Anticipation in the retina and the primary visual cortex : towards an integrated retino-cortical model for motion processing

Bruno Cessac, Selma Souihel, Matteo Di Volo, Frédéric Chavane, Alain Destexhe, Sandrine Chemla, Olivier Marre

Anticipation in the retina and the primary visual cortex : towards an integrated retino-cortical model for motion processing

Bruno Cessac, Selma Souihel

Biovision

Anticipation in the retina and the primary visual cortex : towards an integrated retino-cortical model for motion processing

Bruno Cessac, **Selma Souihel**

Biovision

Anticipation in the retina and the primary visual cortex : towards an integrated retino-cortical model for motion processing

Bruno Cessac, **Selma Souihel**

Biovision

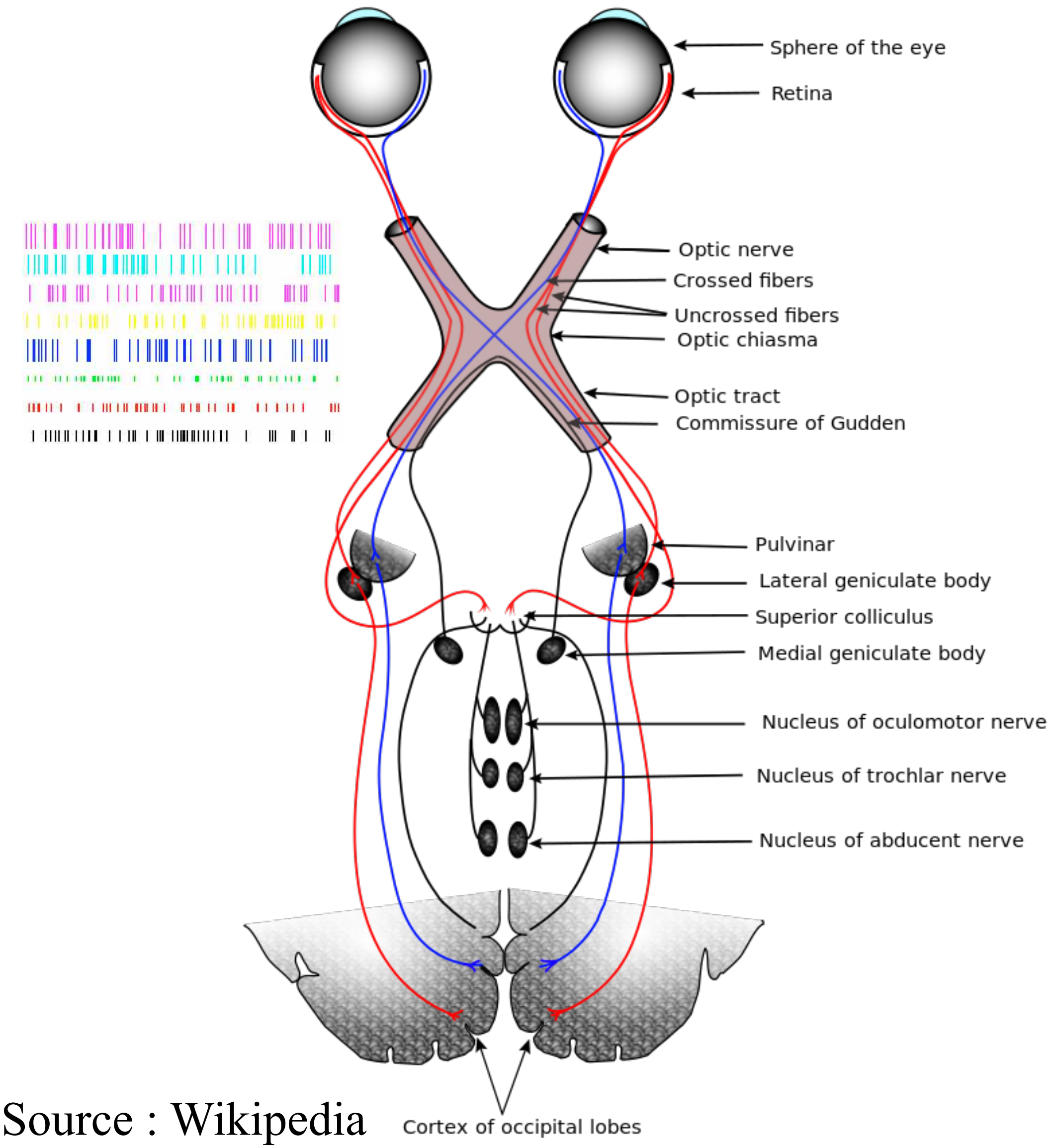
In collaboration with :

Matteo Di Volo
Alain Destexhe

Frédéric Chavane
Sandrine Chemla

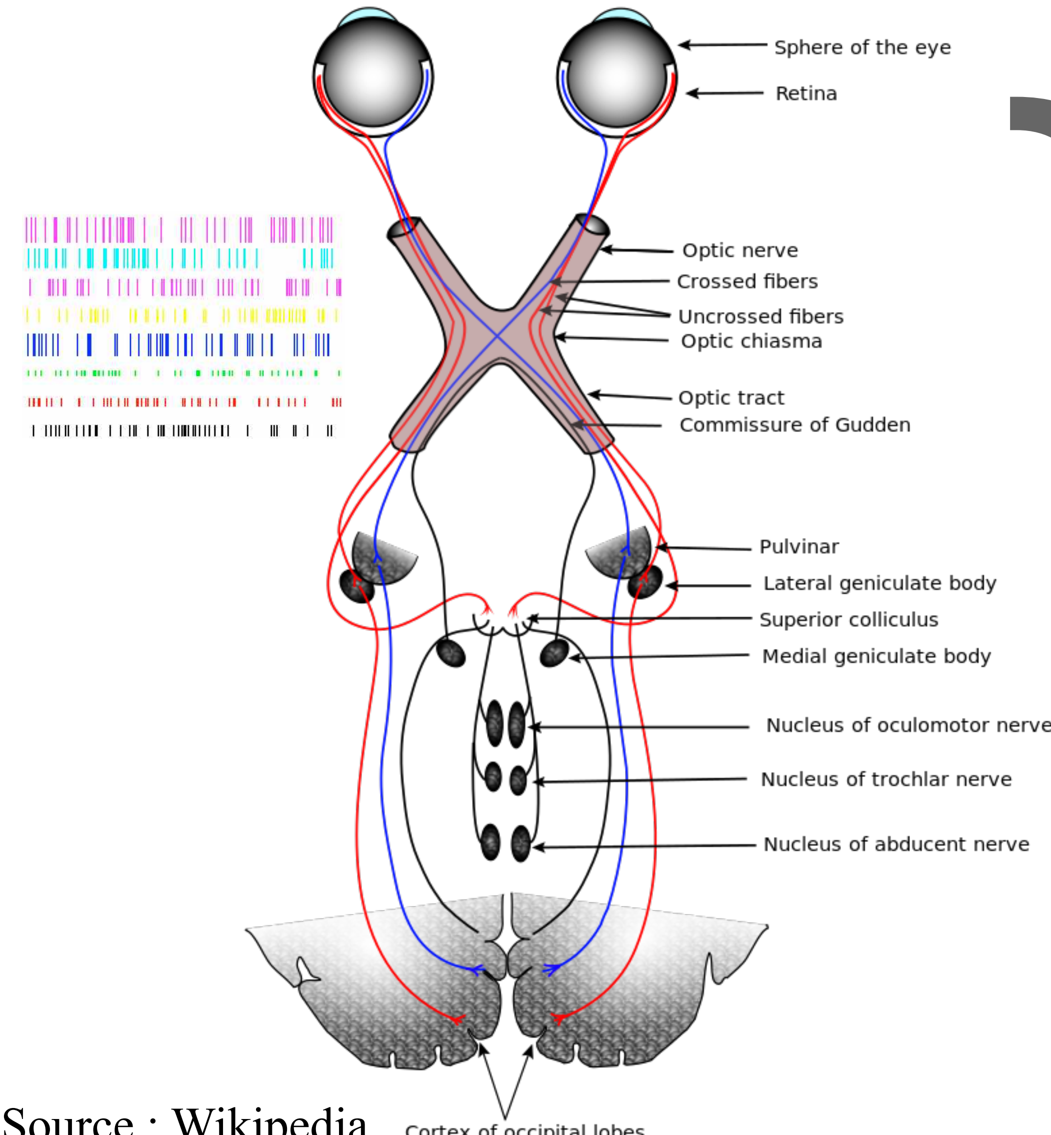
Olivier Marre

The visual flow

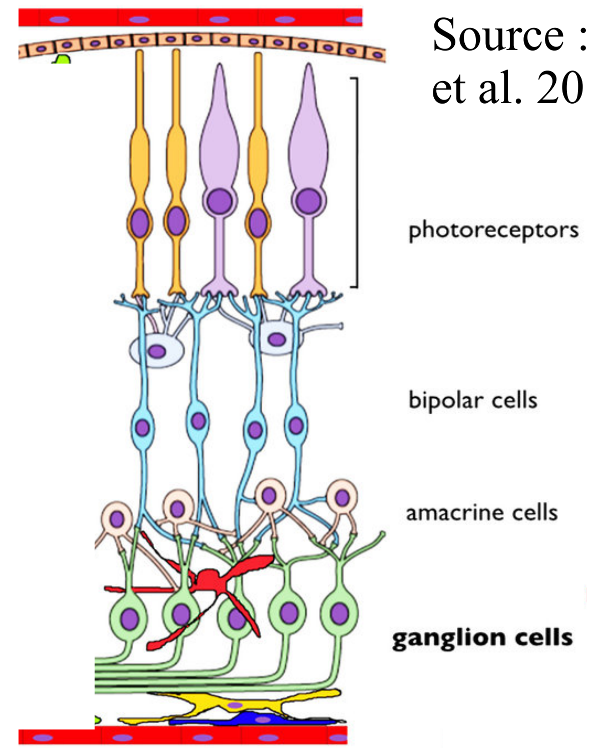


Source : Wikipedia

The visual flow

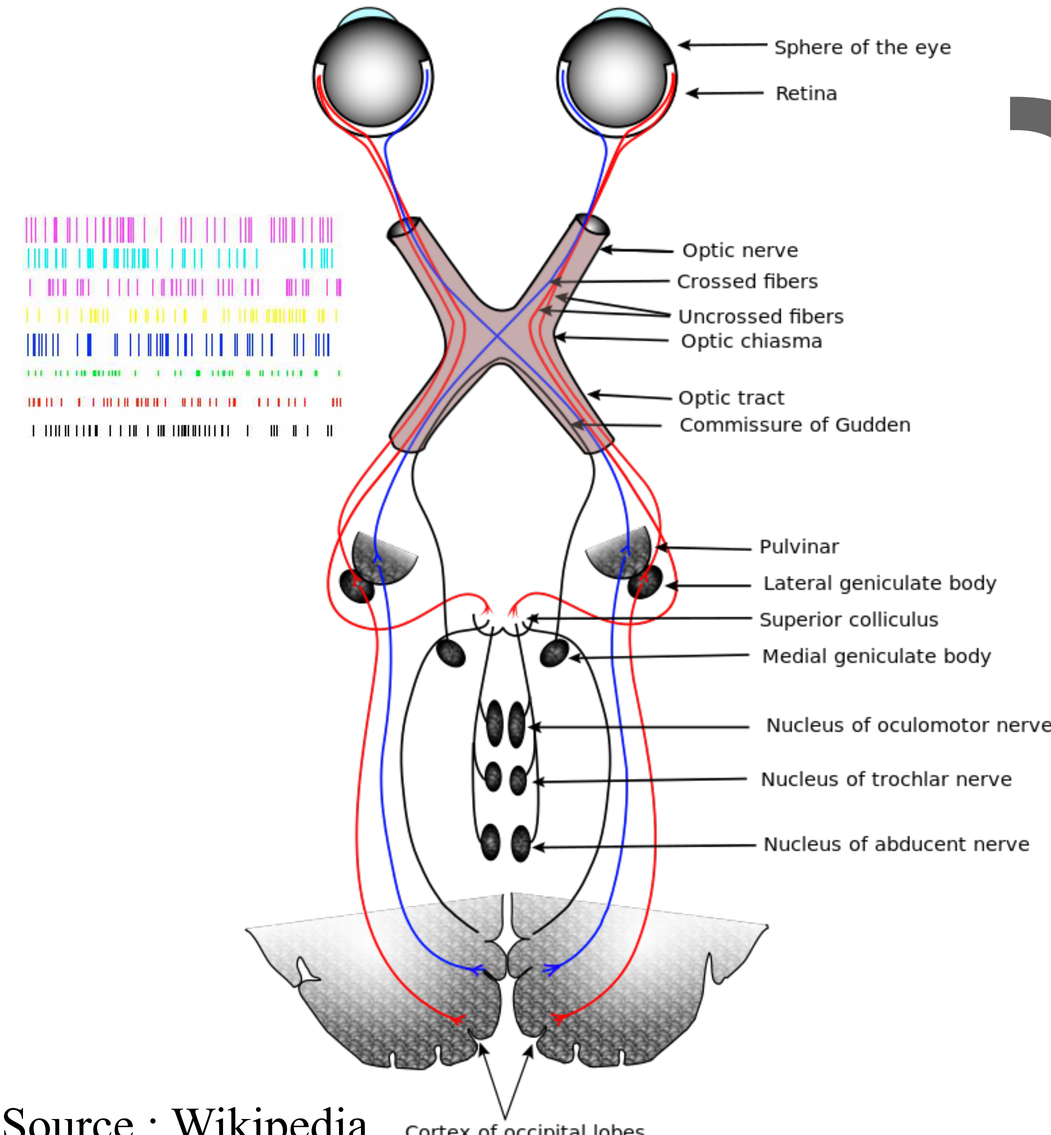


Source : Wikipedia

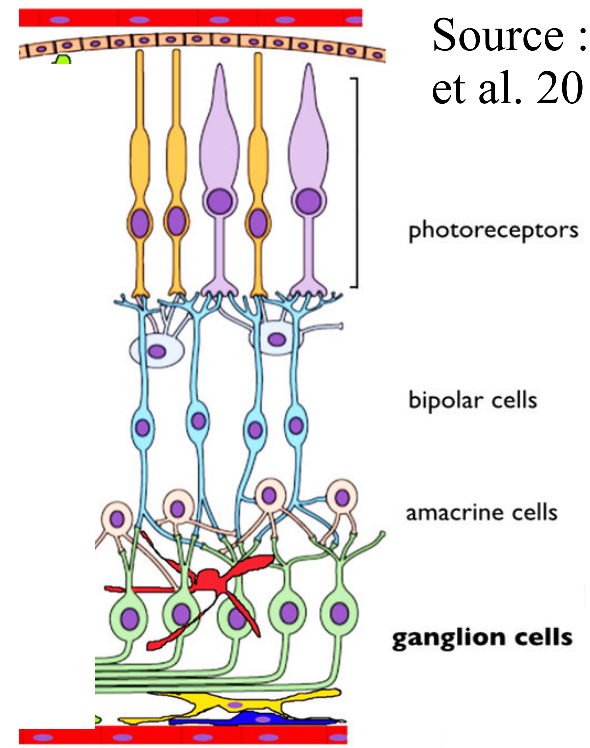


Source : Ryskamp et al. 2014

The visual flow

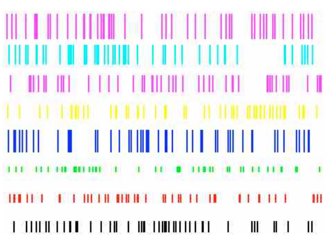


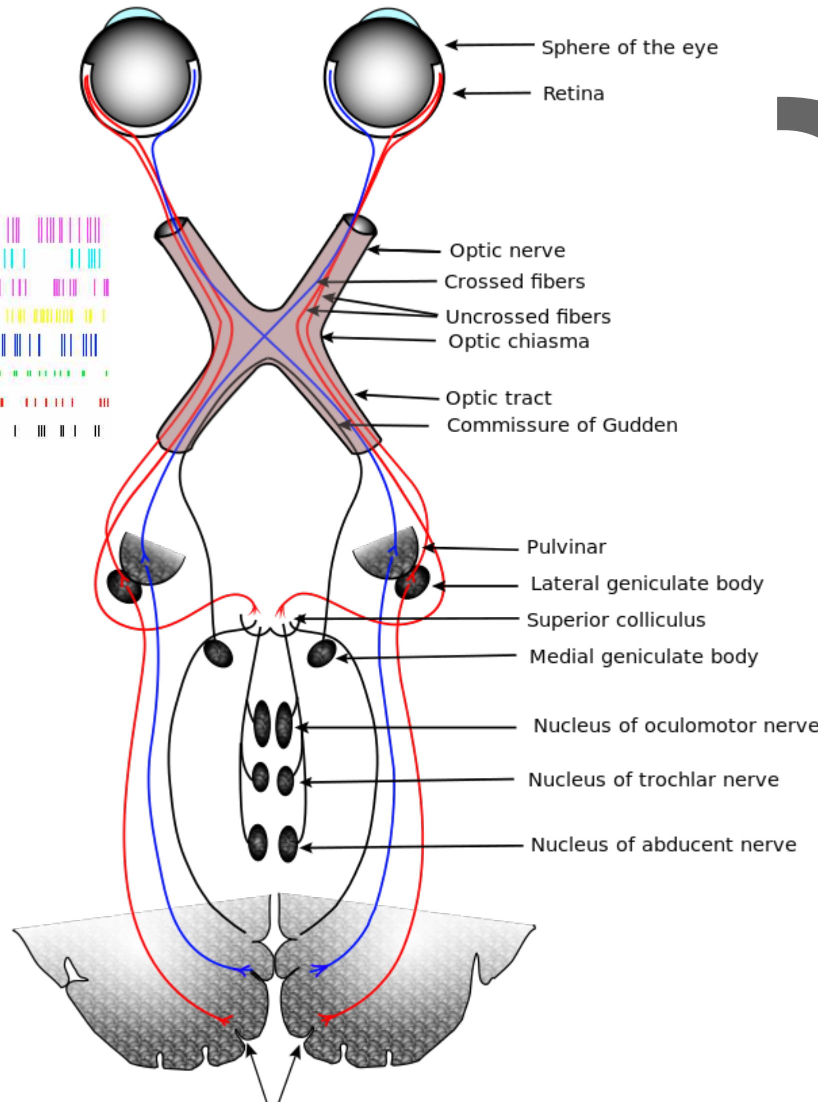
Source : Wikipedia



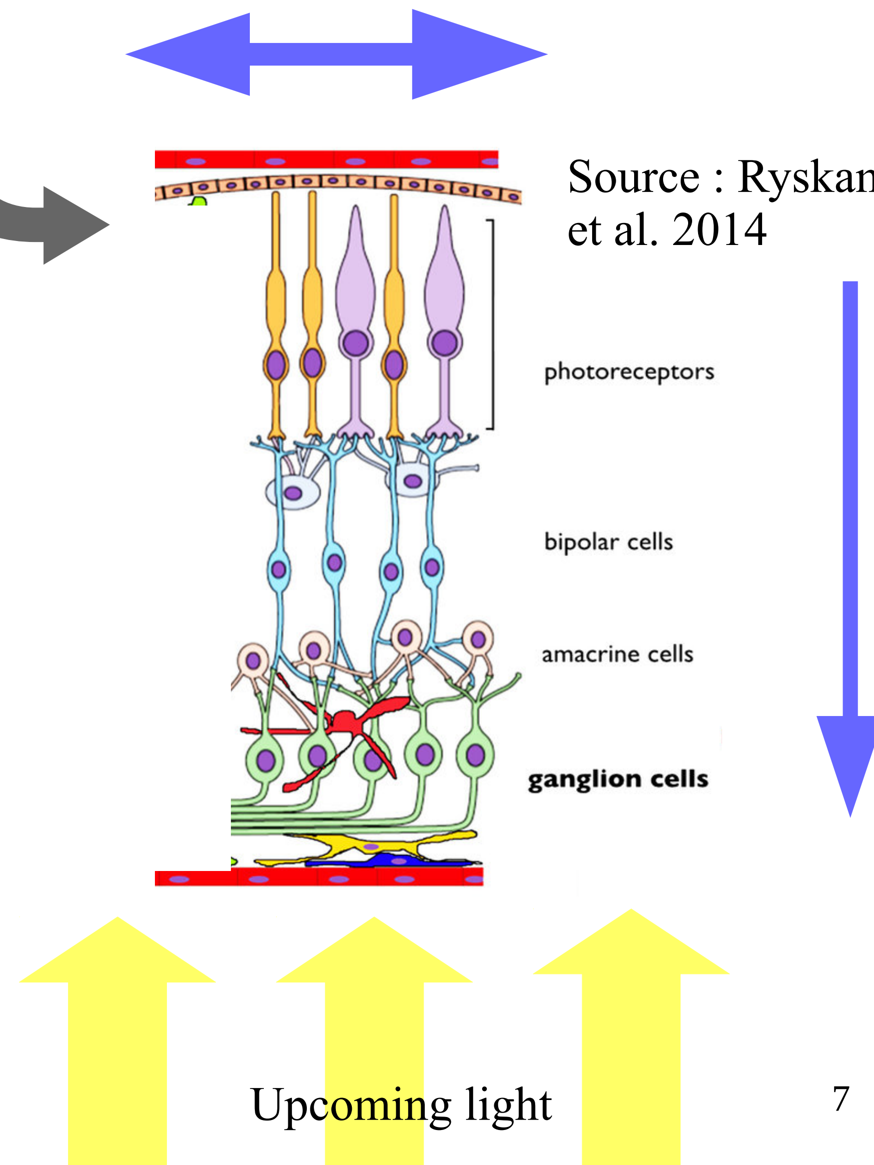
Source : Ryskamp et al. 2014

The visual flow



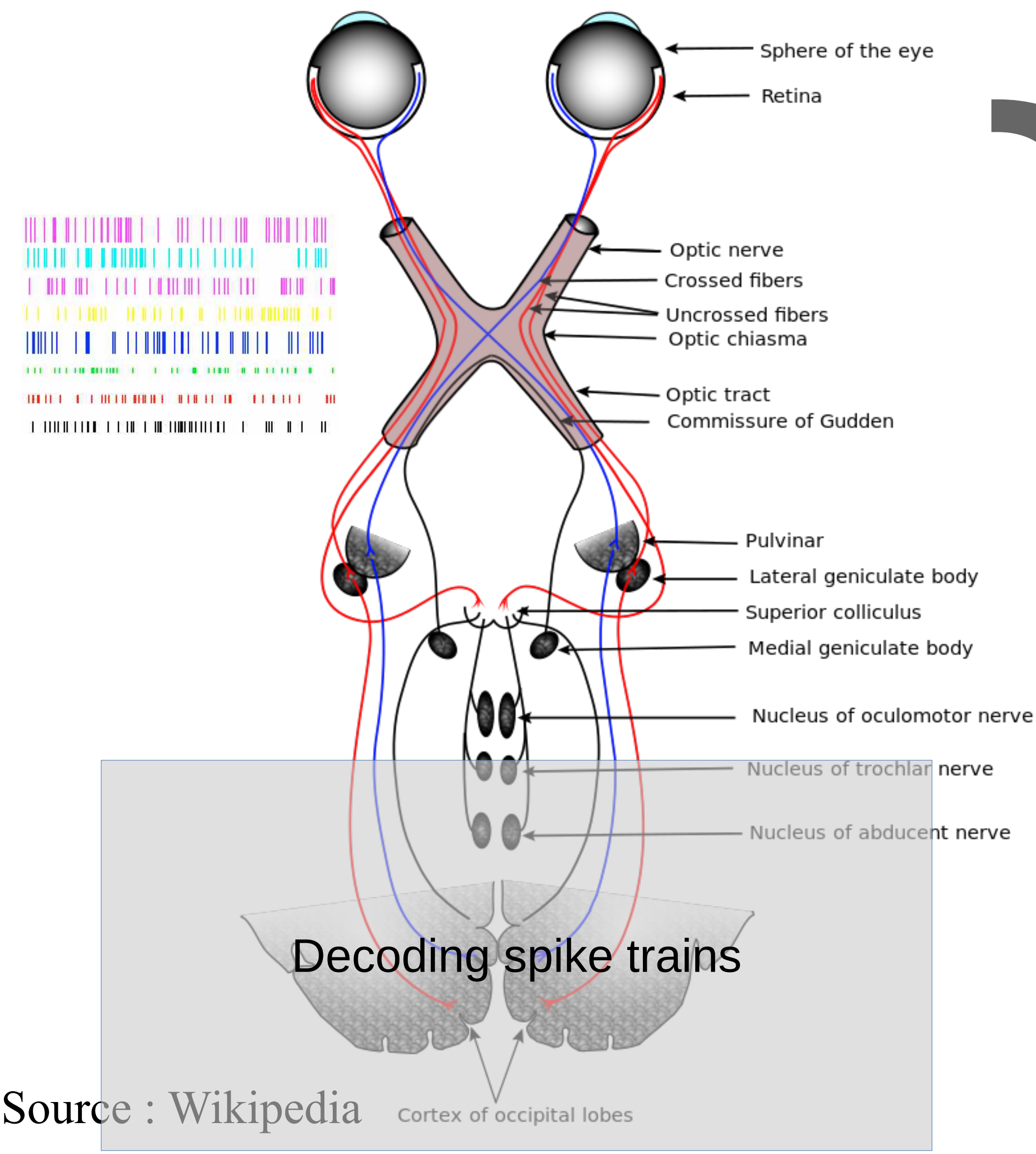


Source : Wikipedia

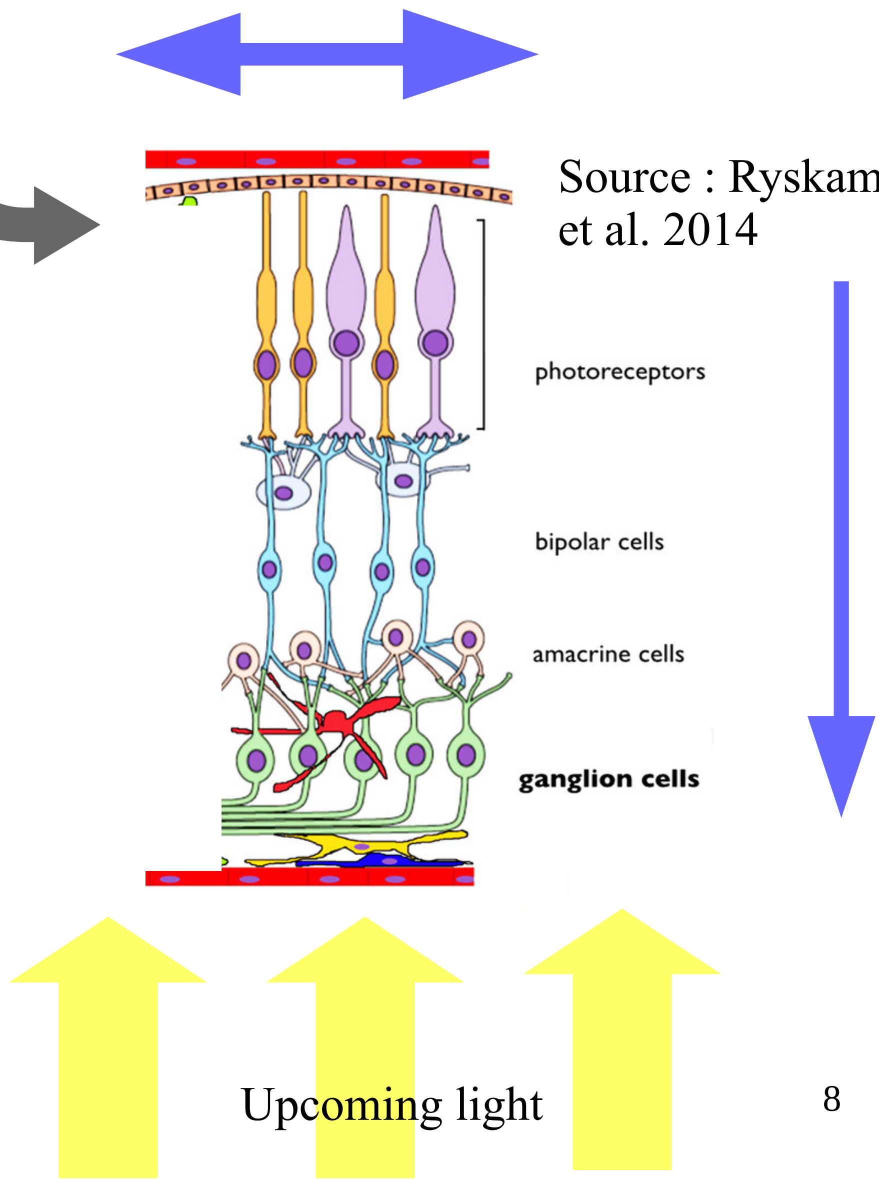


Source : Ryskamp et al. 2014

The visual flow

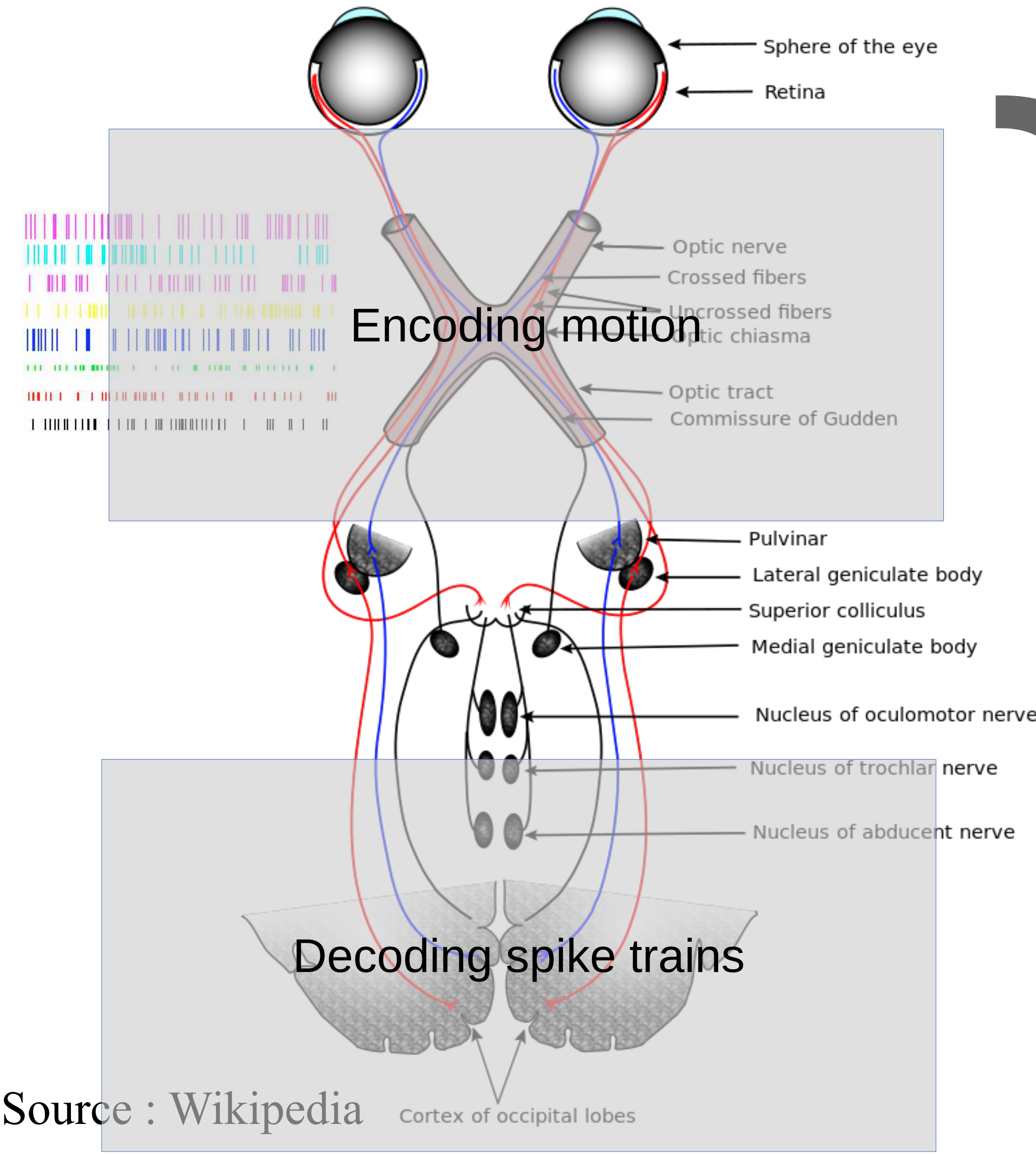


Source : Wikipedia

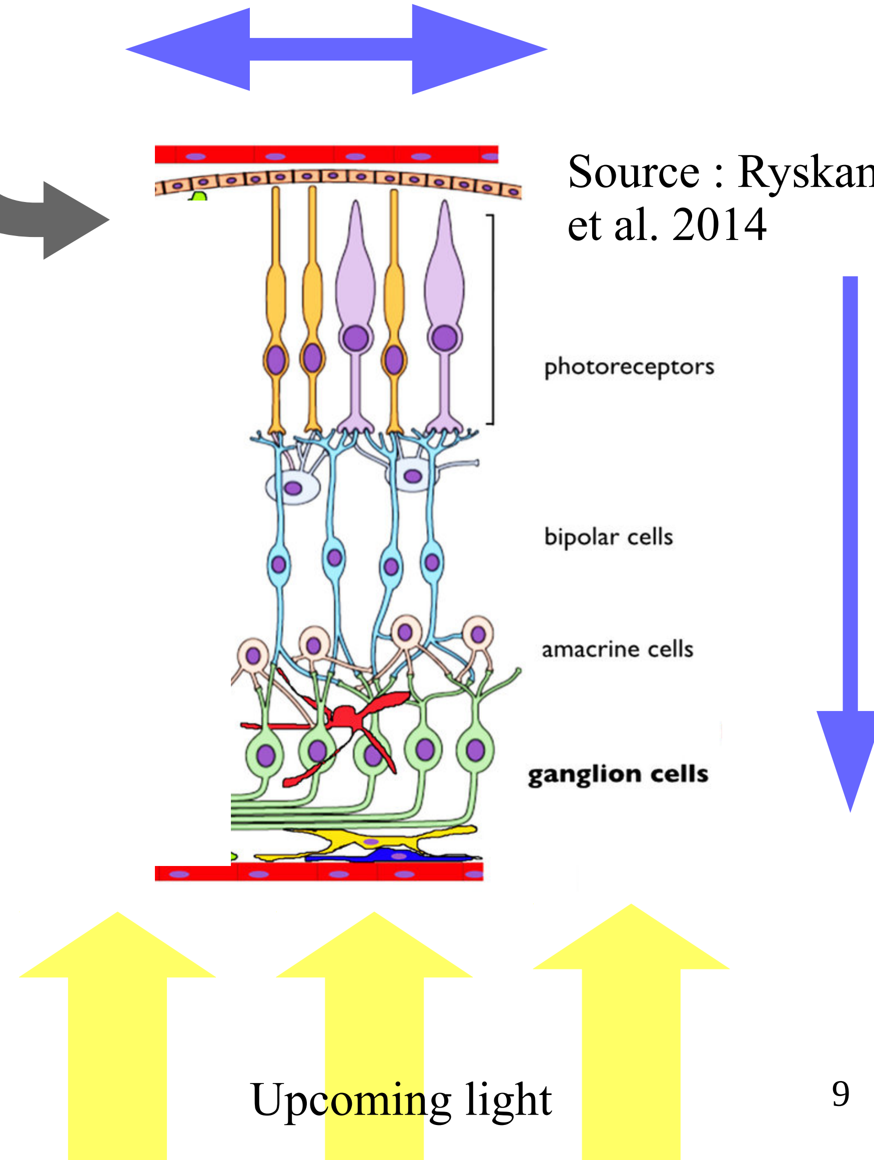


Source : Ryskamp et al. 2014

The visual flow

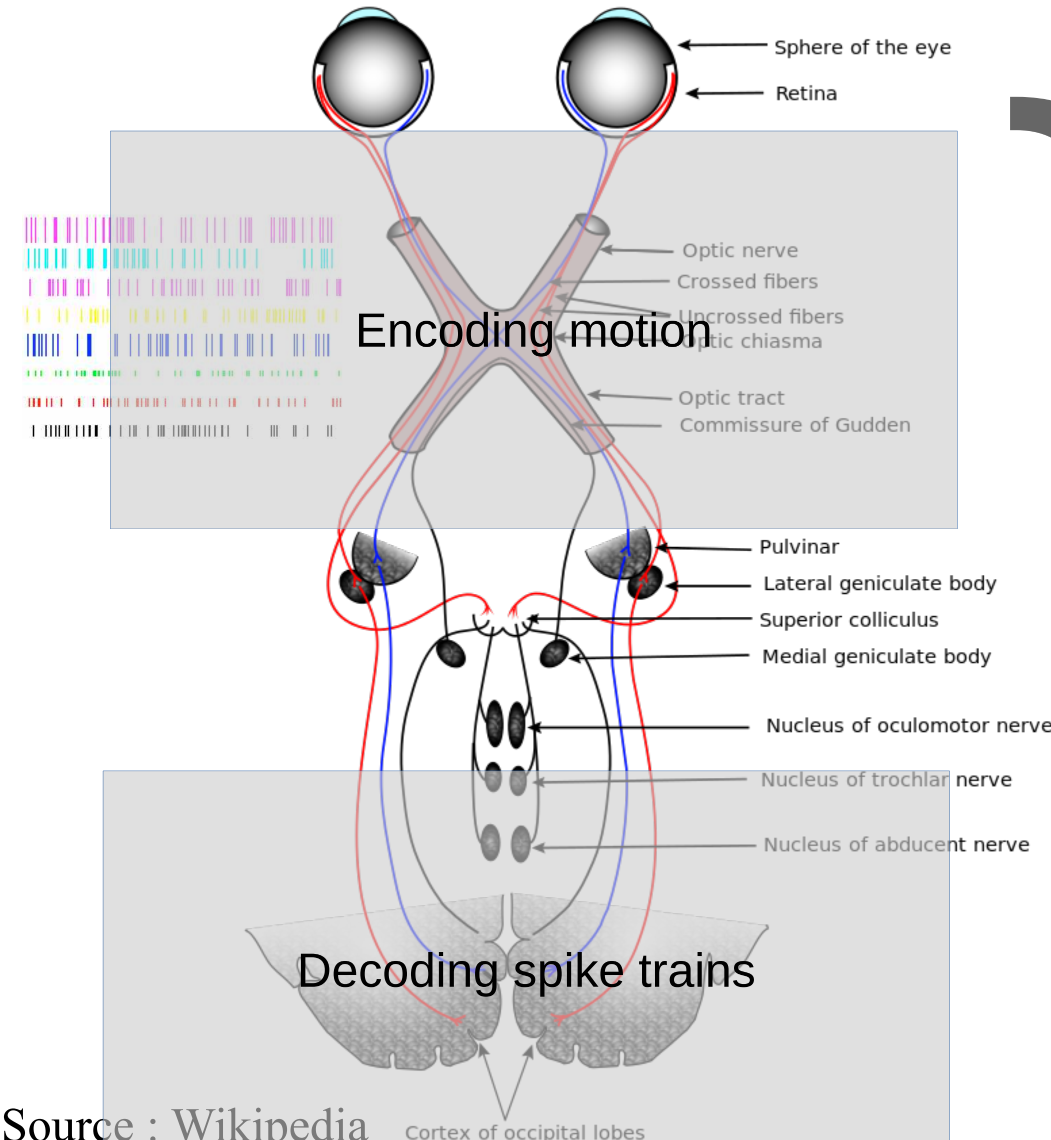


Source : Wikipedia



Source : Ryskamp et al. 2014

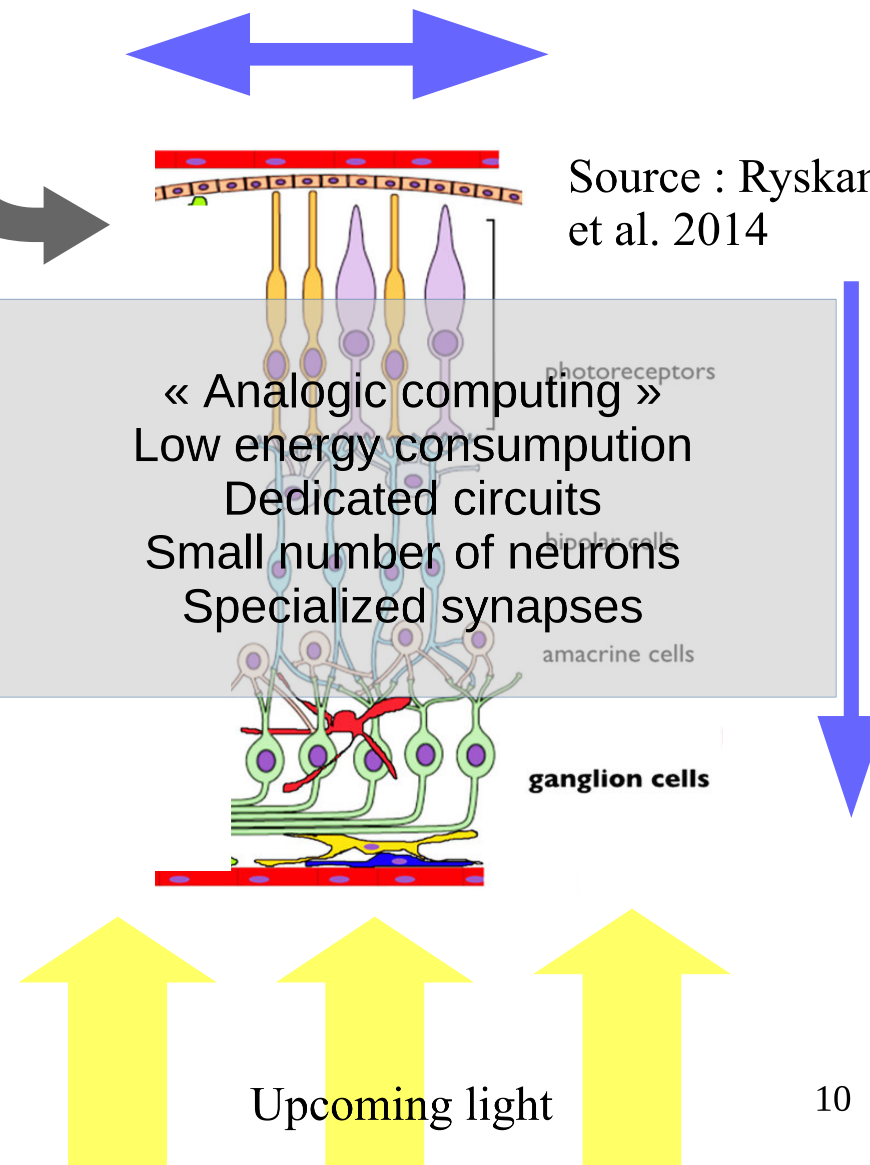
The visual flow



Encoding motion

Decoding spike trains

Source : Wikipedia

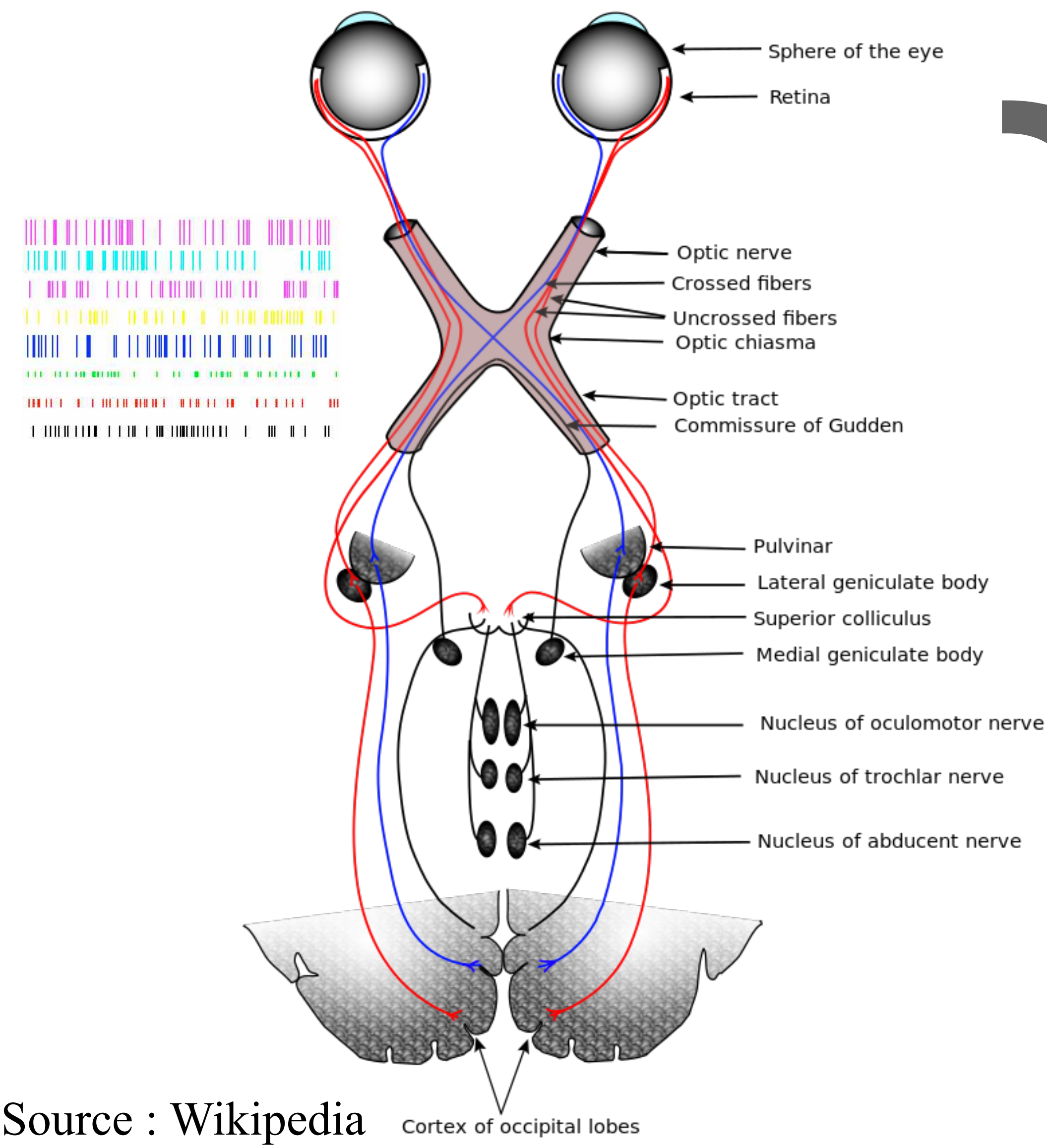


Source : Ryskamp et al. 2014

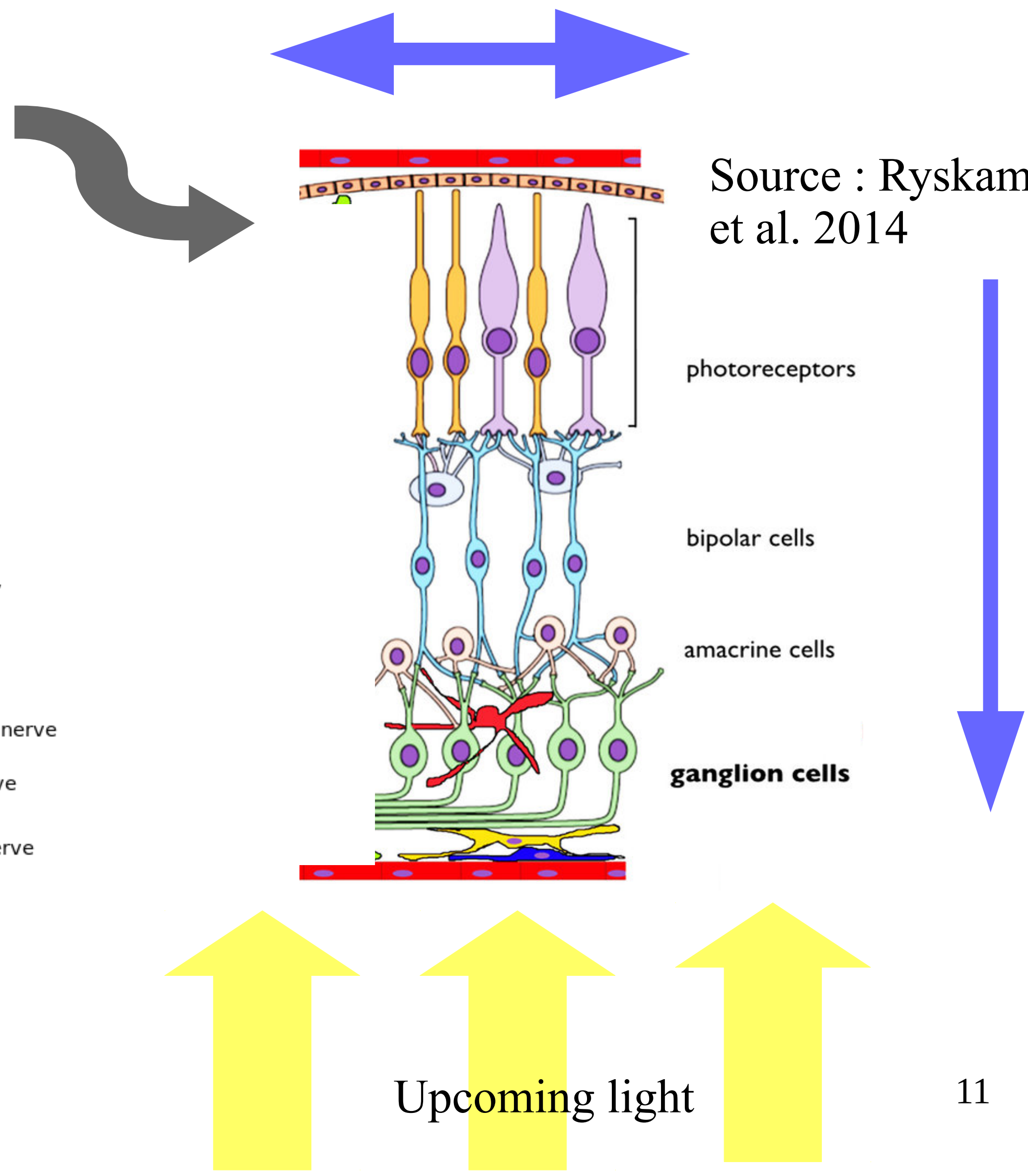
« Analogic computing »
Low energy consumption
Dedicated circuits
Small number of neurons
Specialized synapses

Upcoming light

The visual flow

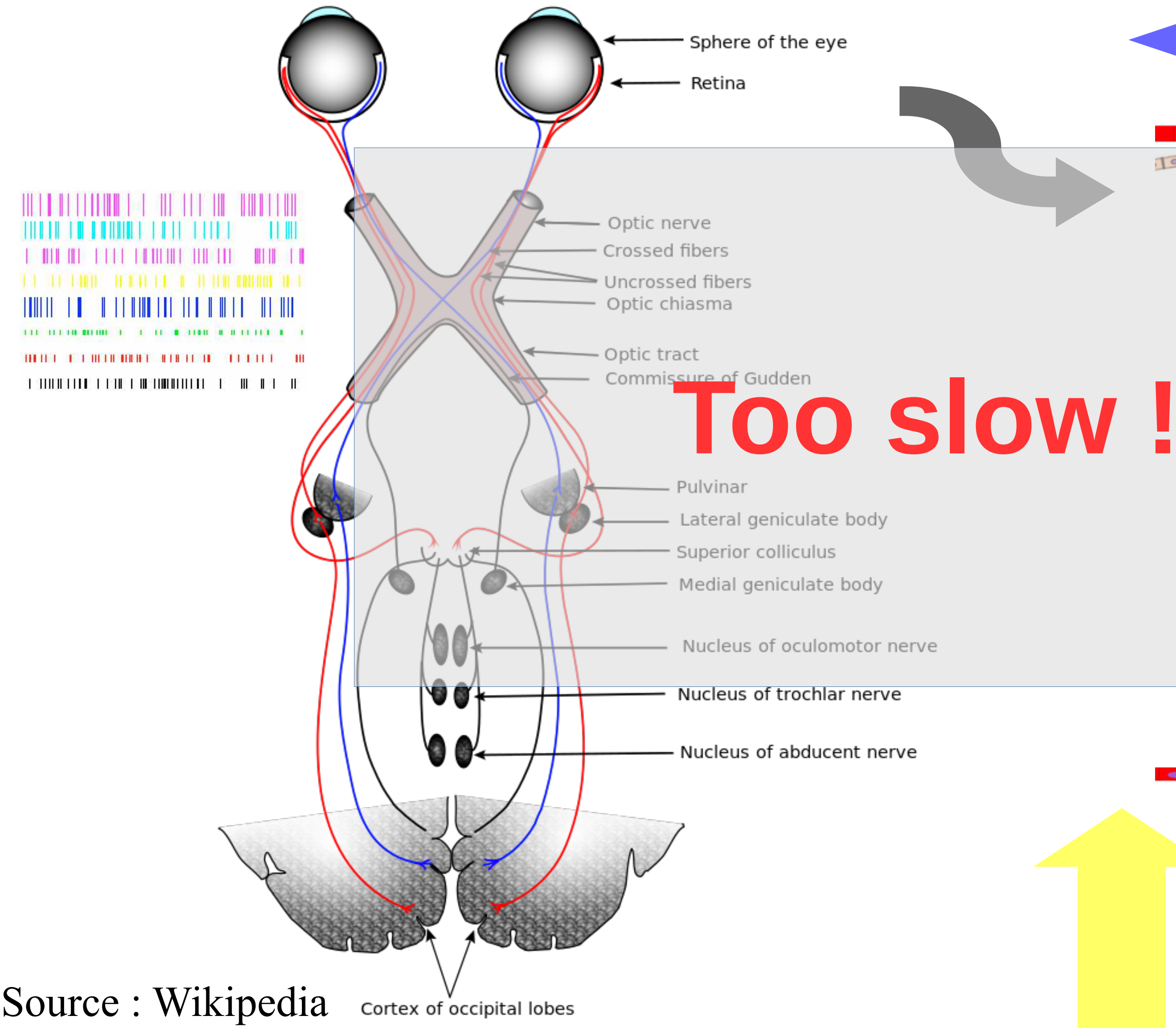


Source : Wikipedia

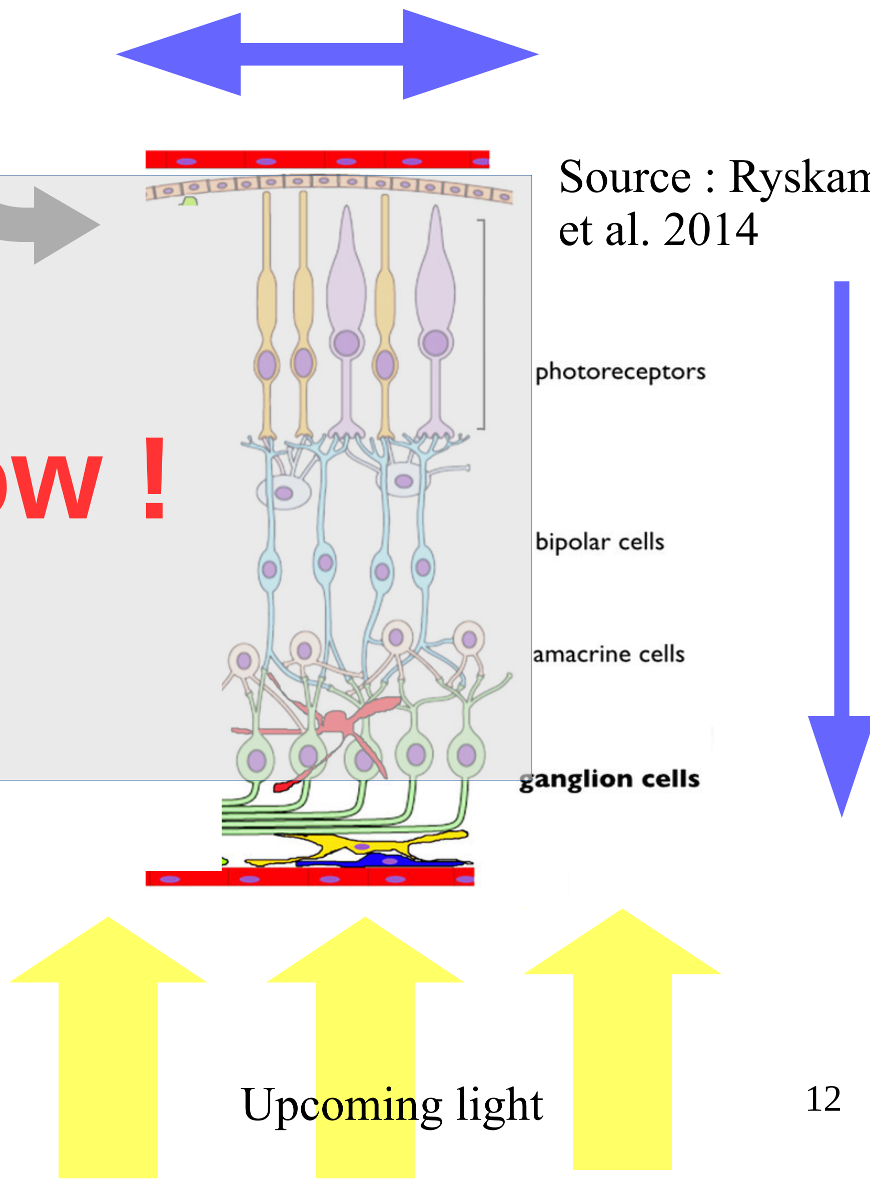


Source : Ryskamp et al. 2014

The visual flow

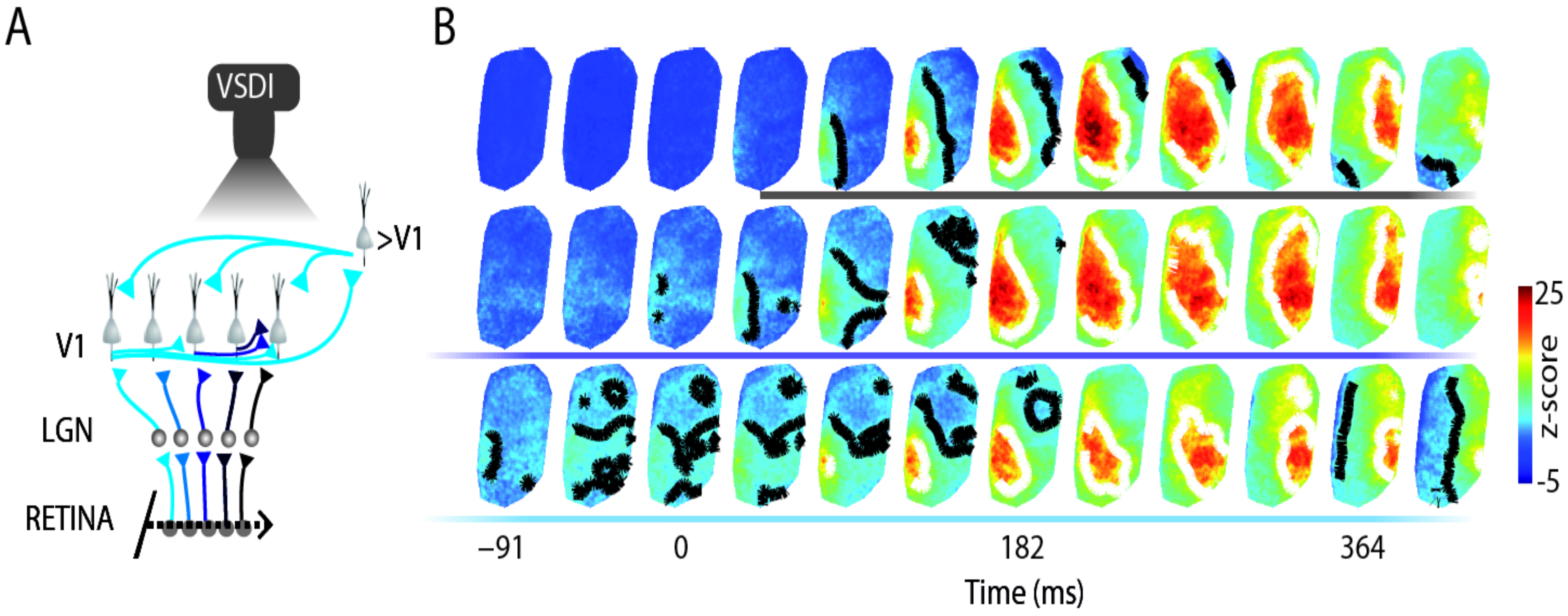


Source : Wikipedia



Source : Ryskamp et al. 2014

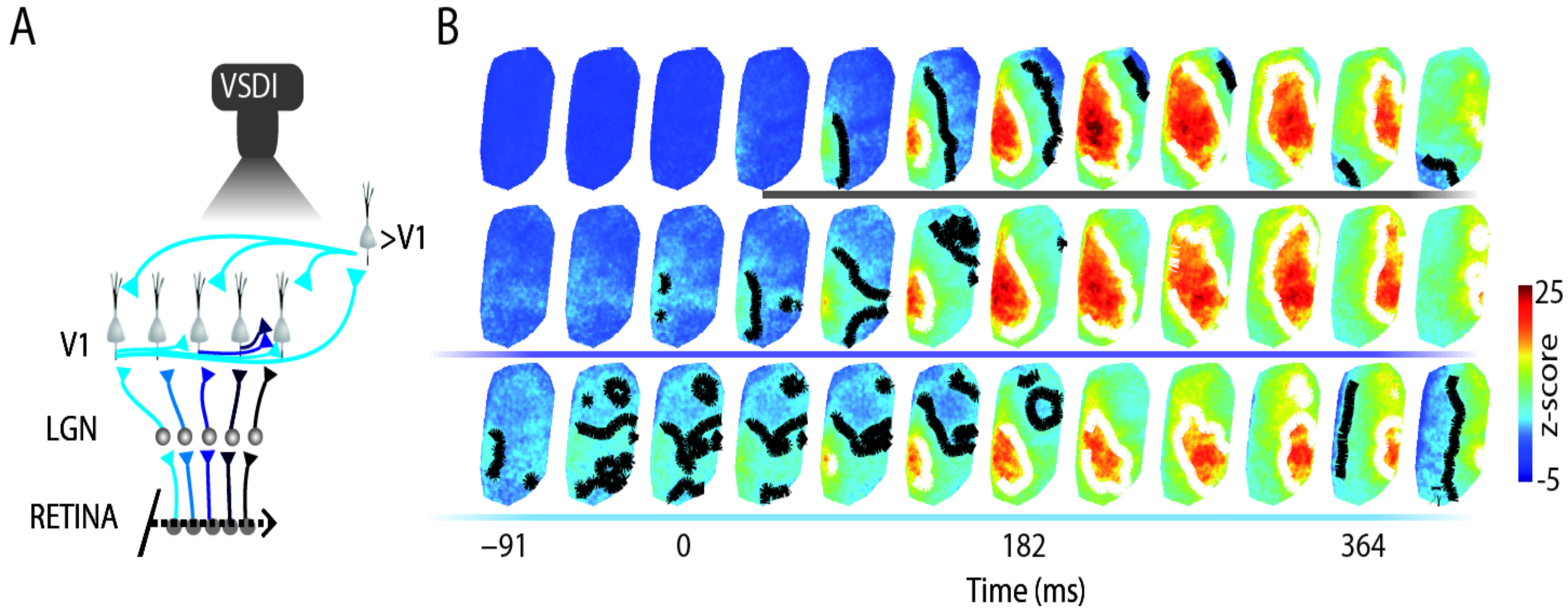
Visual Anticipation



Source : Benvenutti et al. 2015

Visual Anticipation

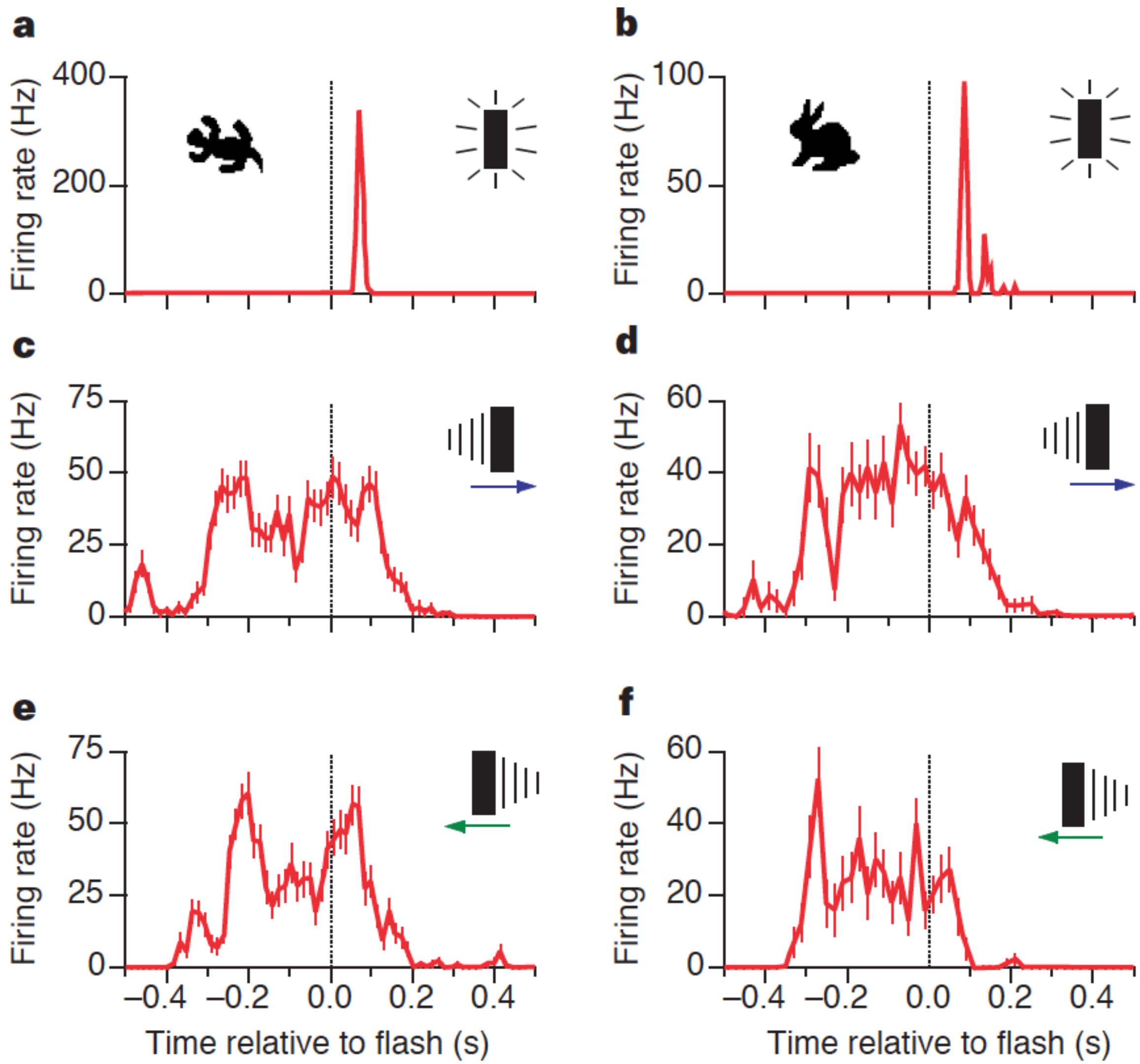
Anticipation is carried out by the primary visual cortex (V1) through an activation wave



Source : Benvenutti et al. 2015

Visual Anticipation

Anticipation also takes place in the retina



Source : Berry et al. 1999

Visual Anticipation

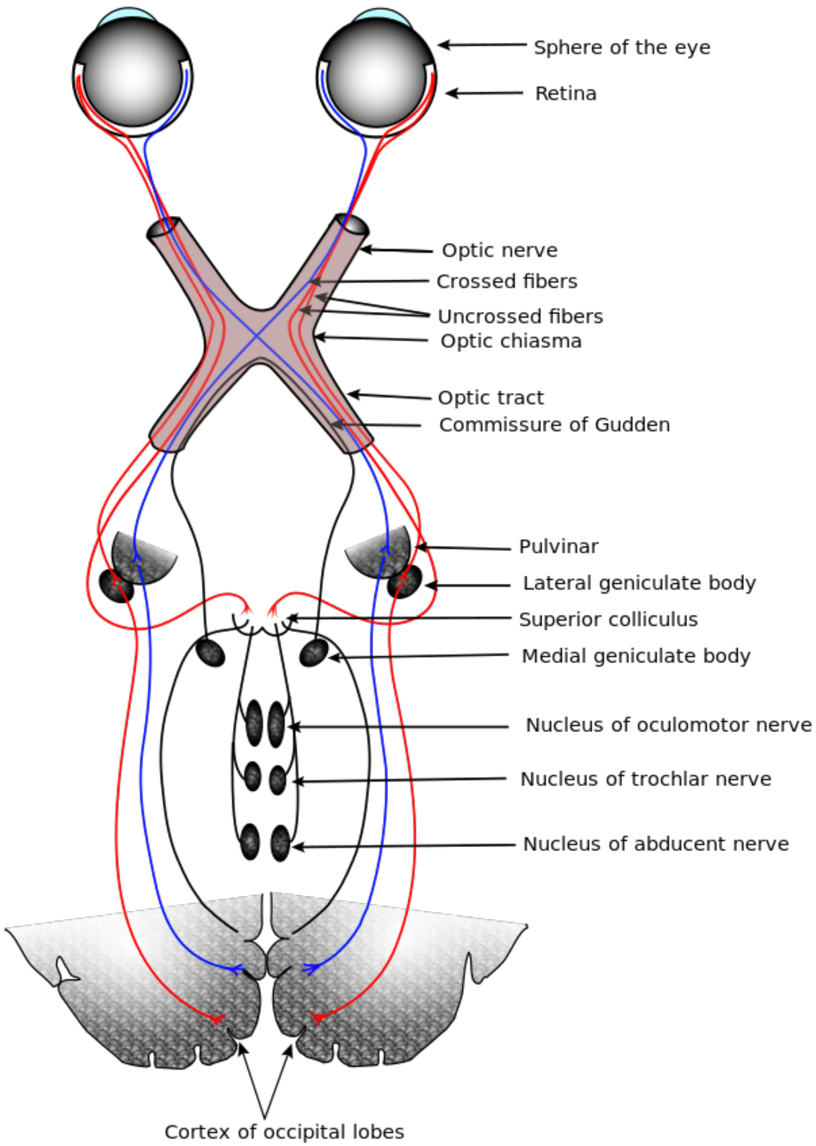
AGENCE NATIONALE DE LA RECHERCHE ANR

Trajectory

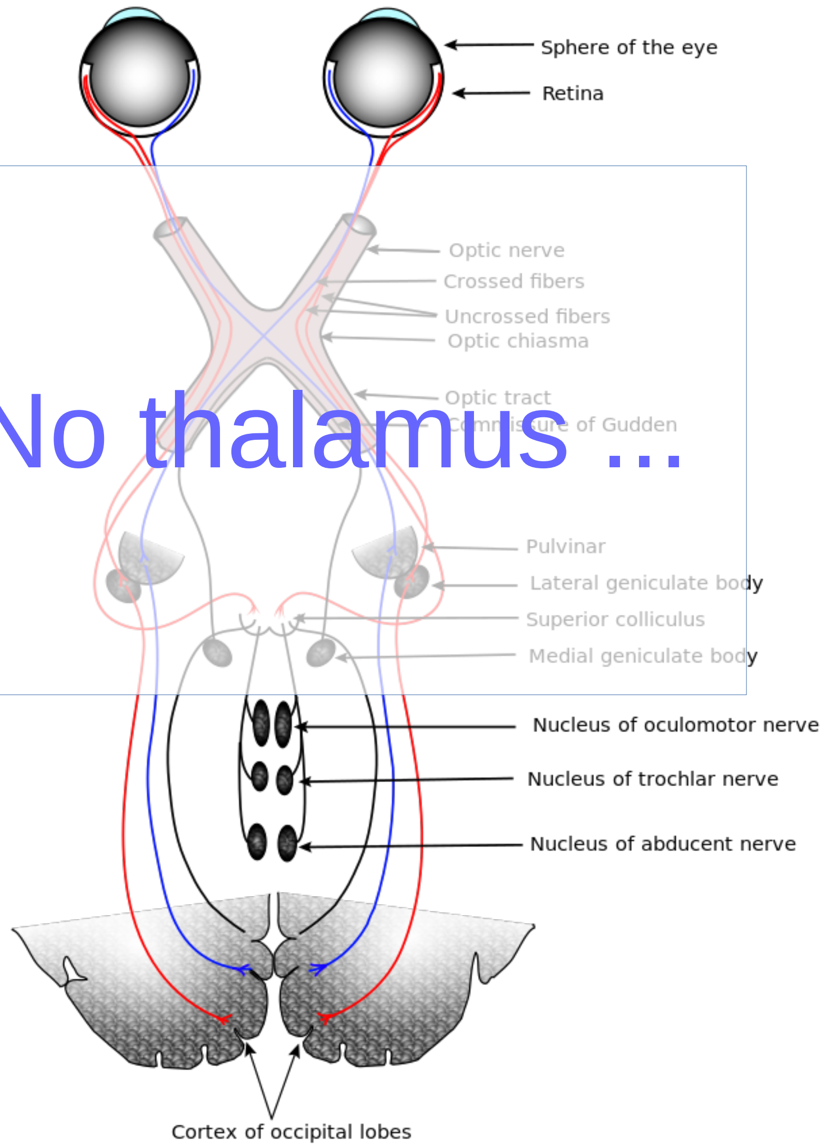
What are the respective :

- **Mechanisms underlying retinal and cortical anticipation?**
- **Role of each part ?**

Visual Anticipation

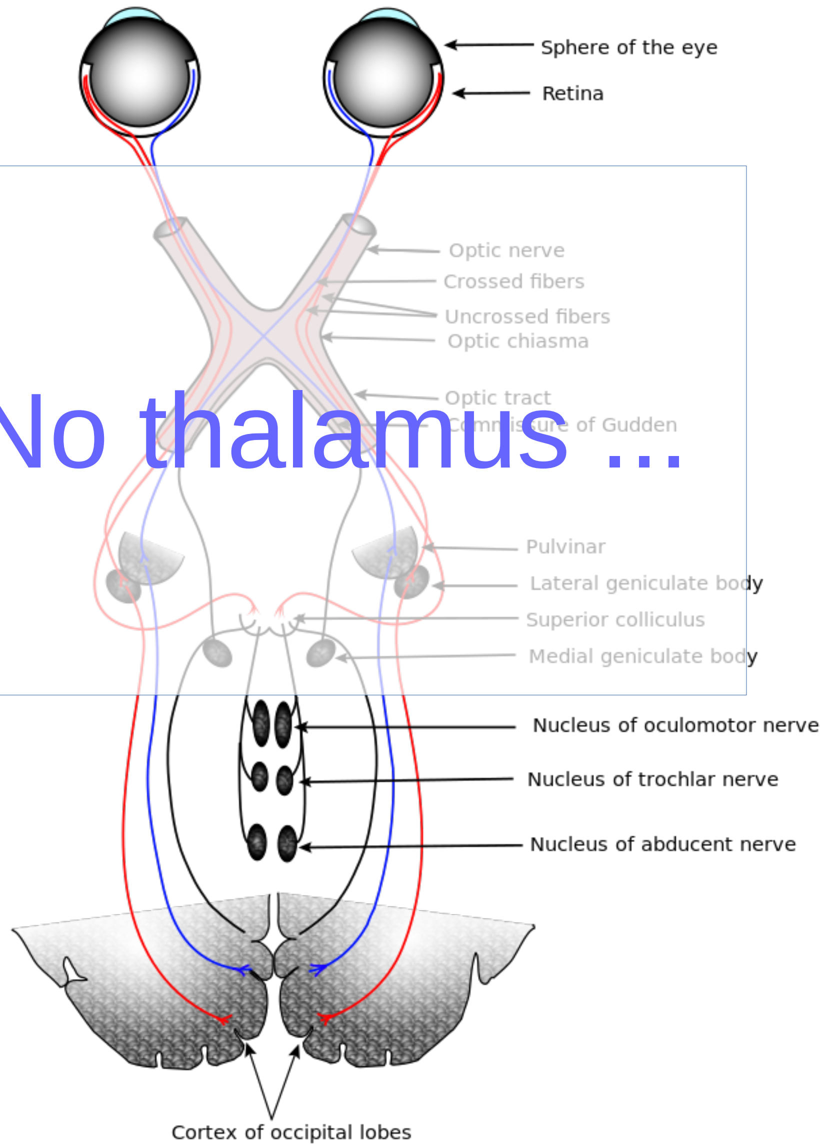


Visual Anticipation



No thalamus ...

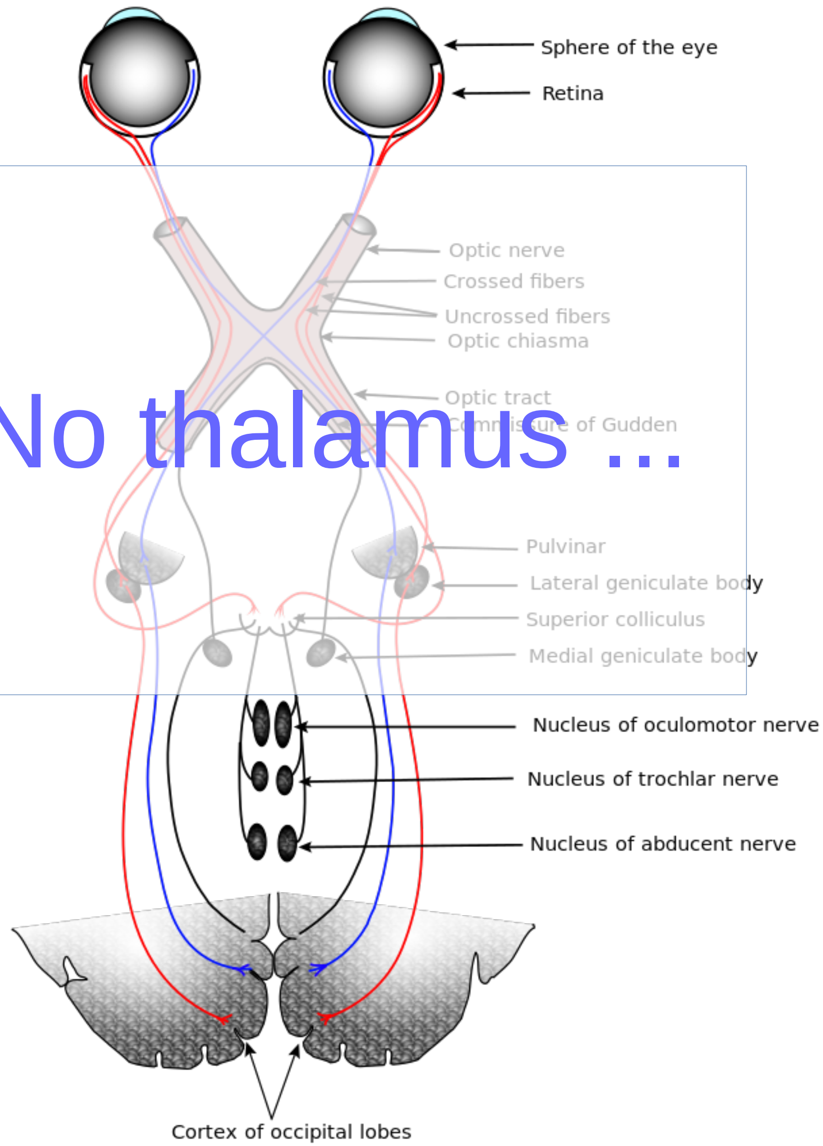
Visual Anticipation



No thalamus ...

Which animal ?

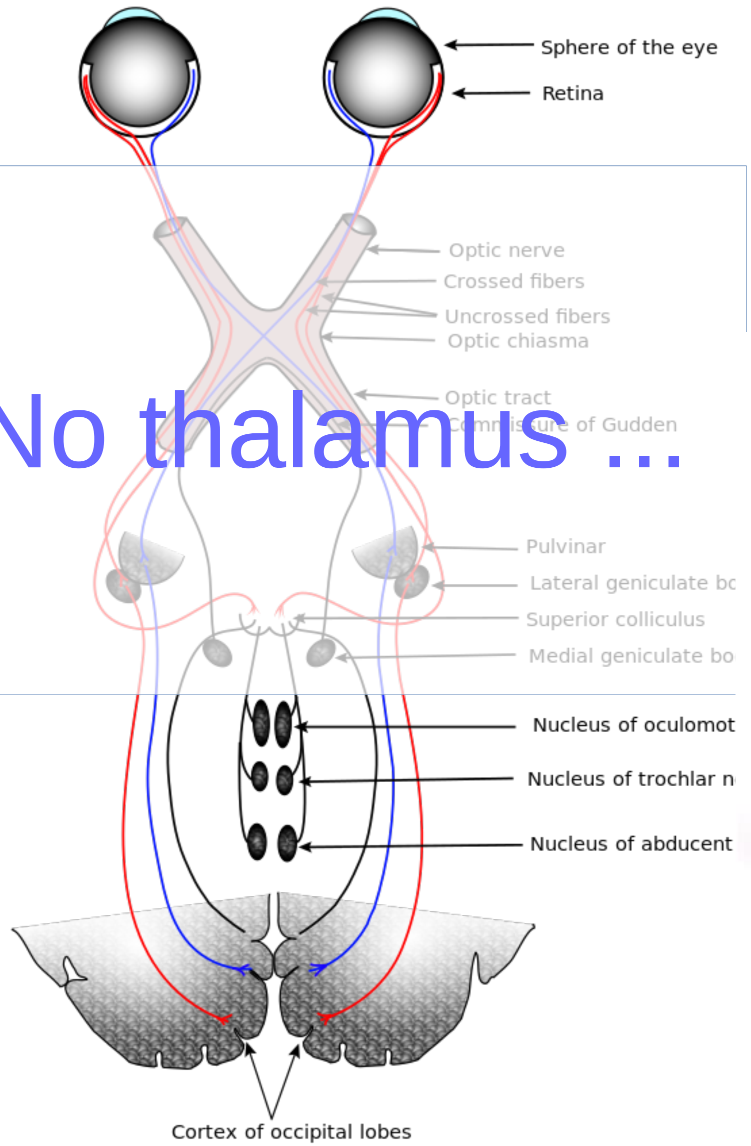
Visual Anticipation



No thalamus ...

Which animal ?

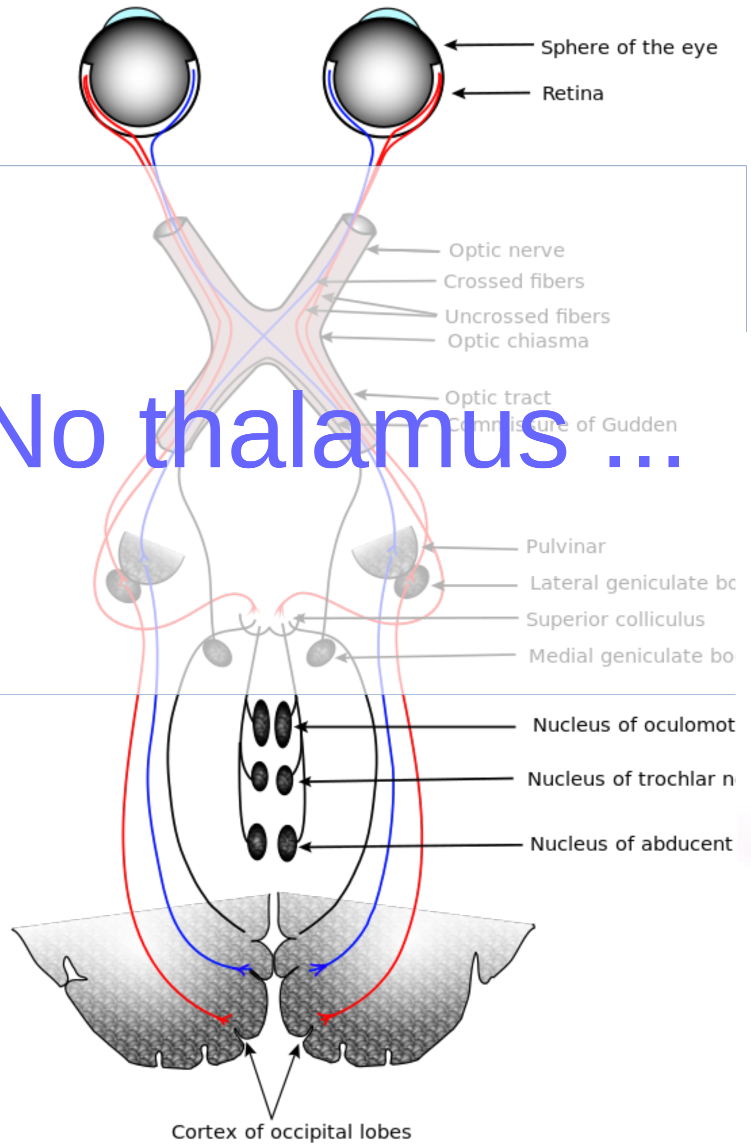
Visual Anticipation



No thalamus ...

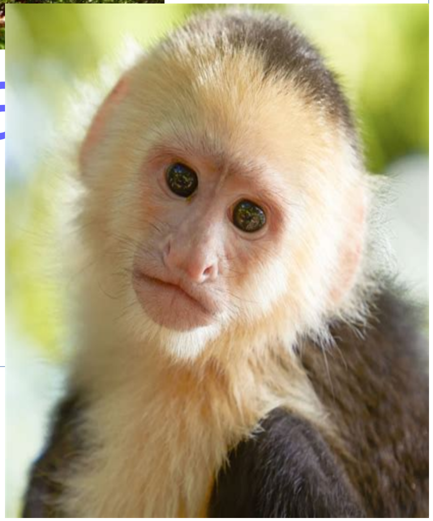
:h animal ?

Visual Anticipation

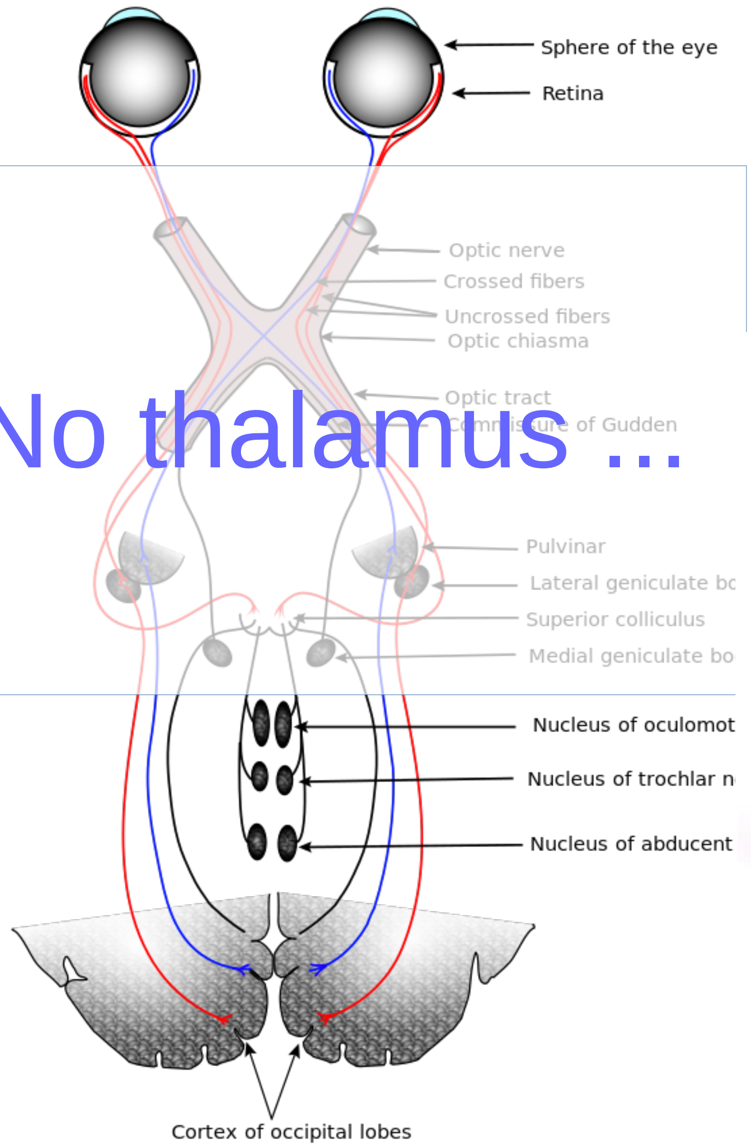


No thalamus ...

:h a



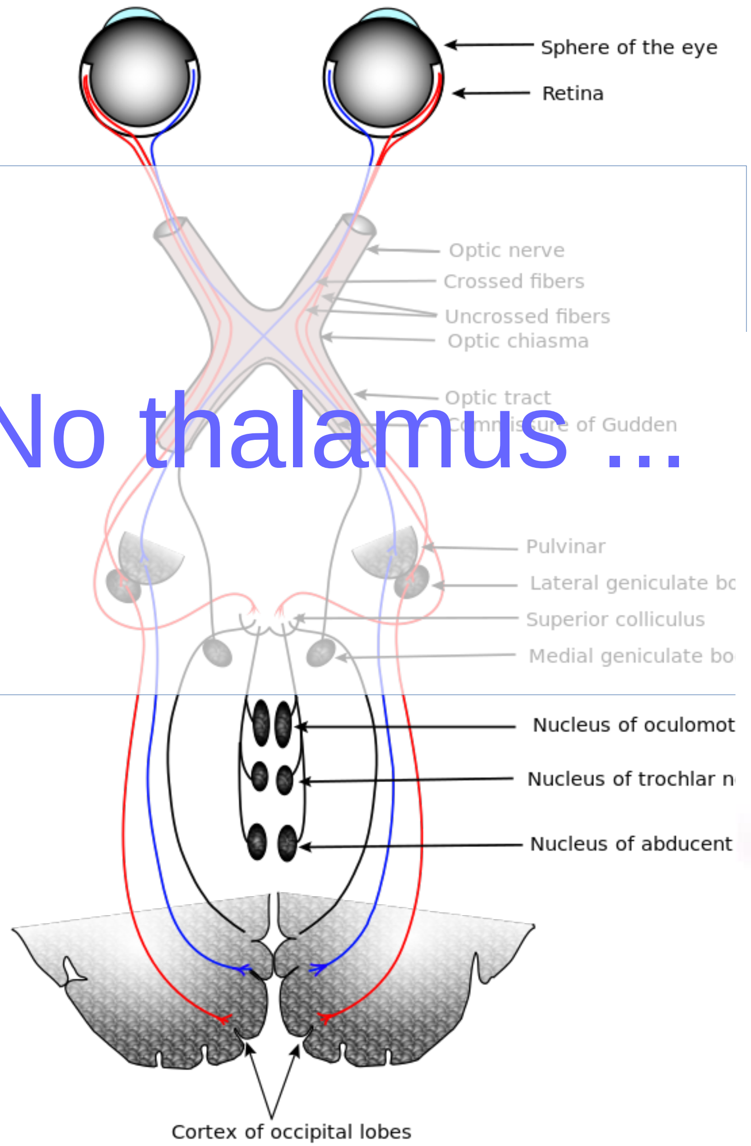
Visual Anticipation



No thalamus ...

ch a

Visual Anticipation



No thalamus ...

Visual Anticipation

Developping a retino-cortical model of anticipation so as to

understand / propose

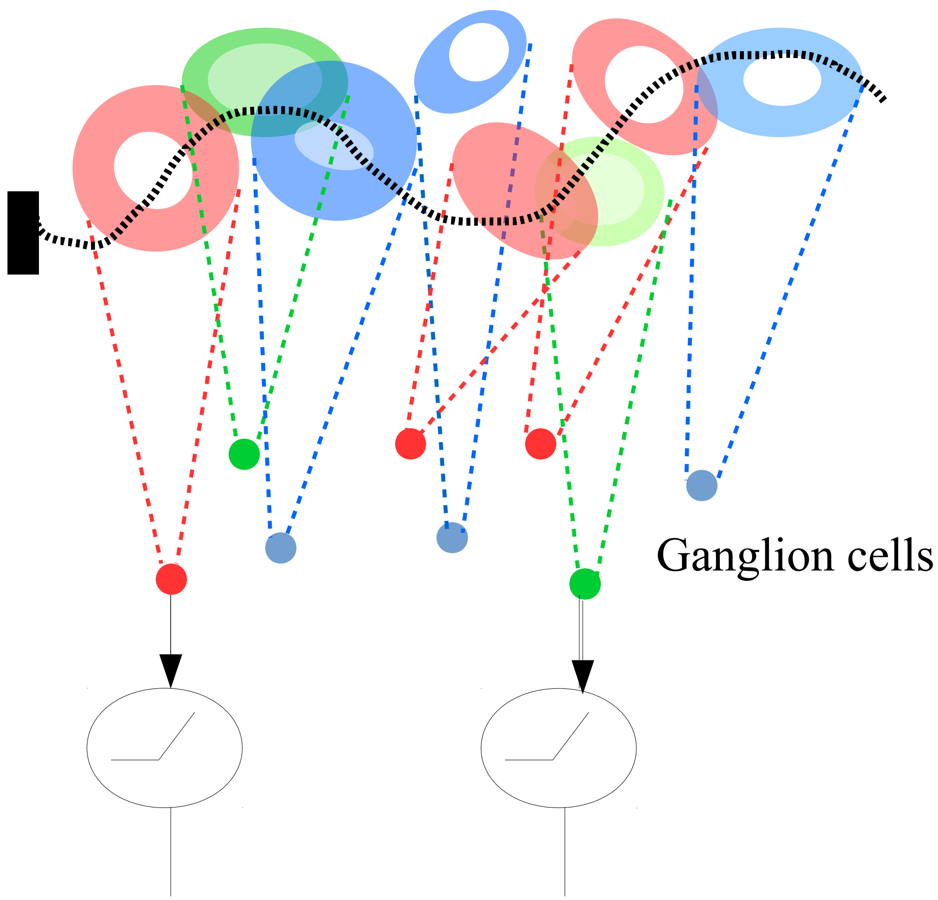
possible mechanisms for anticipation in the retina and in the cortex.

Anticipation in the retina

The Hubel-Wiesel view of vision

Nobel prize 1981

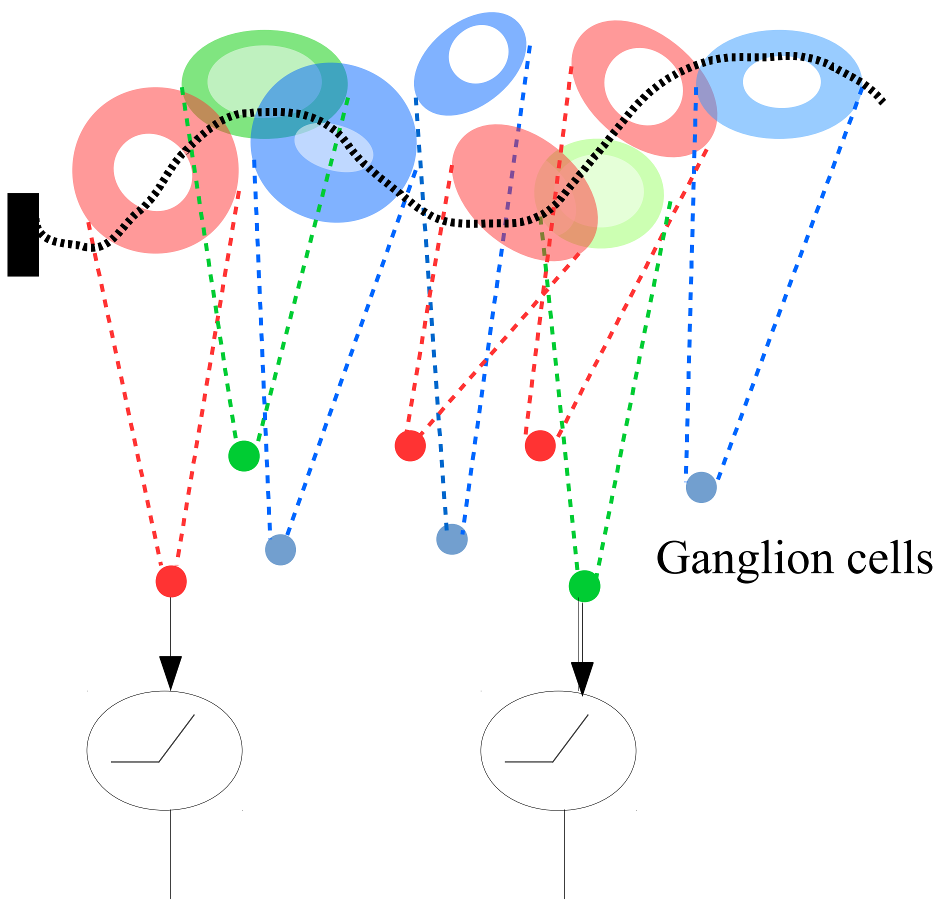
Ganglion cells response is the convolution of the stimulus with a spatio-temporal receptive field followed by a non linearity

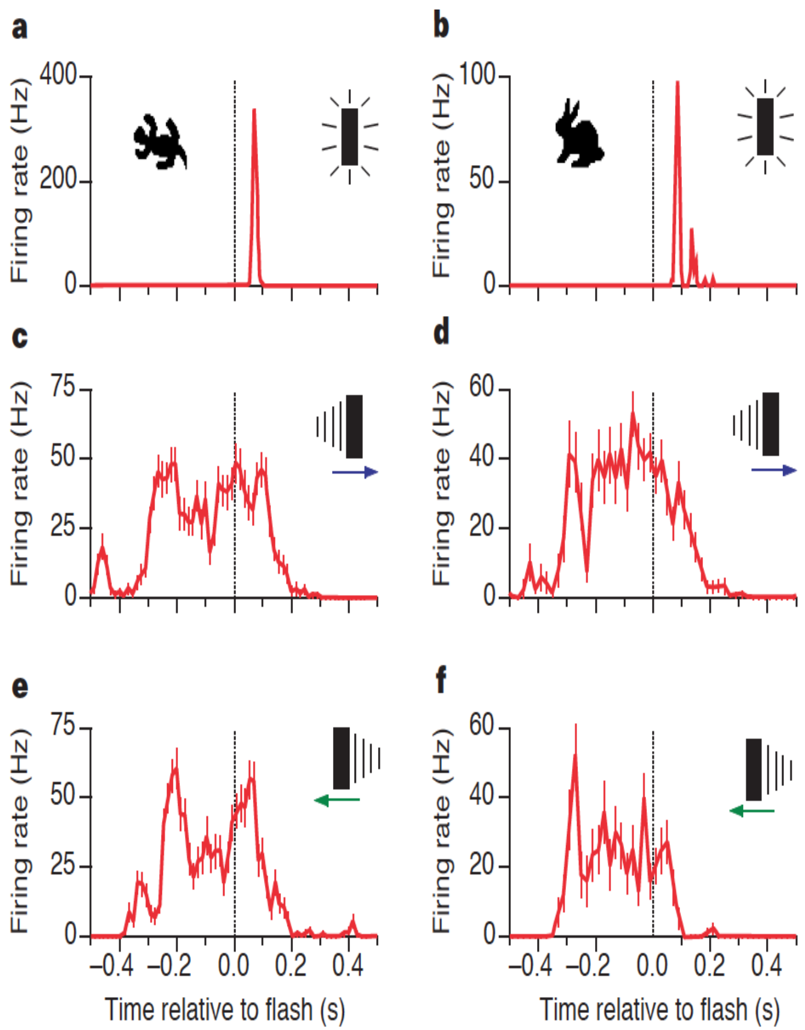


Ganglion cells are independent encoders

The Hubel-Wiesel view of vision

Nobel prize 1981

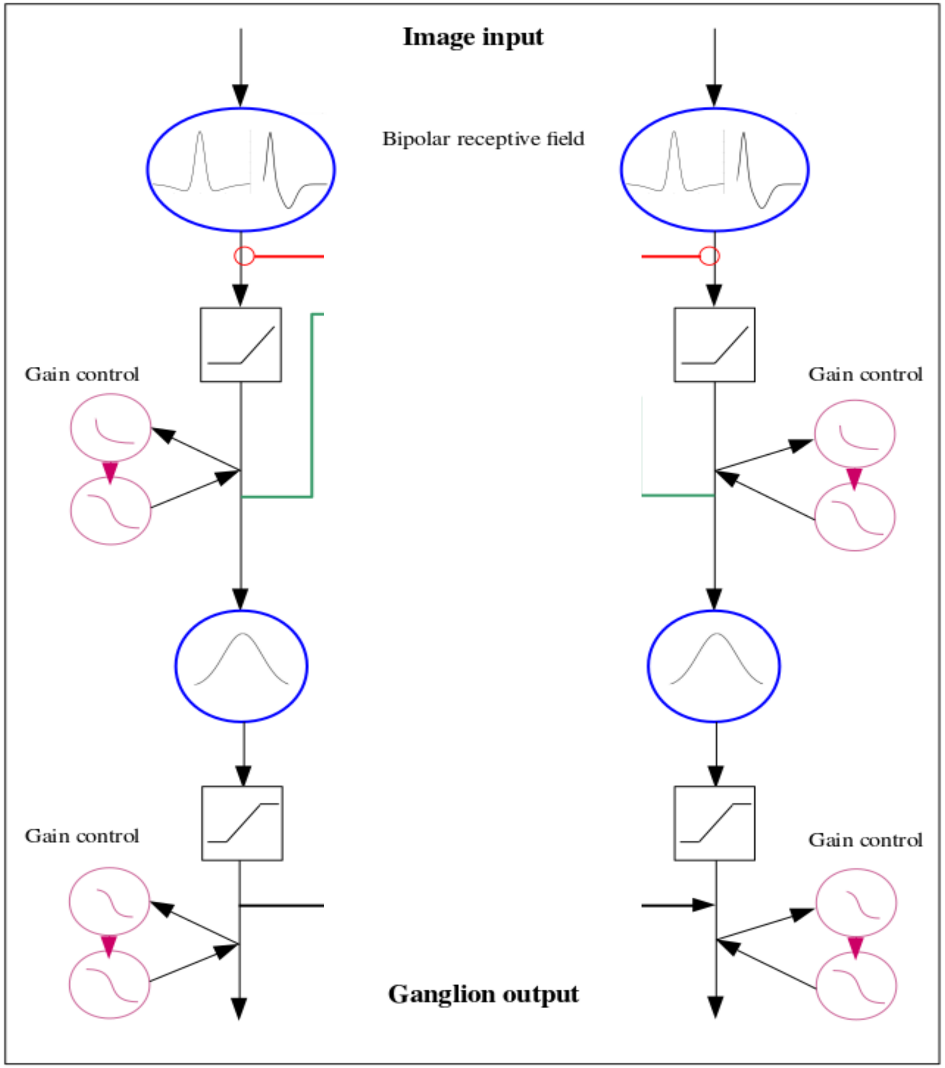




Source : Berry et al. 1999

Building a 2D retina model for motion anticipation

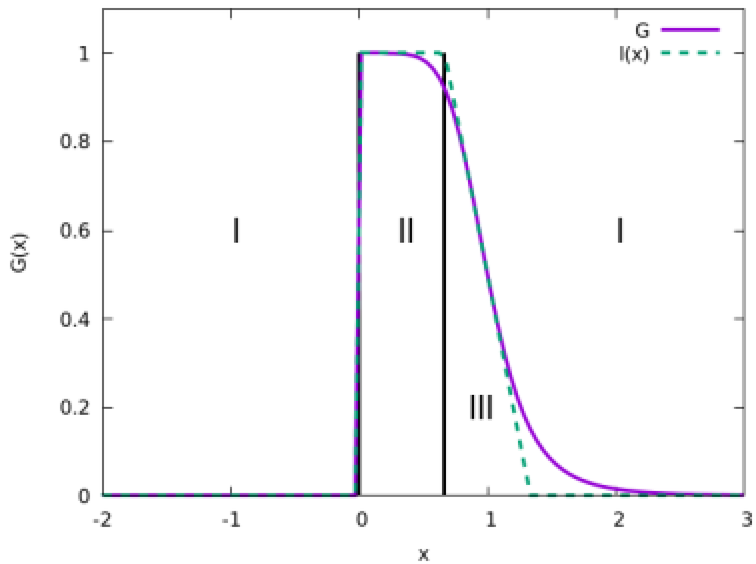
Gain control (Chen et al. 2013)



Building a 2D retina model for motion anticipation

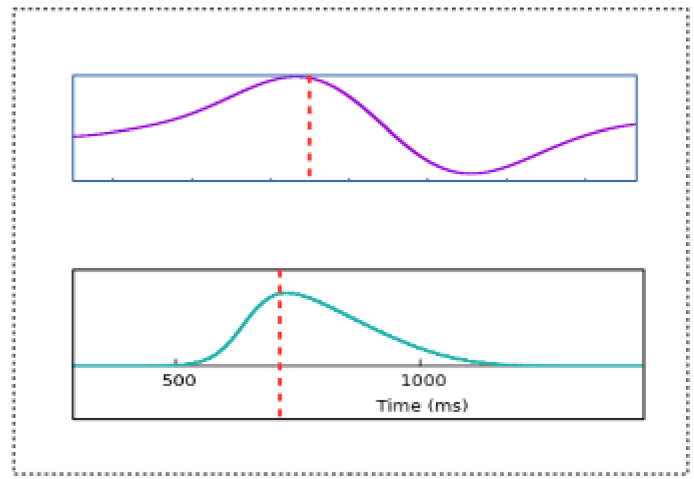
1) Gain control

How does it work ?



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

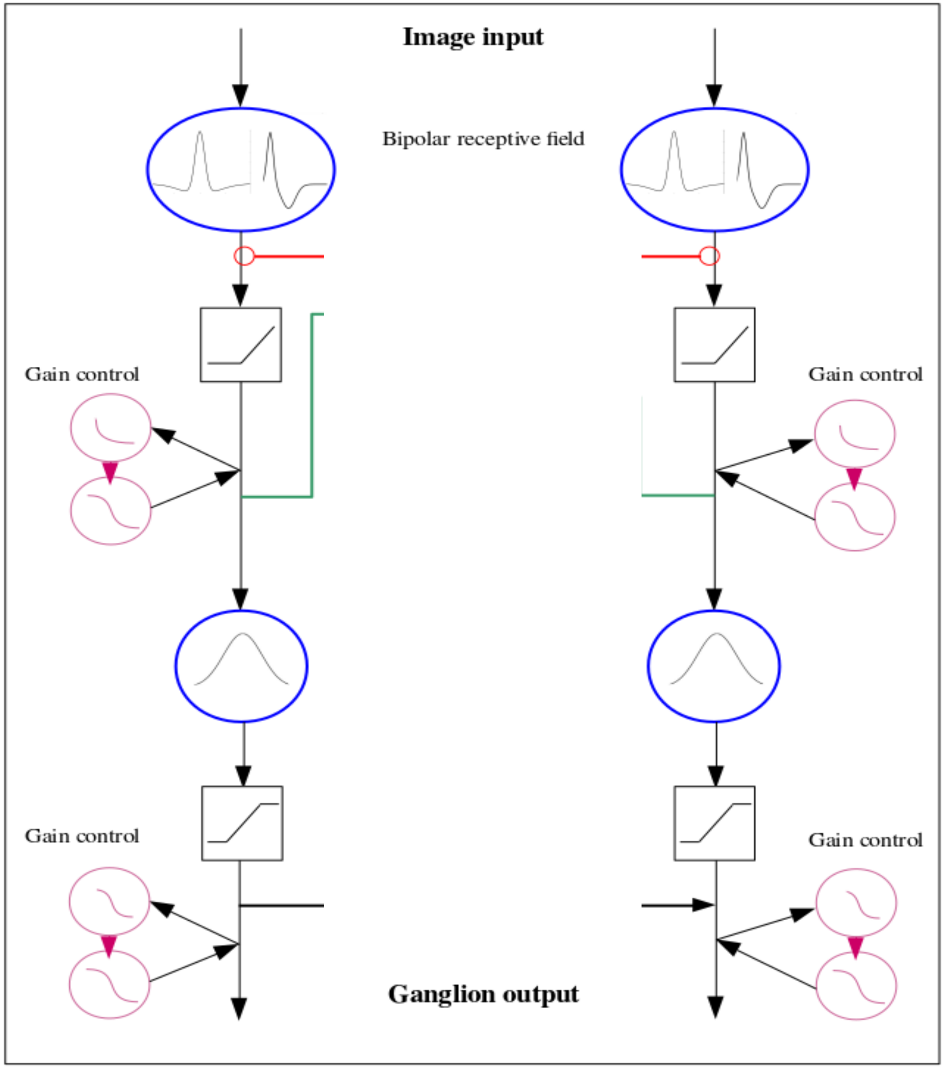
$V_{B_i}(t)$



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

Building a 2D retina model for motion anticipation

Gain control (Chen et al. 2013)



- Bipolar voltage :

$$V_{B_i}(t) = V_{i_{drive}}(t) \cdot$$

- Non-linear function :

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

- Activation function :

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

- Gain Control function :

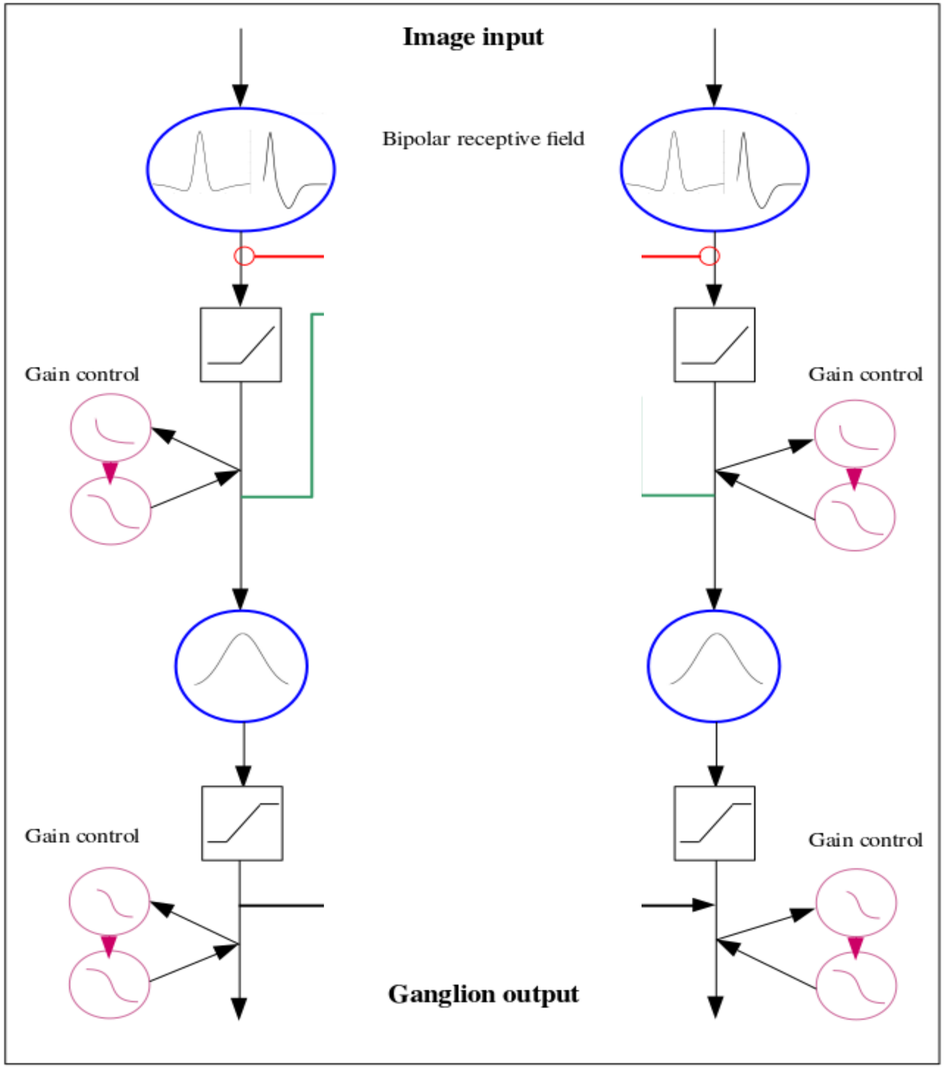
$$\mathcal{G}_B(A) = \begin{cases} 0, & \text{if} \quad A \leq 0; \\ \frac{1}{1+A^6}, & \text{else.} \end{cases}$$

- Output :

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

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 :

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

- Activation function :

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

- Gain Control function :

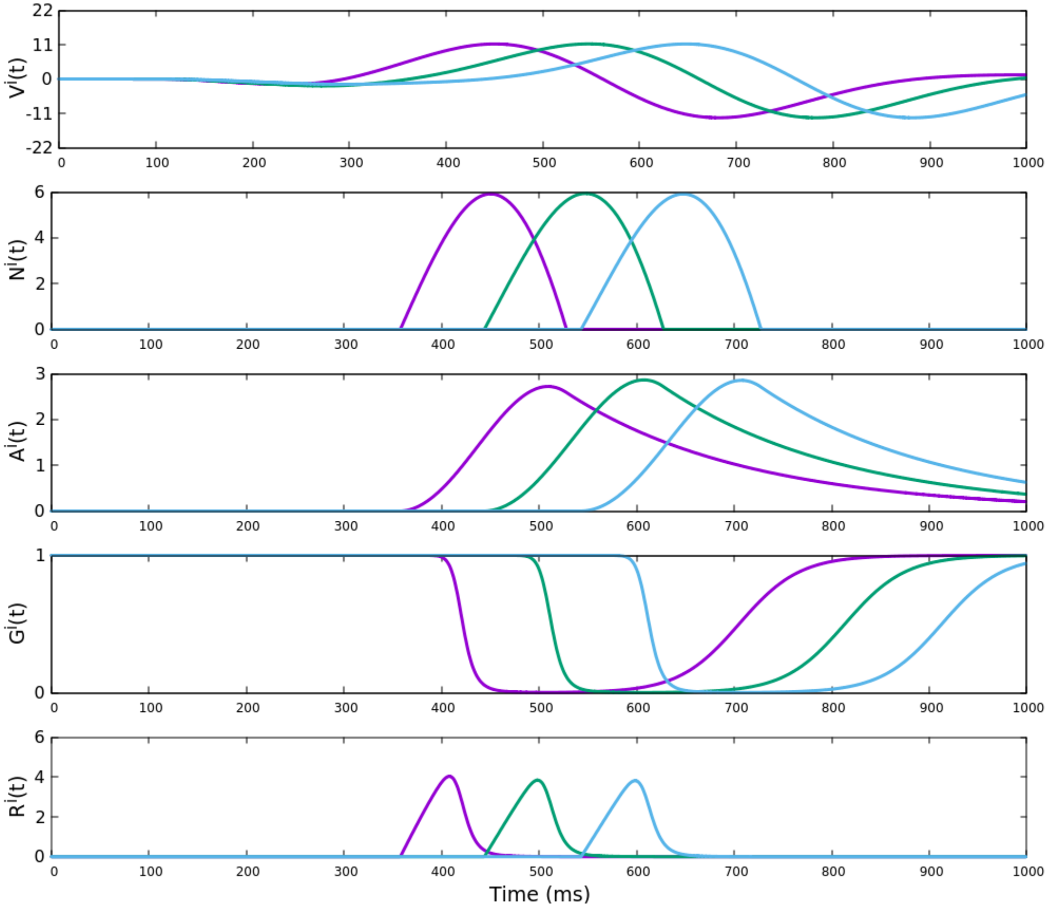
$$\mathcal{G}_{G_F}(A) = \begin{cases} 0, & \text{if} \quad A \leq 0; \\ \frac{1}{1+A}, & \text{else.} \end{cases}$$

- Output :

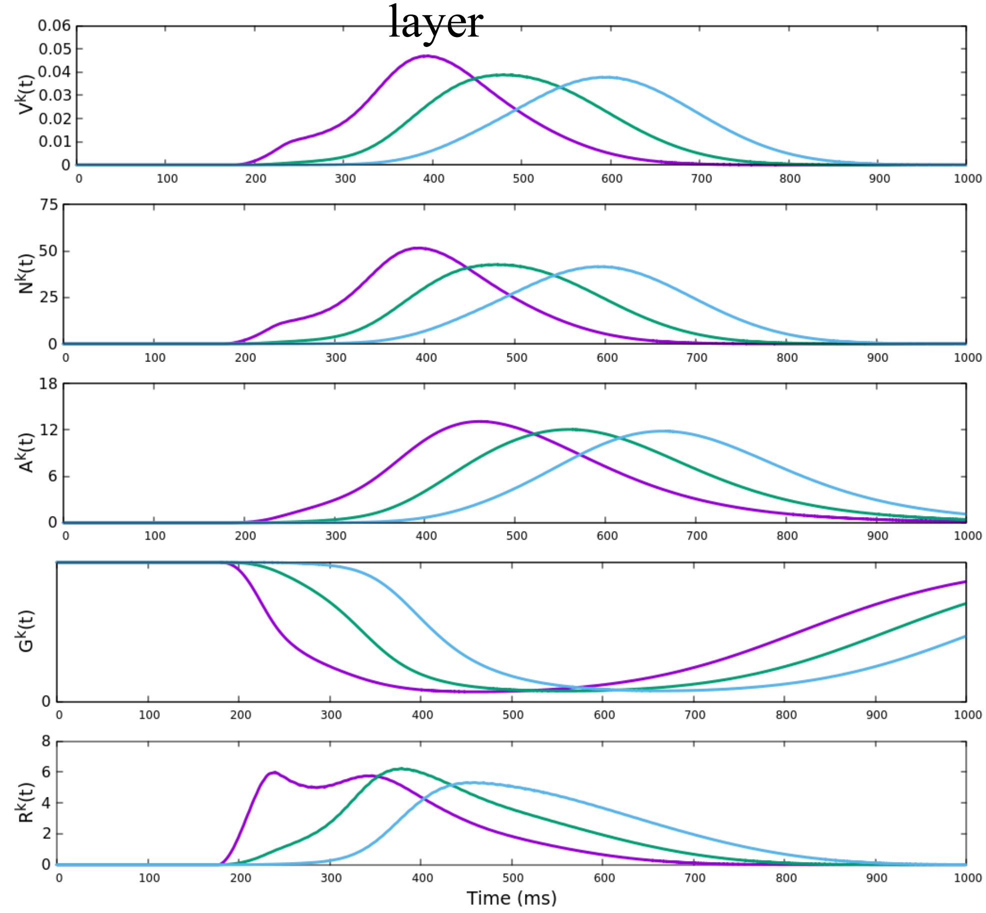
$$R_{G_{F k_F}}\left(V_{G_{F k_F}}, A_{G_{F k_F}}\right) = \mathcal{N}_{G_F}(V_{G_{F k_F}}) \mathcal{G}_{G_F}(A_{G_{F k_F}}).$$

1D results : smooth motion anticipation with gain control

Bipolar layer

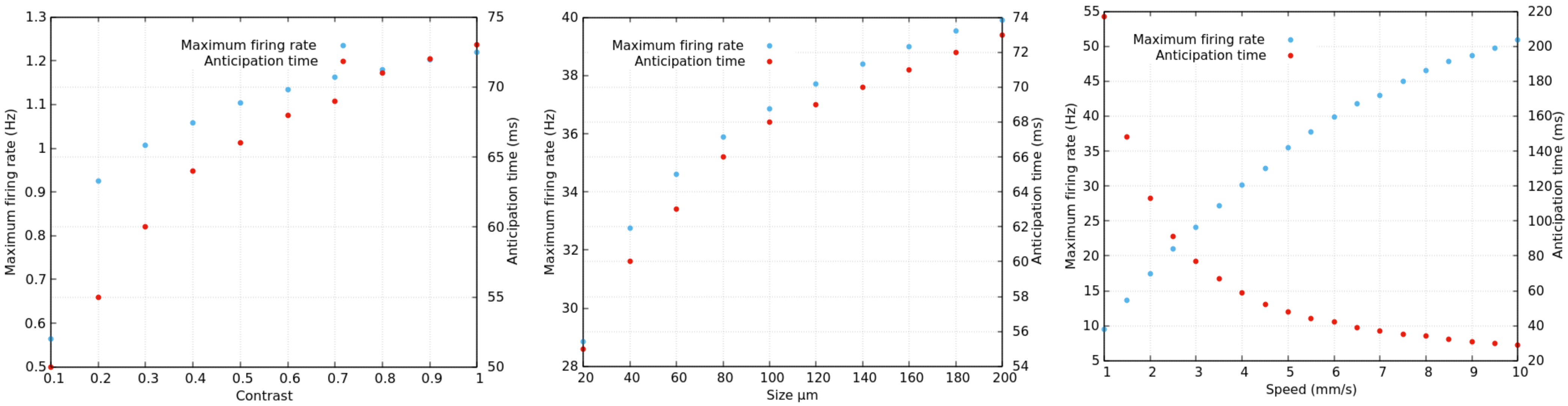


Ganglion layer

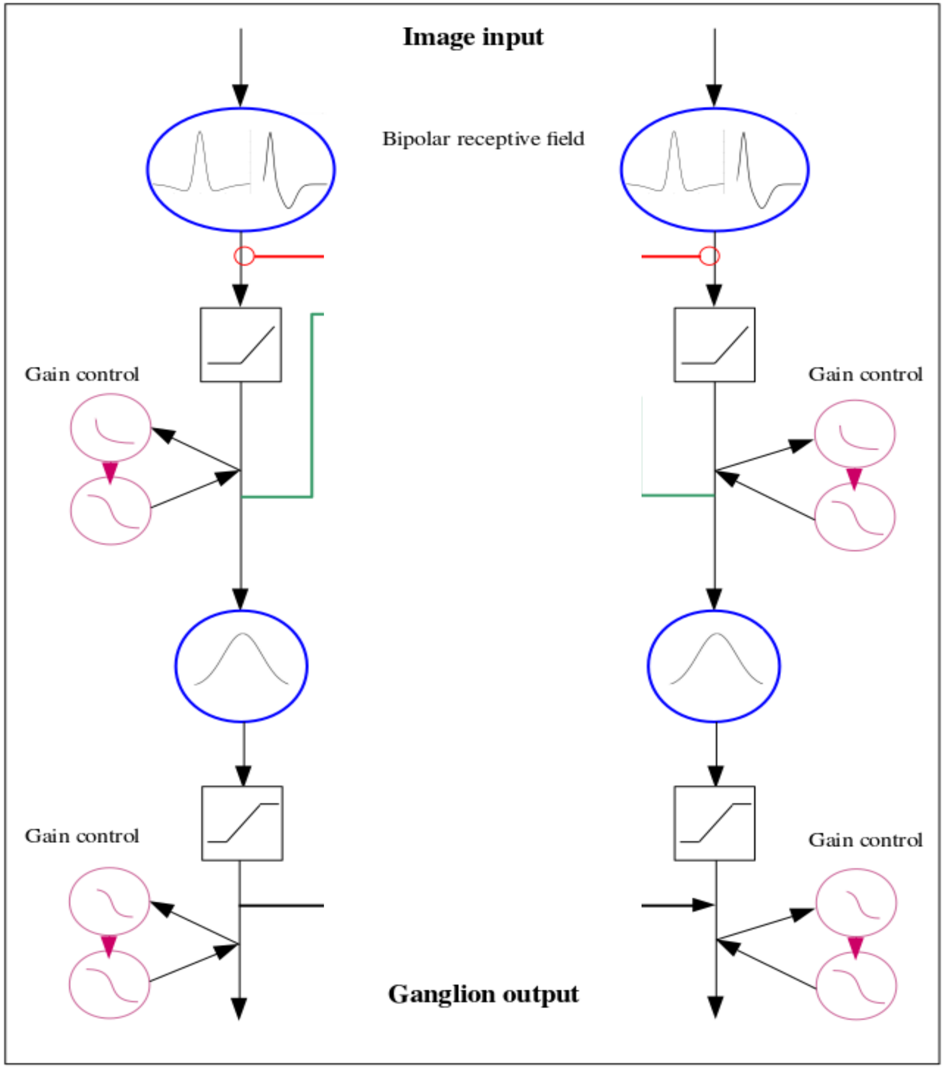


1D results : smooth motion anticipation with gain control

Anticipation variability with stimulus parameters



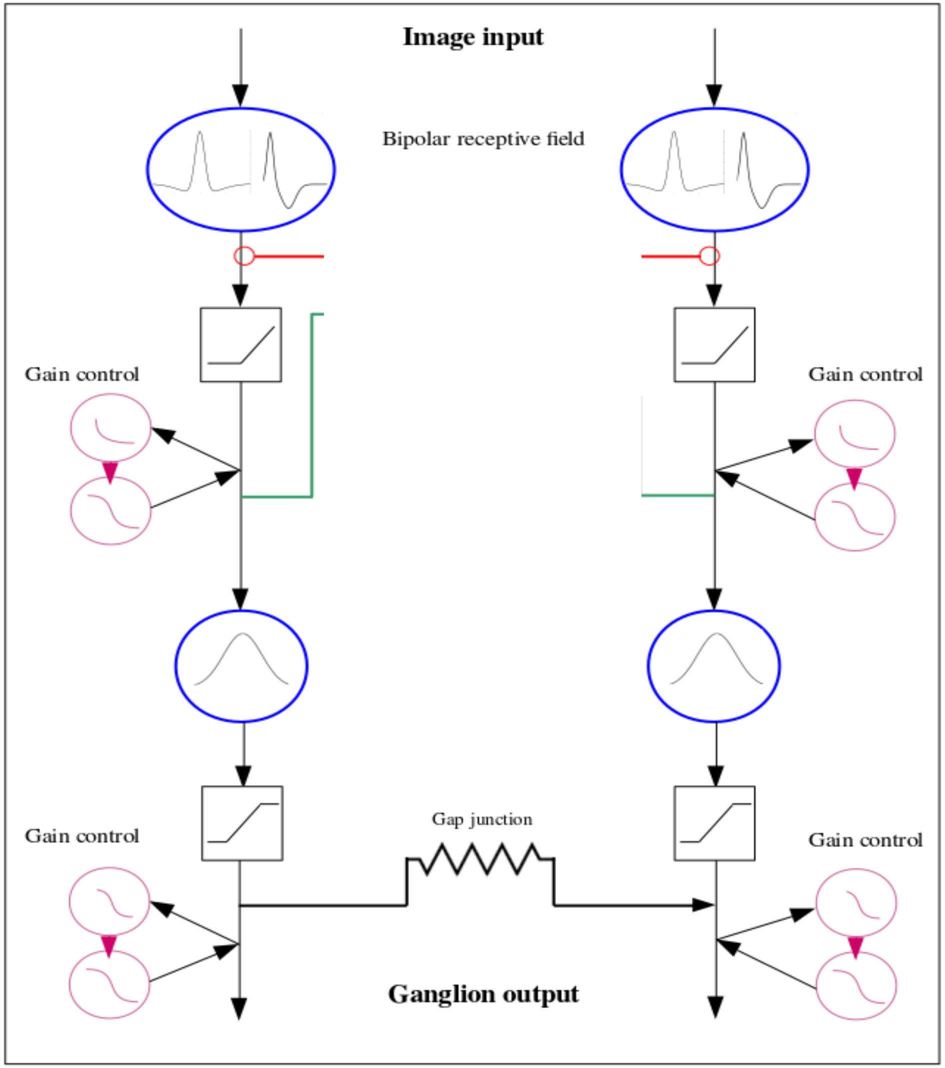
Building a 2D retina model for motion anticipation



Ganglion cells are independent encoders

Building a 2D retina model for motion anticipation

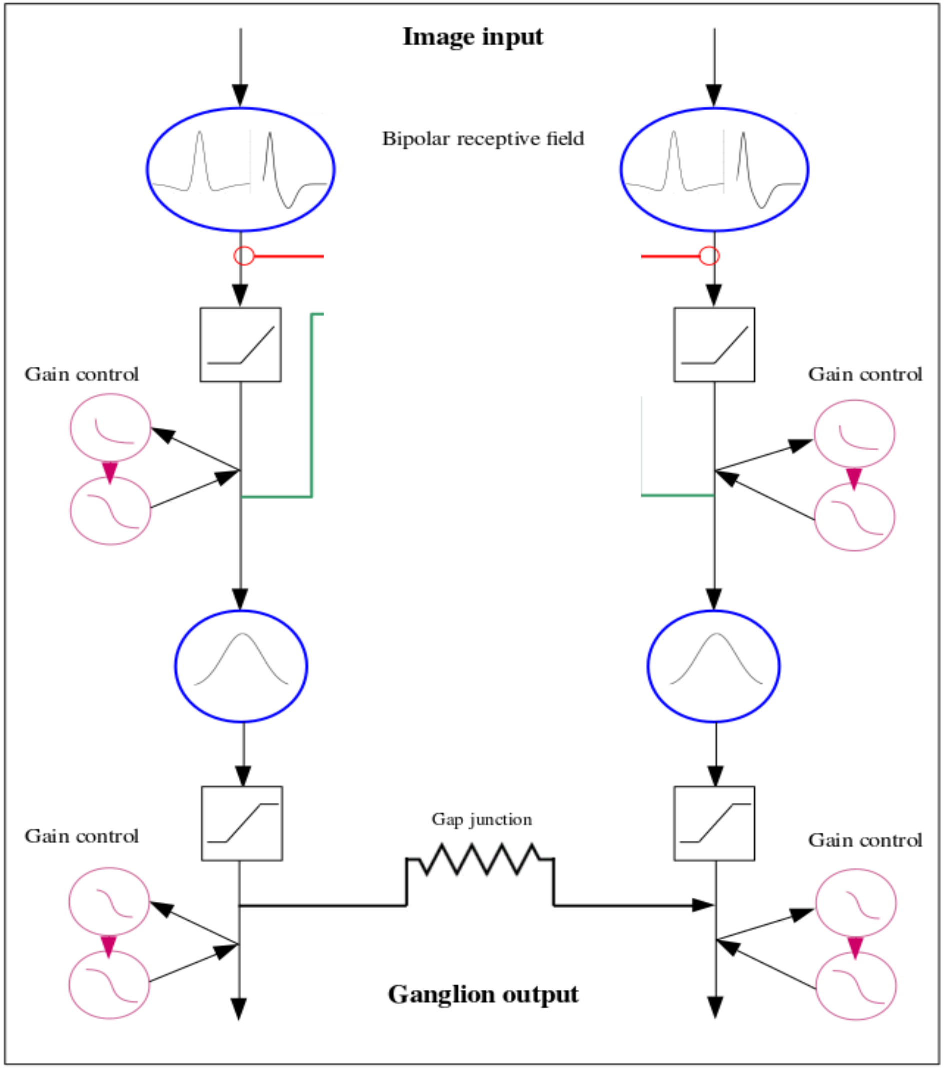
Gap junctions connectivity

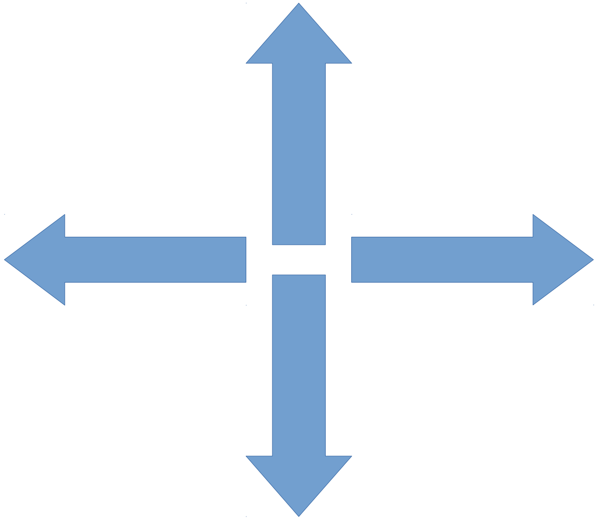


Ganglion cells are **not** independent encoders

Building a 2D retina model for motion anticipation

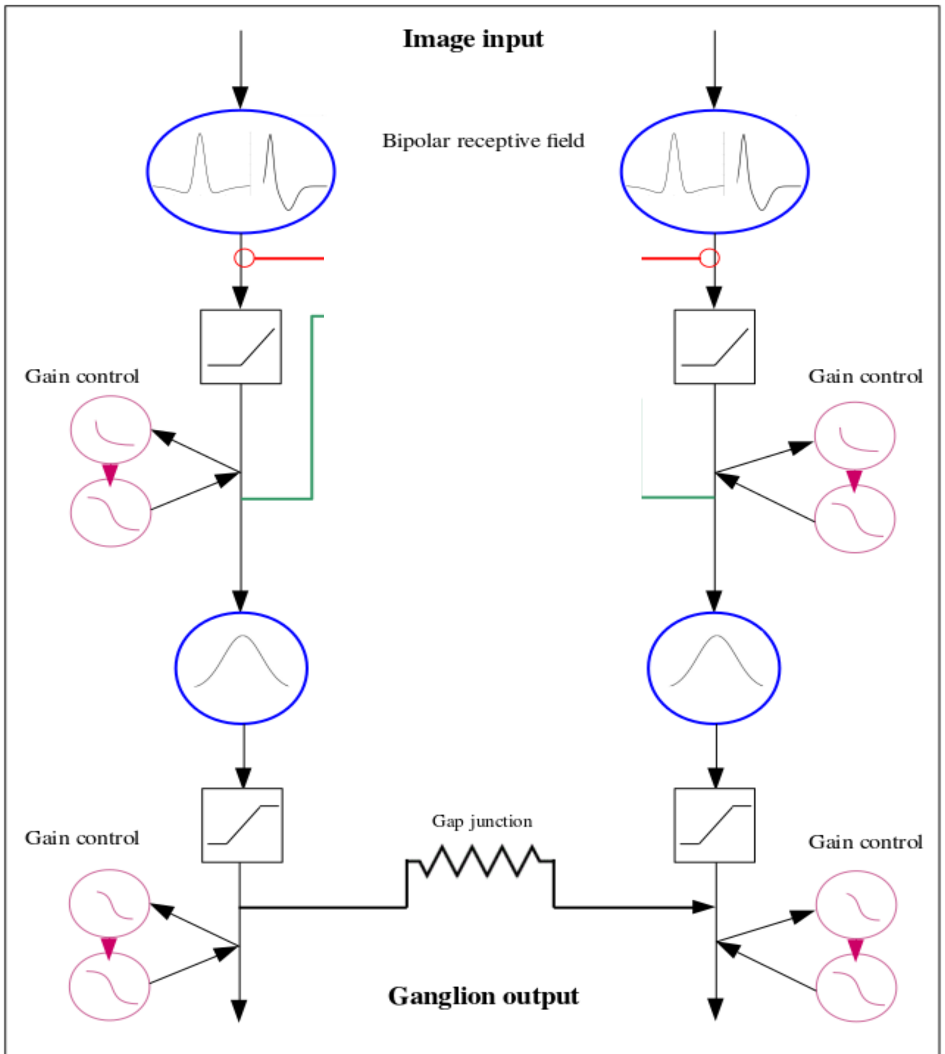
Gap junctions connectivity

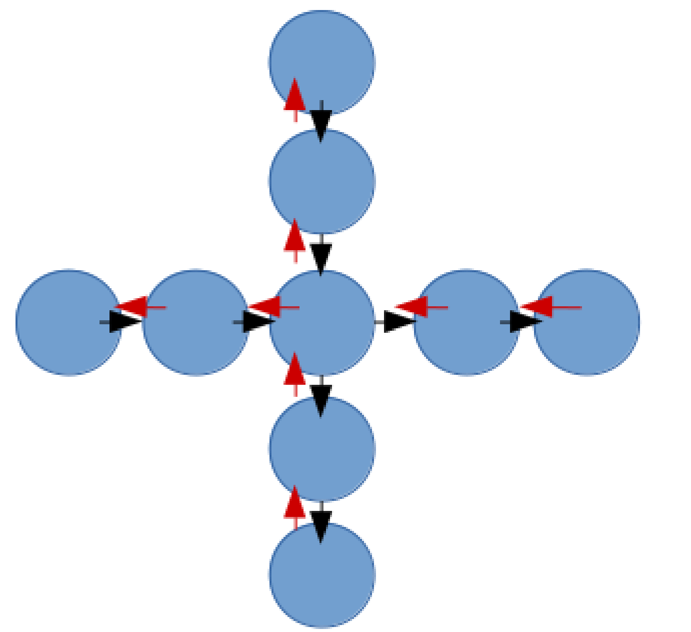




Building a 2D retina model for motion anticipation

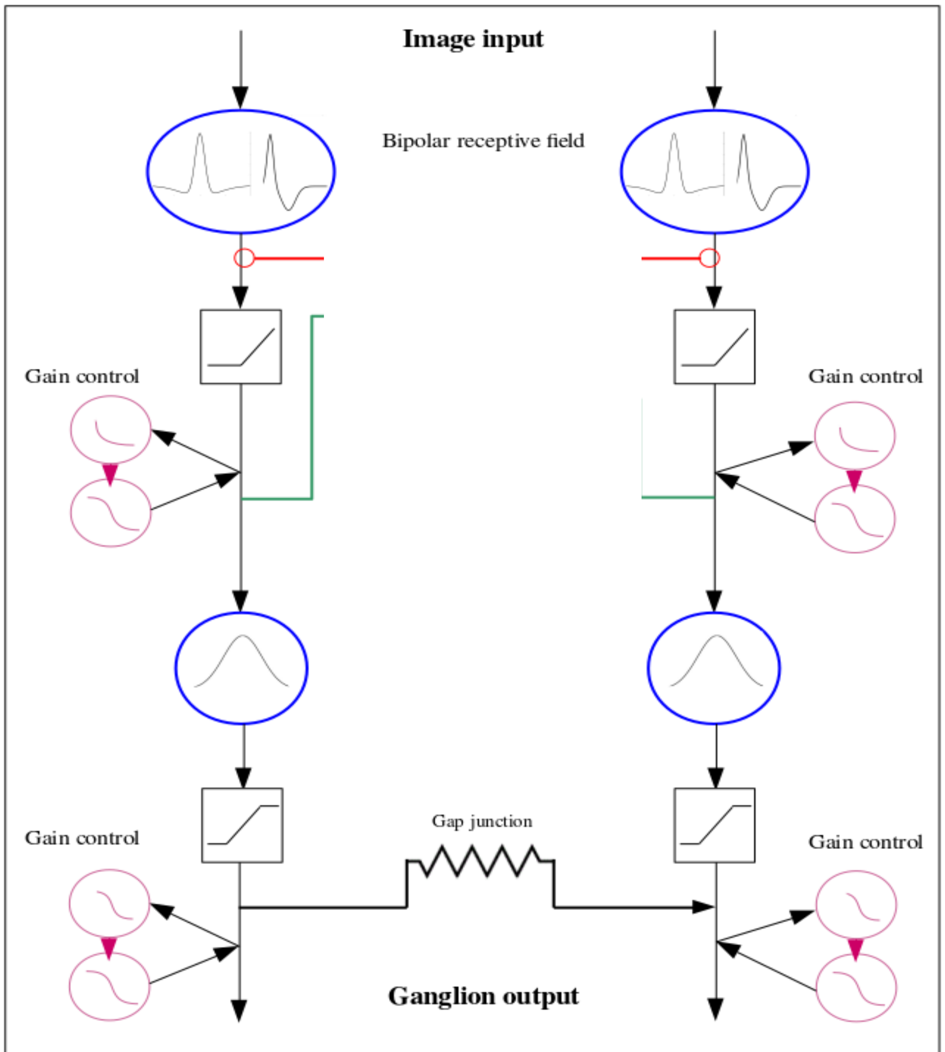
Gap junctions connectivity



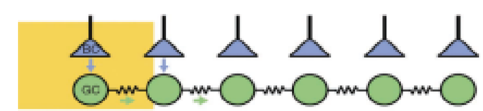


Building a 2D retina model for motion anticipation

Gap junctions connectivity



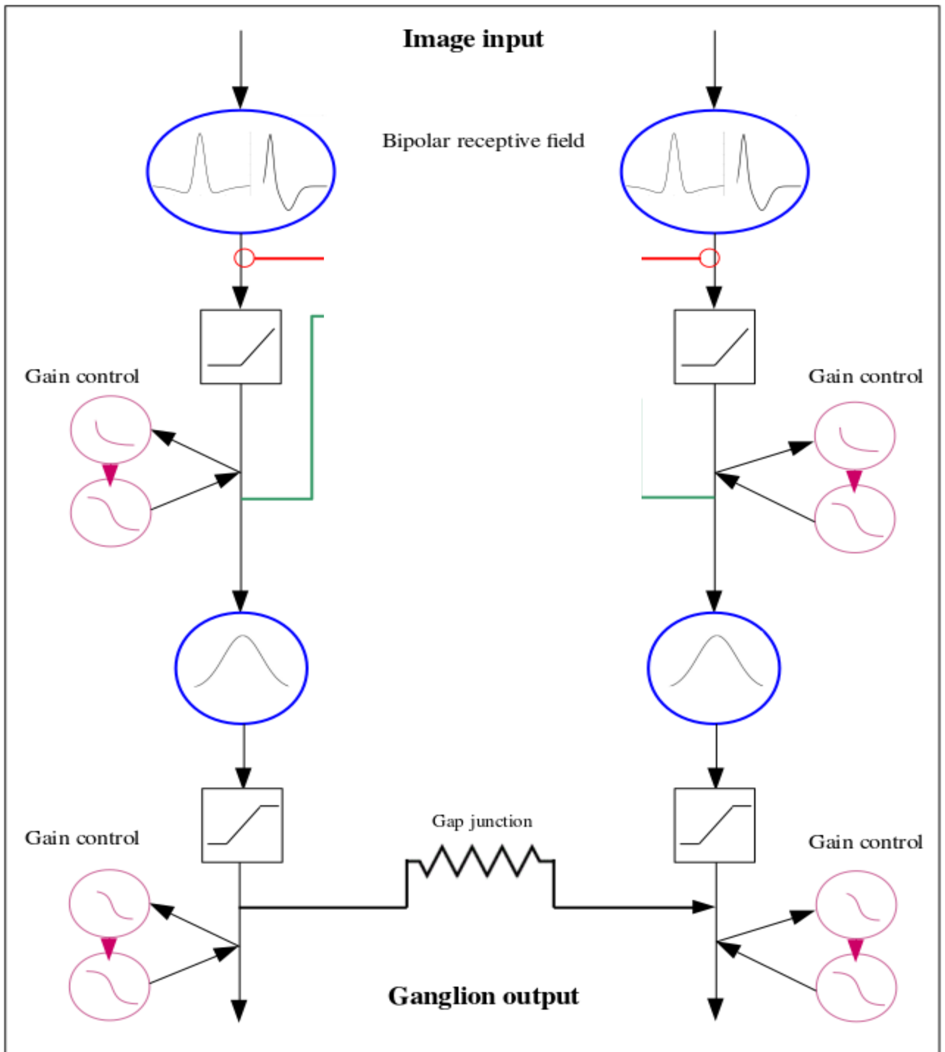
- A class of direction selective RGCs are connected through gap junctions
- Their activity comprises the activity pooled from bipolar cells and the activity coming from the downstream RGCs, in the direction of motion



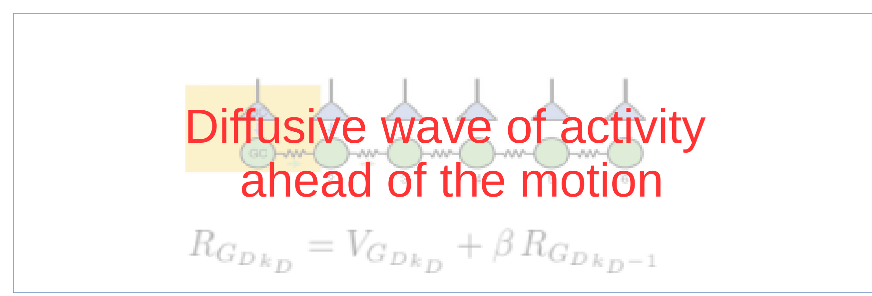
$$R_{G_{D k_D}} = V_{G_{D k_D}} + \beta \, R_{G_{D k_{D-1}}}$$

Building a 2D retina model for motion anticipation

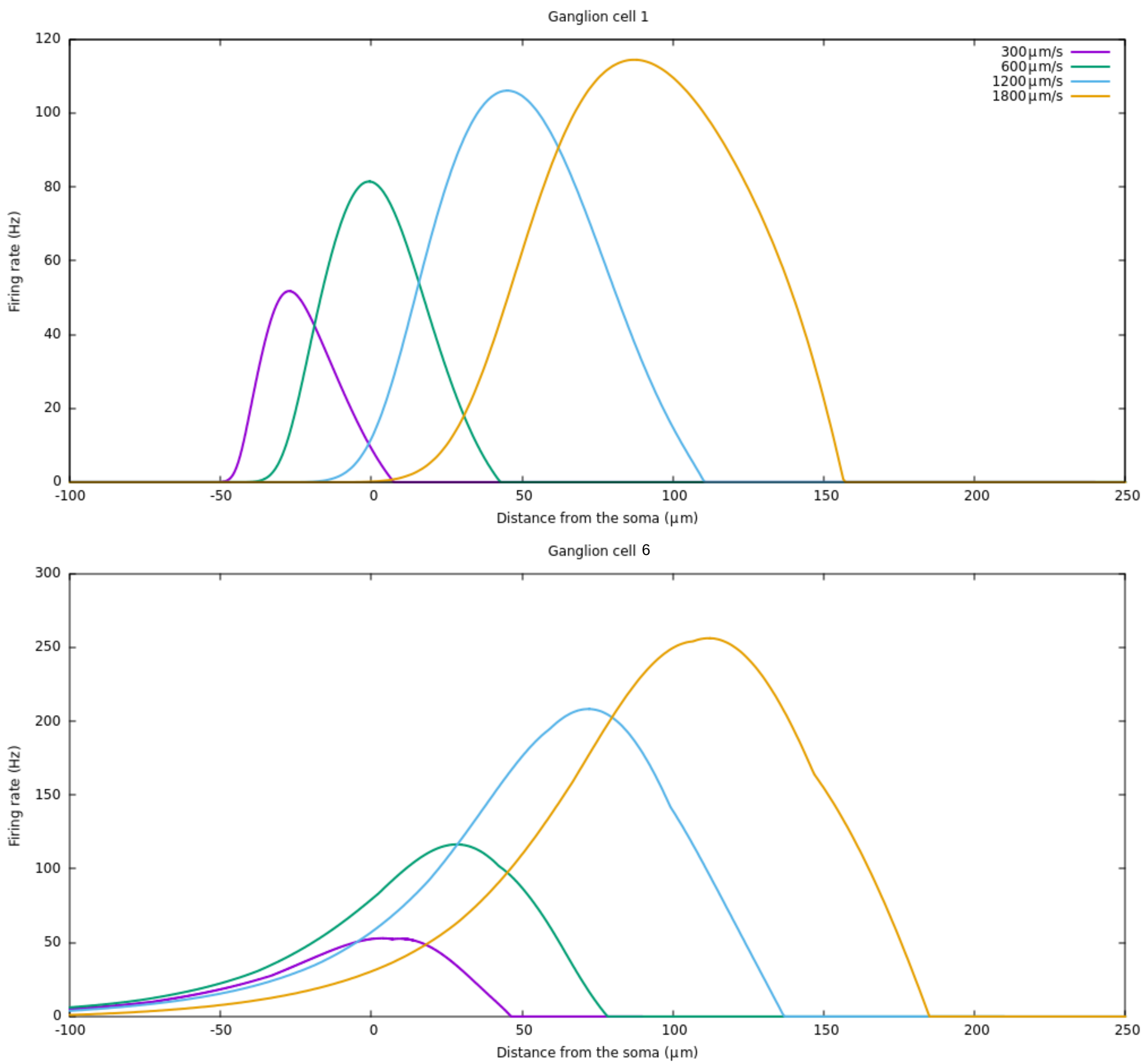
Gap junctions connectivity

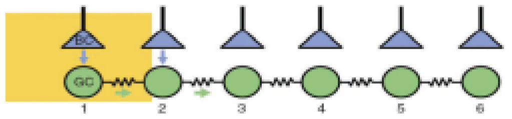


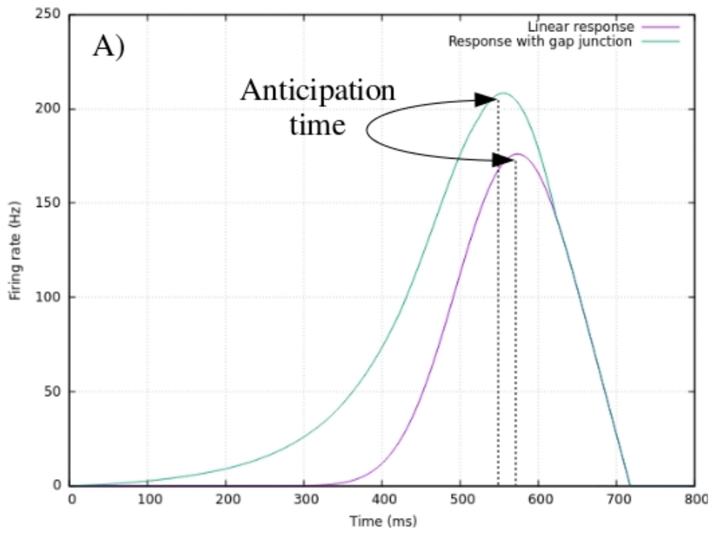
- A class of direction selective RGCs are connected through gap junctions
- Their activity comprises the activity pooled from bipolar cells and the activity coming from the downstream RGCs, in the direction of motion



1D results : smooth motion anticipation with gap junctions

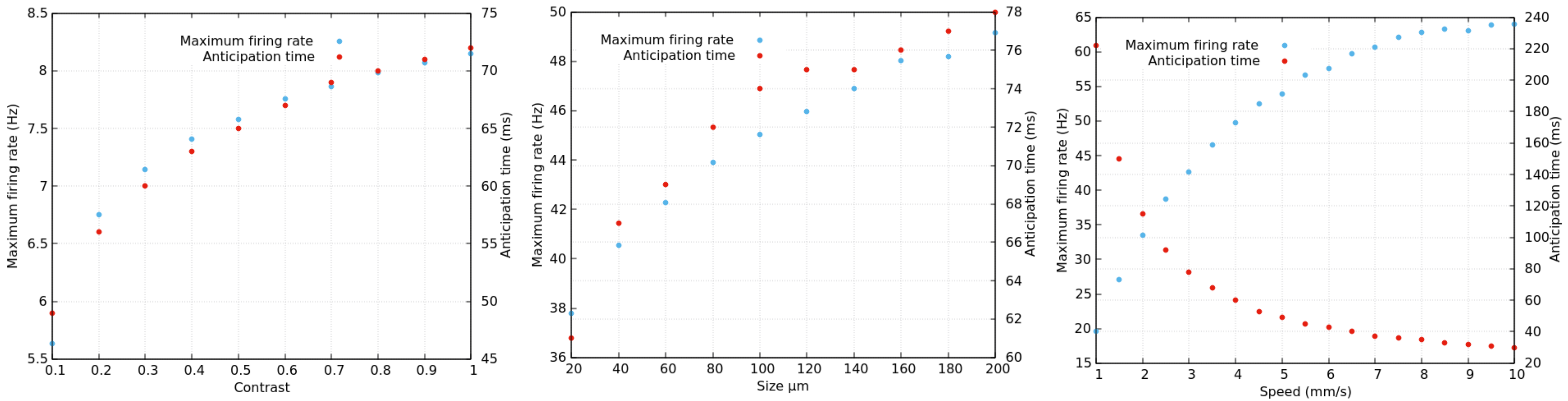




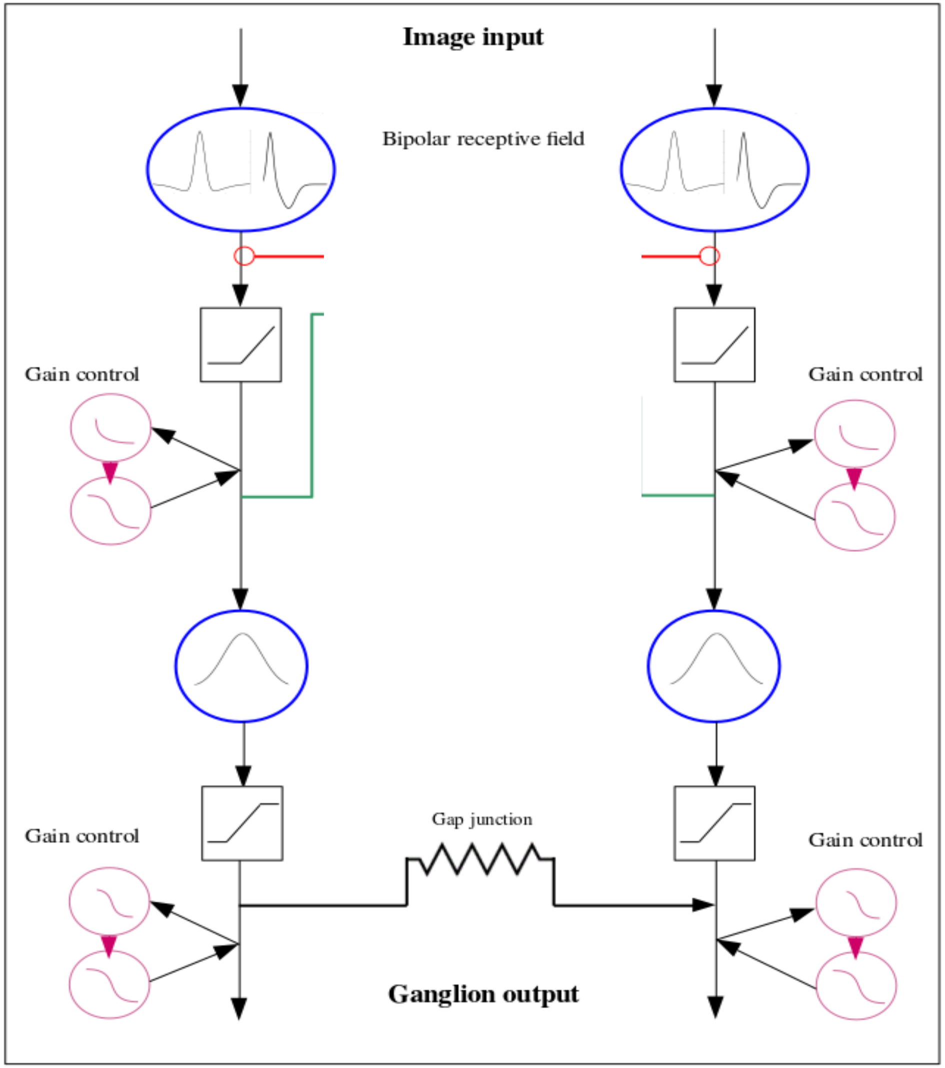


1D results : smooth motion anticipation with gap junctions

Anticipation variability with stimulus parameters

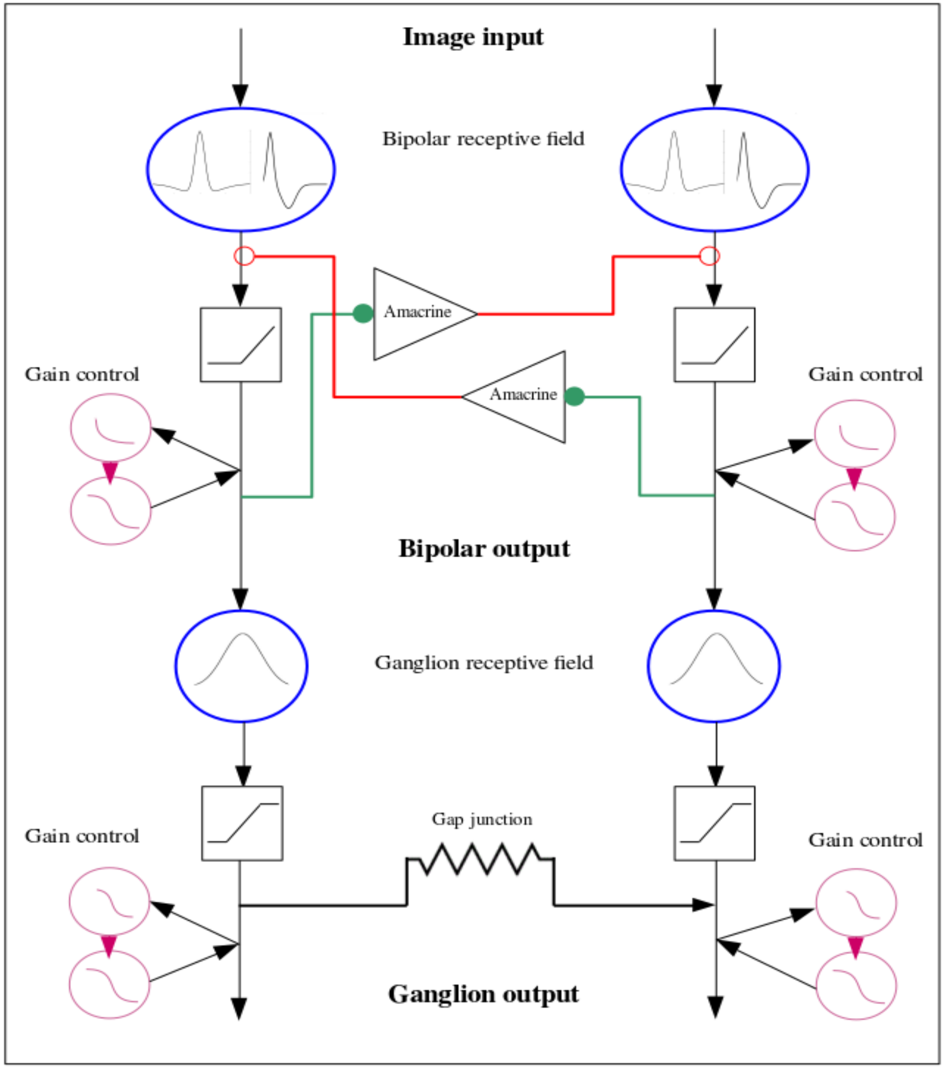


Building a 2D retina model for motion anticipation



Building a 2D retina model for motion anticipation

Amacrine cells connectivity

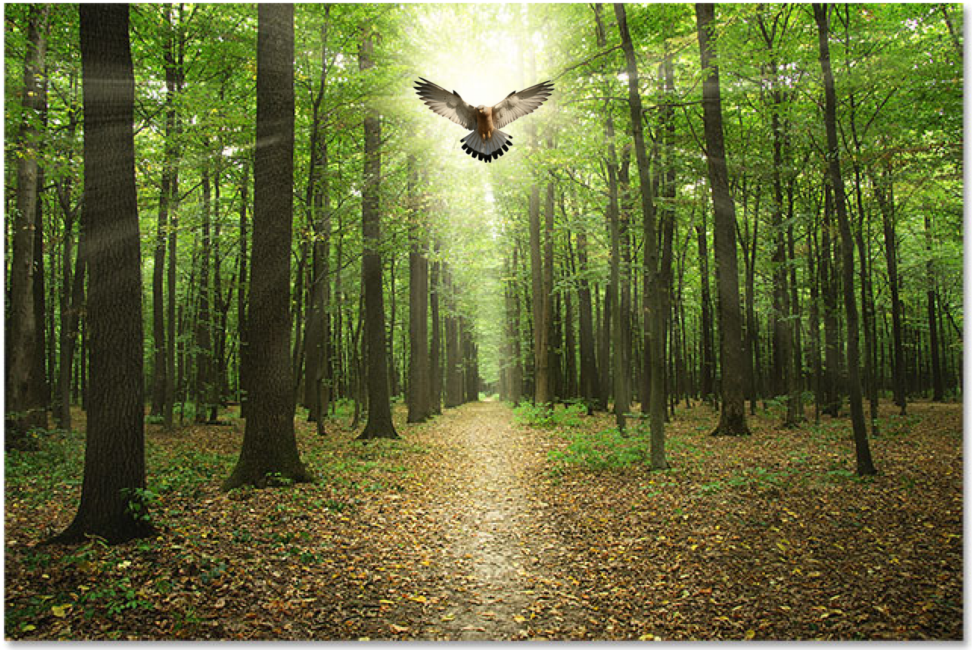


Ganglion cells are **not** independent encoders

Building a 2D retina model for motion anticipation

Amacrine cells connectivity

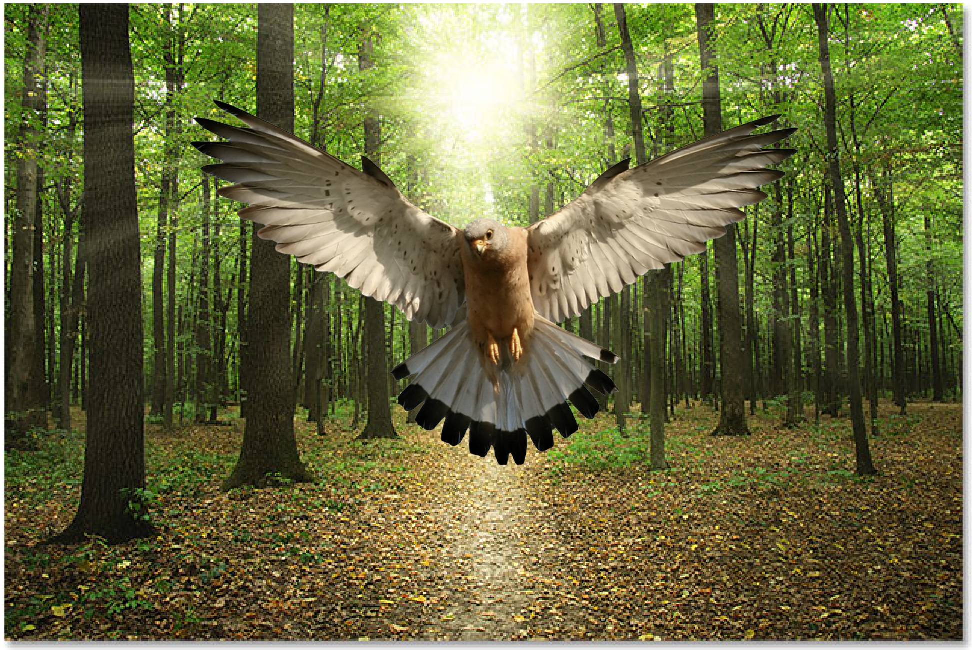
- A class of RGCs are selective to differential motion



Building a 2D retina model for motion anticipation

Amacrine cells connectivity

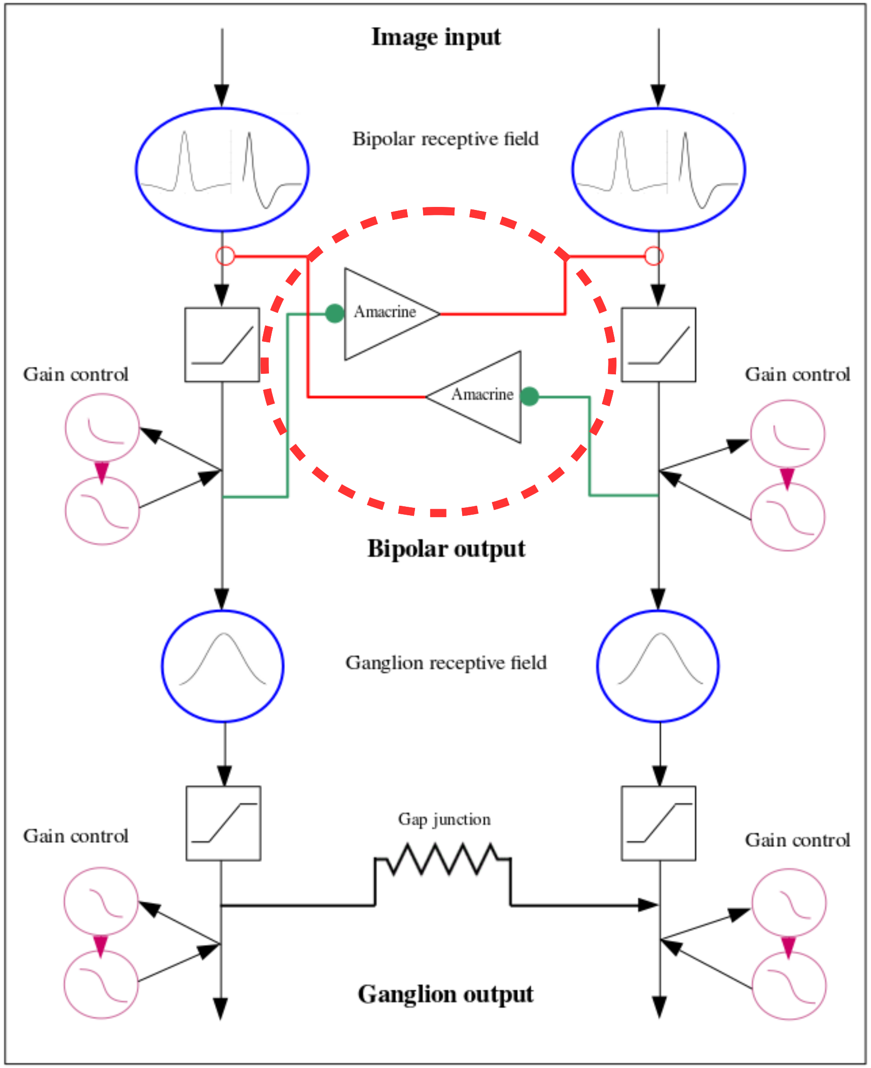
- A class of RGCs are selective to differential motion



- The circuitry involves amacrine cells connectivity upstream of ganglion cells

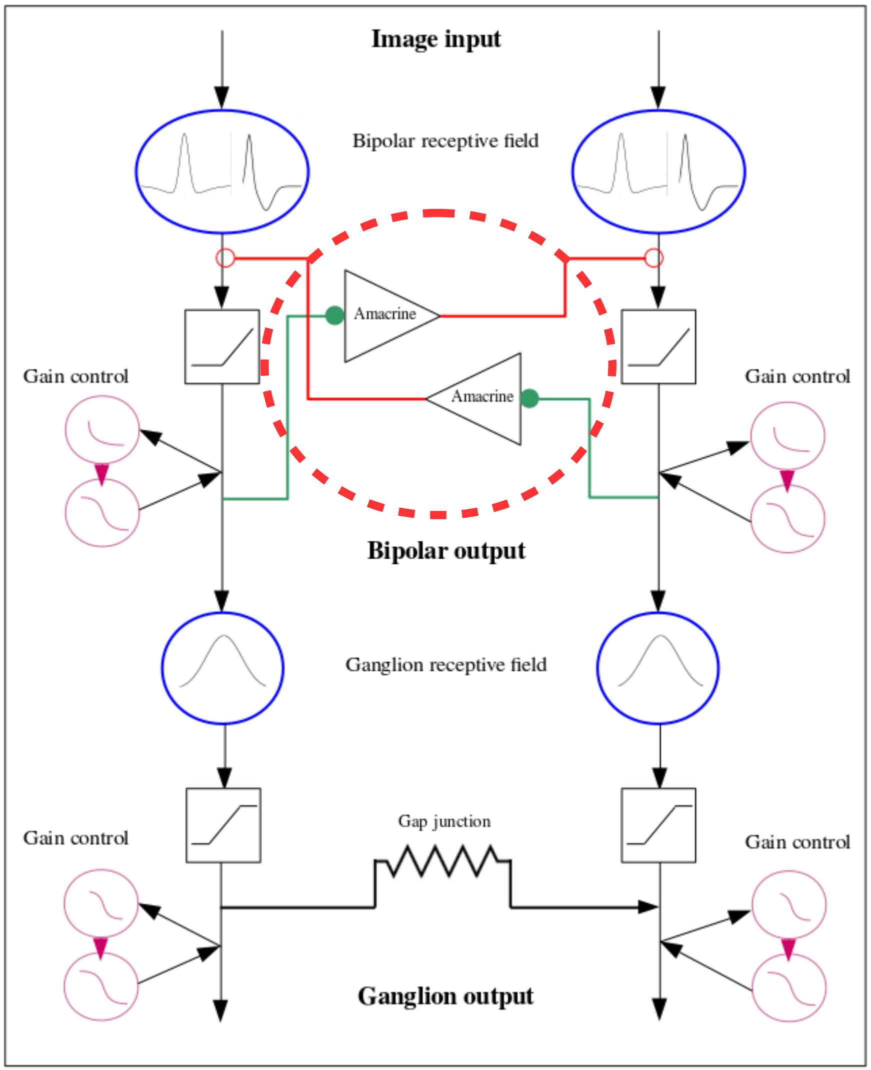
Connectivity pathways

Amacrine cells connectivity



Connectivity pathways

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 :

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

- Amacrine voltage :

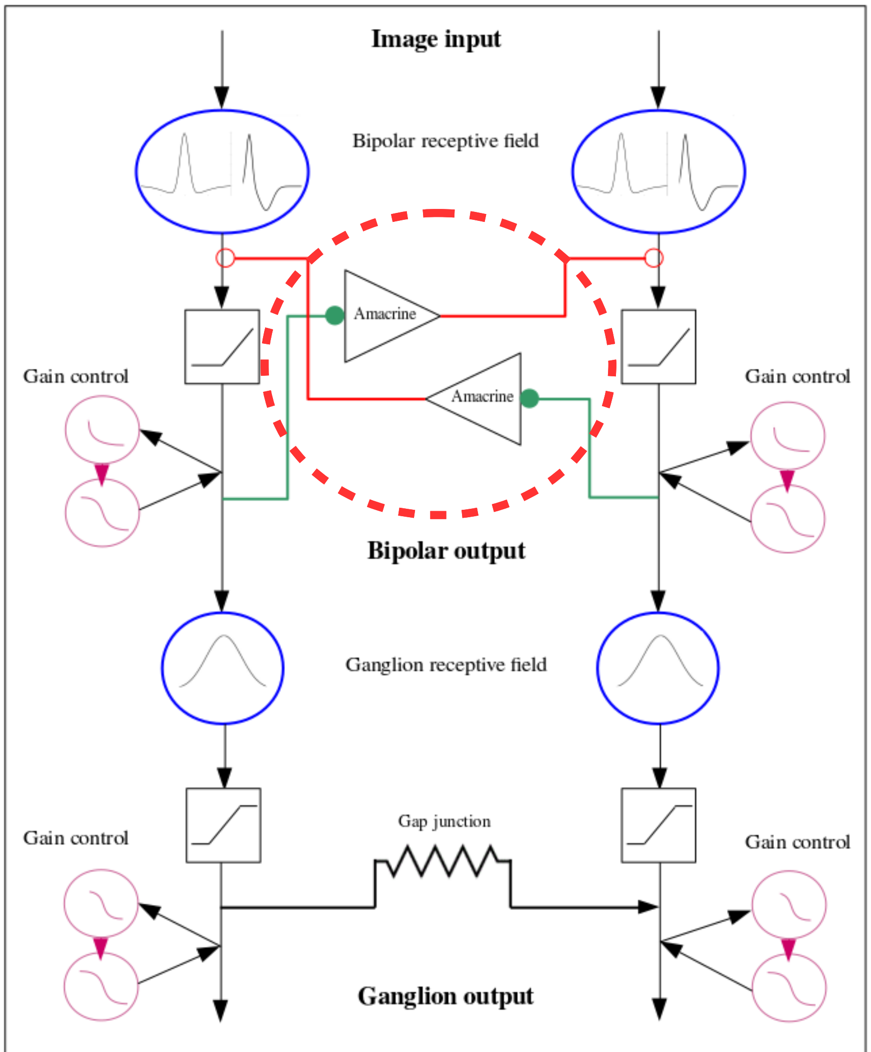
$$\frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_A} W_{A_j}^{B_i} R_{B_i}(t).$$

- Coupled dynamics :

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

Connectivity pathways

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 :

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

- Amacrine voltage :

Anti diffusive wave of activity ahead of the bar

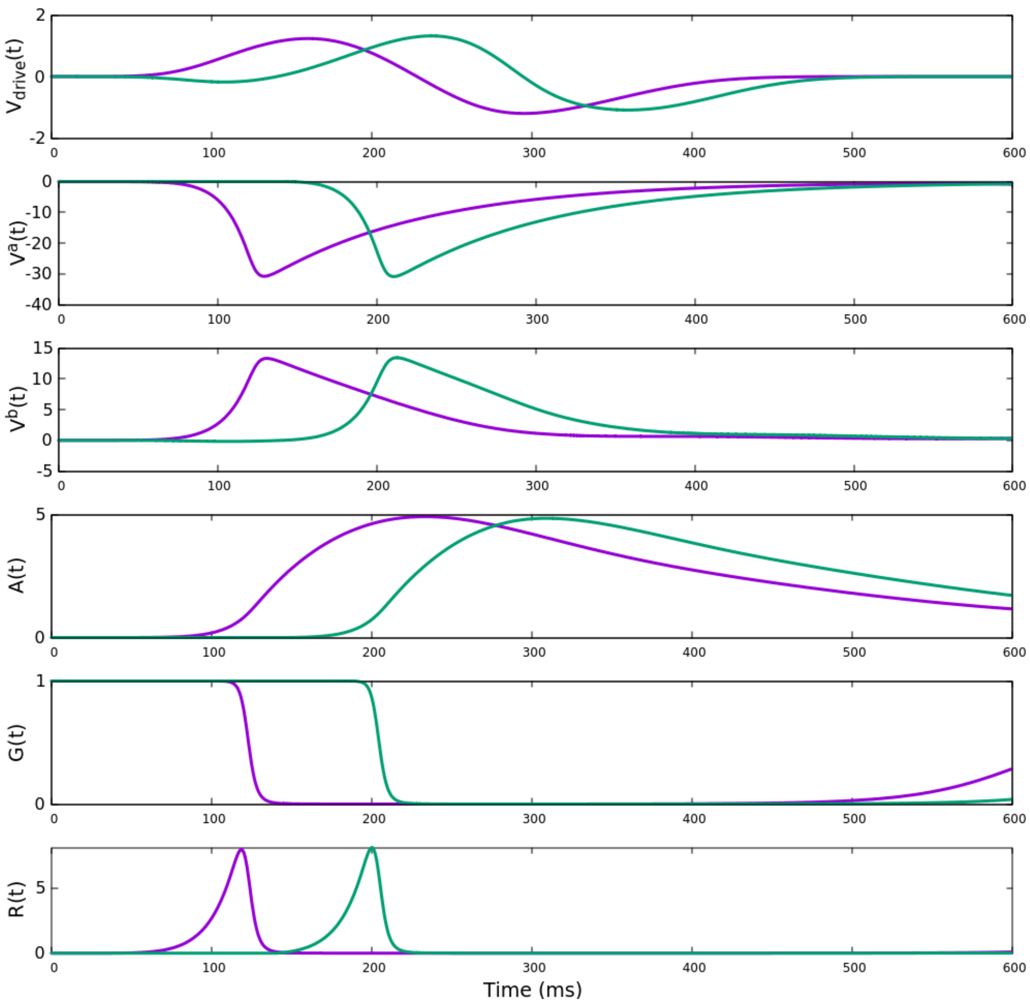
$$\frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_A} W_{A_j}^{B_i} R_{B_i}(t).$$

- Coupled dynamics :

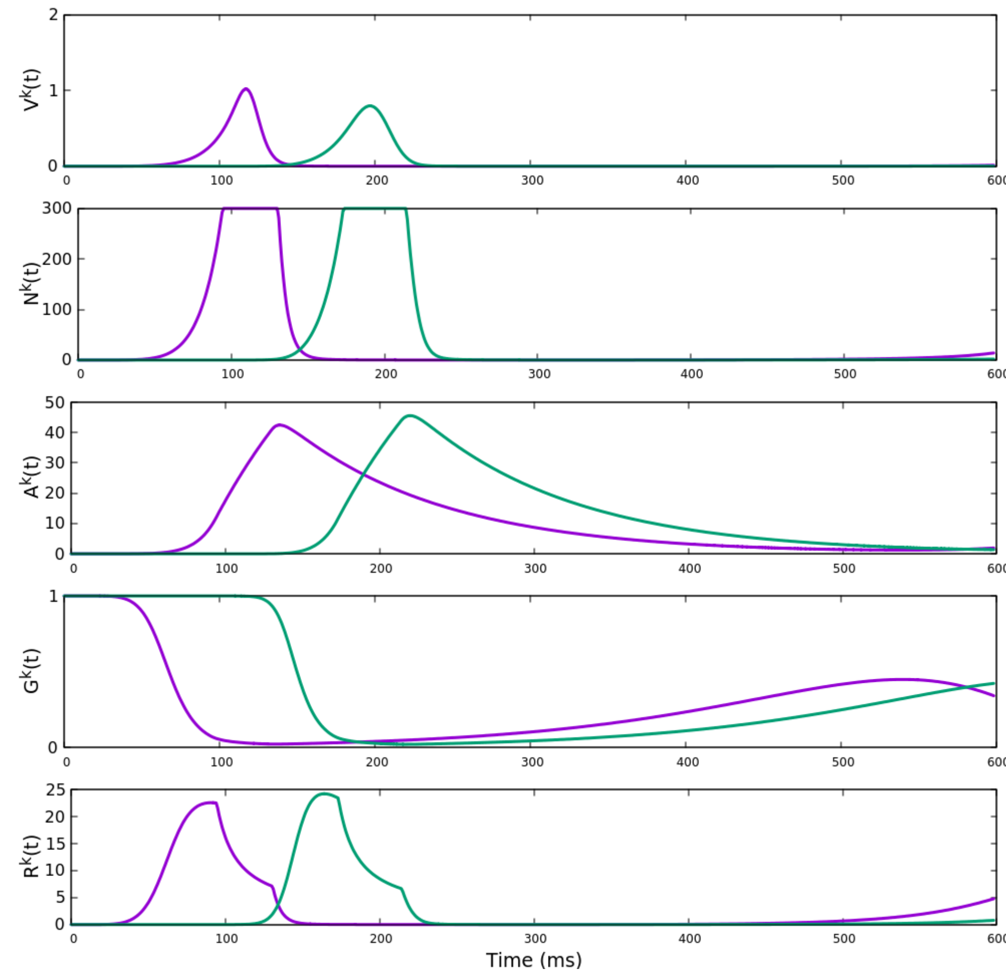
$$\begin{cases} \frac{dV_{B_i}}{dt} &= -\frac{1}{\tau_B} V_{B_i} + \sum_{j=1}^{N_A} W_{B_i}^{A_j} V_{A_j} + F_{B_i}(t) \\ \frac{dA_{B_i}}{dt} &= -\frac{A_{B_i}}{\tau_a} + h\,\mathcal{N}(V_{B_i}(t)), \\ \frac{dV_{A_j}}{dt} &= -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_A} W_{A_j}^{B_i} R_{B_i}(t). \end{cases}$$

1D results : smooth motion anticipation with amacrine connectivity

Bipolar layer

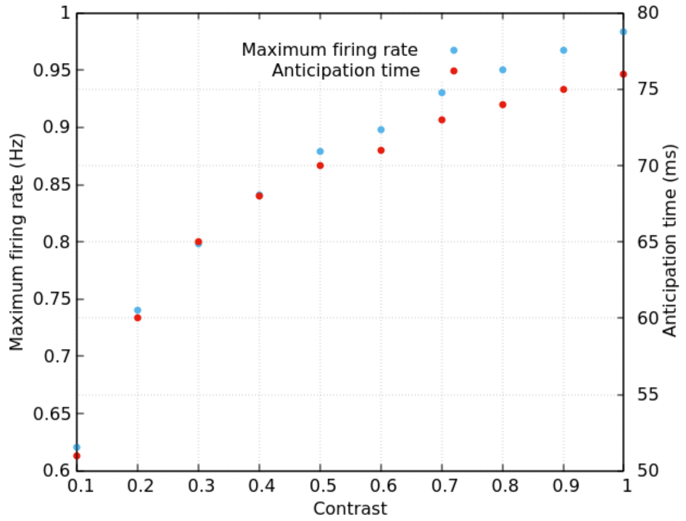


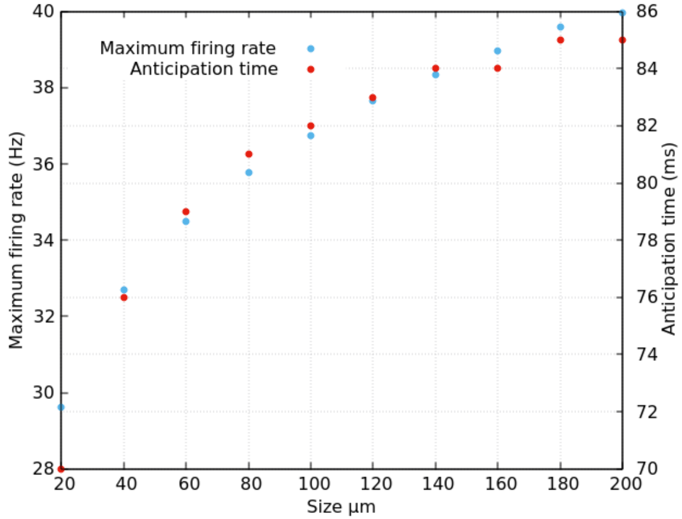
Ganglion layer

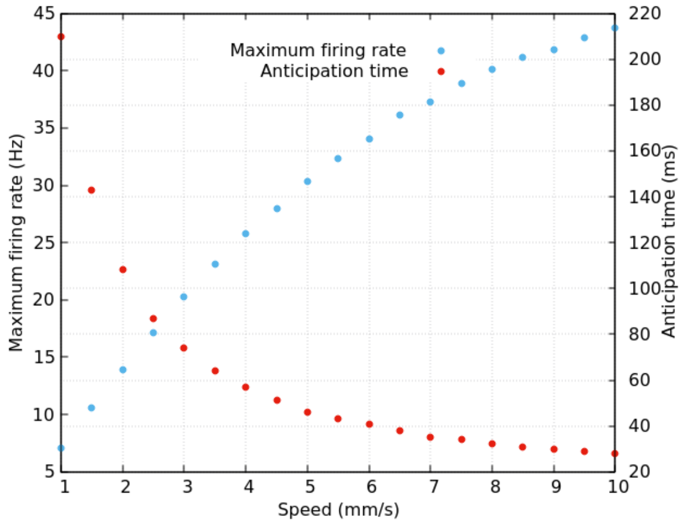


1D results : smooth motion anticipation with amacrine connectivity

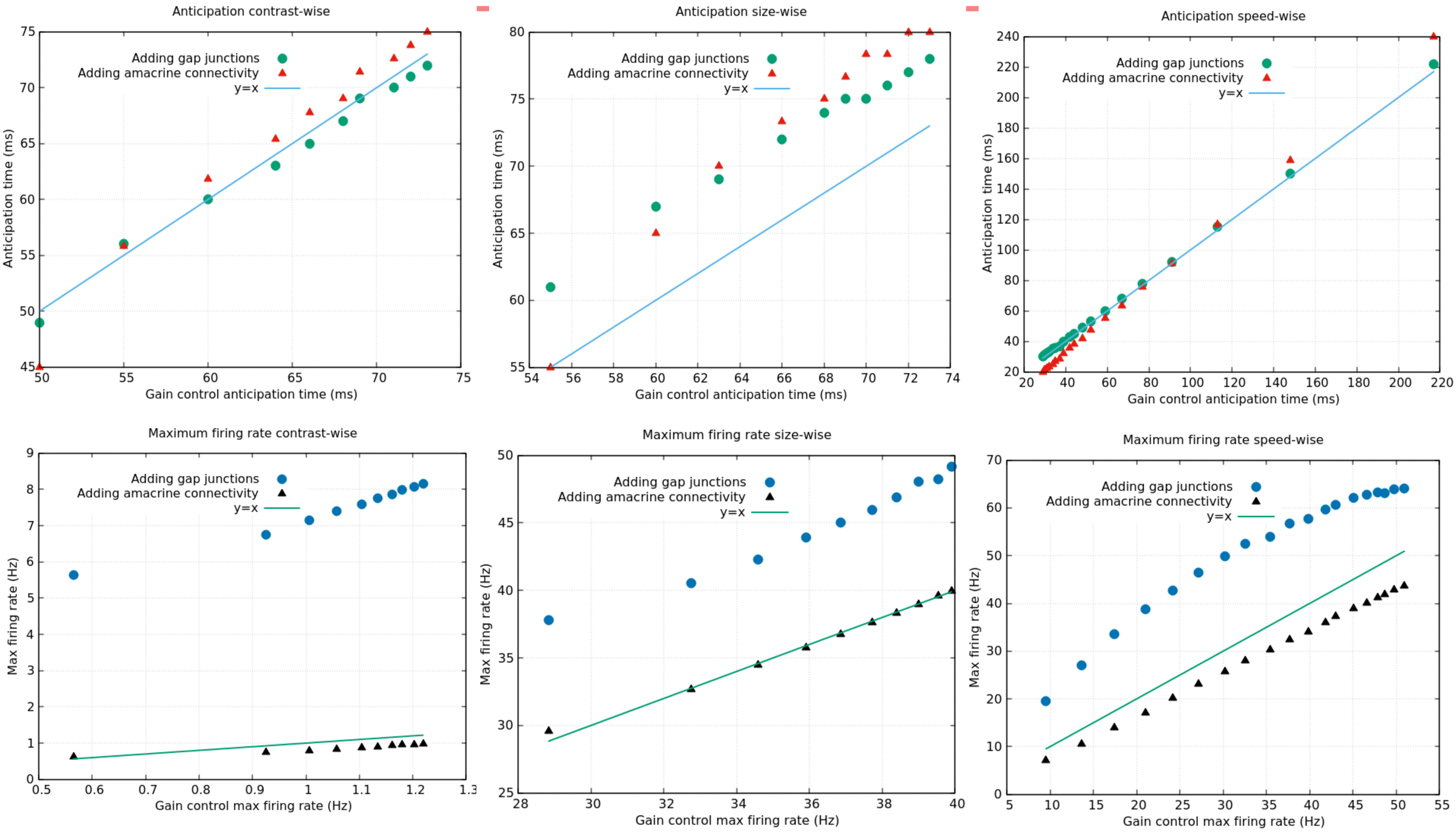
Anticipation variability with stimulus parameters





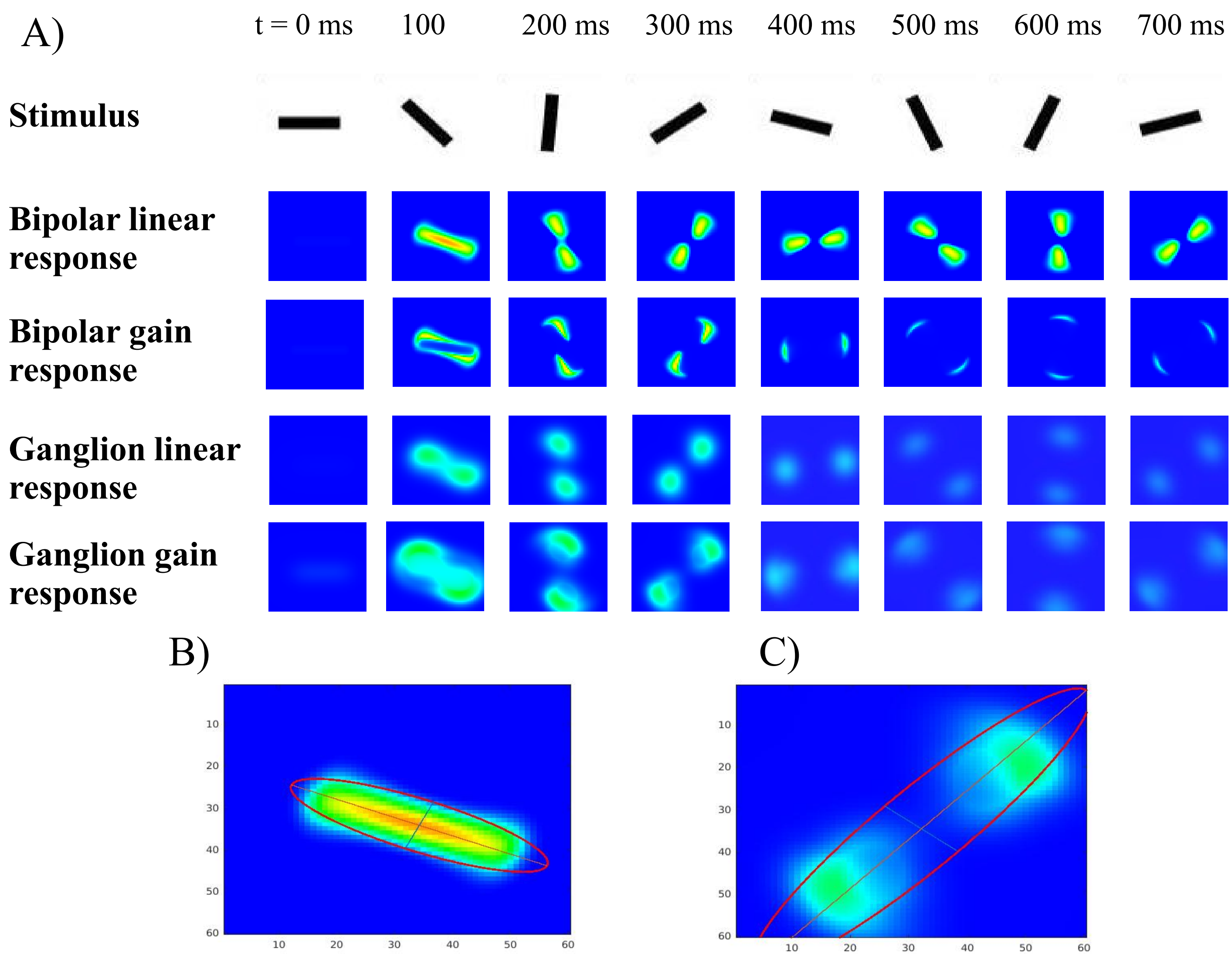


Comparing the performance of the three layers



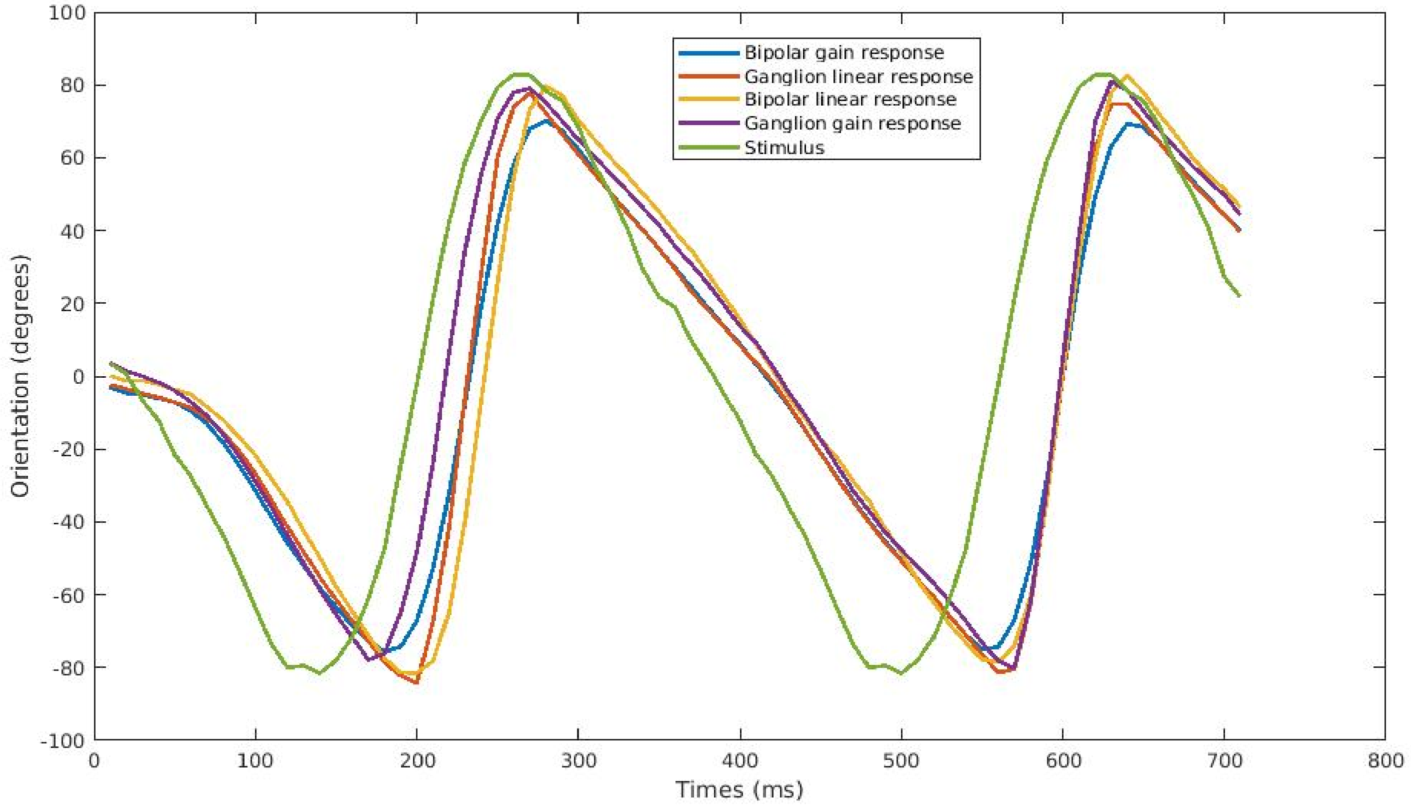
Suggesting new experiments : 2D results

1) Angular anticipation



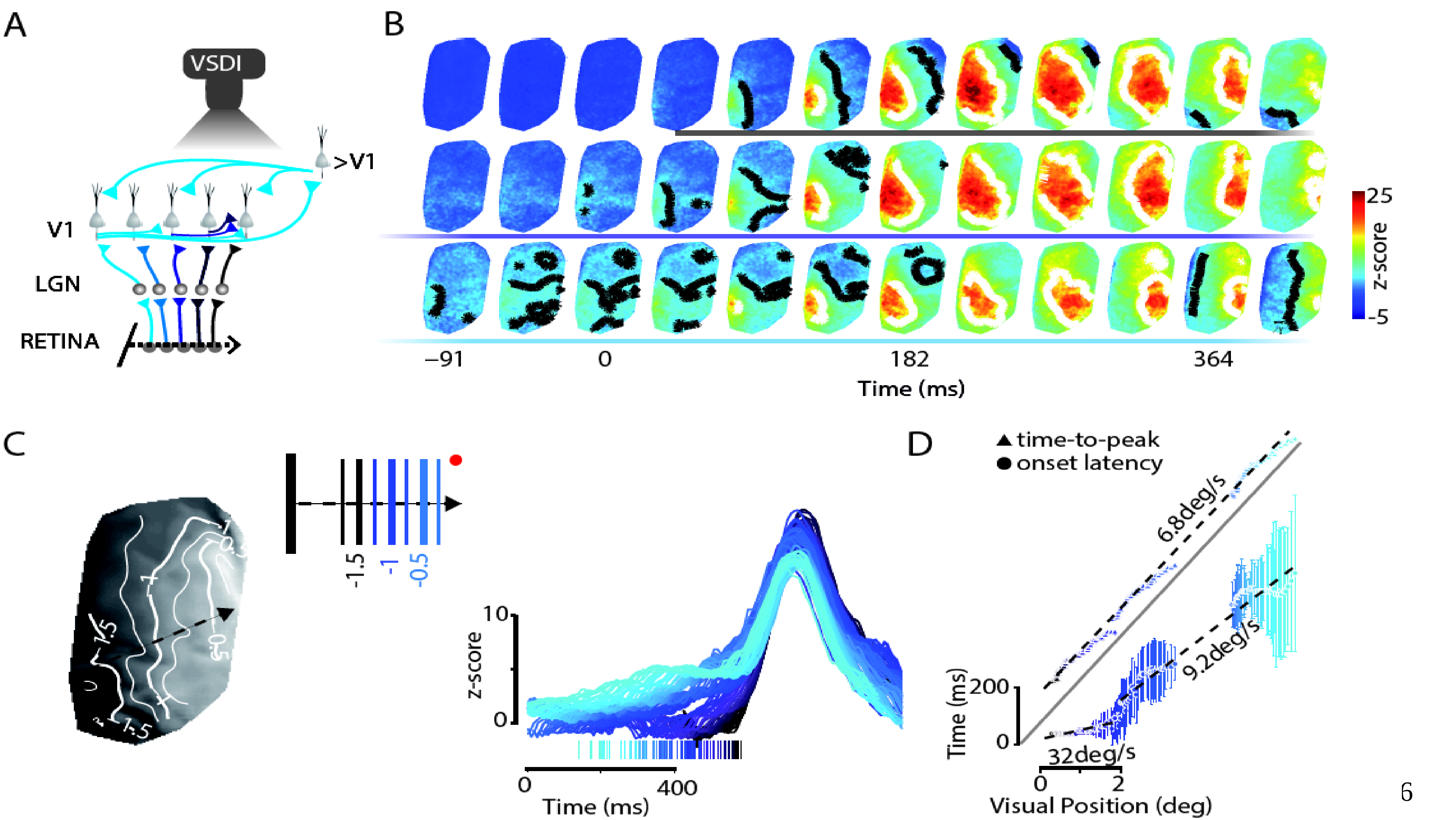
Suggesting new experiments : 2D results

1) Angular anticipation



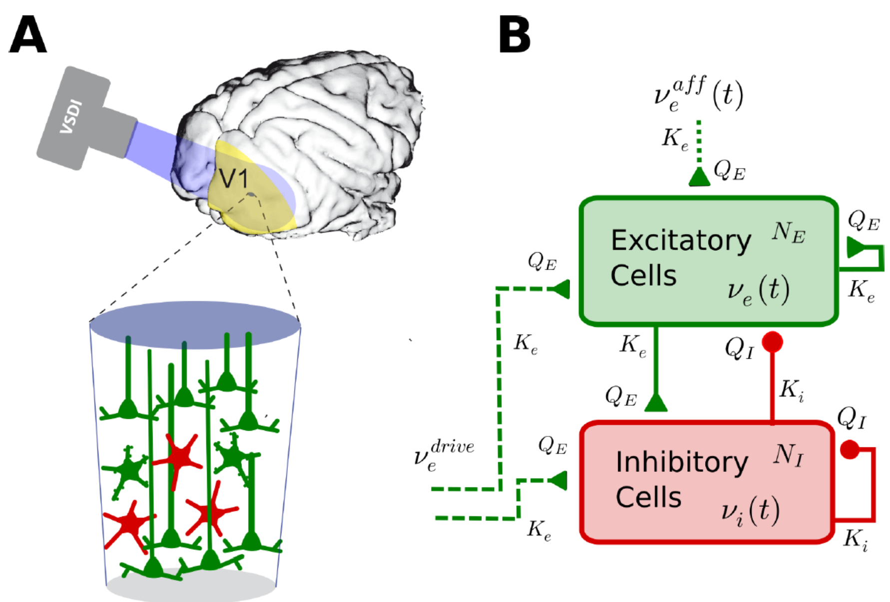
Anticipation in V1

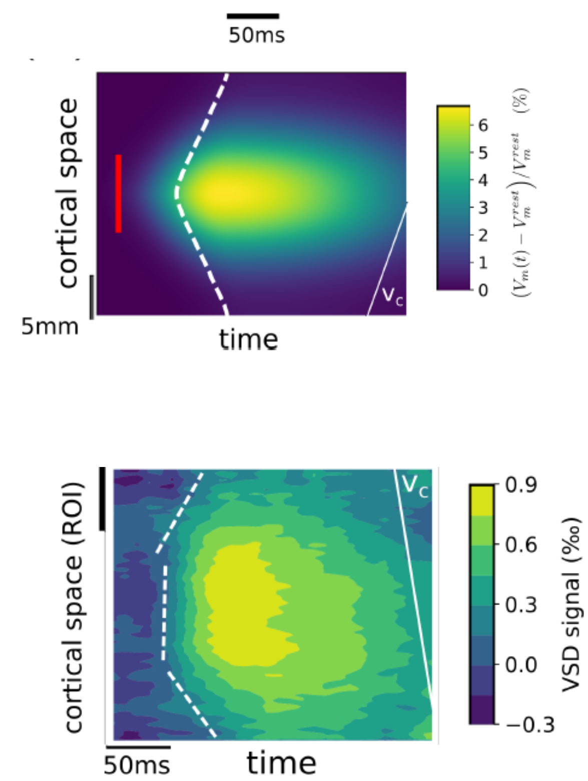
Anticipation in V1



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 :

$$\begin{cases} T\,\dfrac{\partial \nu_\mu}{\partial t} = (\mathcal{F}_\mu - \nu_\mu) + \dfrac{1}{2}\, c_{\lambda\eta}\, \dfrac{\partial^2 \mathcal{F}_\mu}{\partial \nu_\lambda \partial \nu_\eta} \\ T\,\dfrac{\partial c_{\lambda\eta}}{\partial t} = A_{\lambda\eta} + (\mathcal{F}_\lambda - \nu_\lambda)\,(\mathcal{F}_\eta - \nu_\eta) + \\ \qquad c_{\lambda\mu}\,\dfrac{\partial \mathcal{F}_\mu}{\partial \nu_\lambda} + c_{\mu\eta}\,\dfrac{\partial \mathcal{F}_\mu}{\partial \nu_\eta} - 2c_{\lambda\eta} \end{cases} \longrightarrow \quad T\,\frac{\partial \nu_\mu}{\partial t} = \mathcal{F}_\mu - \nu_\mu$$

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

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 :

$$
\begin{cases}
T\,\dfrac{\partial \nu_\mu}{\partial t} = (\mathcal{F}_\mu - \nu_\mu) + \dfrac{1}{2}\, c_{\lambda\eta}\, \dfrac{\partial^2 \mathcal{F}_\mu}{\partial \nu_\lambda \partial \nu_\eta} \\
T\,\dfrac{\partial c_{\lambda\eta}}{\partial t} = A_{\lambda\eta} + (\mathcal{F}_\lambda - \nu_\lambda)(\mathcal{F}_\eta - \nu_\eta) + \\
\qquad c_{\lambda\mu}\, \dfrac{\partial \mathcal{F}_\mu}{\partial \nu_\lambda} + c_{\mu\eta}\, \dfrac{\partial \mathcal{F}_\mu}{\partial \nu_\eta} - 2 c_{\lambda\eta}
\end{cases}
\longrightarrow \quad T\,\frac{\partial \nu_\mu}{\partial t} = \mathcal{F}_\mu - \nu_\mu
$$

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

Affords a retino thalamic input

A mean field model to reproduce VSDI recordings

Zerlaut et al 2016
Chemla et al 2018

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

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

The conductance-based exponential synapse

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

Semi analytical transfer function :

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

$$+ \sum_{x,y \in \{\mu_V, \sigma_V, \tau_V^N\}^2} P_{xy} \cdot \left(\frac{x - x^0}{\delta x^0}\right) \left(\frac{y - y^0}{\delta y^0}\right)$$

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 :

$$\mu_{Ge}(\nu_e,\nu_i) = \nu_e\, K_e\, \tau_e\, Q_e$$

$$\sigma_{Ge}(\nu_e,\nu_i) = \sqrt{\frac{\nu_e\, K_e\, \tau_e}{2}}\, Q_e$$

$$\mu_{Gi}(\nu_e,\nu_i) = \nu_i\, K_i\, \tau_i\, Q_i$$

$$\sigma_{Gi}(\nu_e,\nu_i) = \sqrt{\frac{\nu_i\, K_i\, \tau_i}{2}}\, Q_i$$

→

$$\mu_G(\nu_e,\nu_i) = \mu_{Ge} + \mu_{Gi} + g_L$$

$$\tau_m(\nu_e,\nu_i) = \frac{C_m}{\mu_G}$$

↓

$$\mu_V(\nu_e,\nu_i) = \frac{\mu_{Ge}\, E_e + \mu_{Gi}\, E_i + g_L\, E_L}{\mu_G}$$

$$\sigma_V(\nu_e,\nu_i) = \sqrt{\sum_s K_s\, \nu_s\, \frac{(U_s\cdot\tau_s)^2}{2\,(\tau_m^{\mathrm{eff}} + \tau_s)}}$$

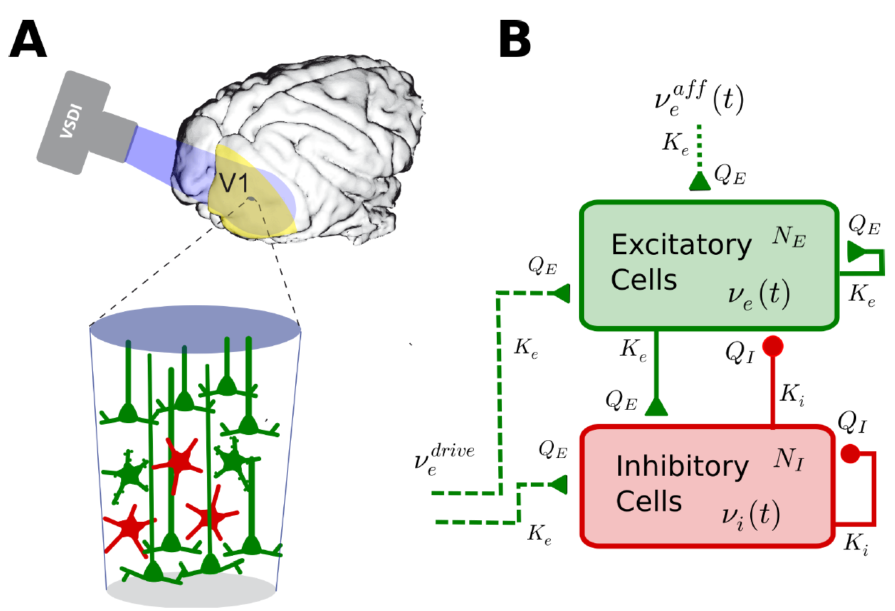
$$\tau_V(\nu_e,\nu_i) = \Big(\frac{\sum_s \big(K_s\, \nu_s\, (U_s\cdot\tau_s)^2\big)}{\sum_s \big(K_s\, \nu_s\, (U_s\cdot\tau_s)^2/(\tau_m^{\mathrm{eff}} + \tau_s)\big)}\Big)$$

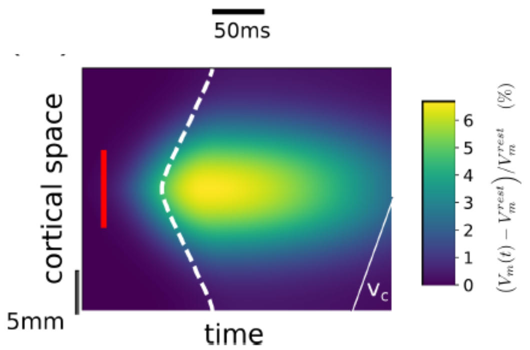
Finally, the transfer function reads :

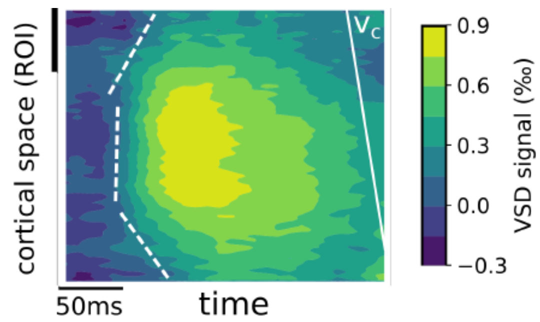
$$\nu_{out} = \mathcal{F}(\nu_e,\nu_i) = \frac{1}{2\,\tau_V}\cdot Erfc\Big(\frac{V_{thre}^{eff} - \mu_V}{\sqrt{2}\,\sigma_V}\Big)$$

A mean field model to reproduce VSDI recordings

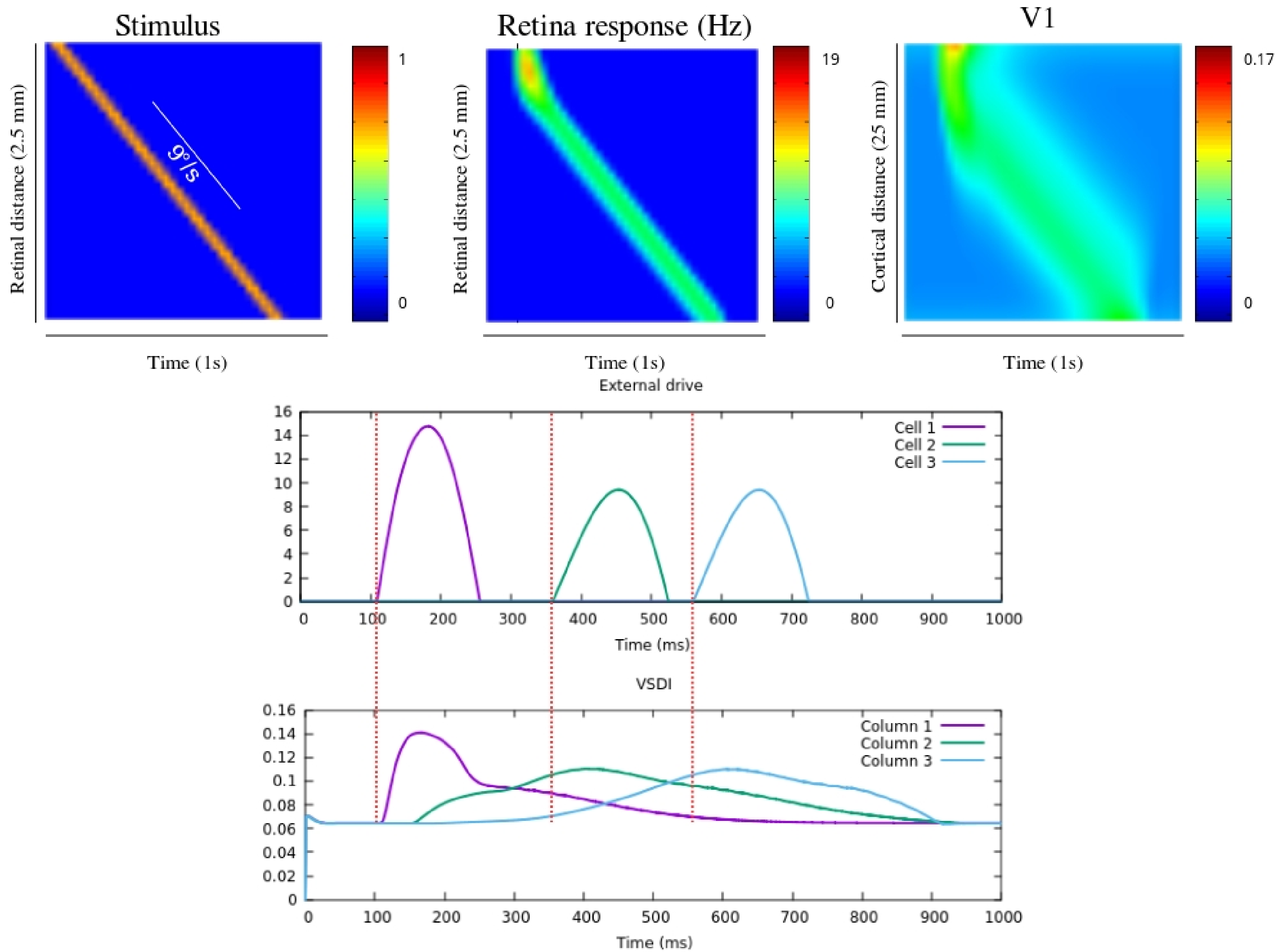
Zerlaut et al 2016
Chemla et al 2018



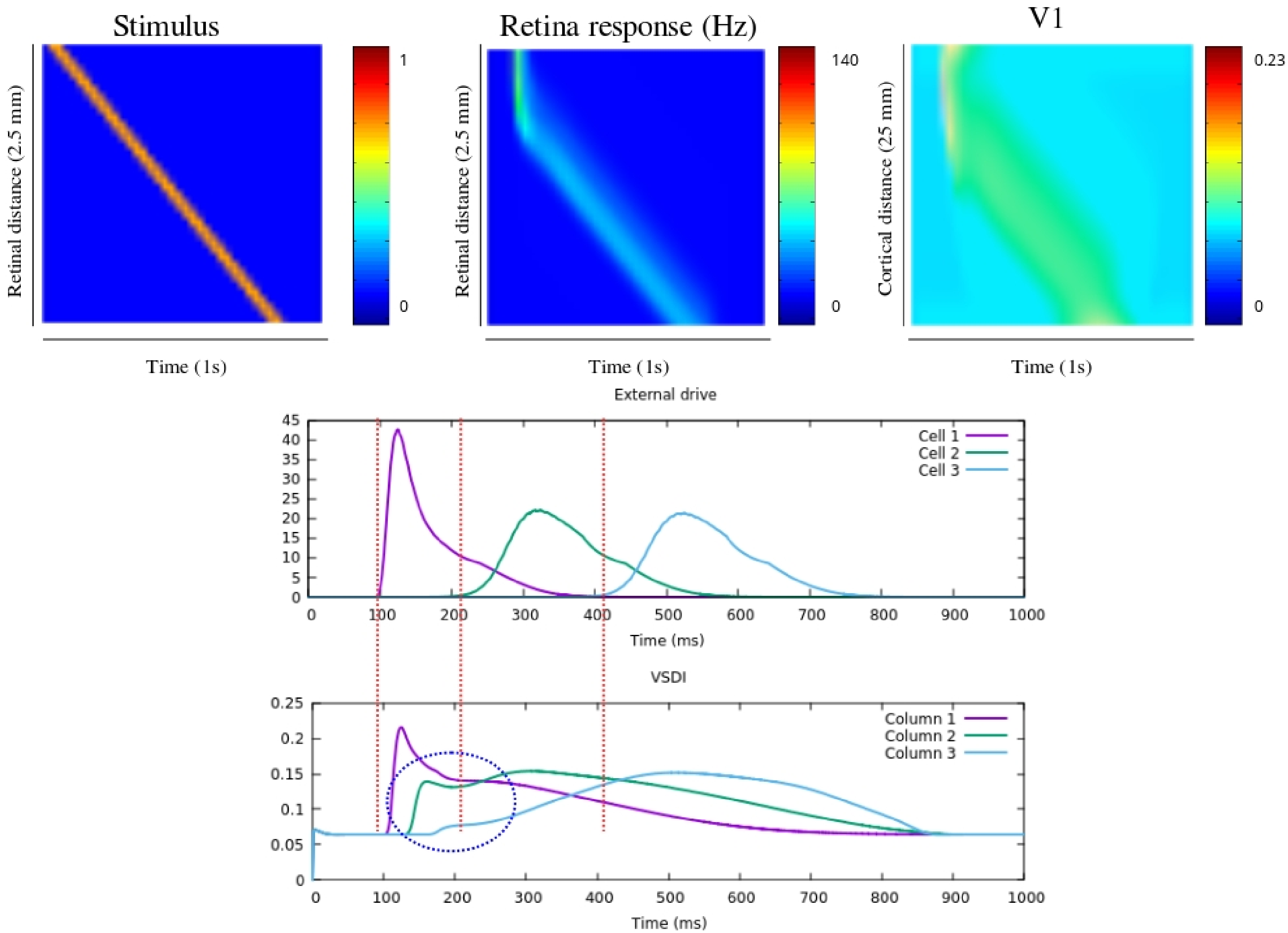




Response of the cortical model to a LN retina drive

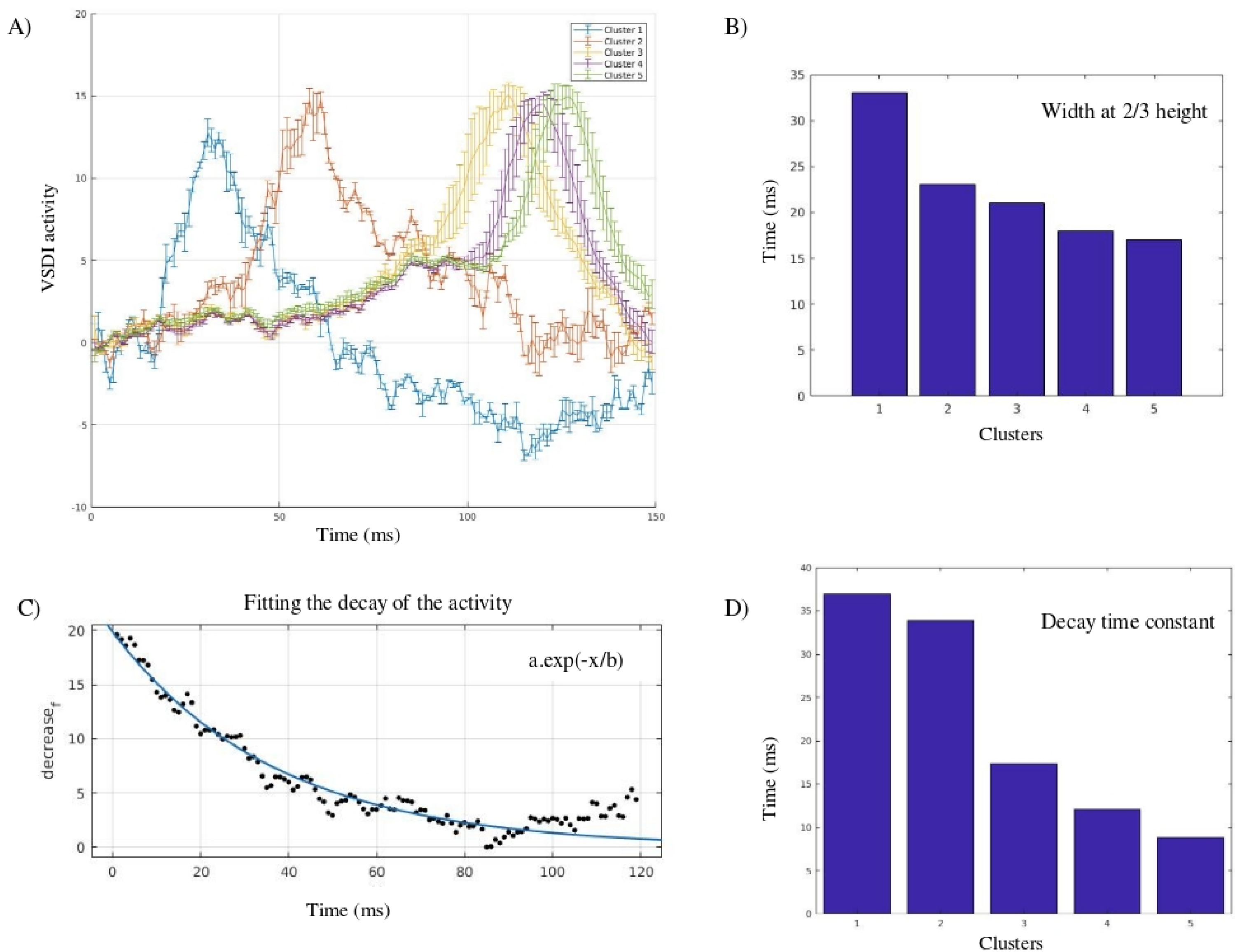


Response of the cortical model to a retina drive with gain control



Anticipation in the cortex : VSDI data analysis

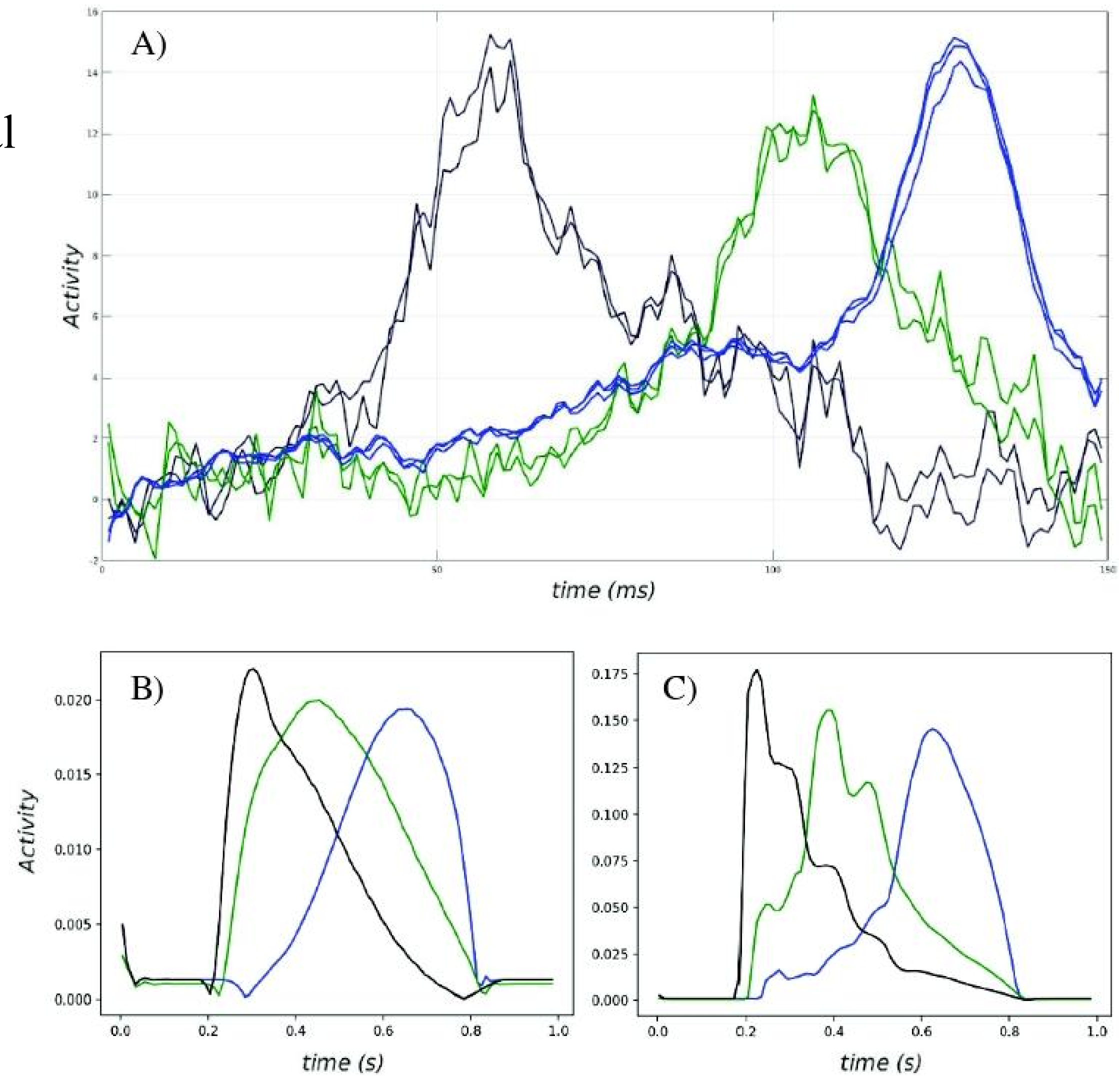
(Data courtesy of F. Chavane et S. Chemla)



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 developped 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 !