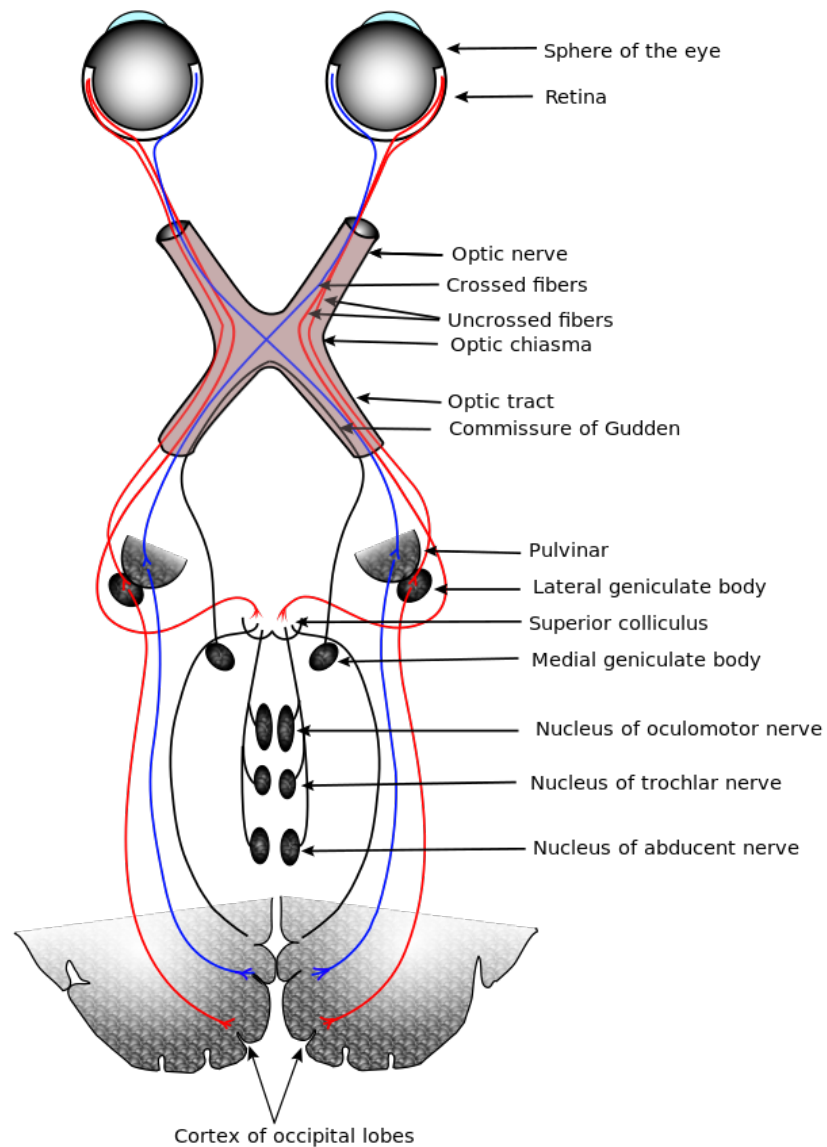


Visual Anticipation



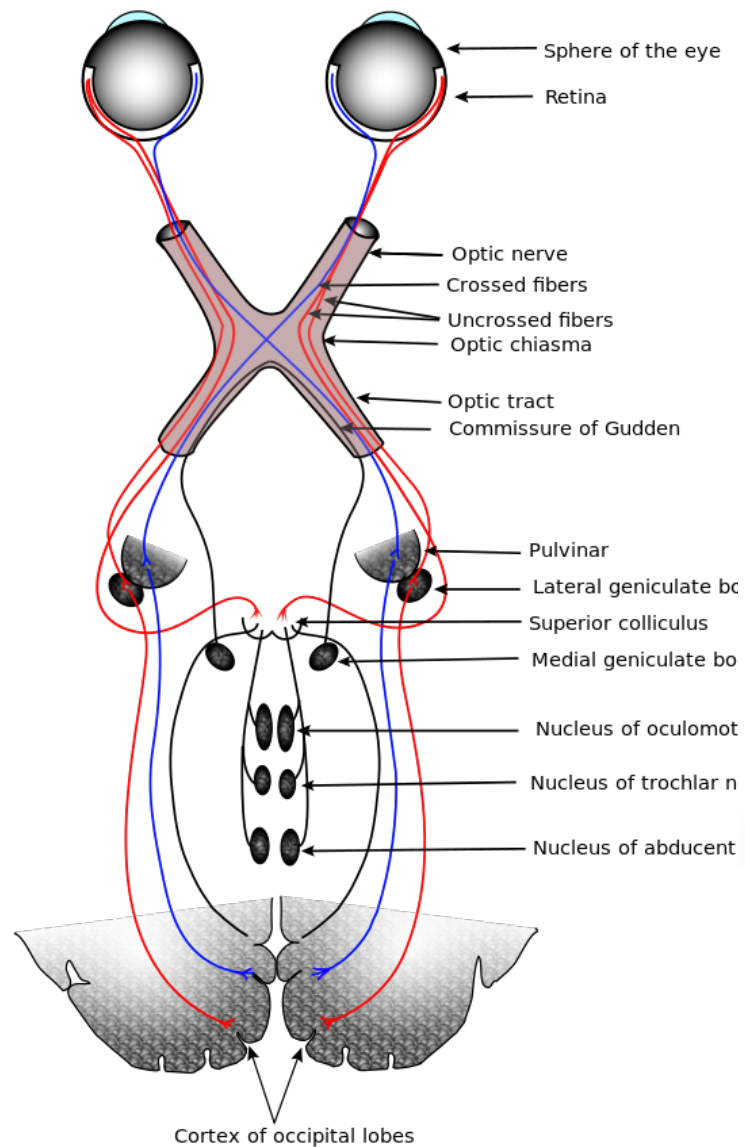
Which animal ?

Visual Anticipation



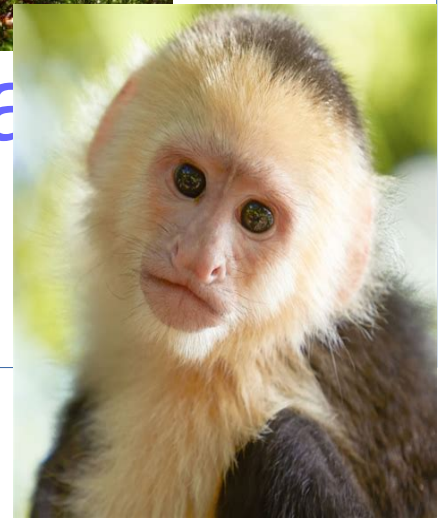
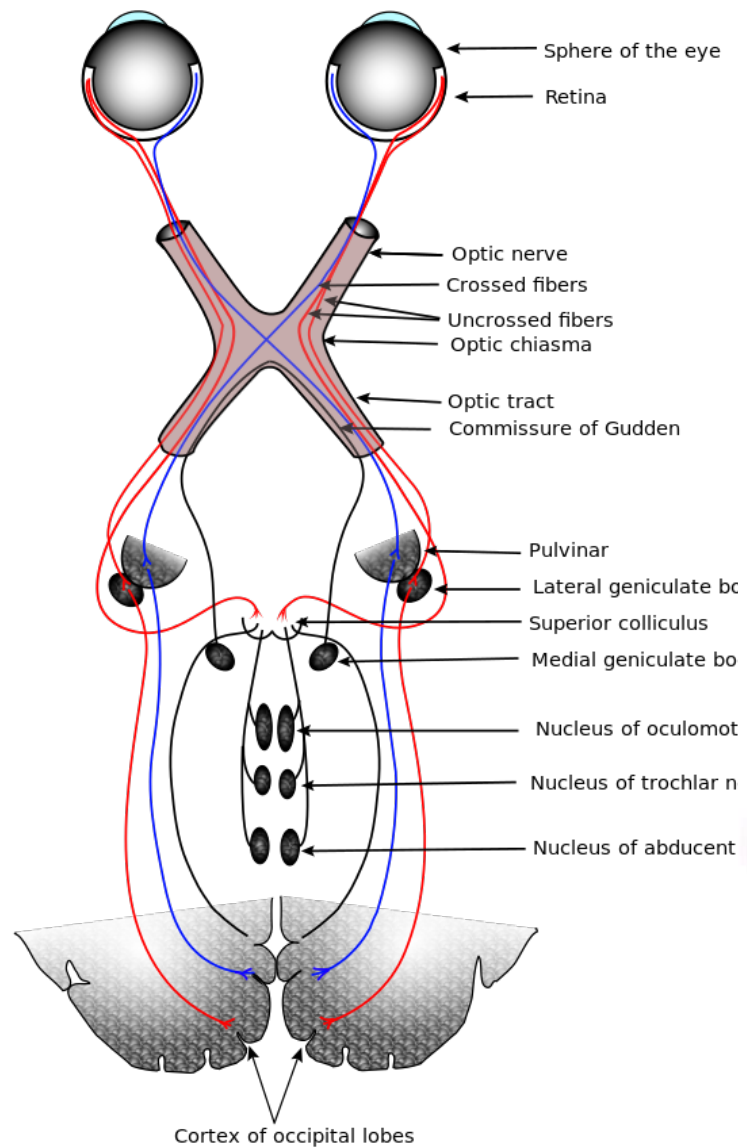
Which animal ?

Visual Anticipation

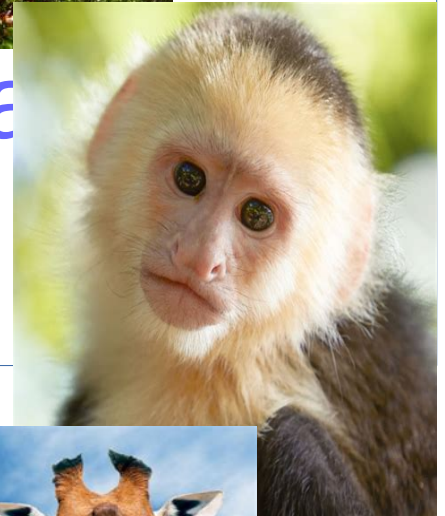
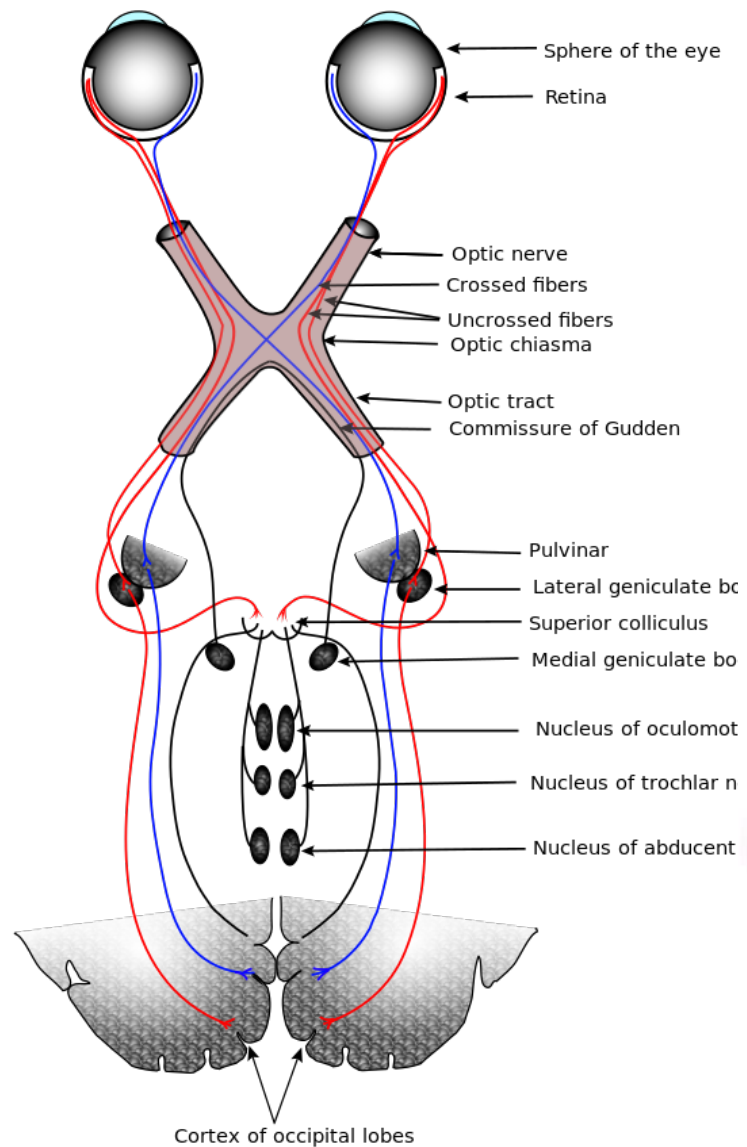


ch animal ?

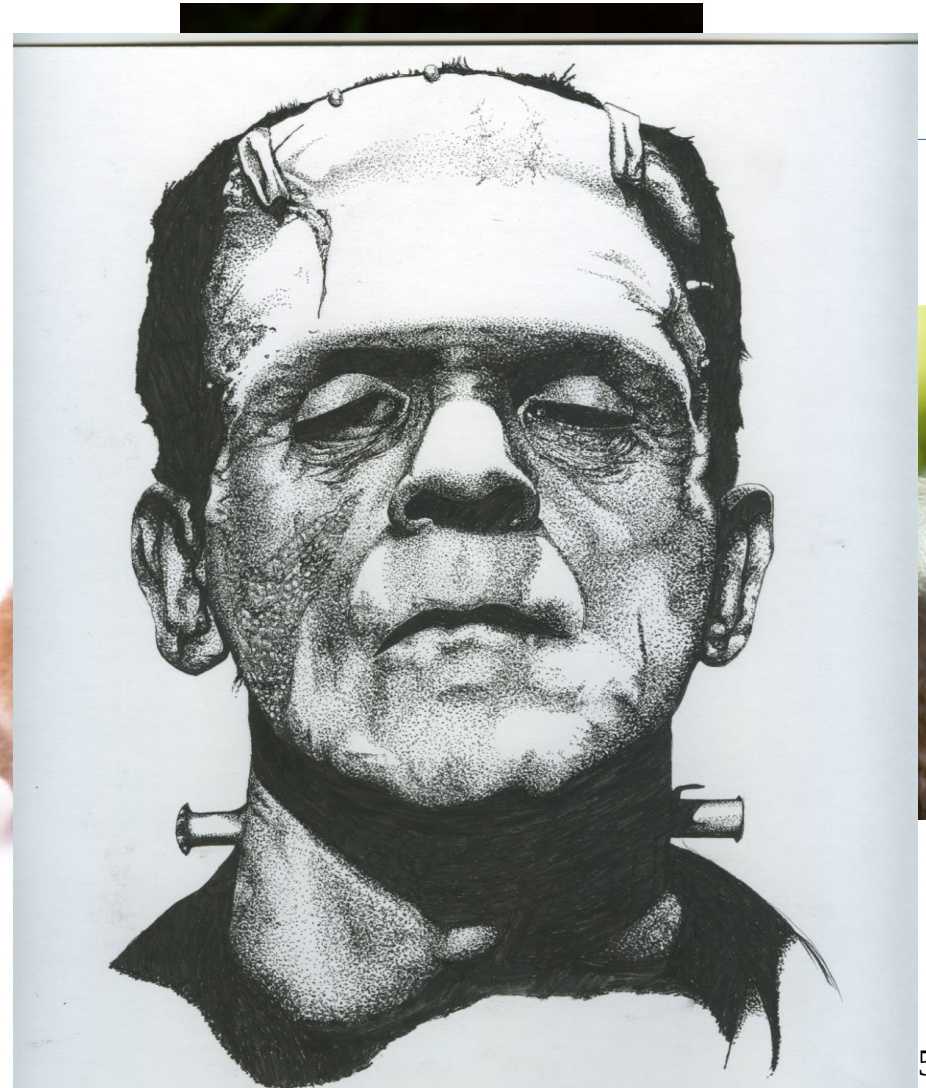
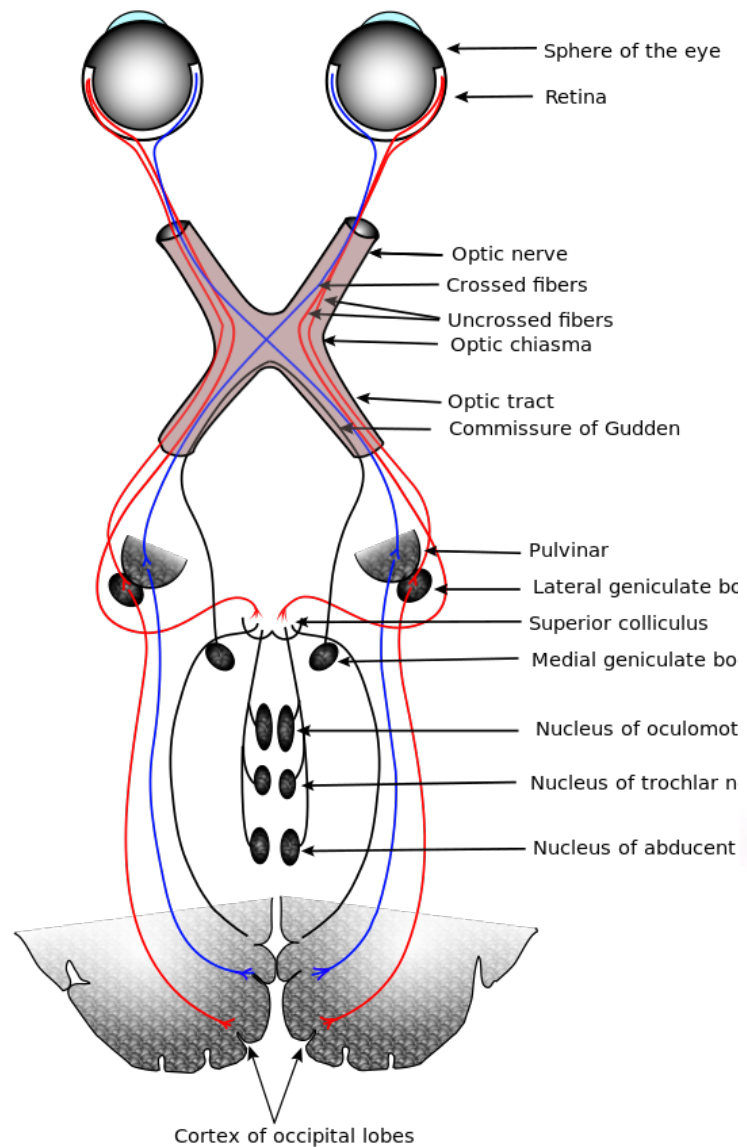
Visual Anticipation



Visual Anticipation



Visual Anticipation



Visual Anticipation

Developing a retino-cortical model of anticipation so as to

understand / propose

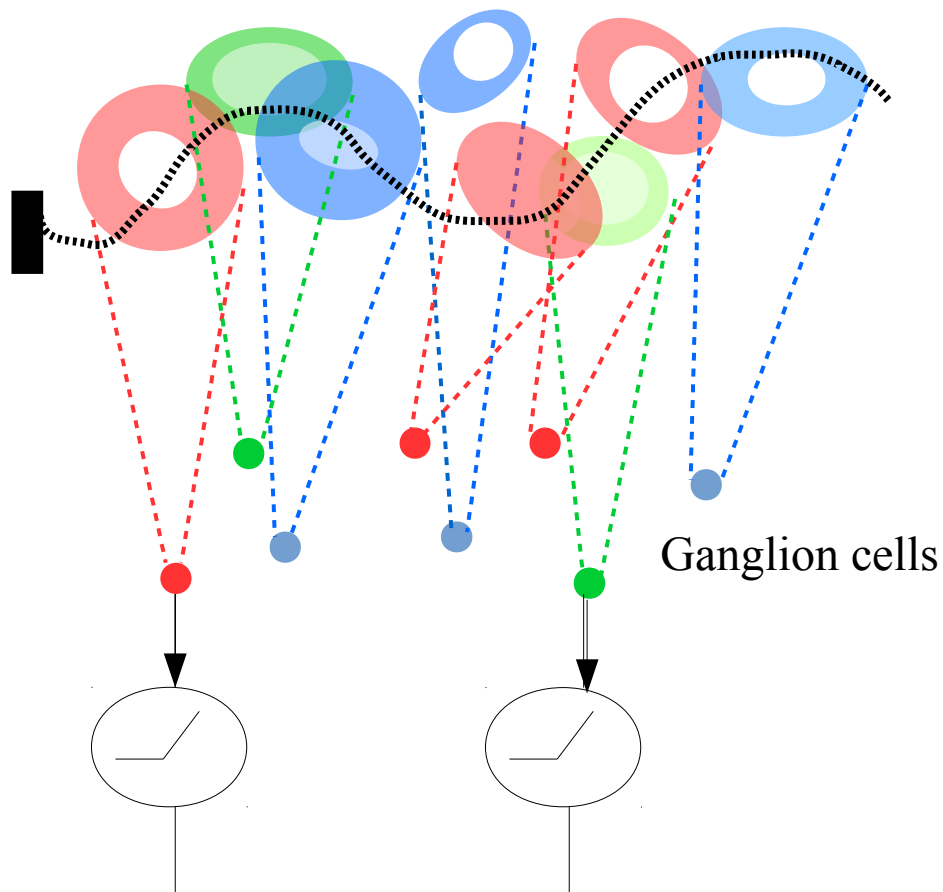
possible generic mechanisms for anticipation in the retina and in the cortex.

Anticipation in the retina

The Hubel-Wiesel view of vision

Nobel prize 1981

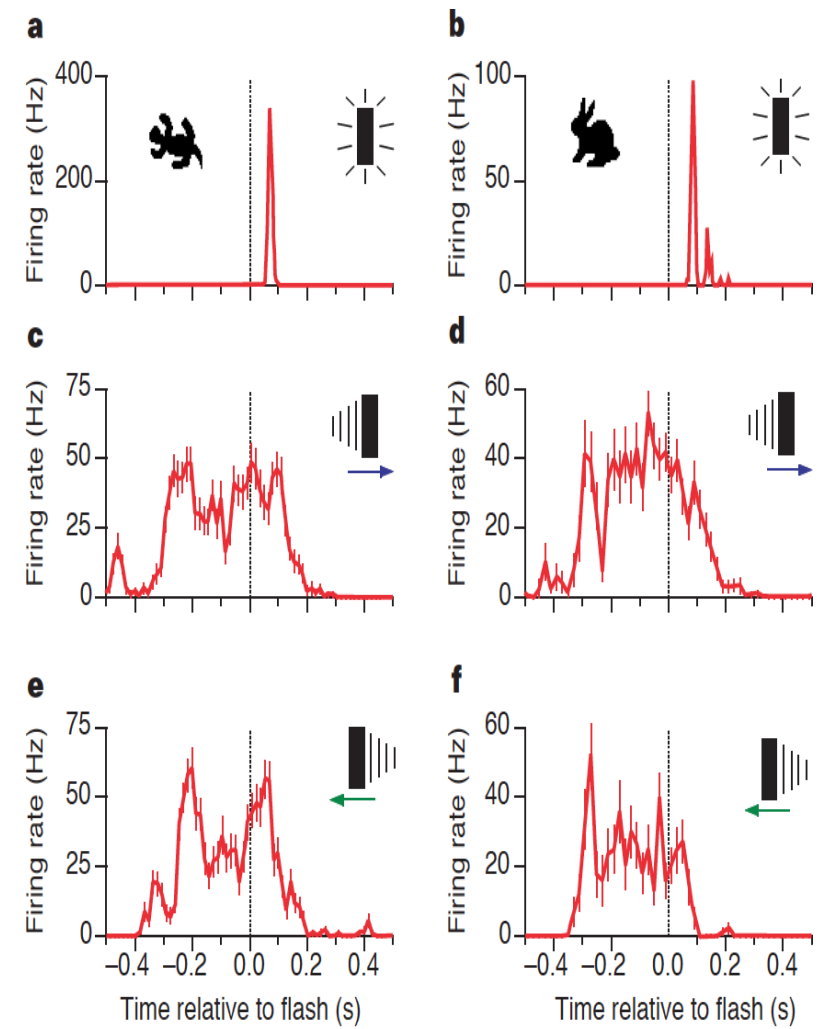
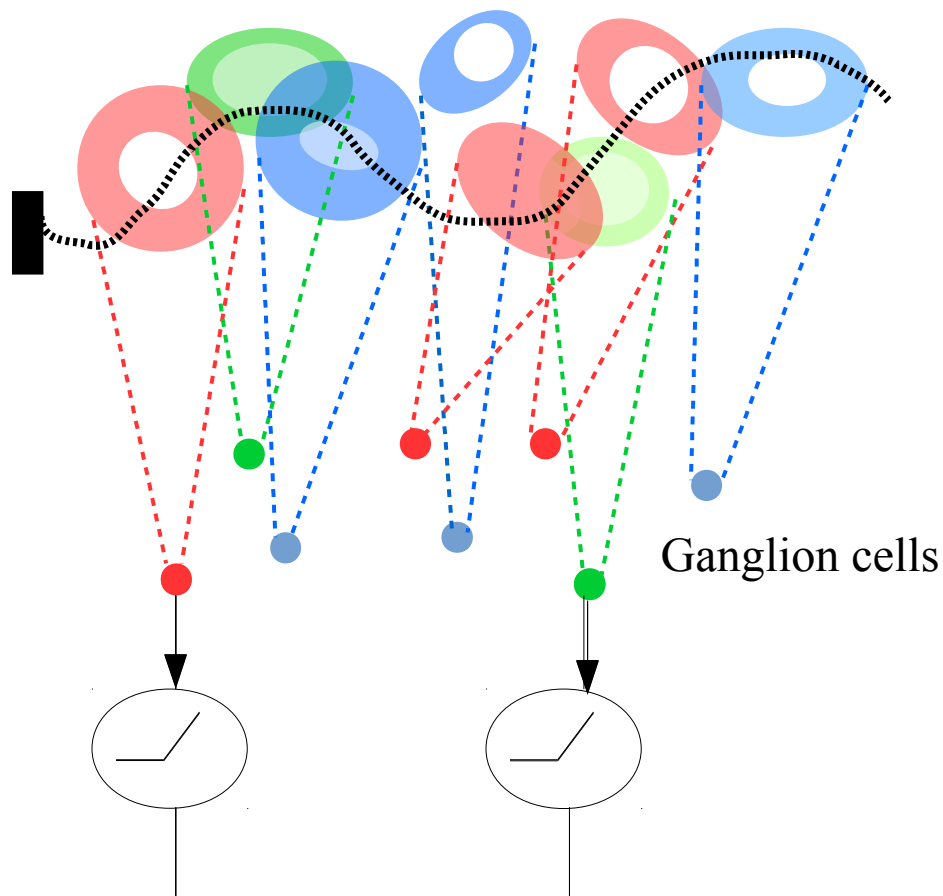
Ganglion cells response is the convolution of the stimulus with a spatio-temporal receptive field followed by a non linearity



Ganglion cells are independent encoders

The Hubel-Wiesel view of vision

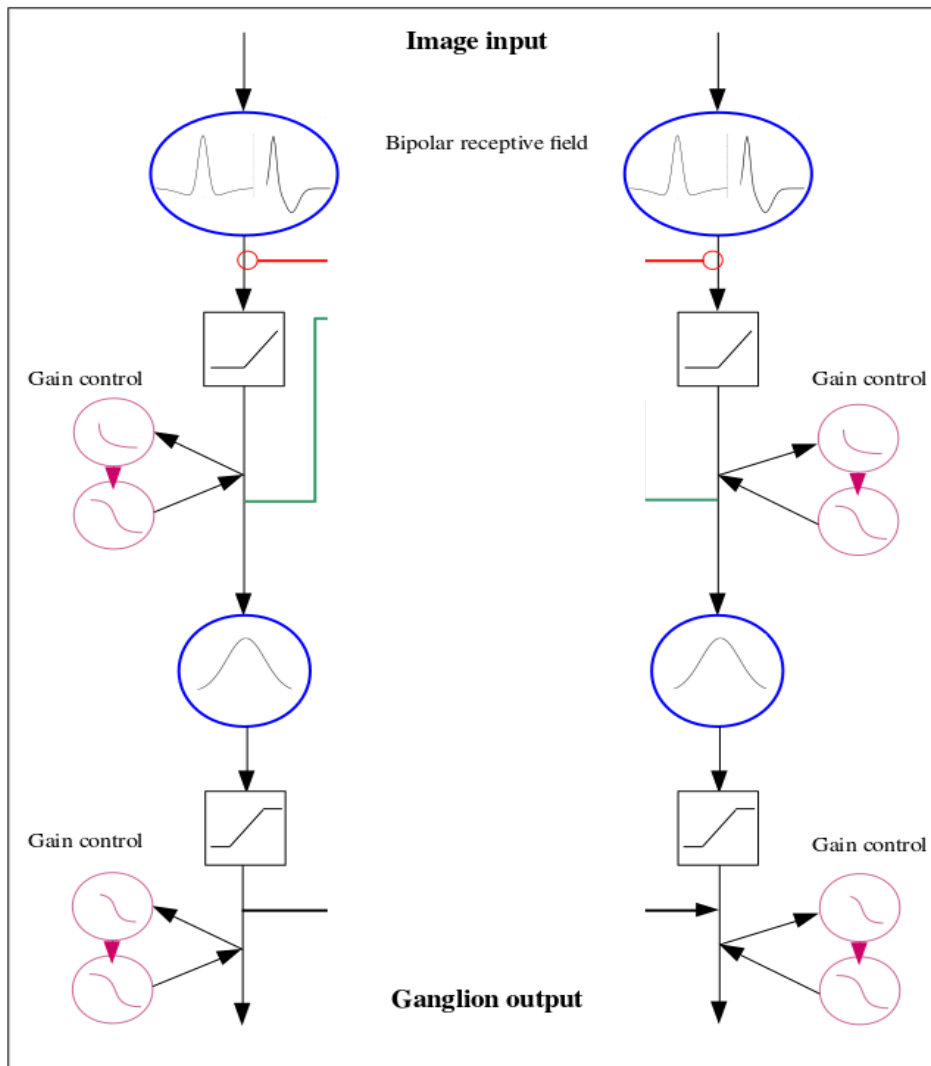
Nobel prize 1981



Source : Berry et al. 1999

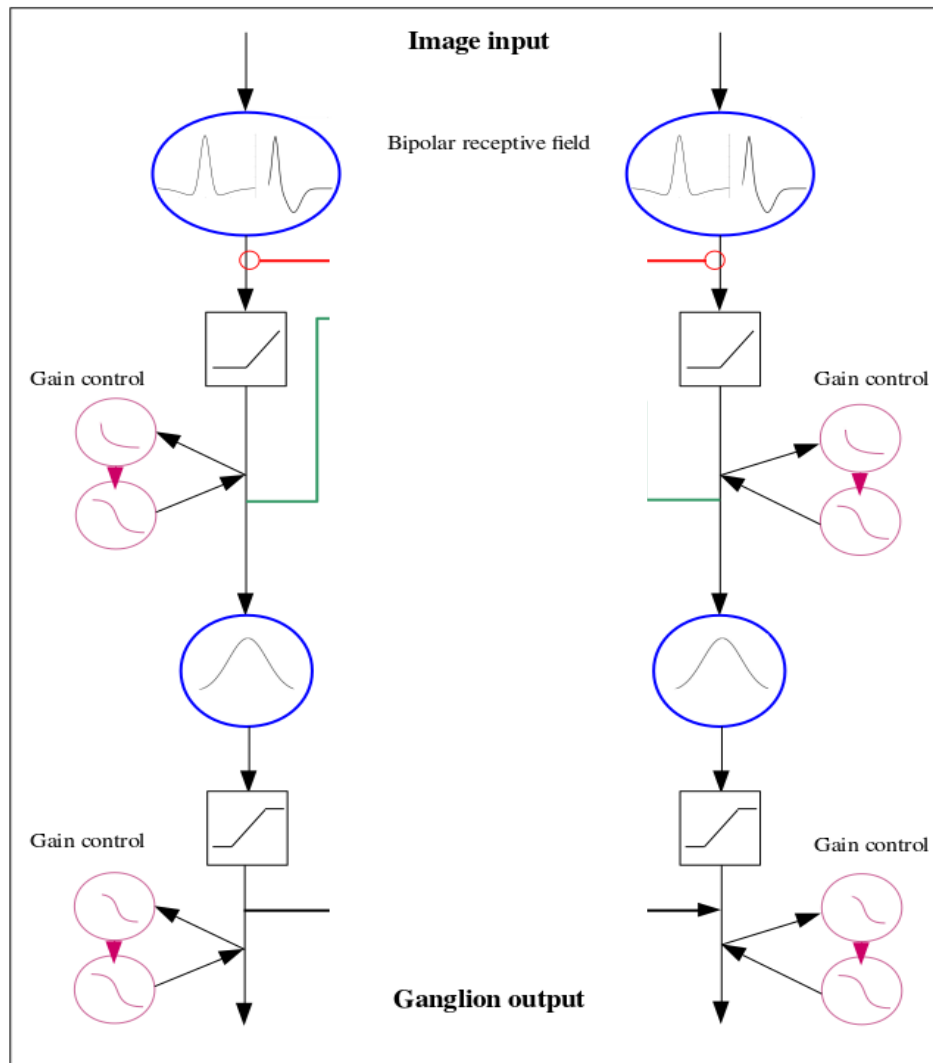
Building a 2D retina model for motion anticipation

Gain control (Berry et al, 1999, Chen et al. 2013)



Building a 2D retina model for motion anticipation

Gain control (Berry et al, 1999, Chen et al. 2013)



- Bipolar voltage :

$$V_{B_i}(t) = V_{i_{drive}}(t).$$

- Non-linear function :

$$\mathcal{N}_B(V_{B_i}) = \begin{cases} 0, & \text{if } V_{B_i} \leq \theta_B; \\ V_{B_i} - \theta_B, & \text{else.} \end{cases}$$

- Activation function :

$$\frac{dA_{B_i}}{dt} = -\frac{A_{B_i}}{\tau_a} + h\mathcal{N}(V_{B_i}(t)).$$

- Gain Control function :

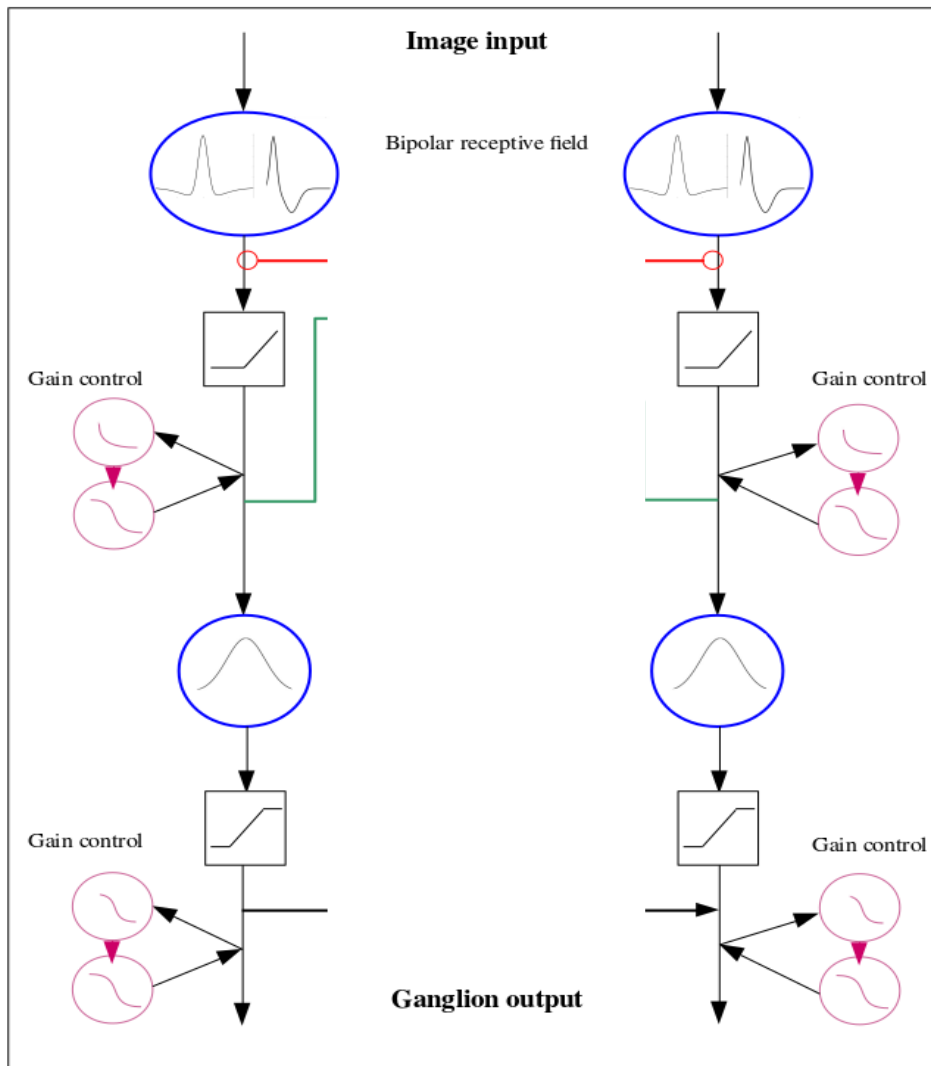
$$\mathcal{G}_B(A) = \begin{cases} 0, & \text{if } A \leq 0; \\ \frac{1}{1+A^6}, & \text{else.} \end{cases}$$

- Output :

$$R_{B_i} = \mathcal{N}_B(V_{B_i}) \mathcal{G}_B(A_{B_i}).$$

Building a 2D retina model for motion anticipation

Gain control (Chen et al. 2013)



- Ganglion voltage

$$V_{G_k} = \sum_i W_{G_k}^{B_i} R_{B_i}$$

- Non-linear function :

$$\mathcal{N}_{G_F}(V) = \begin{cases} 0, & \text{if } V \leq 0; \\ \alpha_{G_F}(V - \theta_{G_F}), & \text{if } \theta_{G_F} \leq V \leq N_{G_F}^{max}/\alpha_{G_F} + \theta_{G_F}; \\ N_{G_F}^{max}, & \text{else.} \end{cases}$$

- Activation function :

$$\frac{dA_{G_F k_F}}{dt} = -\frac{A_{G_F k_F}}{\tau_{G_F}} + h_{G_F} \mathcal{N}_{G_F}(V_{G_F k_F})$$

- Gain Control function :

$$\mathcal{G}_{G_F}(A) = \begin{cases} 0, & \text{if } A \leq 0; \\ \frac{1}{1+A}, & \text{else.} \end{cases}$$

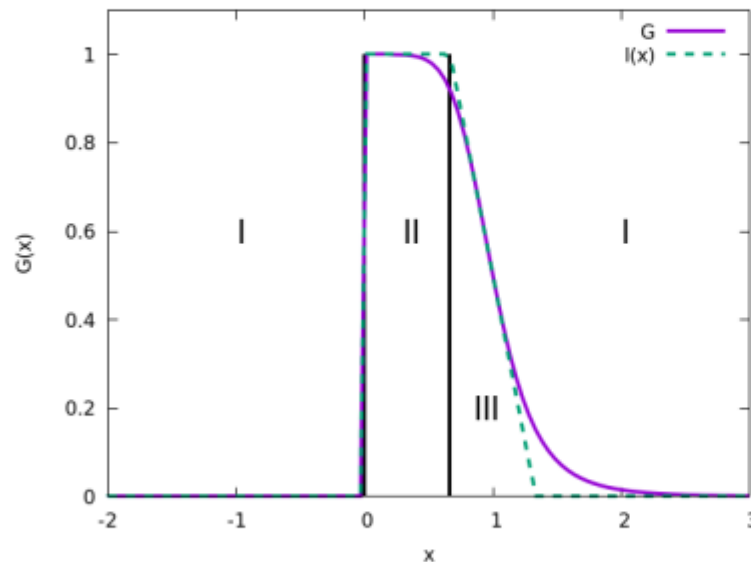
- Output :

$$R_{G_F k_F}(V_{G_F k_F}, A_{G_F k_F}) = \mathcal{N}_{G_F}(V_{G_F k_F}) \mathcal{G}_{G_F}(A_{G_F k_F}).$$

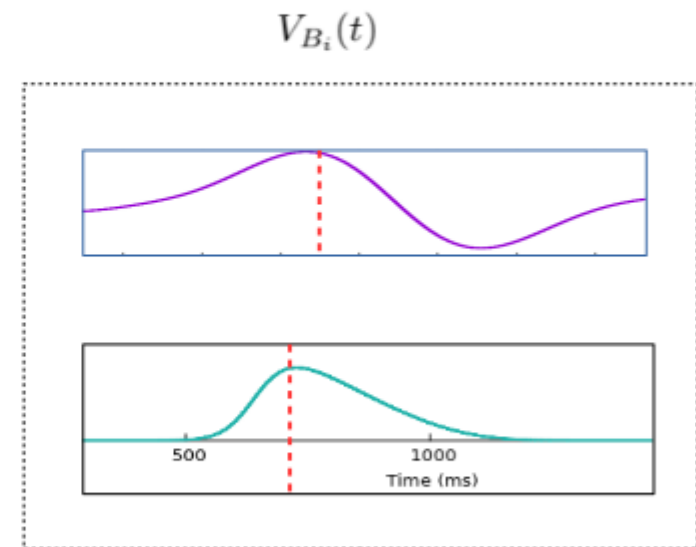
Building a 2D retina model for motion anticipation

1) Gain control

How does it work ?



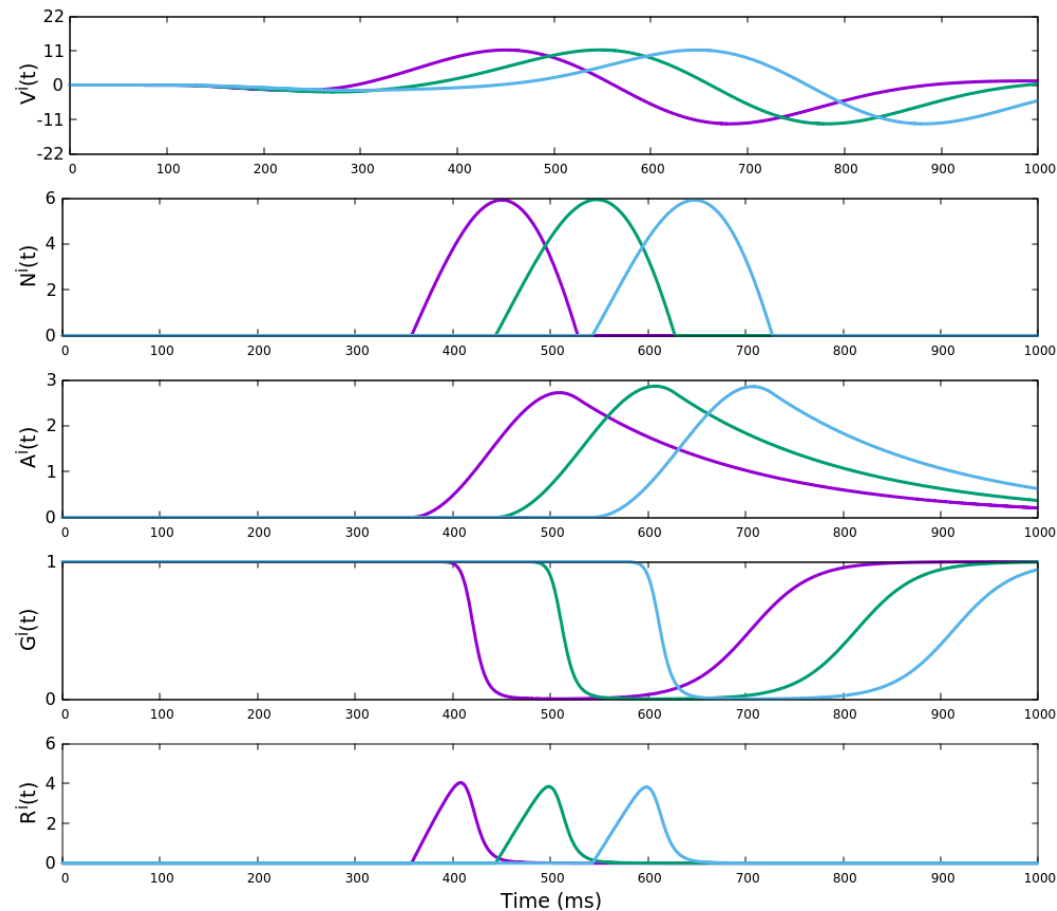
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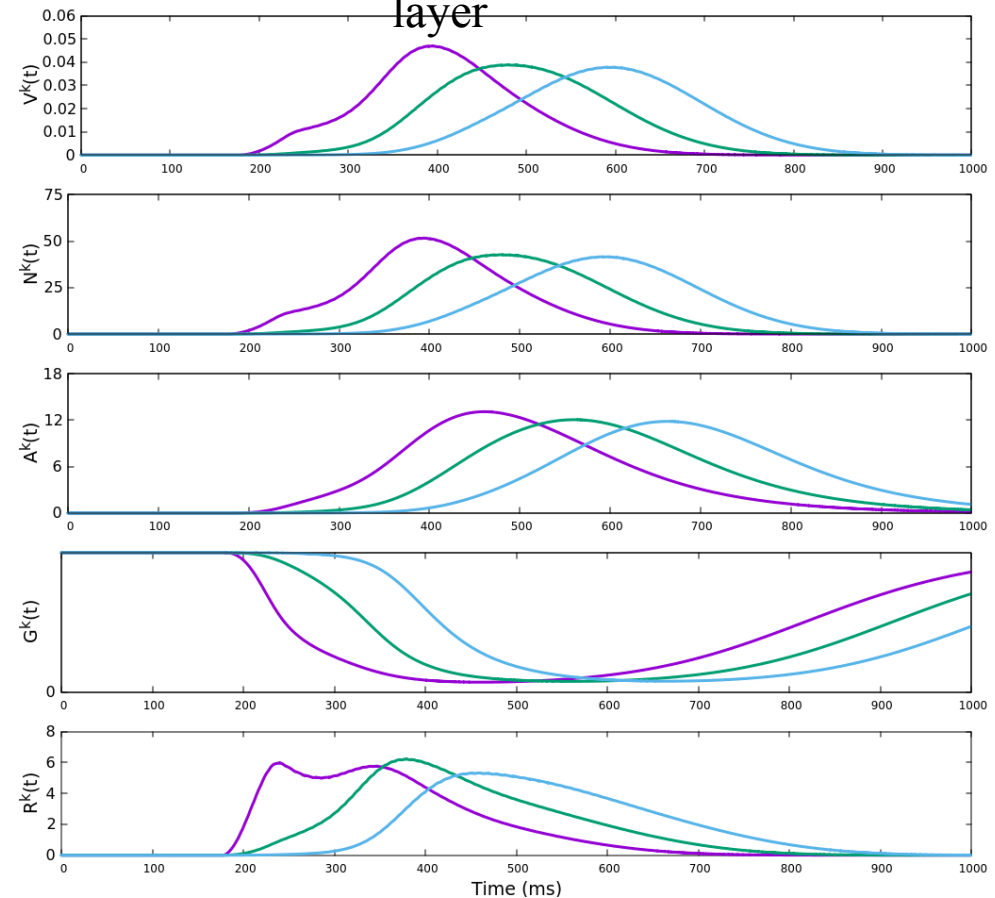
$$R_{B_i} = \mathcal{N}_B(V_{B_i}) \mathcal{G}_B(A_{B_i}).$$

1D results : smooth motion anticipation with gain control

Bipolar layer

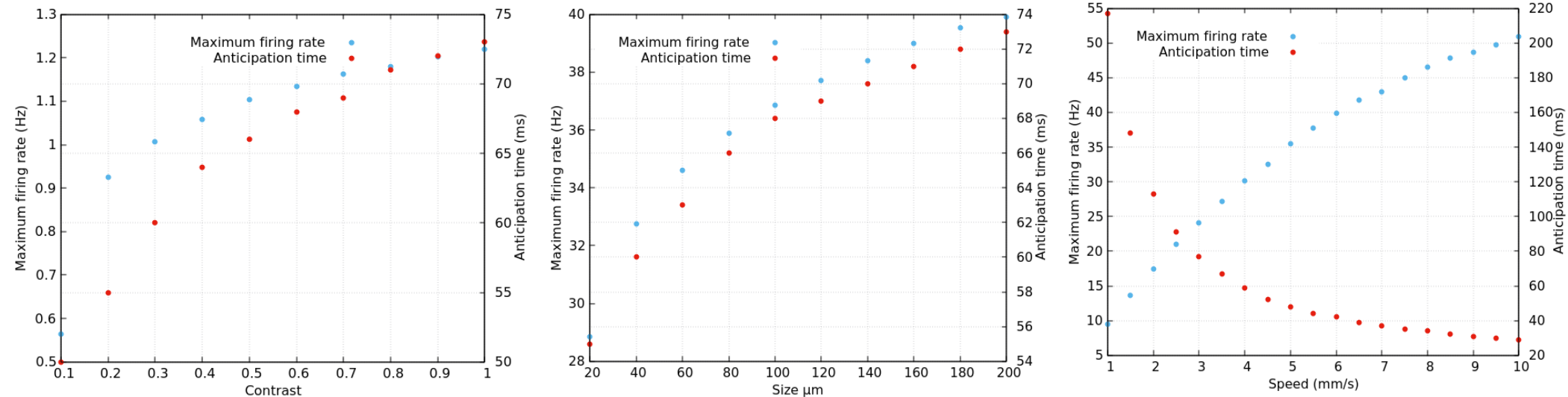


Ganglion layer

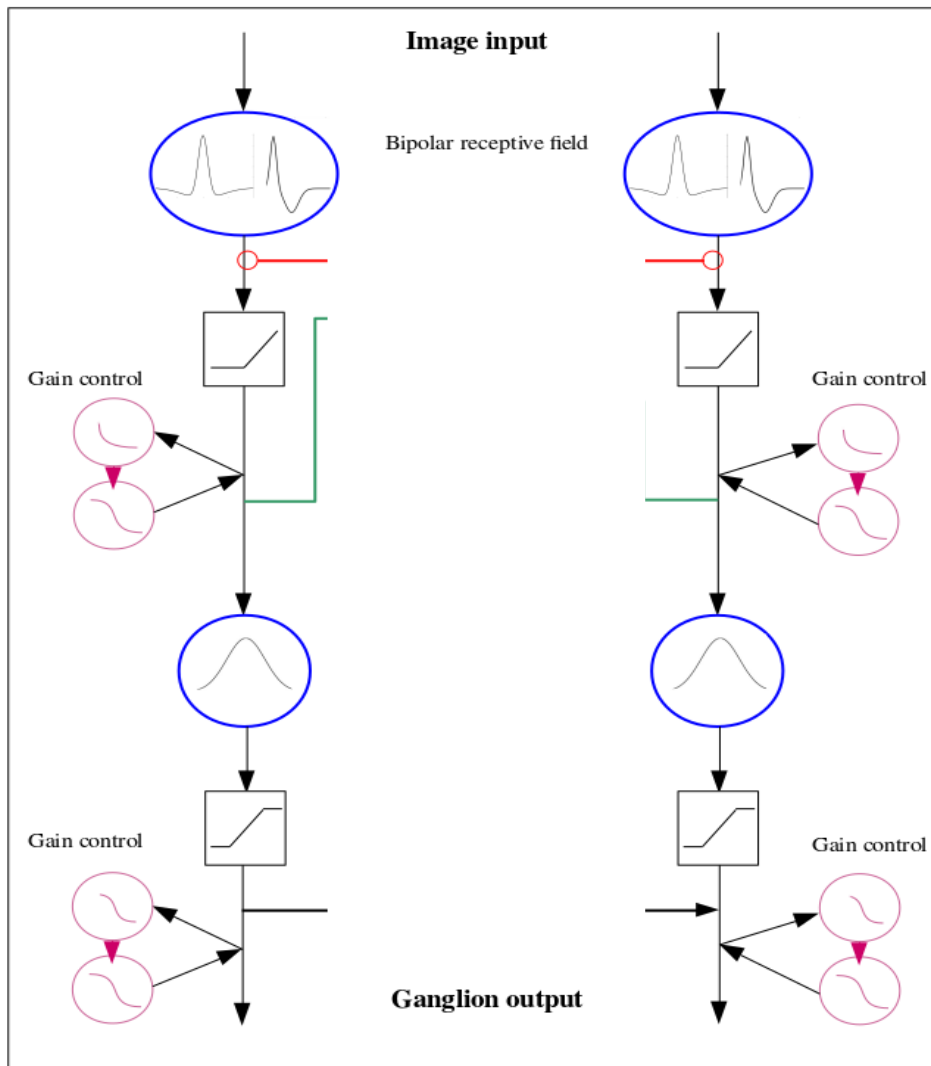


1D results : smooth motion anticipation with gain control

Anticipation variability with stimulus
parameters



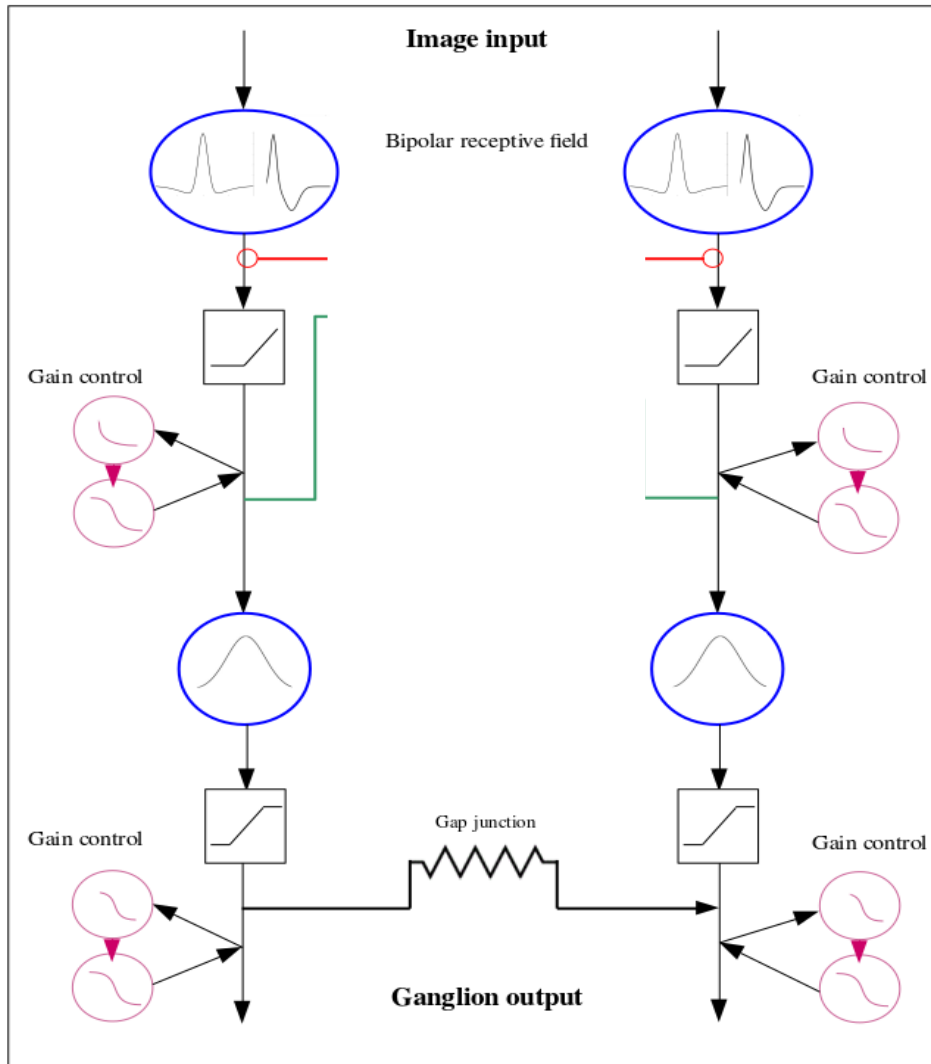
Building a 2D retina model for motion anticipation



Ganglion cells are independent encoders

Building a 2D retina model for motion anticipation

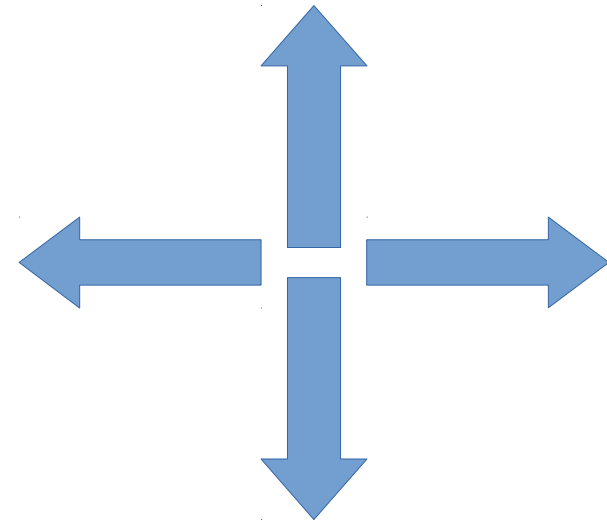
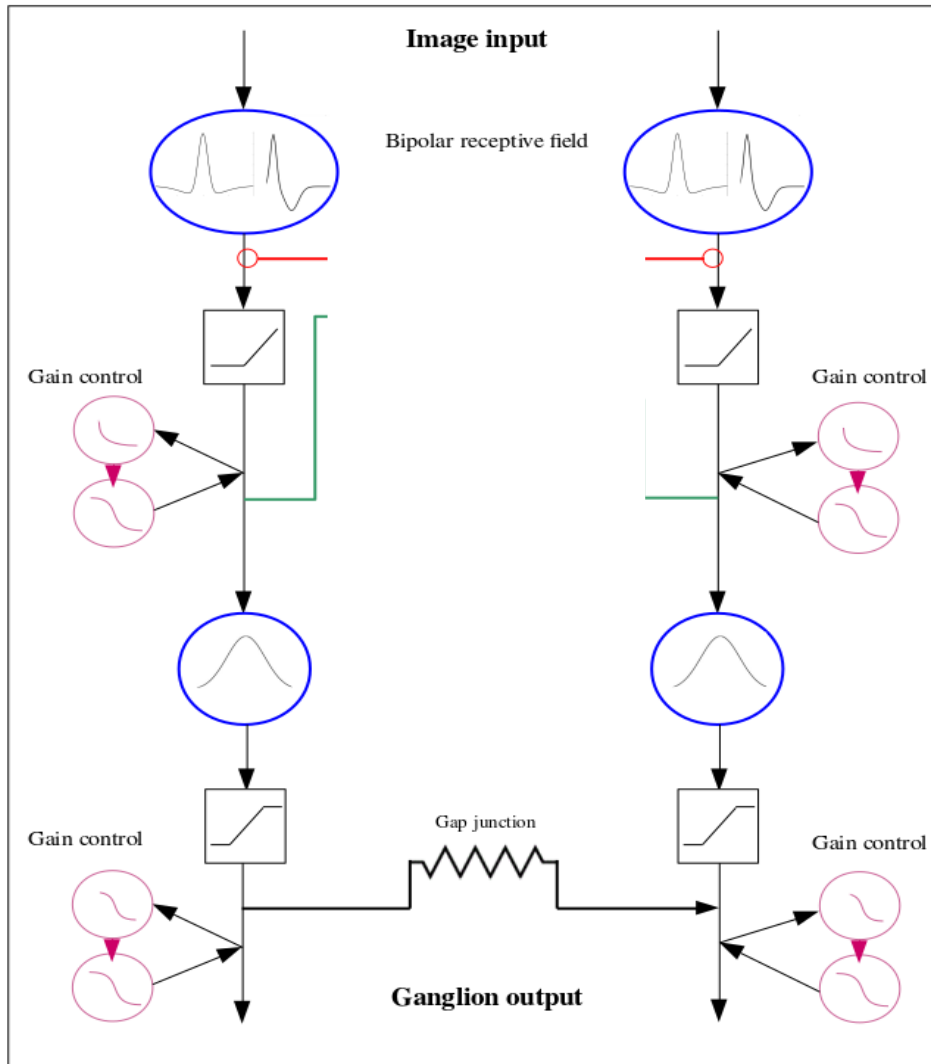
Gap junctions connectivity



Ganglion cells are **not** independent encoders

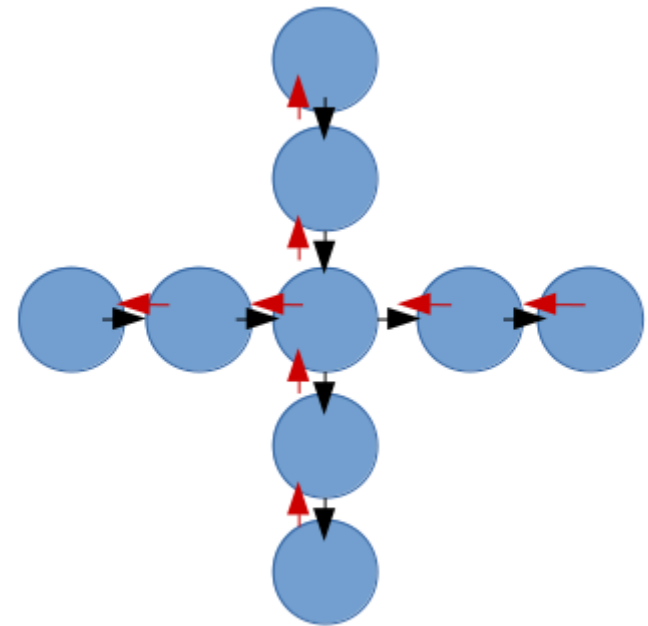
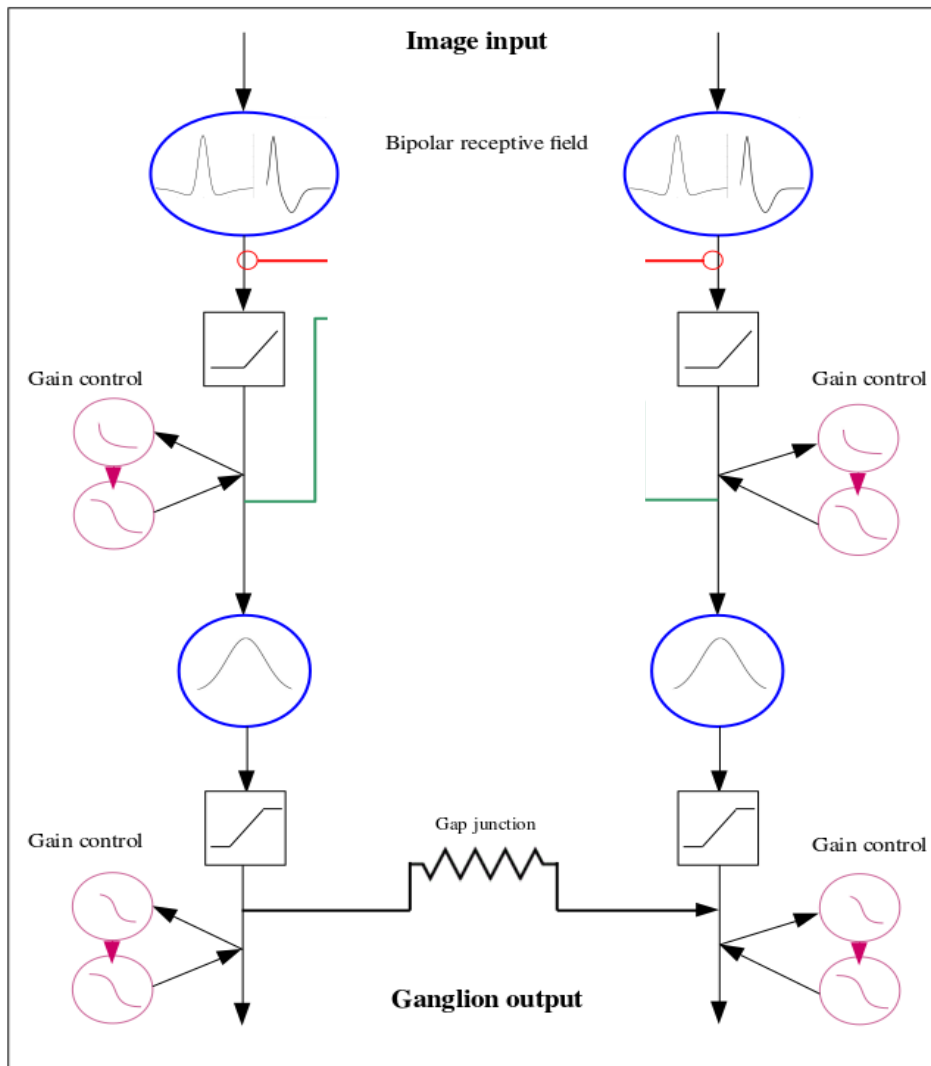
Building a 2D retina model for motion anticipation

Gap junctions connectivity



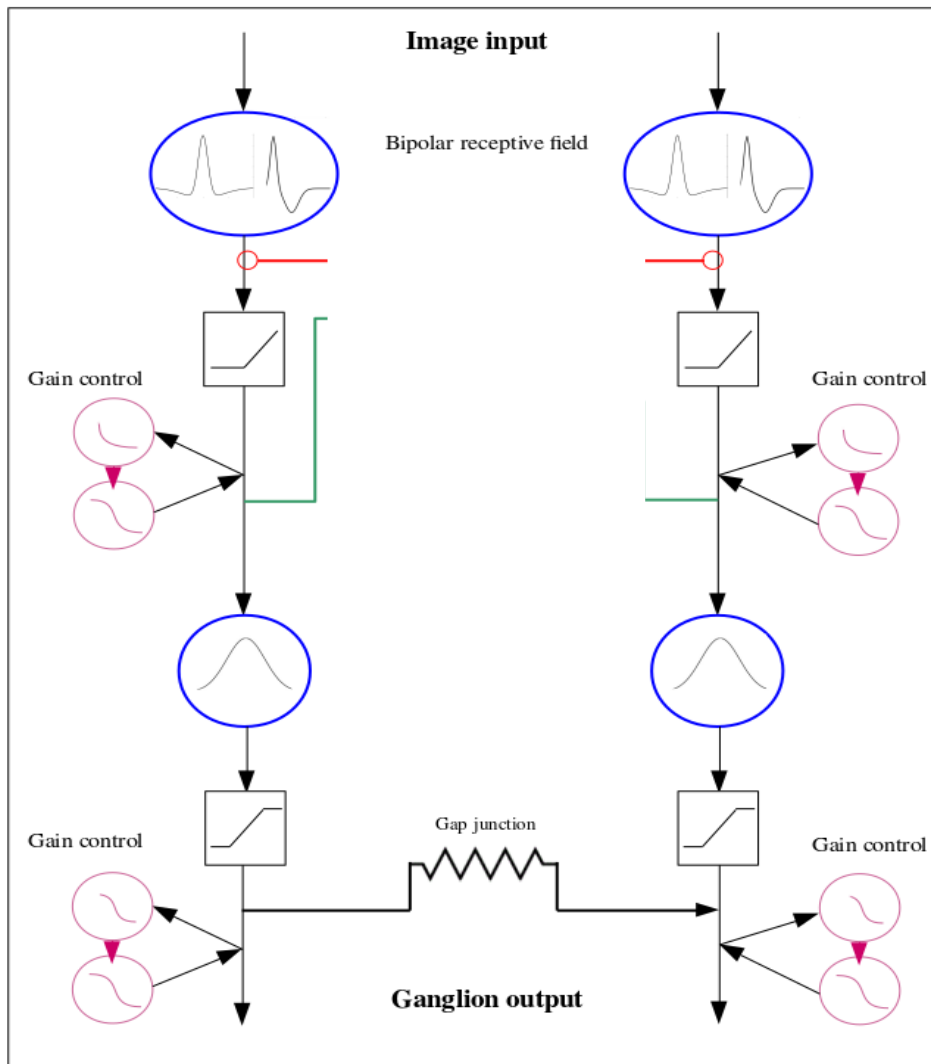
Building a 2D retina model for motion anticipation

Gap junctions connectivity

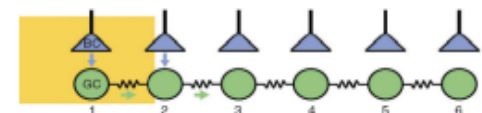


Building a 2D retina model for motion anticipation

Gap junctions connectivity



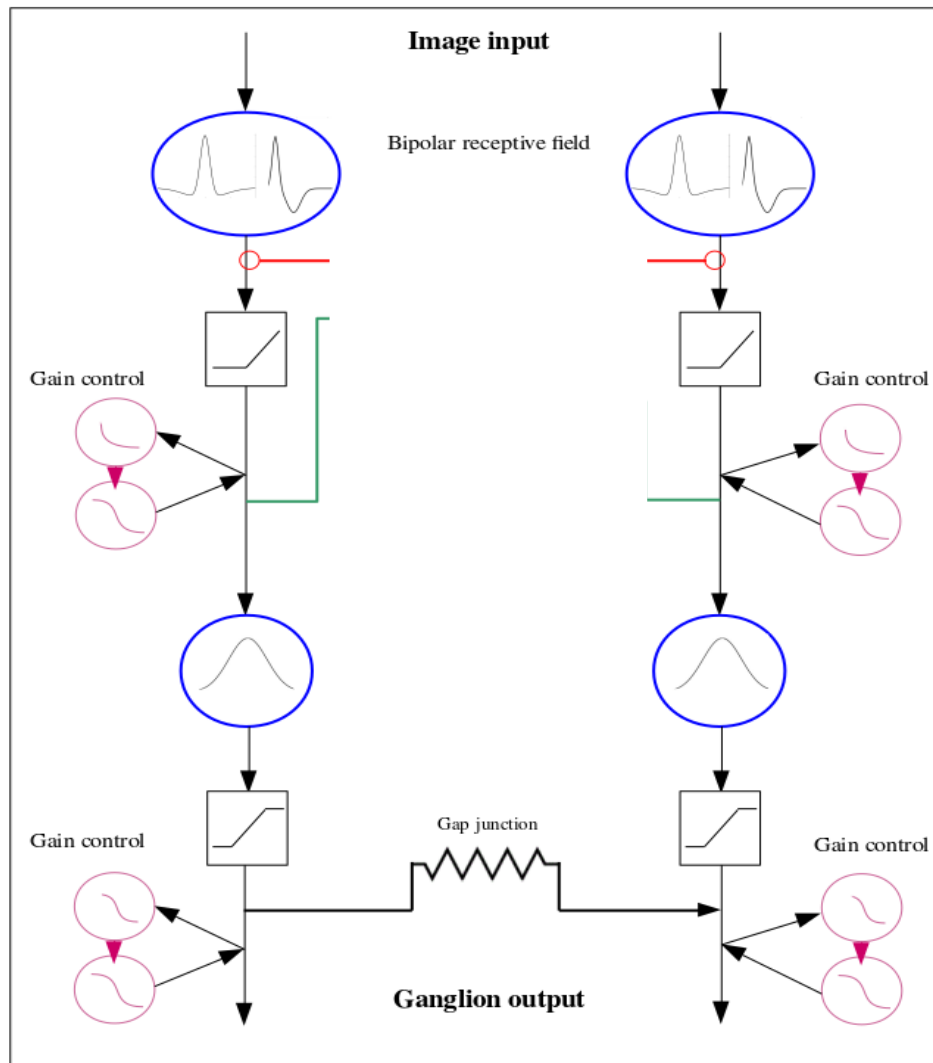
- A class of direction selective RGCs are connected through gap junctions
- Their activity comprises the activity pooled from bipolar cells and the activity coming from the downstream RGCs, in the direction of motion



$$R_{GDk_D} = V_{GDk_D} + \beta R_{GDk_D-1}$$

Building a 2D retina model for motion anticipation

Gap junctions connectivity

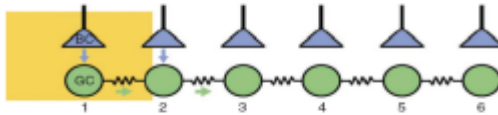


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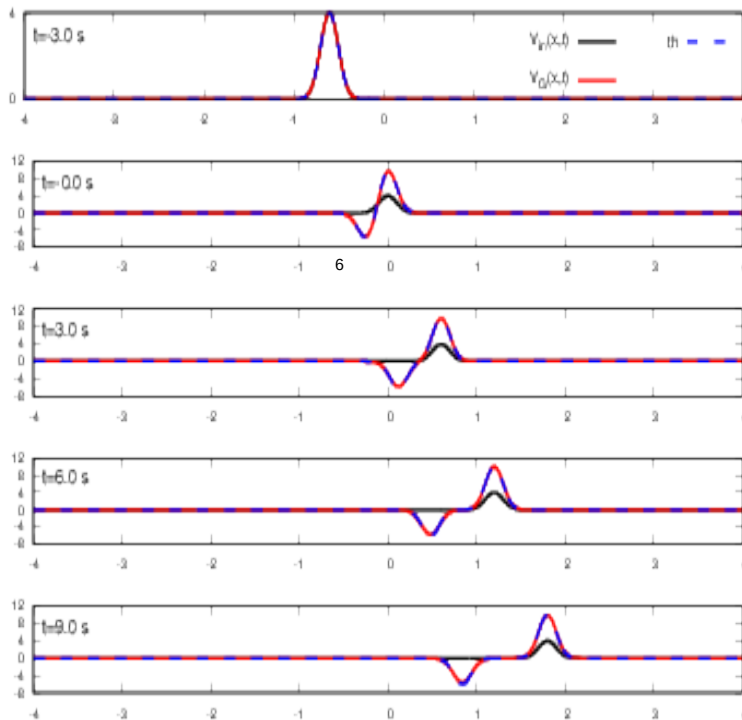
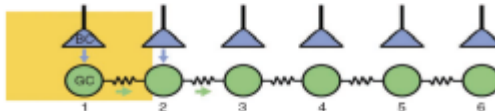
Diffusive wave of activity
ahead of the motion

$$R_{GDk_D} = V_{GDk_D} + \beta R_{GDk_D-1}$$

Smooth motion anticipation with gap junctions

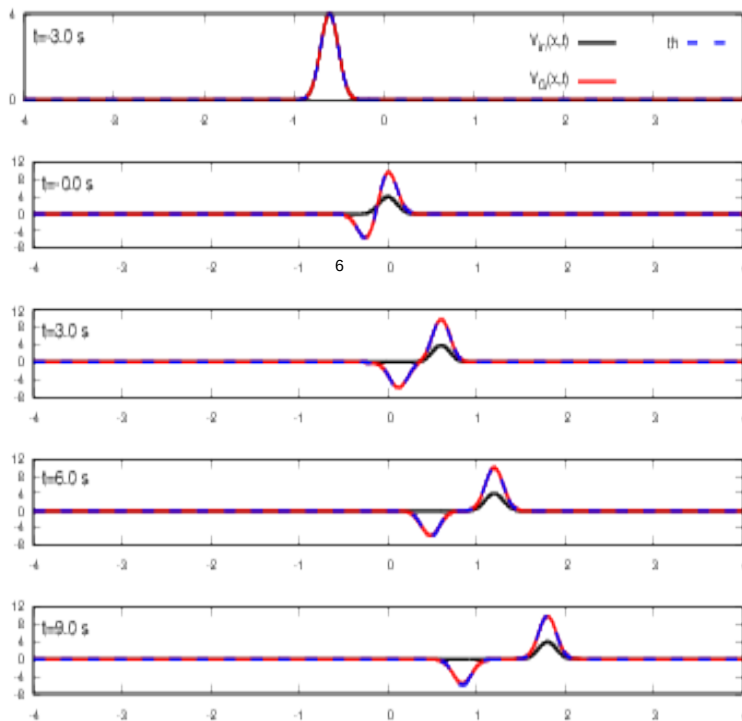
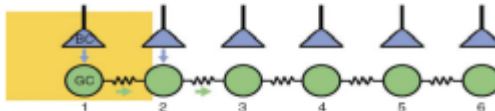


Smooth motion anticipation with gap junctions

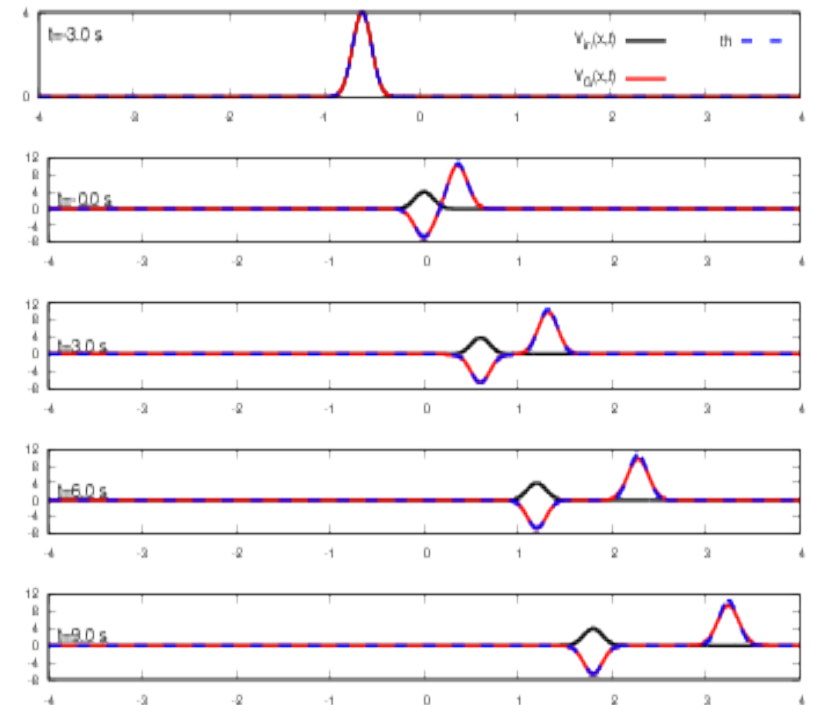


Low gap junction conductance

Smooth motion anticipation with gap junctions

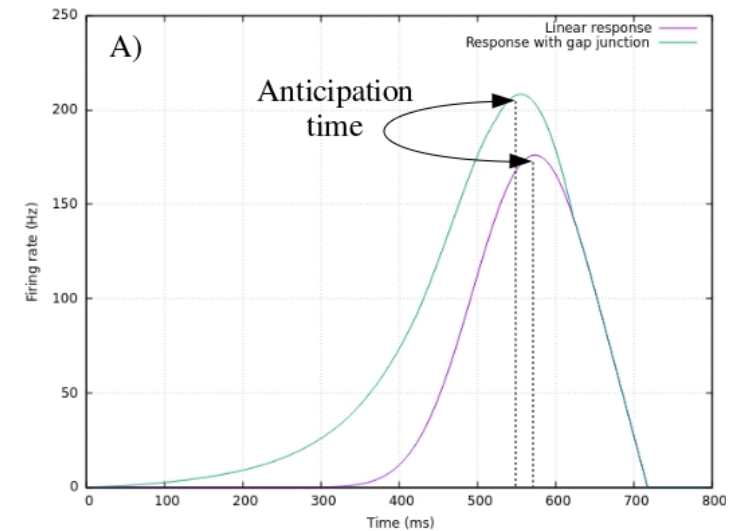
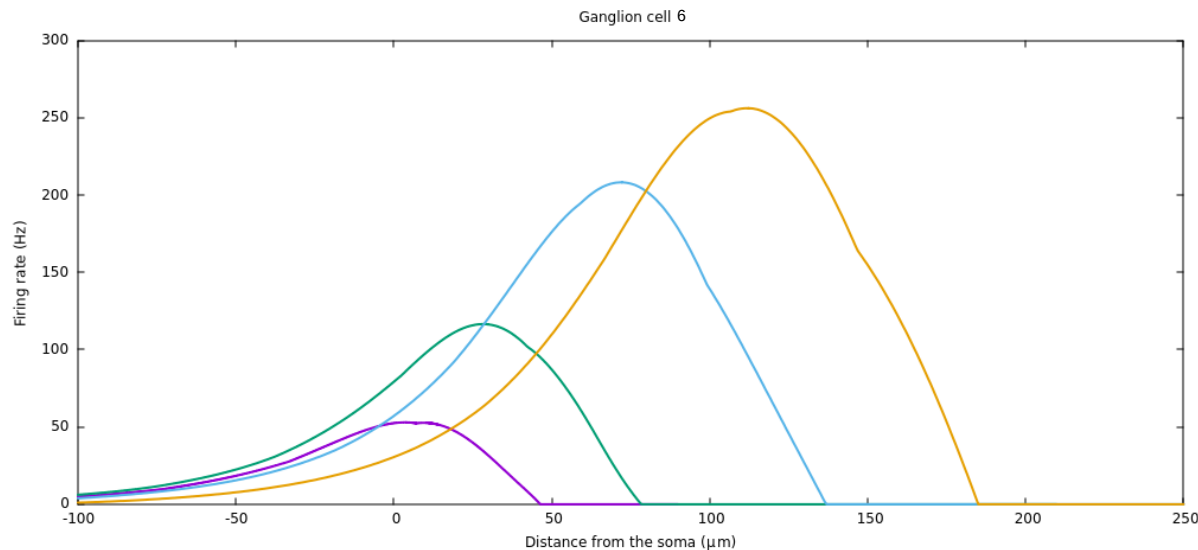
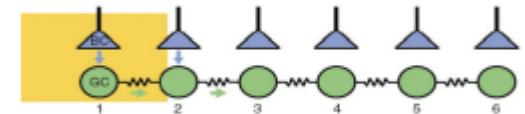


Low gap junction conductance



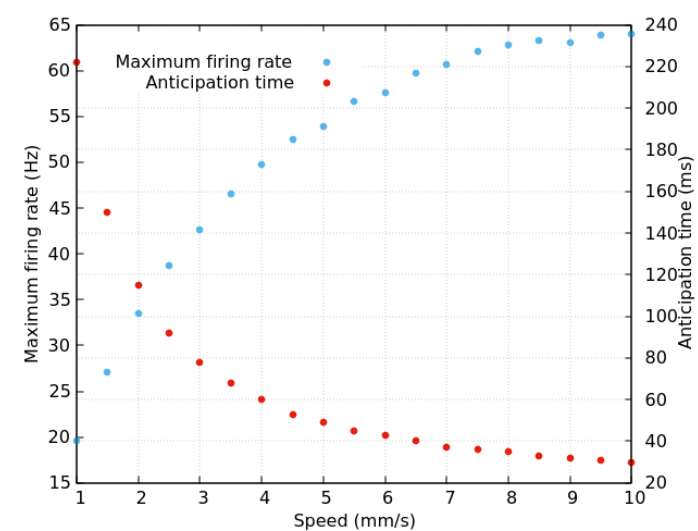
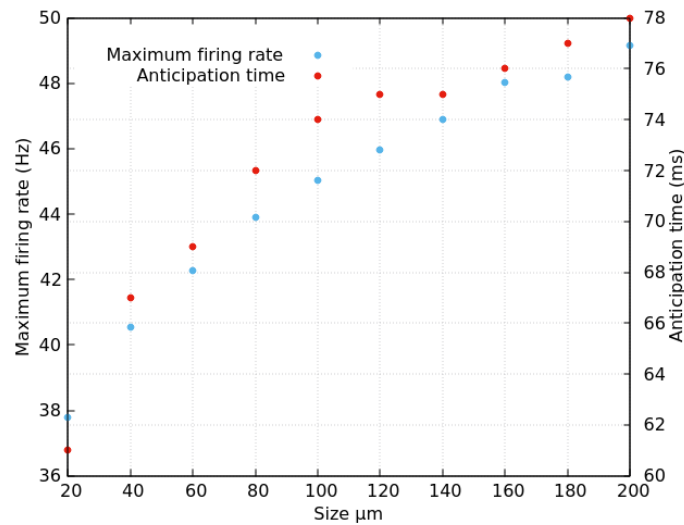
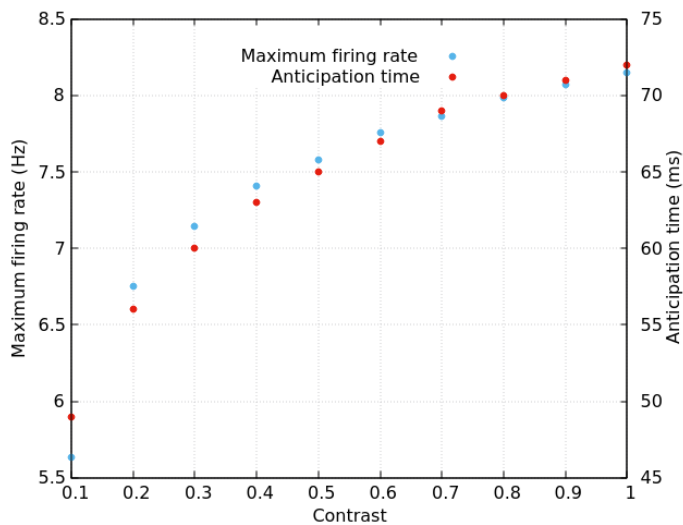
High gap junction conductance

Smooth motion anticipation with gap junctions

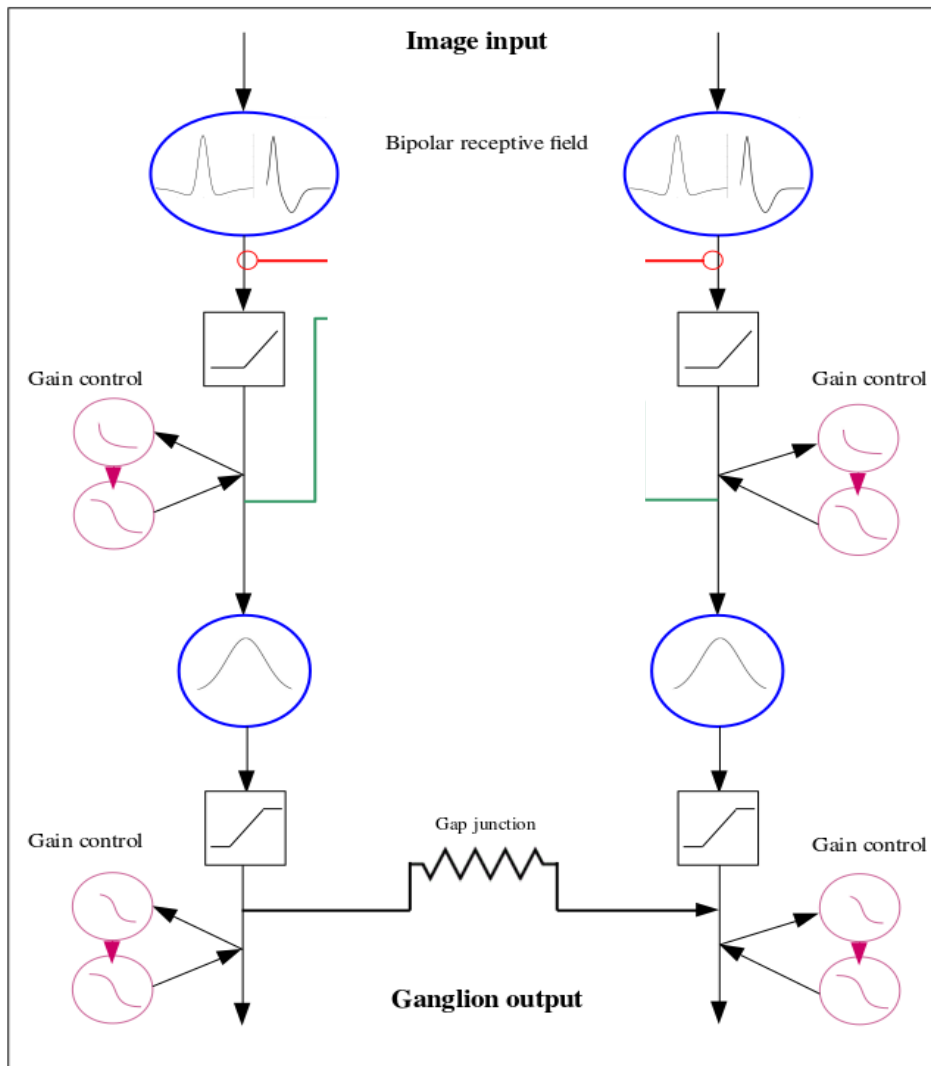


Smooth motion anticipation with gap junctions

Anticipation variability with stimulus parameters

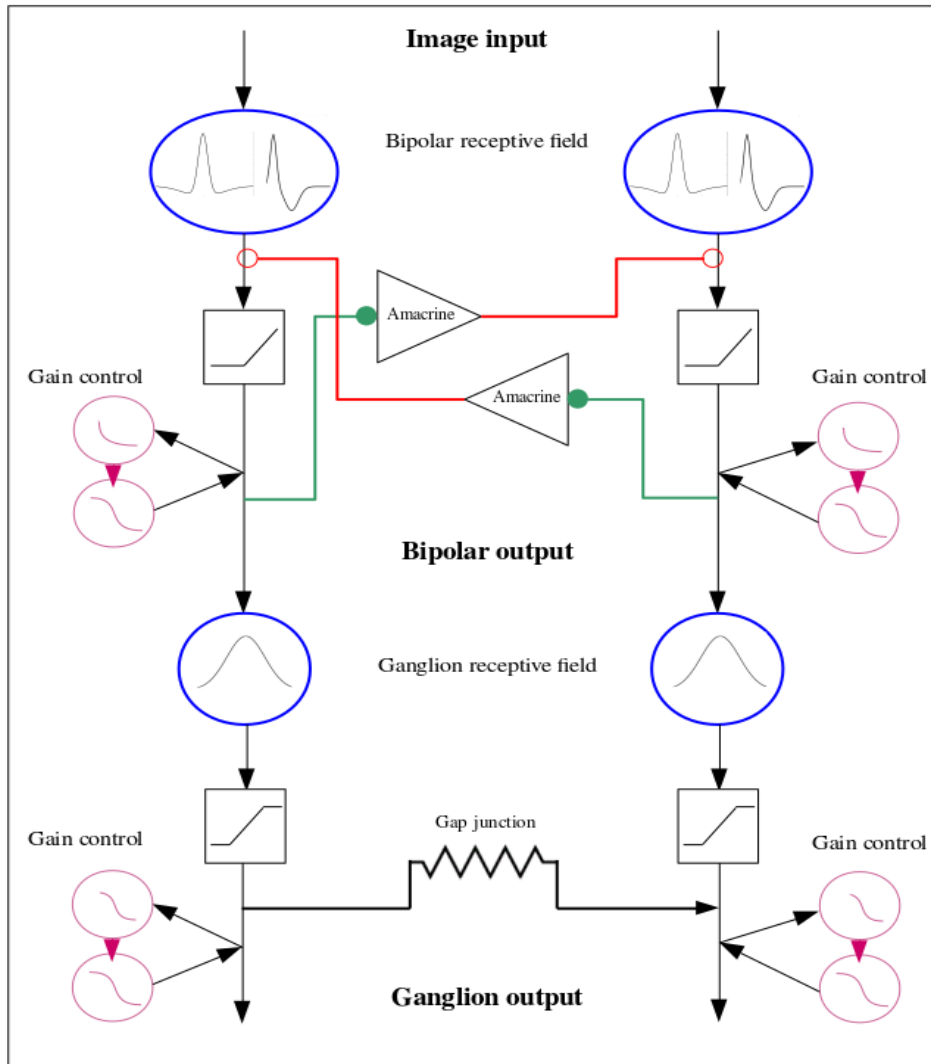


Building a 2D retina model for motion anticipation



Building a 2D retina model for motion anticipation

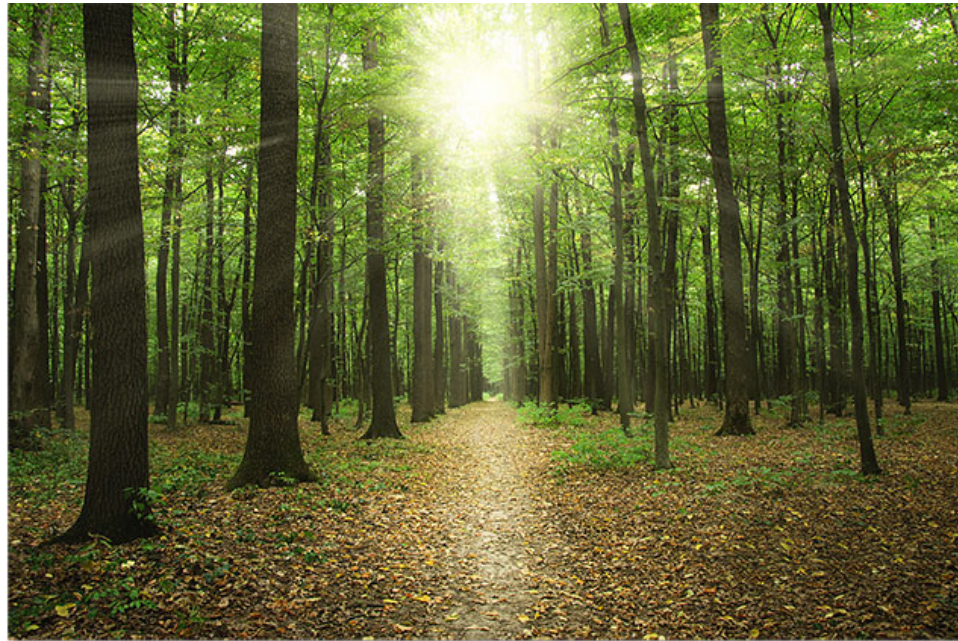
Amacrine cells connectivity



Ganglion cells are **not** independent encoders

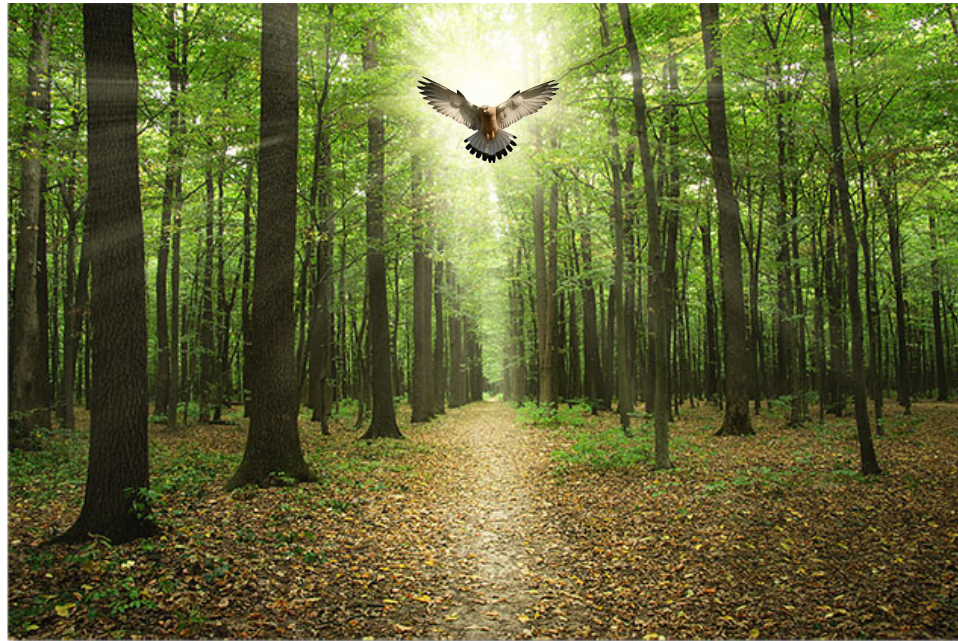
Building a 2D retina model for motion anticipation

Amacrine cells connectivity



Building a 2D retina model for motion anticipation

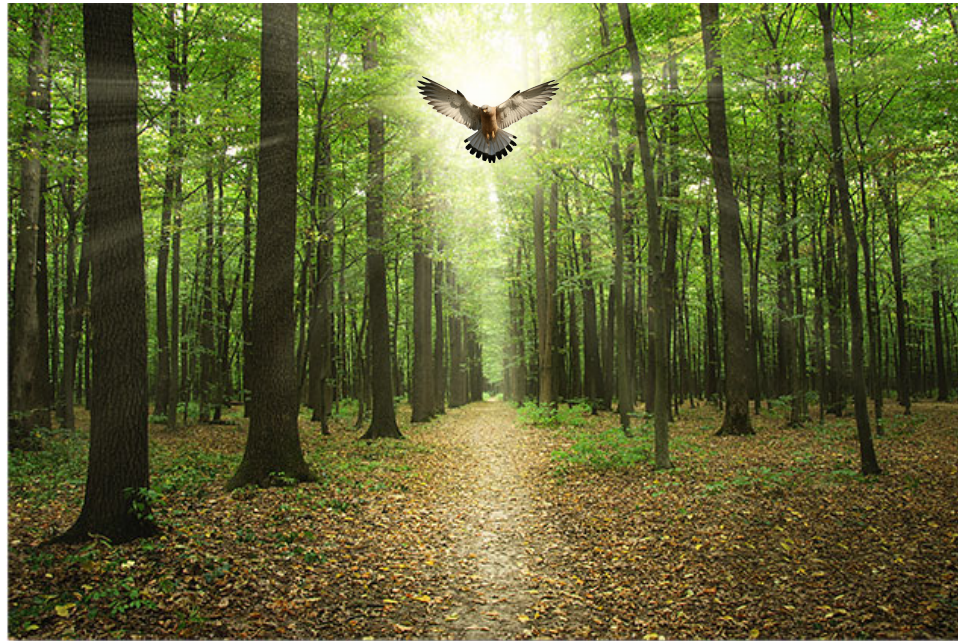
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Building a 2D retina model for motion anticipation

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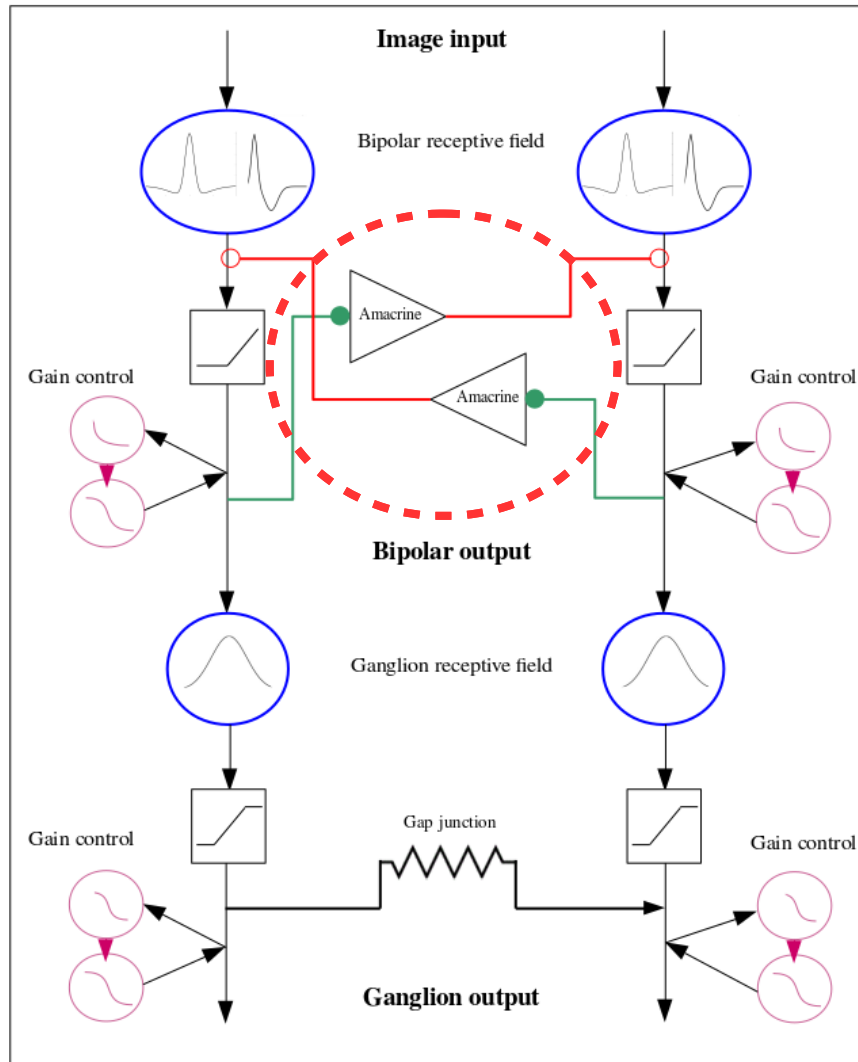
- A class of RGCs are selective to differential motion



- The circuitry involves amacrine cells connectivity upstream of ganglion cells

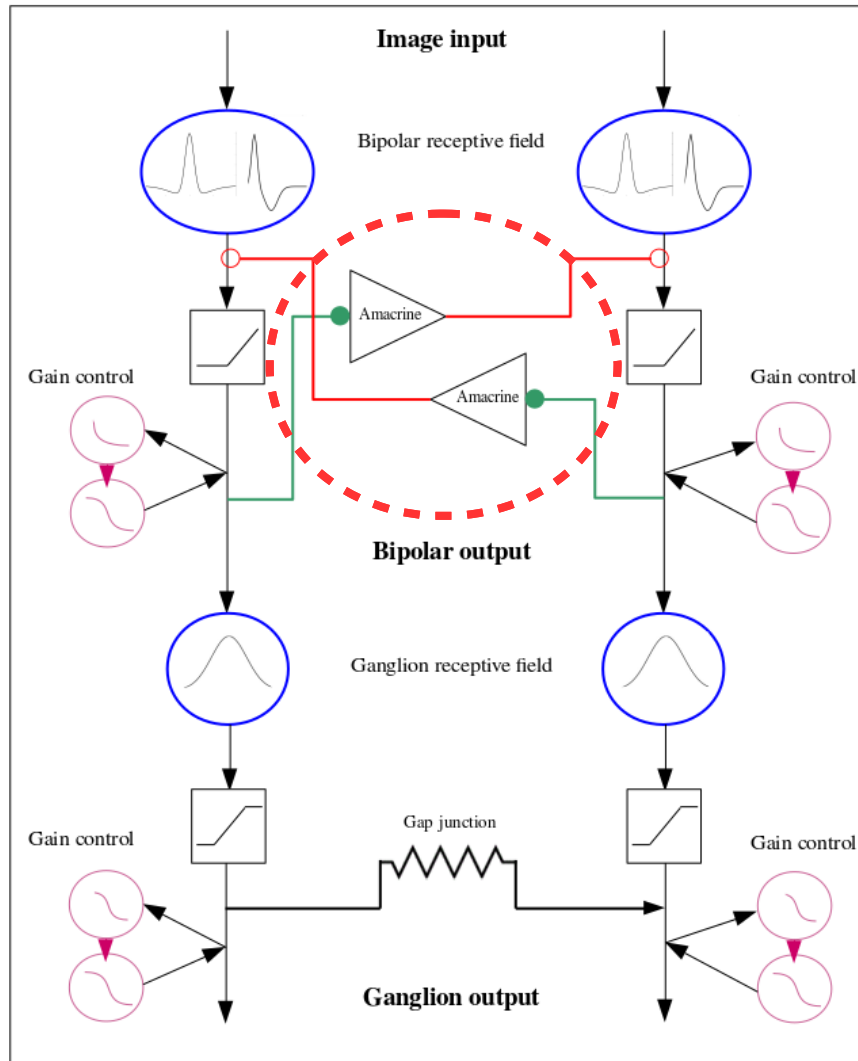
Building a 2D retina model for motion anticipation

Amacrine cells connectivity



Building a 2D retina model for motion anticipation

Amacrine cells connectivity



- Bipolar voltage :

$$\frac{dV_{B_i}}{dt} = -\frac{1}{\tau_B} V_{B_i} + \sum_{j=1}^{N_A} W_{B_i}^{A_j} V_{A_j} + F_{B_i}(t).$$

- External drive :

$$F_{B_i}(t) = \left[K_i^{S,t} * \left(\frac{S}{\tau_B} + \frac{dS}{dt} \right) \right] (t)$$

- Amacrine voltage :

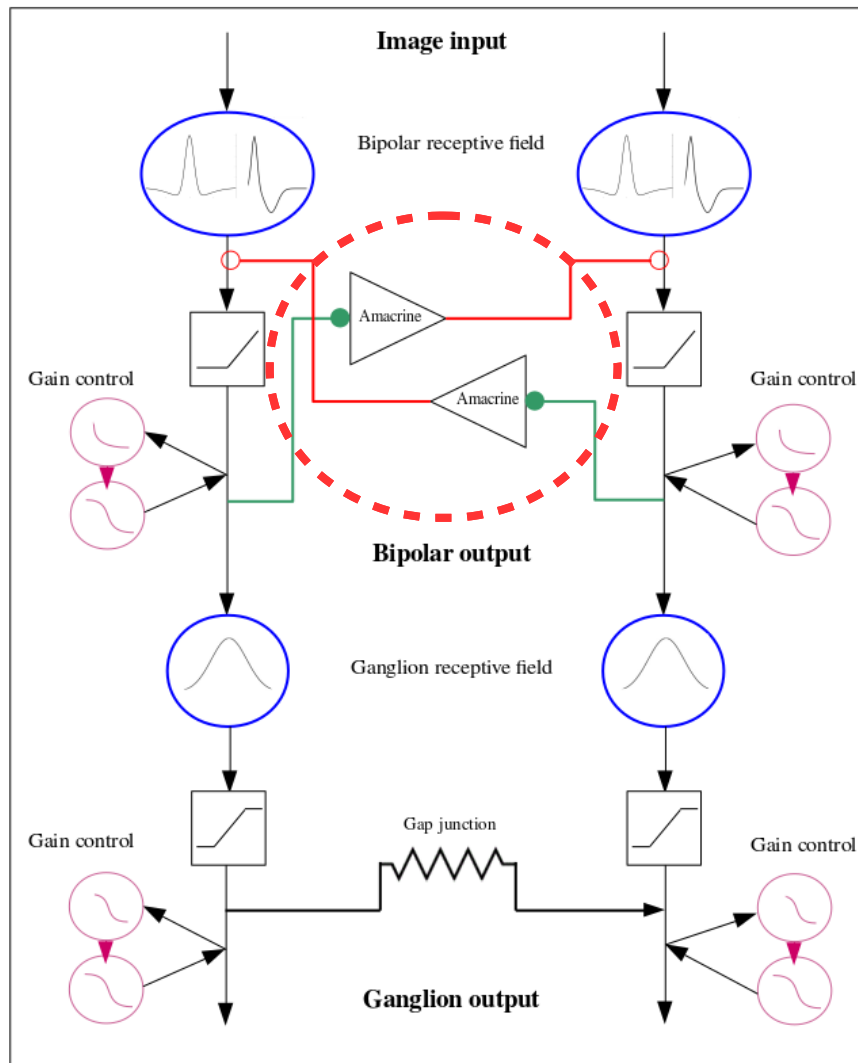
$$\frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_A} W_{A_j}^{B_i} R_{B_i}(t).$$

- Coupled dynamics :

$$\begin{cases} \frac{dV_{B_i}}{dt} = -\frac{1}{\tau_B} V_{B_i} + \sum_{j=1}^{N_A} W_{B_i}^{A_j} V_{A_j} + F_{B_i}(t) \\ \frac{dA_{B_i}}{dt} = -\frac{A_{B_i}}{\tau_a} + h \mathcal{N}(V_{B_i}(t)), \\ \frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_A} W_{A_j}^{B_i} R_{B_i}(t). \end{cases}$$

Building a 2D retina model for motion anticipation

Amacrine cells connectivity



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- External drive :

$$F_{B_i}(t) = \left[K_i \frac{S_i}{S_i + 1} \left(\frac{S}{\tau_B} + \frac{dS}{dt} \right) \right] (t)$$

- Amacrine voltage :

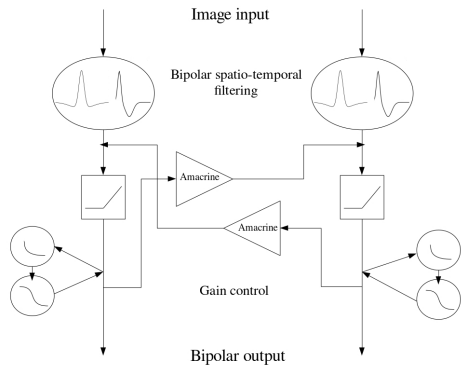
$$\frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j} + \sum_{i=1}^{N_B} W_{A_j}^{B_i} R_{B_i}(t).$$

Diffusive wave of activity ahead of the bar

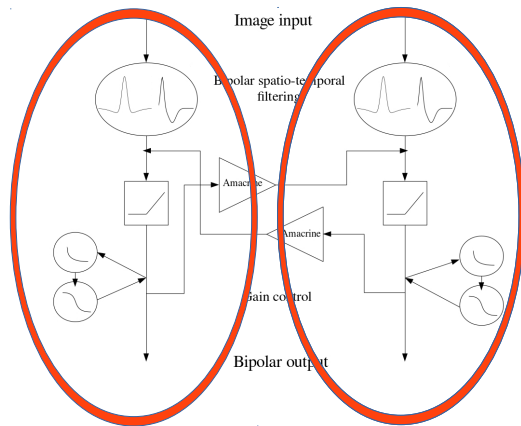
- Coupled dynamics :

$$\begin{cases} \frac{dV_{B_i}}{dt} = -\frac{1}{\tau_B} V_{B_i} + \sum_{j=1}^{N_A} W_{B_i}^{A_j} V_{A_j} + F_{B_i}(t) \\ \frac{dA_{B_i}}{dt} = -\frac{A_{B_i}}{\tau_a} + h \mathcal{N}(V_{B_i}(t)), \\ \frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_B} W_{A_j}^{B_i} R_{B_i}(t). \end{cases}$$

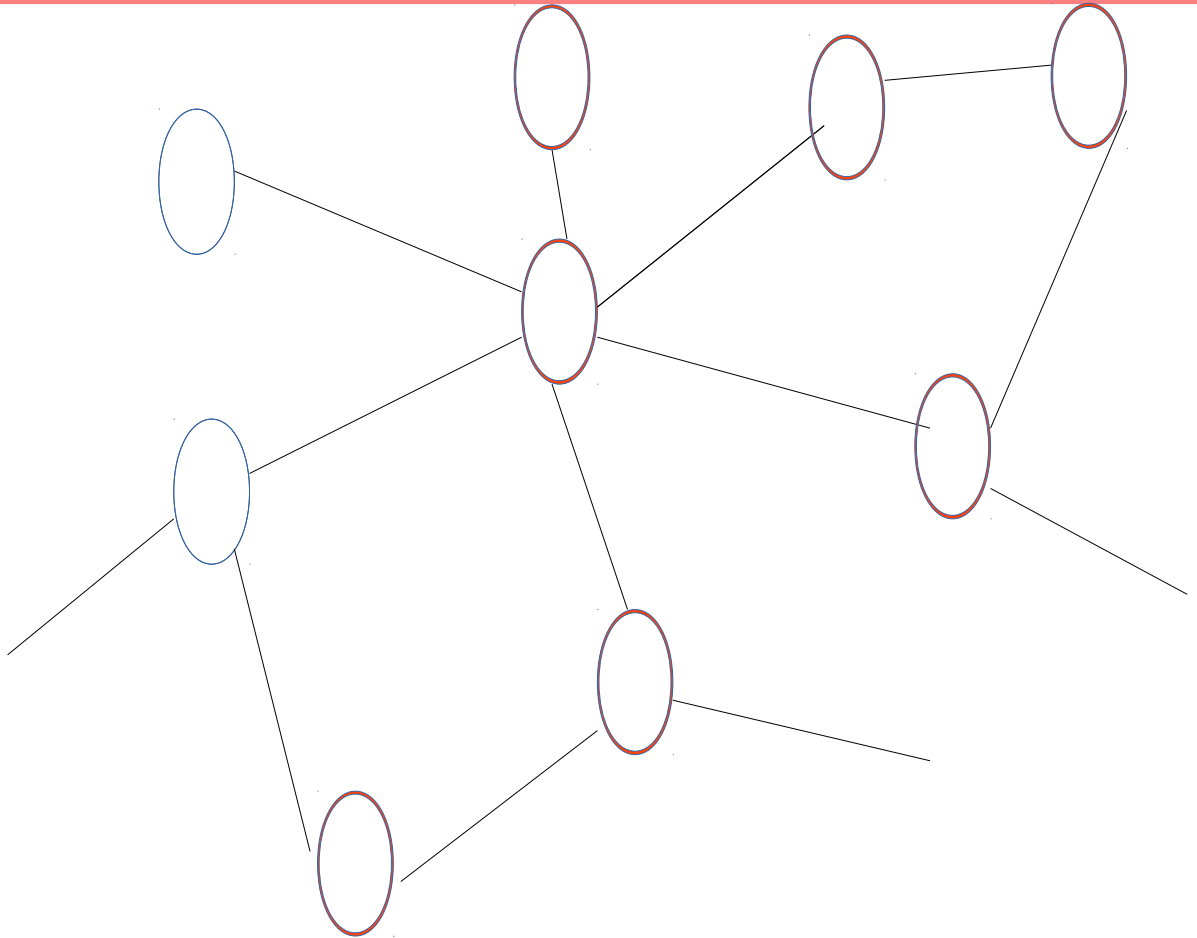
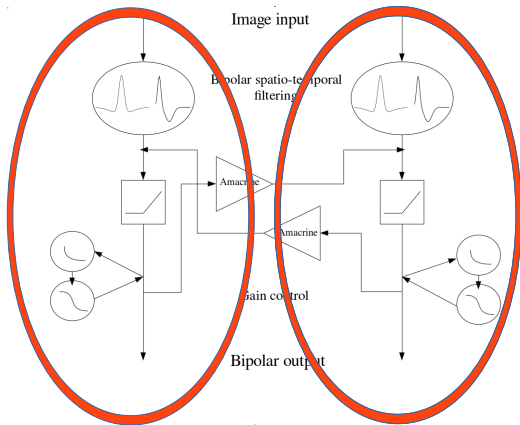
Building a 2D retina model for motion anticipation



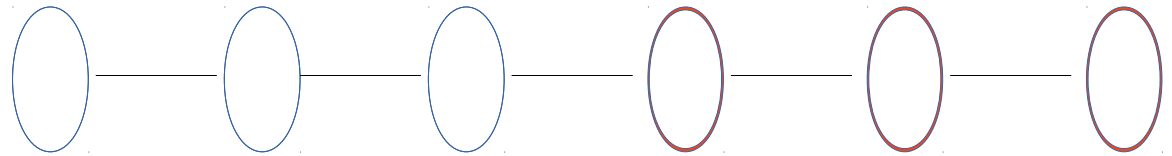
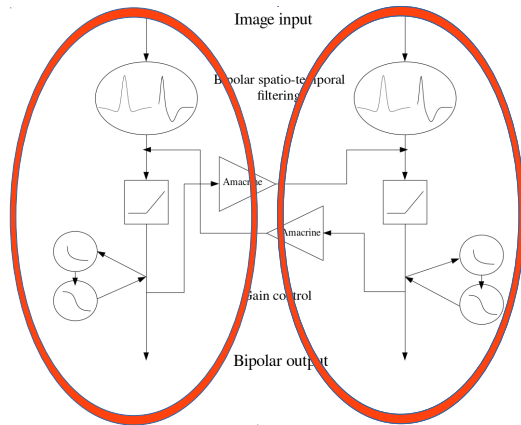
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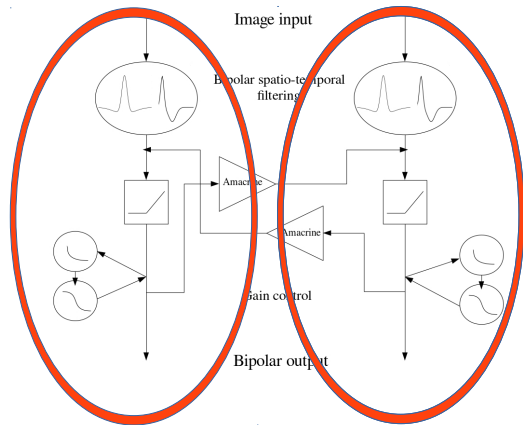
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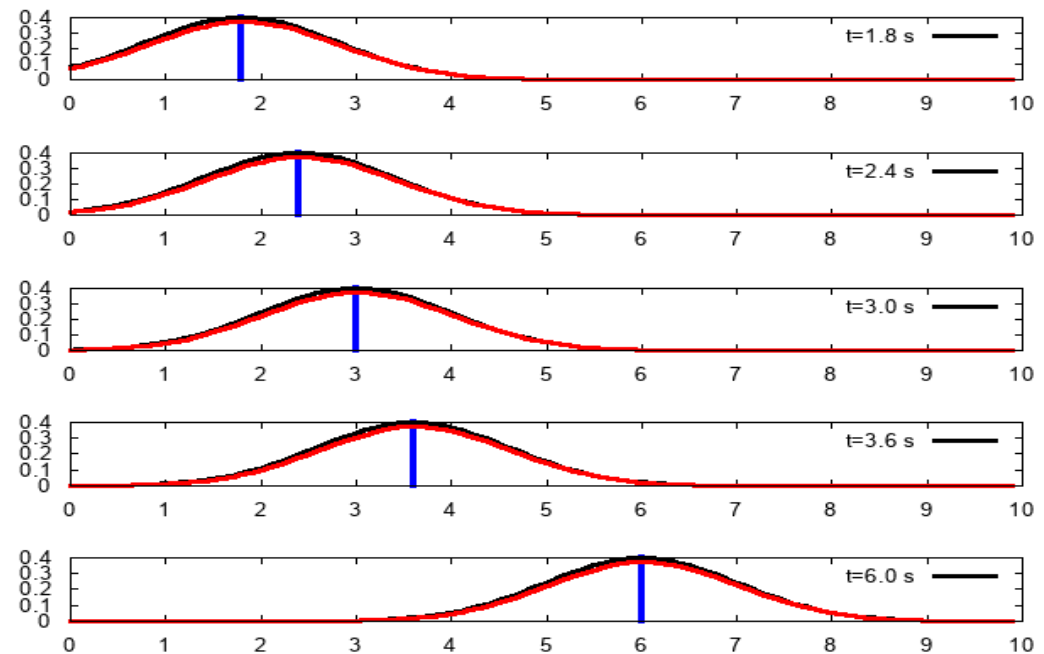
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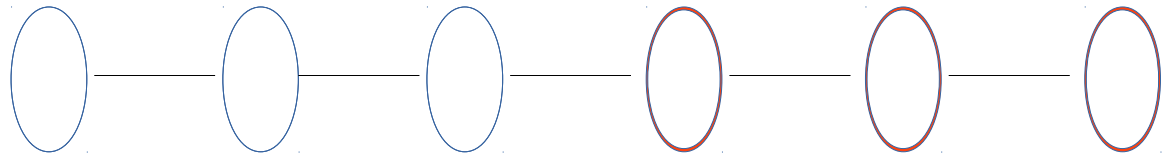
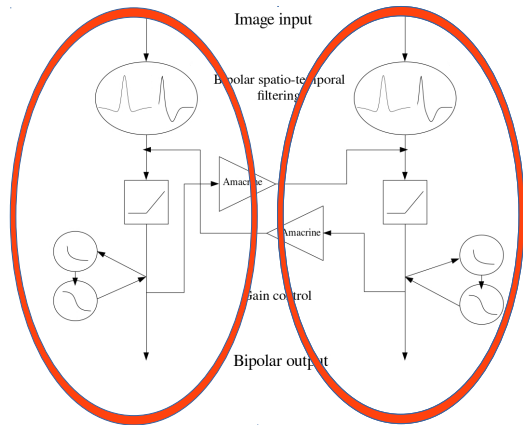


Spatial profiles $w=1$

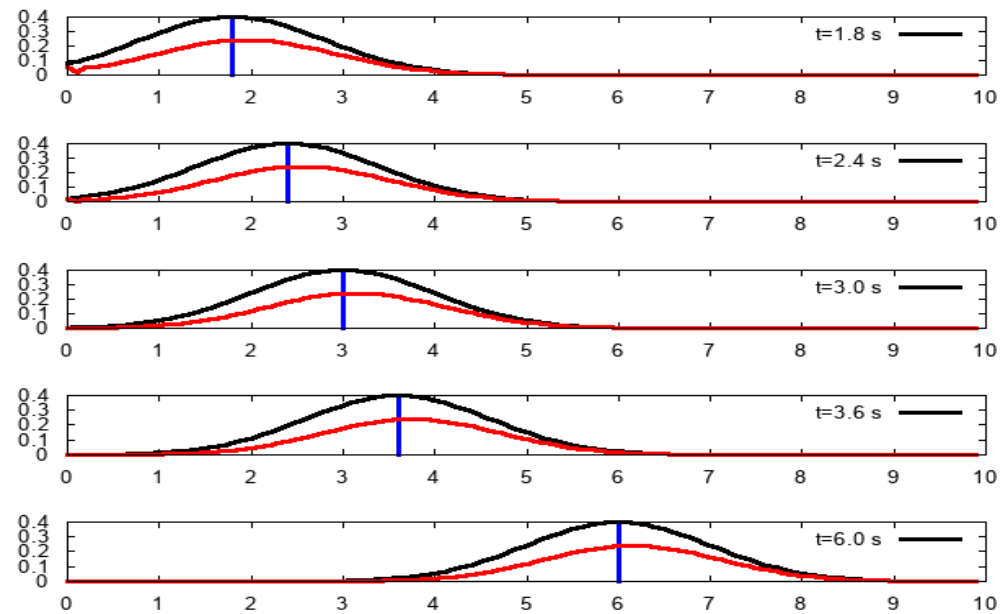


X

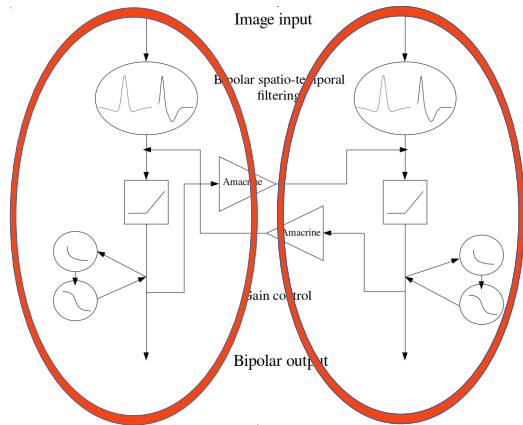
Building a 2D retina model for motion anticipation



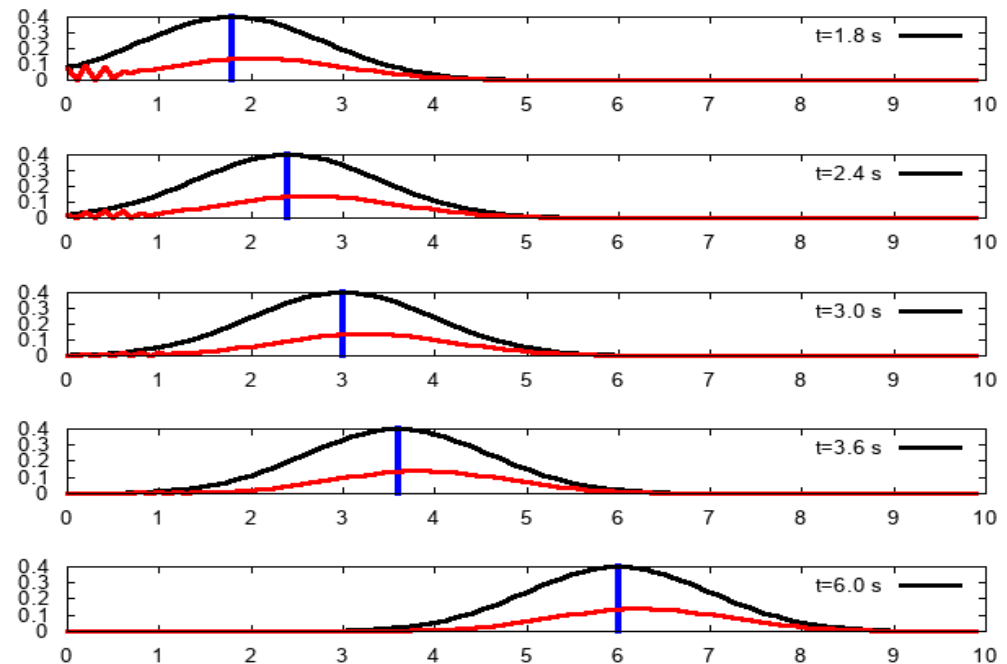
Spatial profiles $w=3$



Building a 2D retina model for motion anticipation

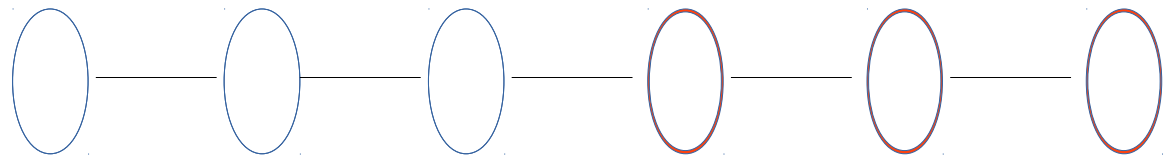
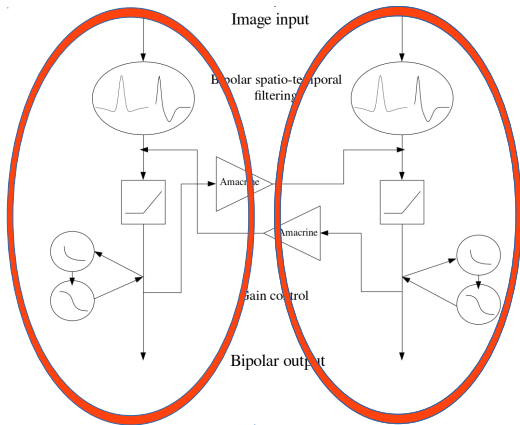


Spatial profiles $w=5$

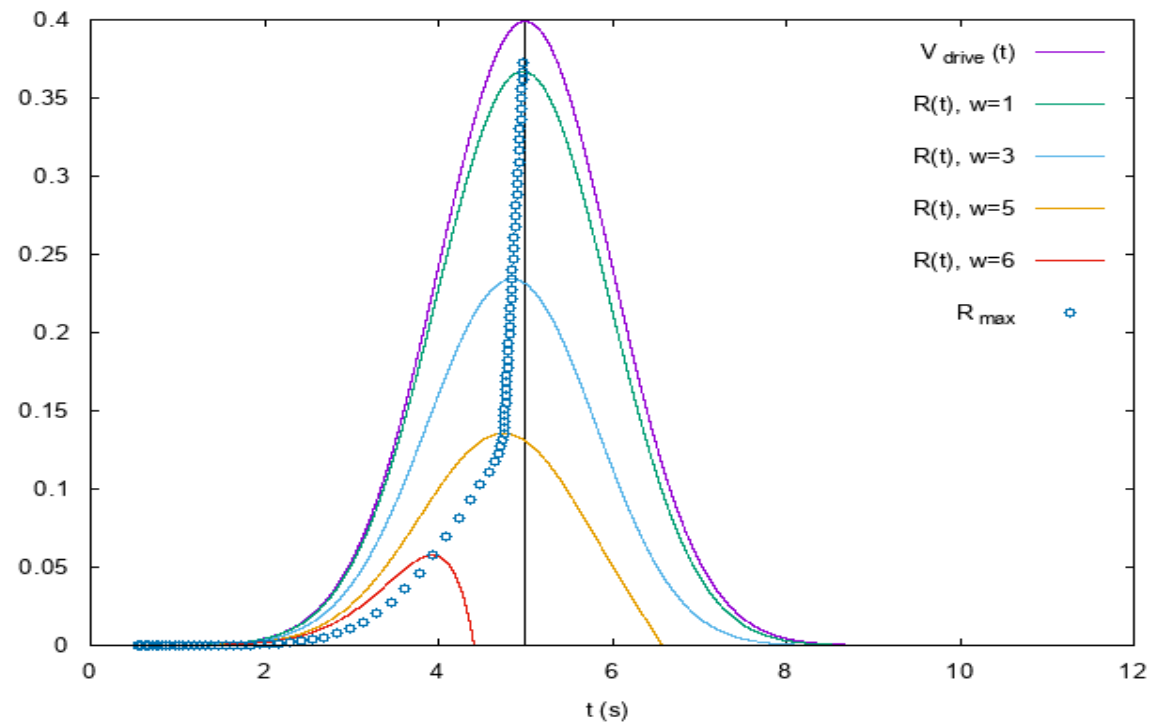


x

Building a 2D retina model for motion anticipation

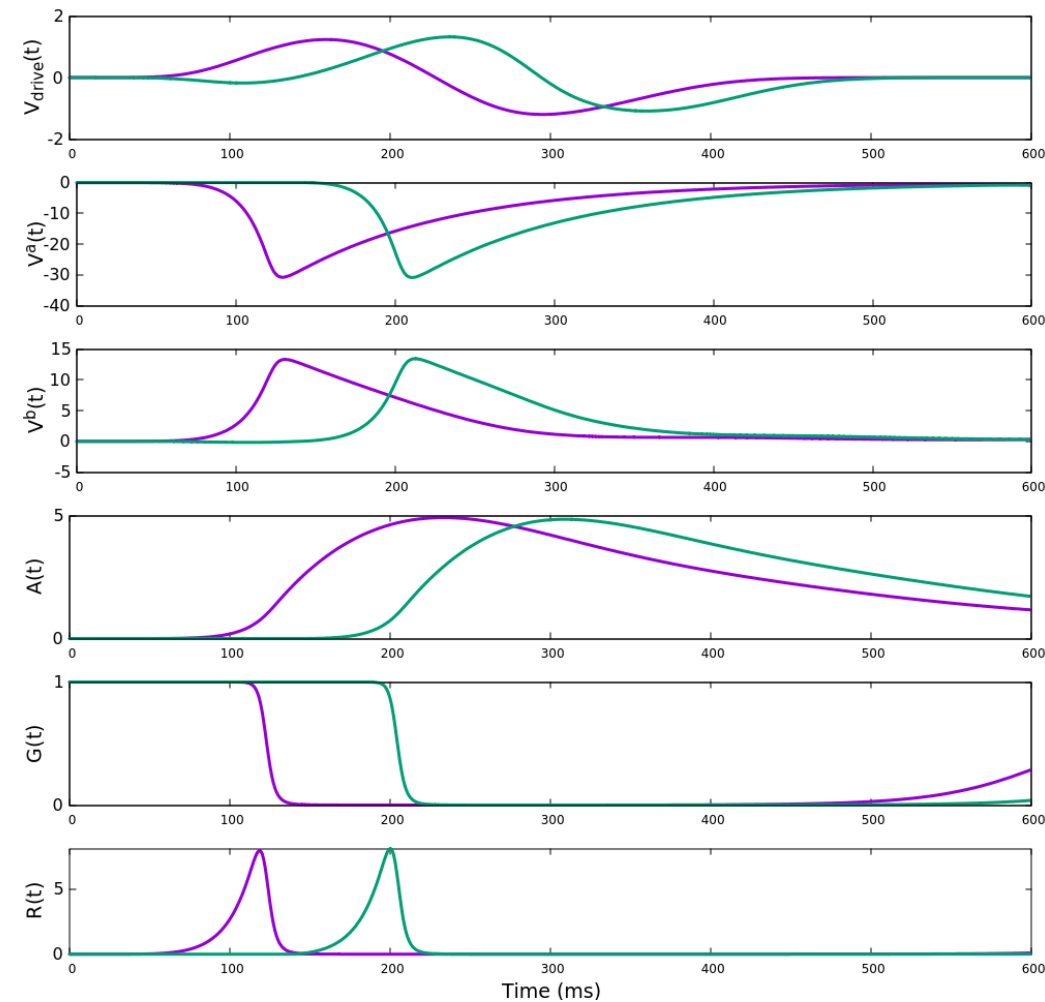


Temporal profile of the middle cell

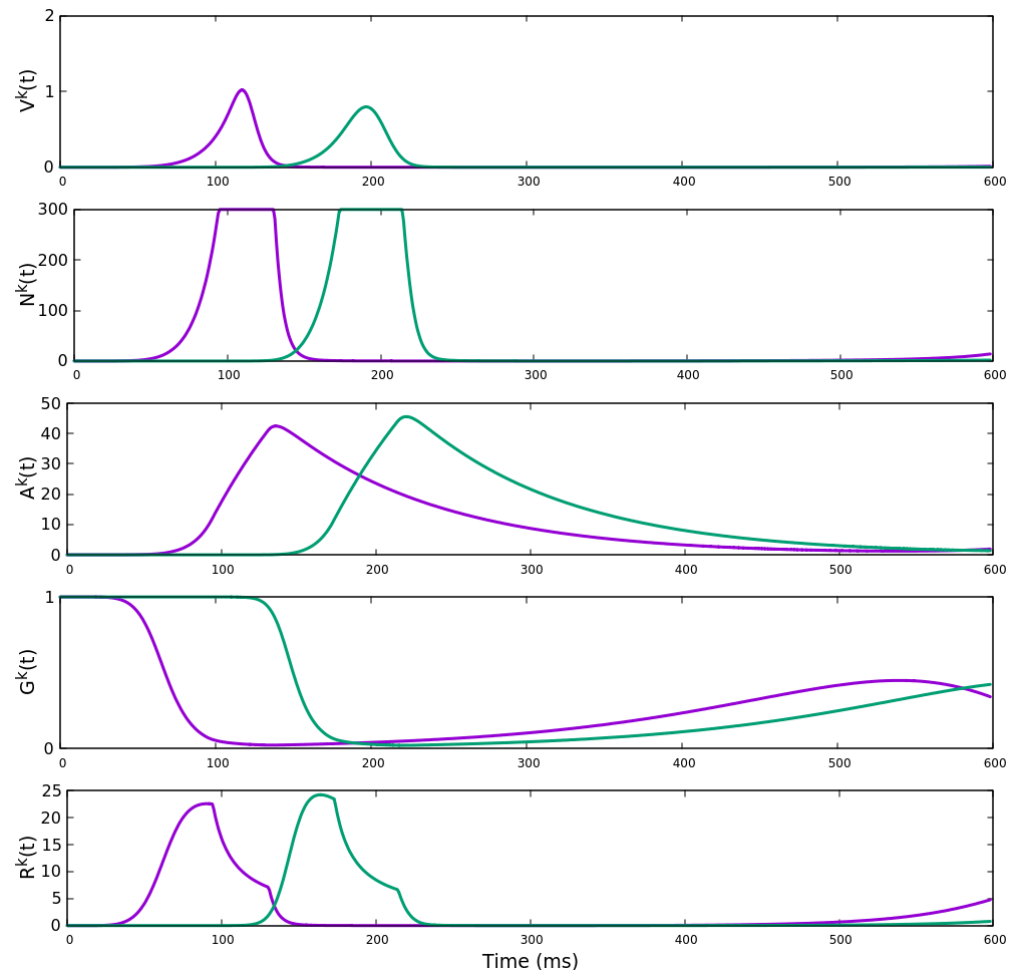


1D results : smooth motion anticipation with amacrine connectivity

Bipolar layer

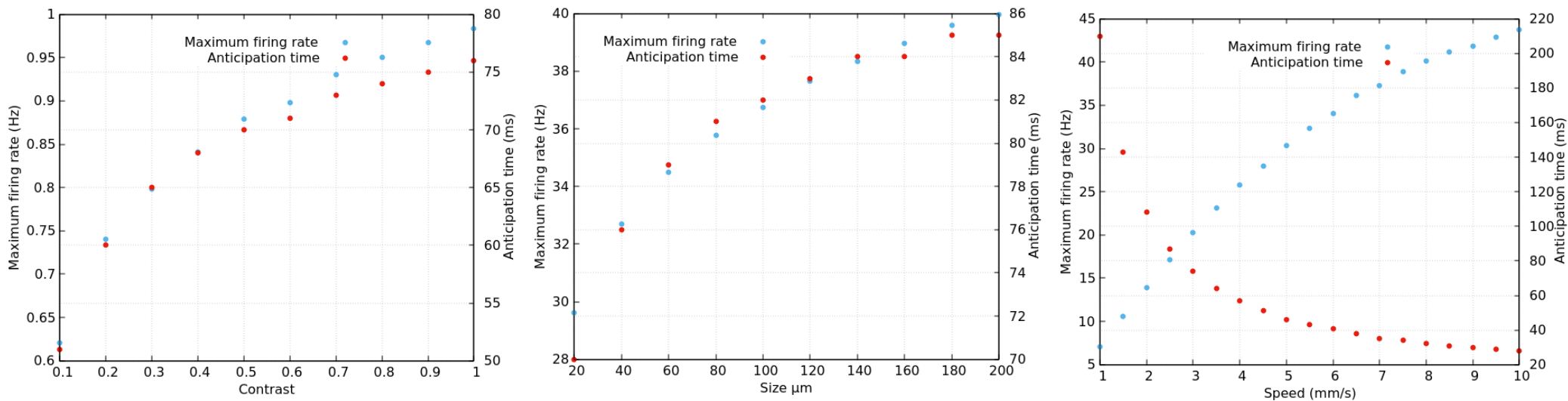


Ganglion layer

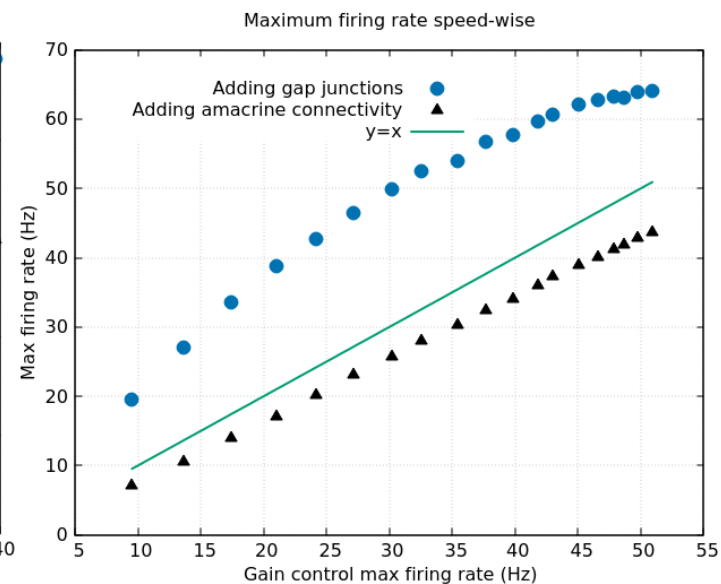
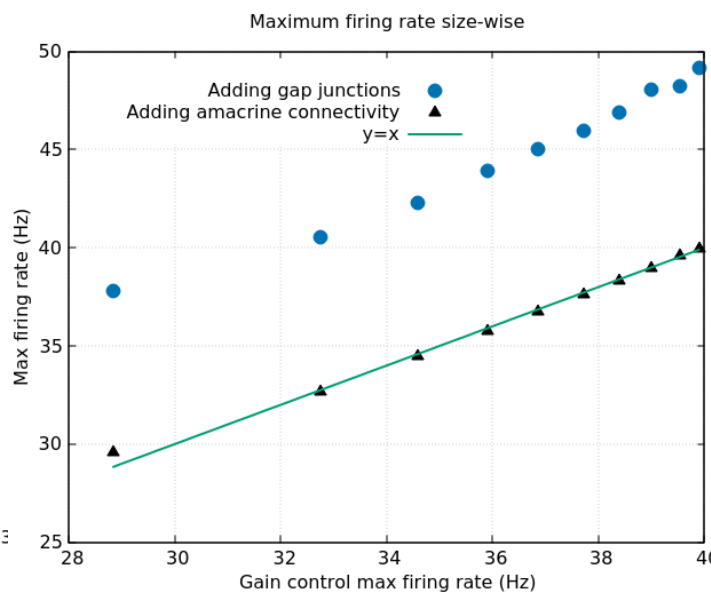
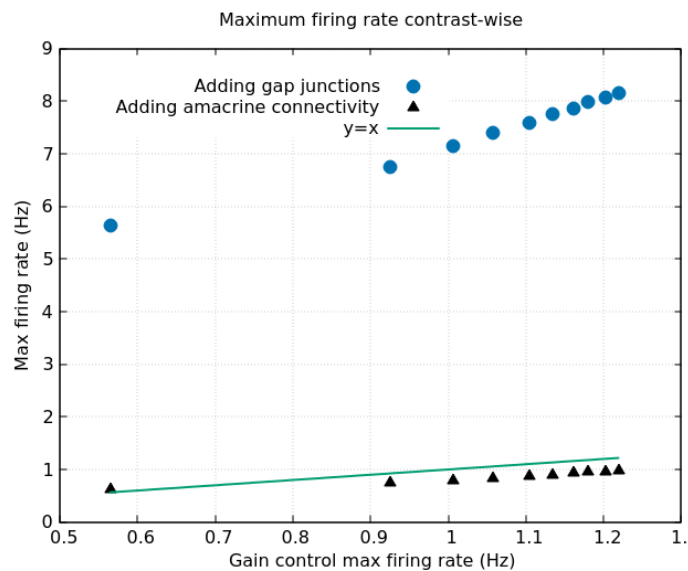
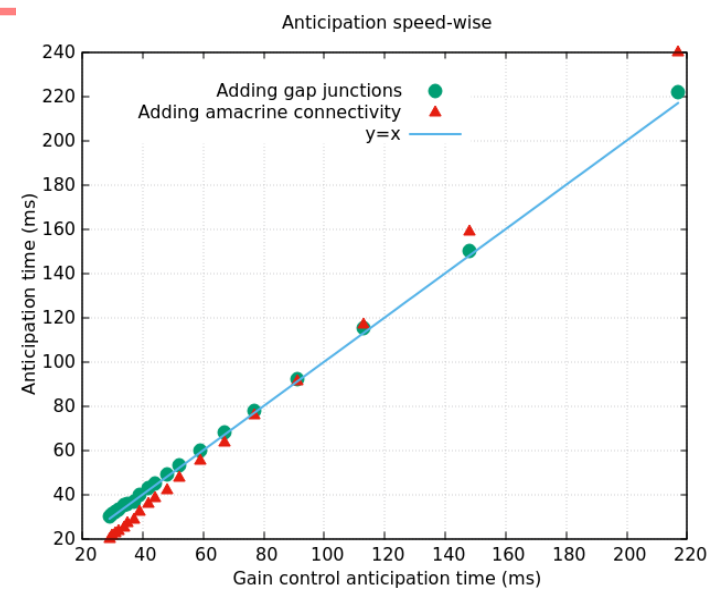
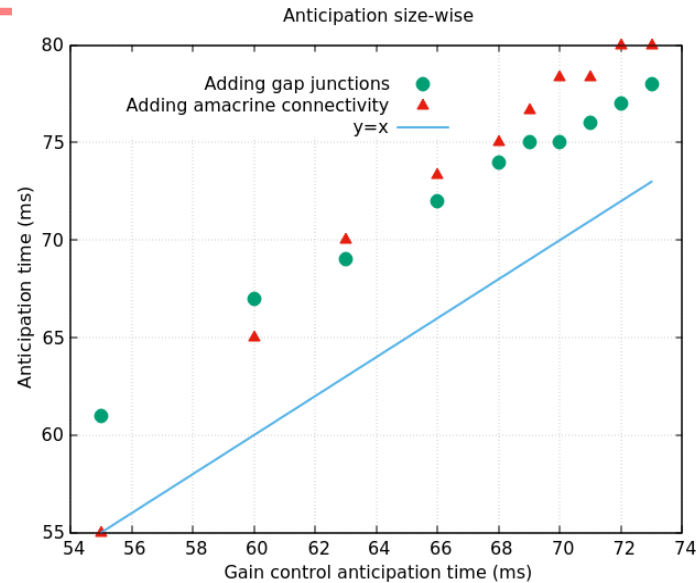
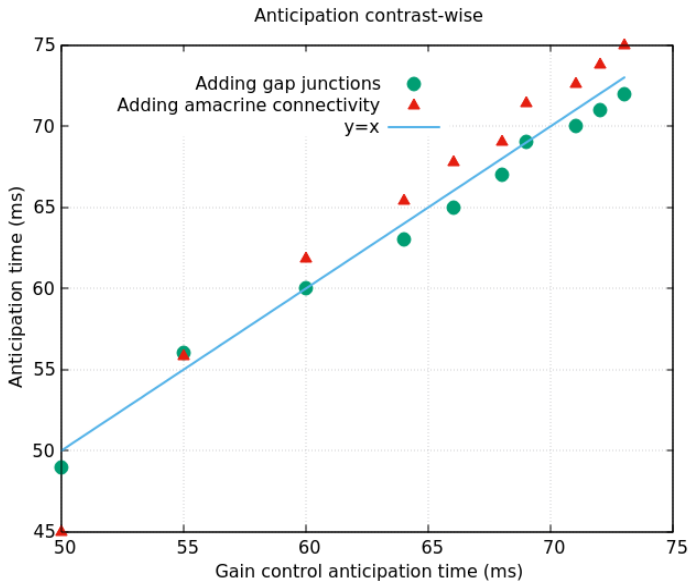


1D results : smooth motion anticipation with amacrine connectivity

Anticipation variability with stimulus
parameters

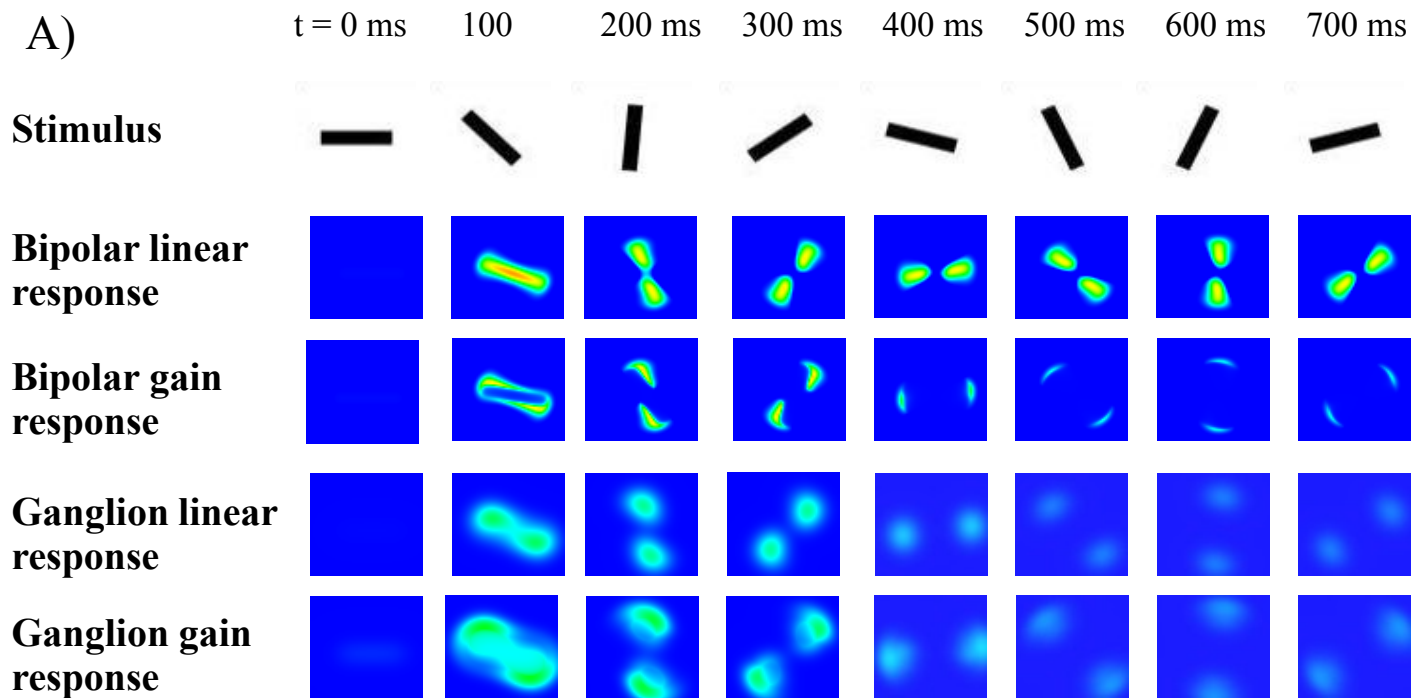


Comparing the performance of the three layers

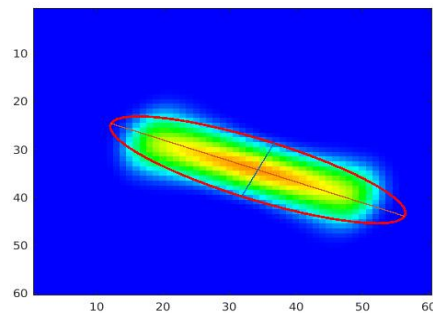


Suggesting new experiments : 2D results

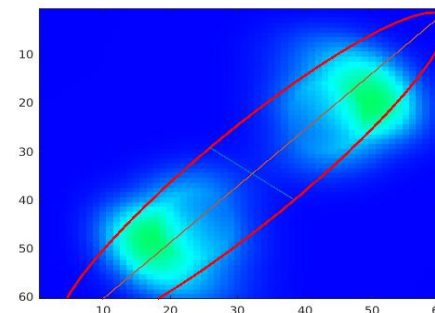
1) Angular anticipation



B)

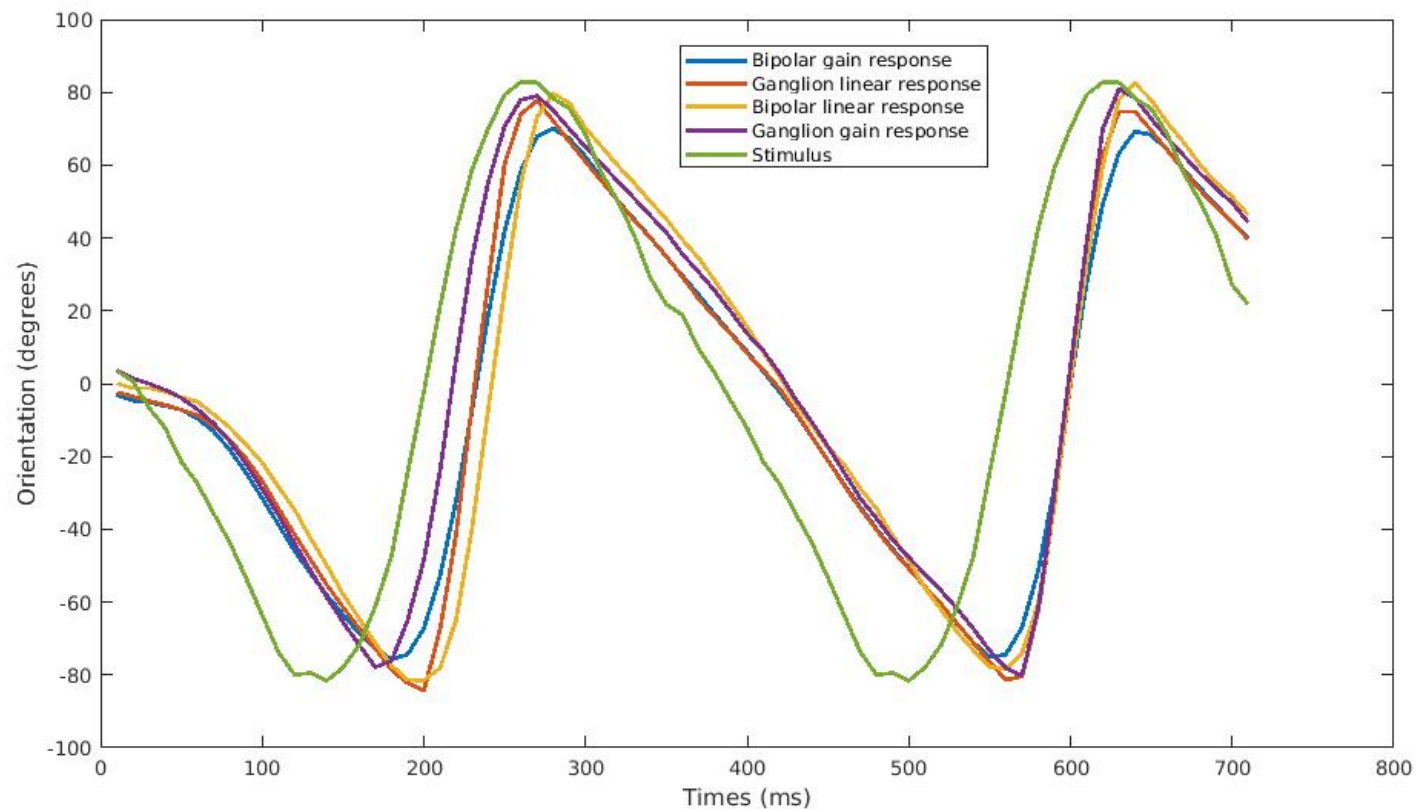


C)



Suggesting new experiments : 2D results

1) Angular anticipation



Conclusions

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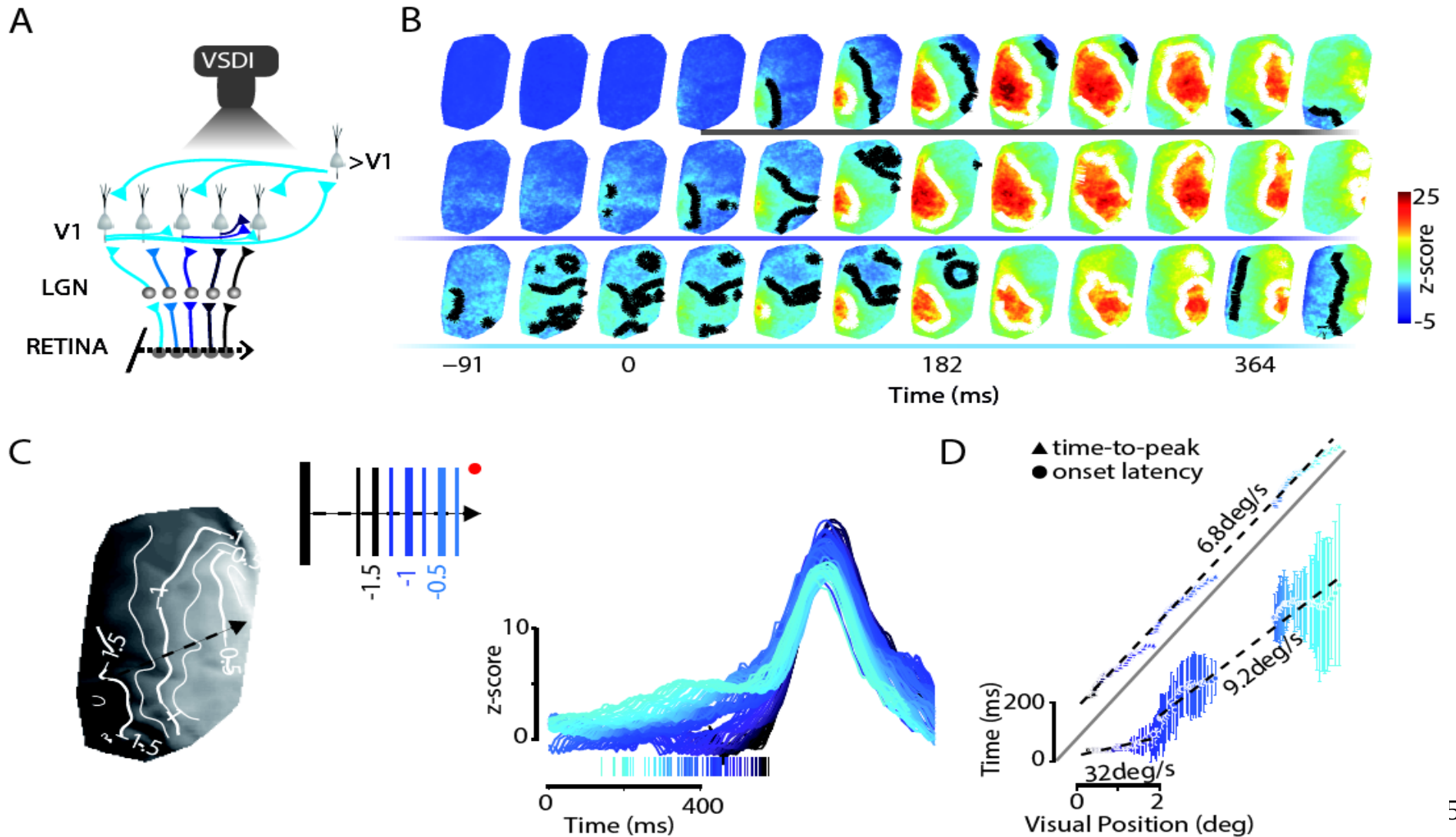
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- Useful paradigms for :
 - 1) Computer vision ?
 - 2) Retinal prostheses ?

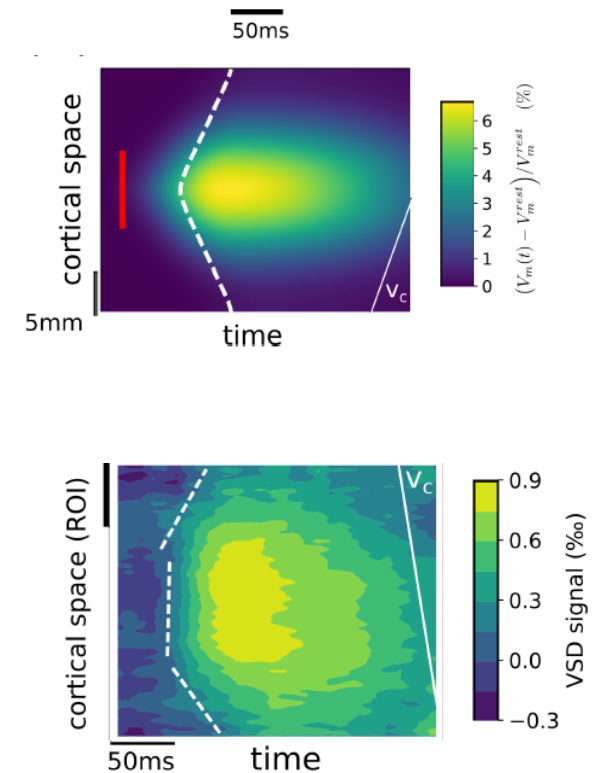
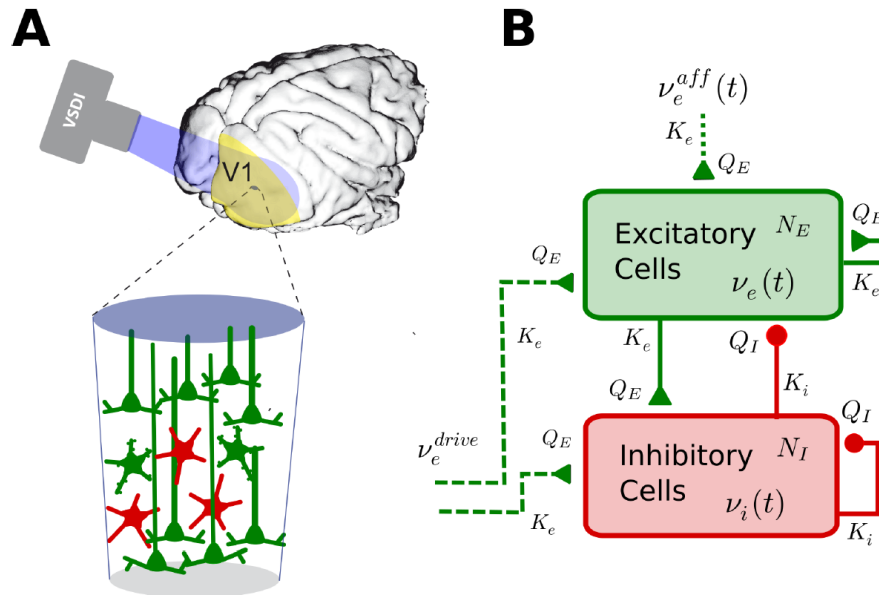
Anticipation in V1

Anticipation in V1



A mean field model to reproduce VSDI recordings

Zerlaut et al 2016
Chemla et al 2018



A mean field model to reproduce VSDI recordings

Zerlaut et al 2016
Chemla et al 2018

Master equation for first and second moments local population dynamics (El Boustani and Destexhe, 2009) read :

$$\left\{ \begin{array}{l} T \frac{\partial \nu_\mu}{\partial t} = (\mathcal{F}_\mu - \nu_\mu) + \frac{1}{2} c_{\lambda\eta} \frac{\partial^2 \mathcal{F}_\mu}{\partial \nu_\lambda \partial \nu_\eta} \\ T \frac{\partial c_{\lambda\eta}}{\partial t} = A_{\lambda\eta} + (\mathcal{F}_\lambda - \nu_\lambda) (\mathcal{F}_\eta - \nu_\eta) + \\ \quad c_{\lambda\mu} \frac{\partial \mathcal{F}_\mu}{\partial \nu_\lambda} + c_{\mu\eta} \frac{\partial \mathcal{F}_\mu}{\partial \nu_\eta} - 2c_{\lambda\eta} \end{array} \right. \longrightarrow T \frac{\partial \nu_\mu}{\partial t} = \mathcal{F}_\mu - \nu_\mu$$

$$A_{\lambda\eta} = \begin{cases} \frac{\mathcal{F}_\lambda (1/T - \mathcal{F}_\lambda)}{N_\lambda} & \text{if } \lambda = \eta \\ 0 & \text{otherwise} \end{cases}$$

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Affords a retino thalamic input

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A mean field model to reproduce VSDI recordings

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Single neuron model (The adaptative exponential integrate and fire model Brette and Gerstner, 2005)

$$\begin{cases} C_m \frac{dV}{dt} = g_L (E_L - V) + I_{syn}(V, t) + k_a e^{\frac{V - V_{thre}}{k_a}} - I_w \\ \tau_w \frac{dI_w}{dt} = -I_w + a \cdot (V - E_L) + \sum_{t_s \in \{t_{spike}\}} b \delta(t - t_s) \end{cases}$$

The conductance-based exponential synapse

$$I_{syn}(V, t) = \sum_{s \in \{e, i\}} \sum_{t_s \in \{t_s\}} Q_s (E_s - V) e^{-\frac{t - t_s}{\tau_s}} \mathcal{H}(t - t_s)$$

Semi analytical transfer function :

$$\nu_{out} = \mathcal{F}(\nu_e, \nu_i) = \frac{1}{2\tau_V} \cdot \text{Erfc}\left(\frac{V_{thre}^{eff} - \mu_V}{\sqrt{2}\sigma_V}\right) \quad \text{with} \quad V_{thre}^{eff}(\mu_V, \sigma_V, \tau_V^N) = P_0 + \sum_{x \in \{\mu_V, \sigma_V, \tau_V^N\}} P_x \cdot \left(\frac{x - x^0}{\delta x^0}\right) + P_{\mu_G} \log\left(\frac{\mu_G}{g_L}\right) \\ + \sum_{x, y \in \{\mu_V, \sigma_V, \tau_V^N\}^2} P_{xy} \cdot \left(\frac{x - x^0}{\delta x^0}\right) \left(\frac{y - y^0}{\delta y^0}\right)$$

A mean field model to reproduce VSDI recordings

Zerlaut et al 2016
Chemla et al 2018

The mean, standard deviation and auto-correlation time of the excitatory and inhibitory conductance read :

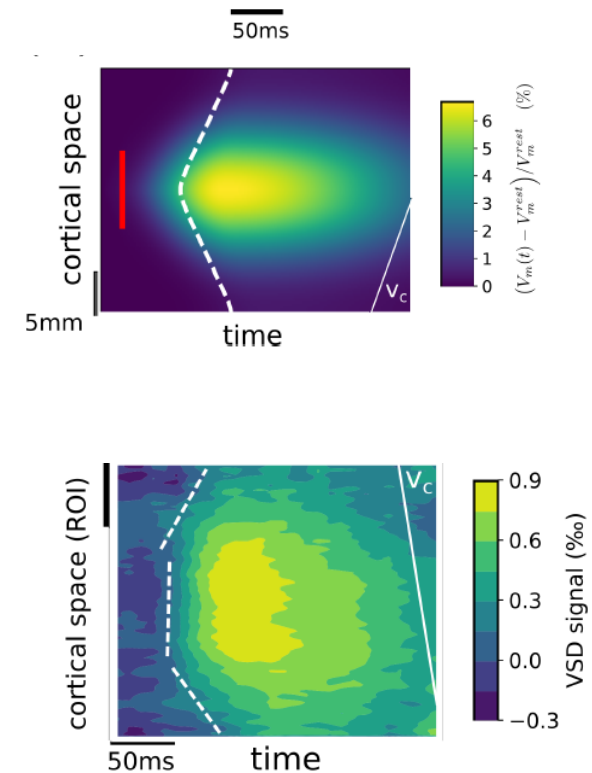
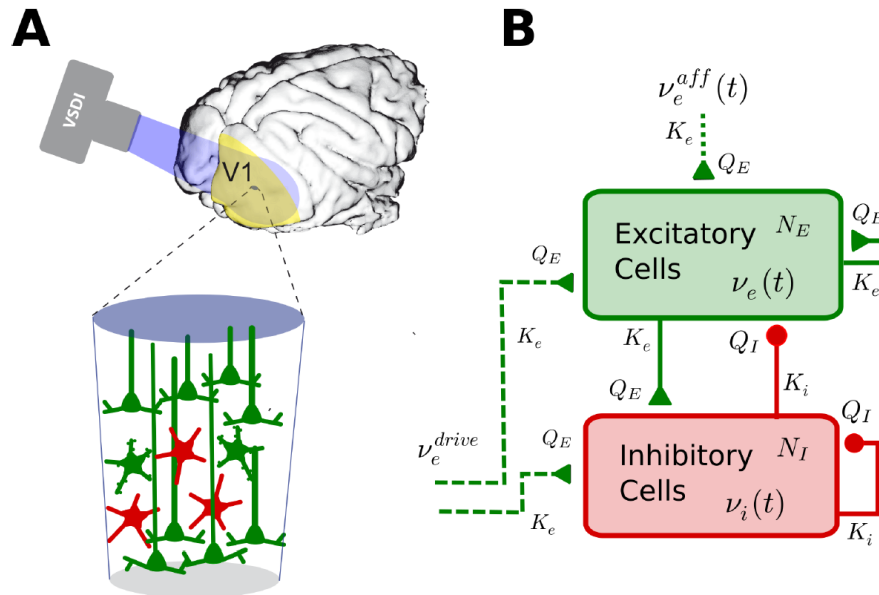
$$\begin{array}{ll}
 \mu_{Ge}(\nu_e, \nu_i) = \nu_e K_e \tau_e Q_e & \longrightarrow \mu_G(\nu_e, \nu_i) = \mu_{Ge} + \mu_{Gi} + g_L \\
 \sigma_{Ge}(\nu_e, \nu_i) = \sqrt{\frac{\nu_e K_e \tau_e}{2}} Q_e & \tau_m(\nu_e, \nu_i) = \frac{C_m}{\mu_G} \\
 \mu_{Gi}(\nu_e, \nu_i) = \nu_i K_i \tau_i Q_i & \downarrow \\
 \sigma_{Gi}(\nu_e, \nu_i) = \sqrt{\frac{\nu_i K_i \tau_i}{2}} Q_i & \mu_V(\nu_e, \nu_i) = \frac{\mu_{Ge} E_e + \mu_{Gi} E_i + g_L E_L}{\mu_G} \\
 & \sigma_V(\nu_e, \nu_i) = \sqrt{\sum_s K_s \nu_s \frac{(U_s \cdot \tau_s)^2}{2(\tau_m^{\text{eff}} + \tau_s)}} \\
 & \tau_V(\nu_e, \nu_i) = \left(\frac{\sum_s (K_s \nu_s (U_s \cdot \tau_s)^2)}{\sum_s (K_s \nu_s (U_s \cdot \tau_s)^2 / (\tau_m^{\text{eff}} + \tau_s))} \right)
 \end{array}$$

Finally, the transfer function reads :

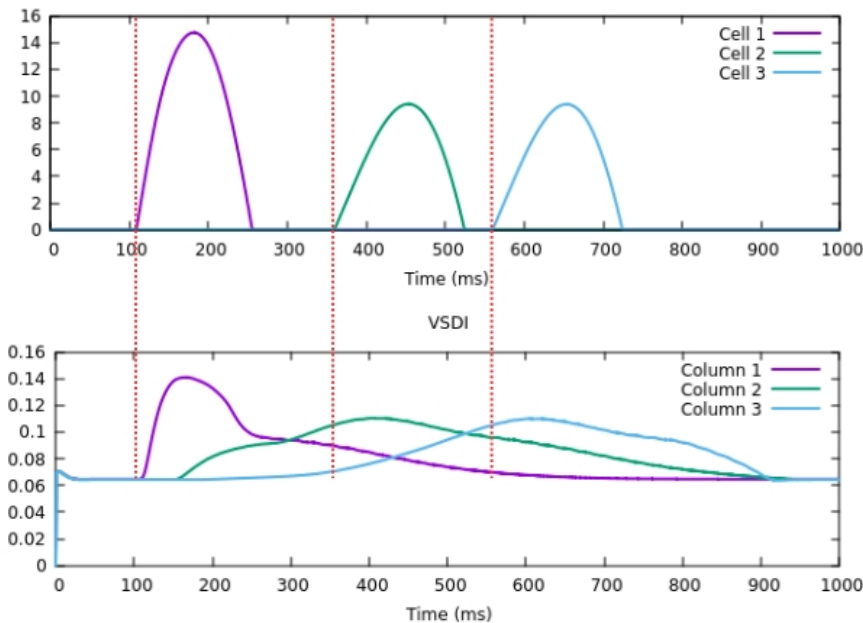
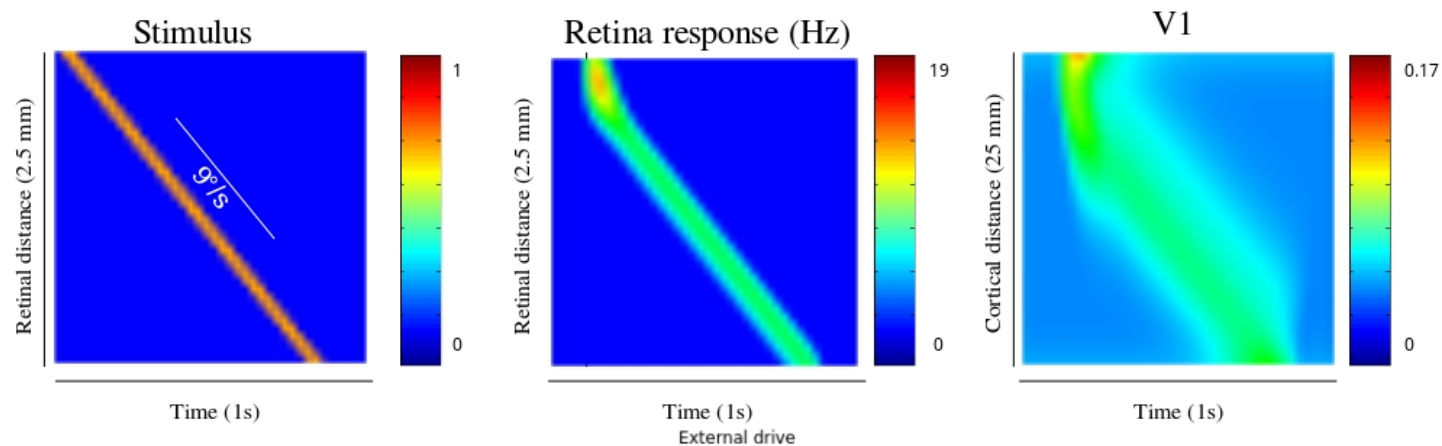
$$\nu_{out} = \mathcal{F}(\nu_e, \nu_i) = \frac{1}{2\tau_V} \cdot \text{Erfc}\left(\frac{V_{thre}^{eff} - \mu_V}{\sqrt{2}\sigma_V}\right)$$

A mean field model to reproduce VSDI recordings

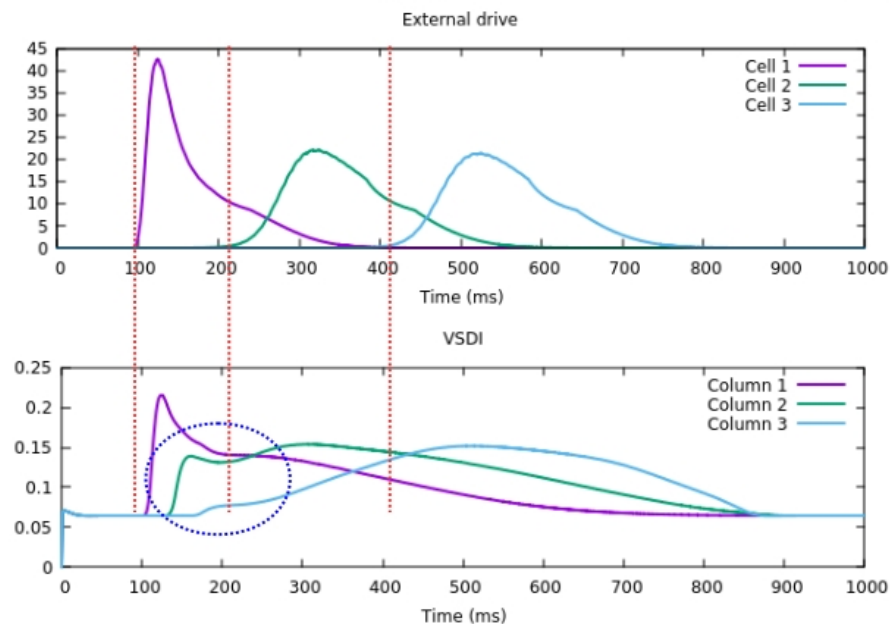
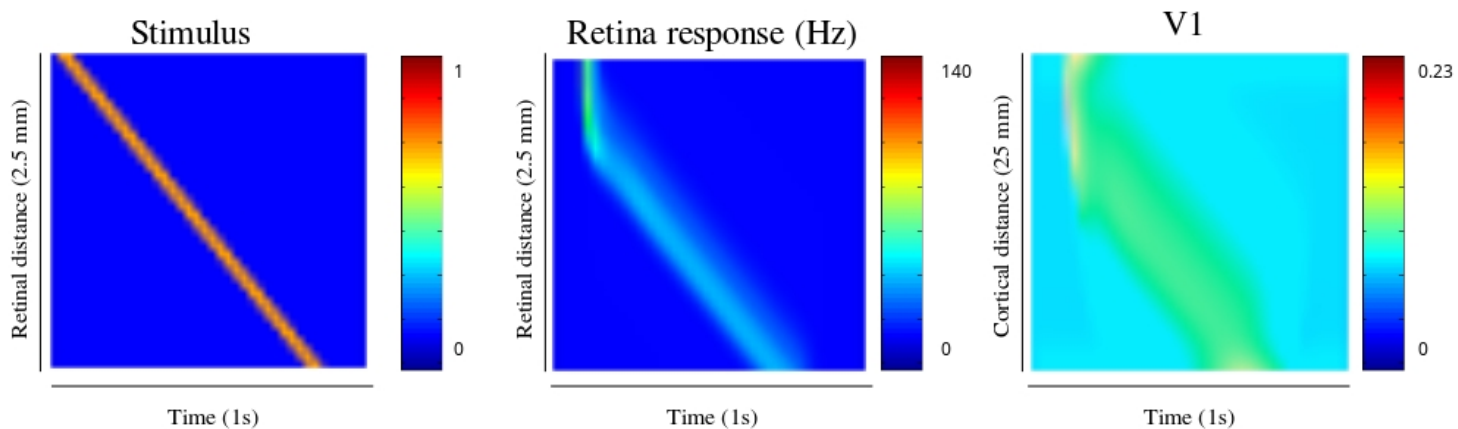
Zerlaut et al 2016
Chemla et al 2018



Response of the cortical model to a LN retina drive

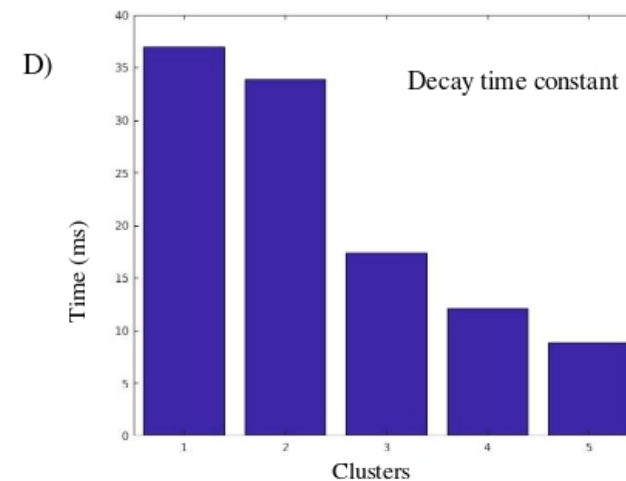
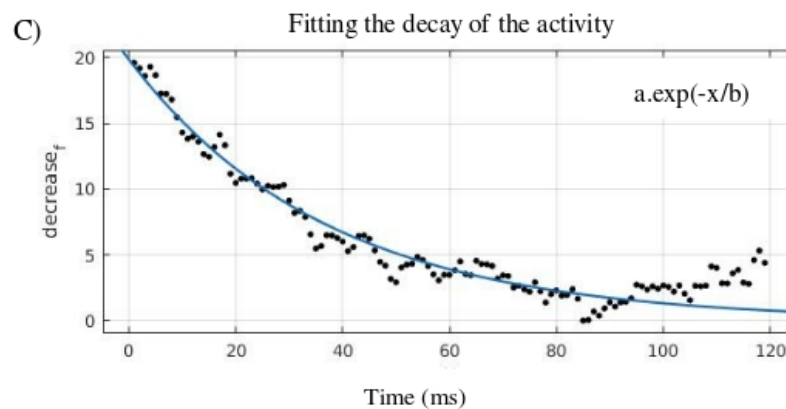
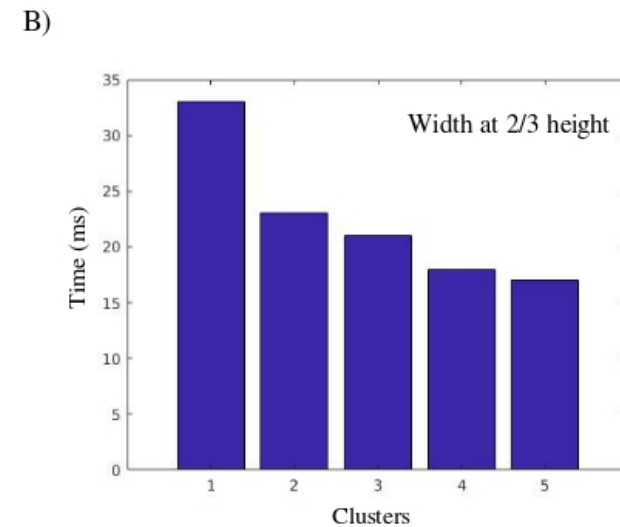
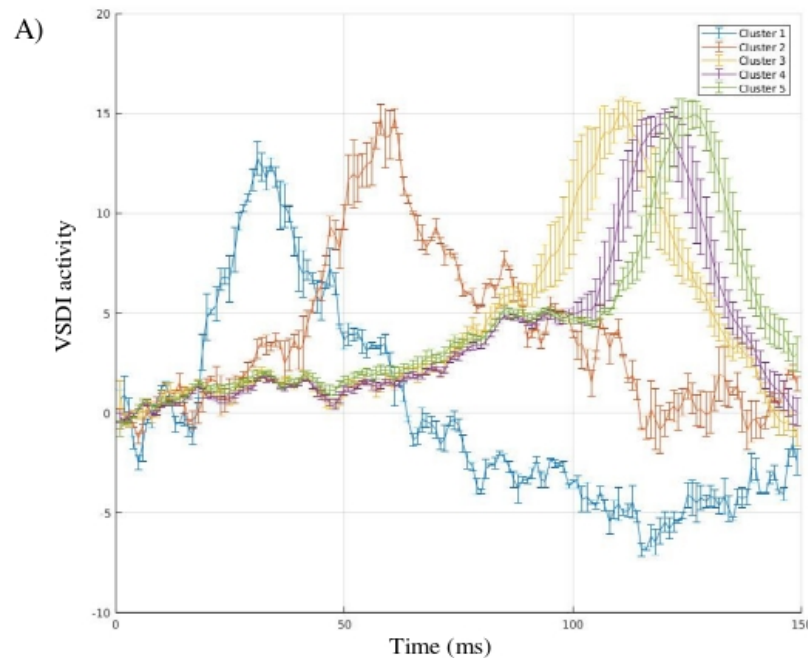


Response of the cortical model to a retina drive with gain control



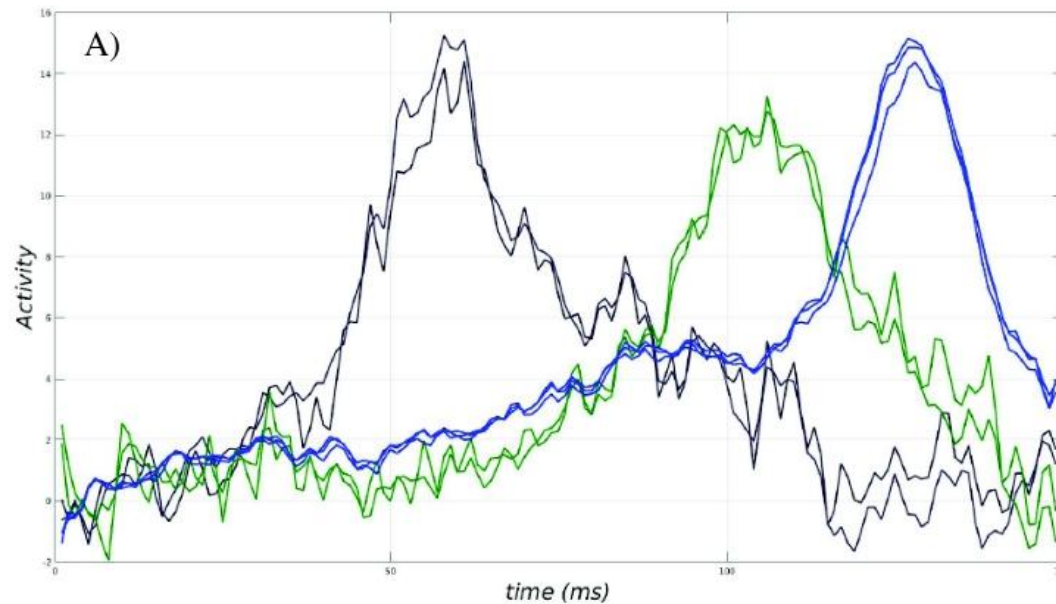
Anticipation in the cortex : VSDI data analysis

(Data courtesy of F. Chavane et S. Chemla)

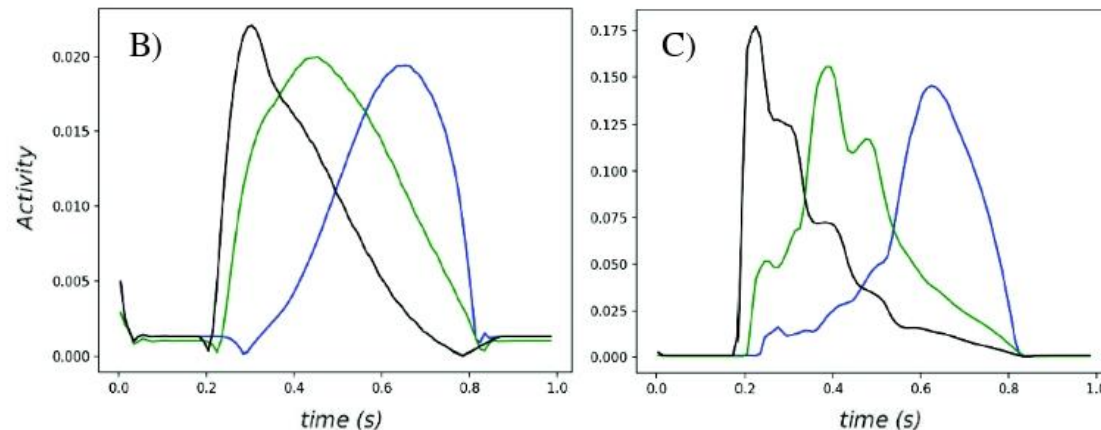


Comparing simulation results to VSDI recordings

Cortex experimental recordings



Simulation results
Response to an LN
model of the retina



Simulation results
Response to a gain
control model of the
retina

Conclusions

- We developed a 2D retina with three ganglion cell layers, implementing gain control and connectivity.
- We use the output of our model as an input to a mean field model of V1, and were able to reproduce anticipation as observed in VSDI

Conclusions

- How to improve object identification
 - 1) exploring the model's parameters and
 - 2) using connectivity ?
- Is our model able to anticipate more complex trajectories, with accelerations for instance ?
- How to calibrate connectivity using biology ?
- How does anticipation affect higher order correlations ?
- Would it be possible to design psycho-physical tests clearly showing the role of the retina in visual anticipation ?

Thank you for your attention !