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# 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

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

Bruno Cessac, Selma Souihel  
Biovision



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In collaboration with :

Matteo Di Volo  
Alain Destexhe



Frédéric Chavane  
Sandrine Chemla

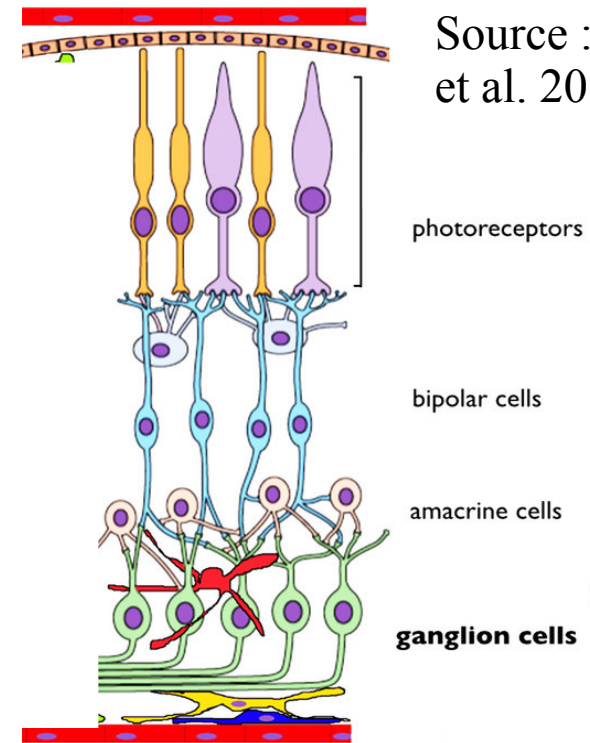
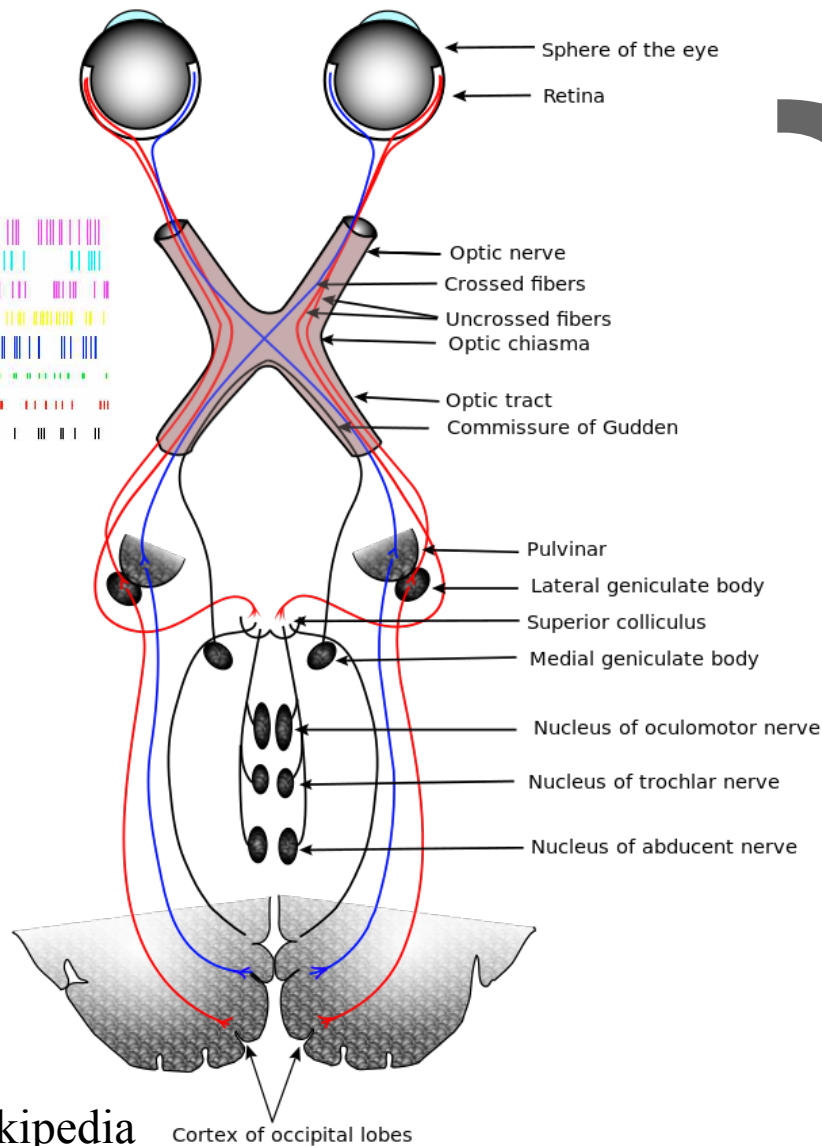


Olivier Marre





# The visual flow

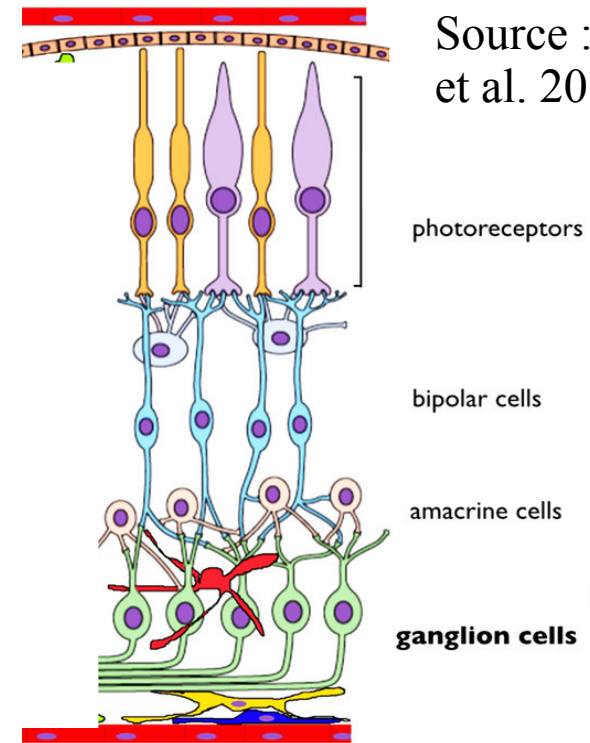
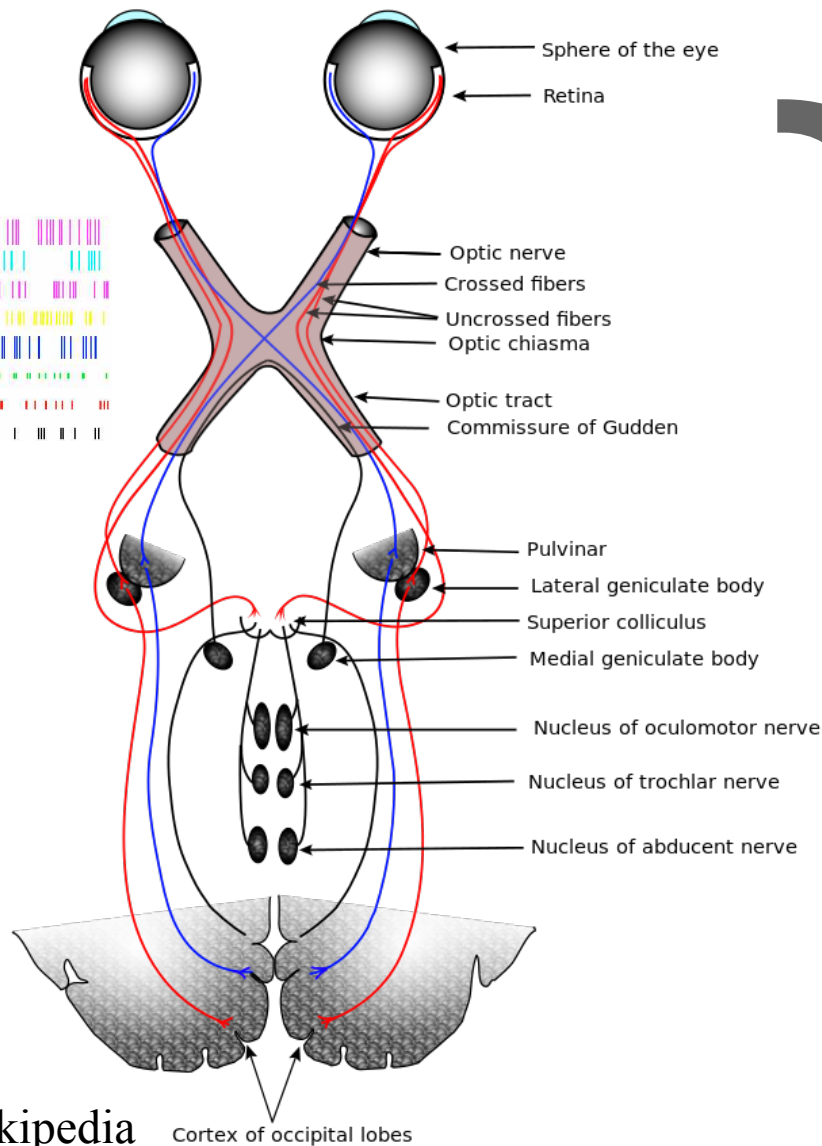


Source : Ryskamp et al. 2014



Upcoming light

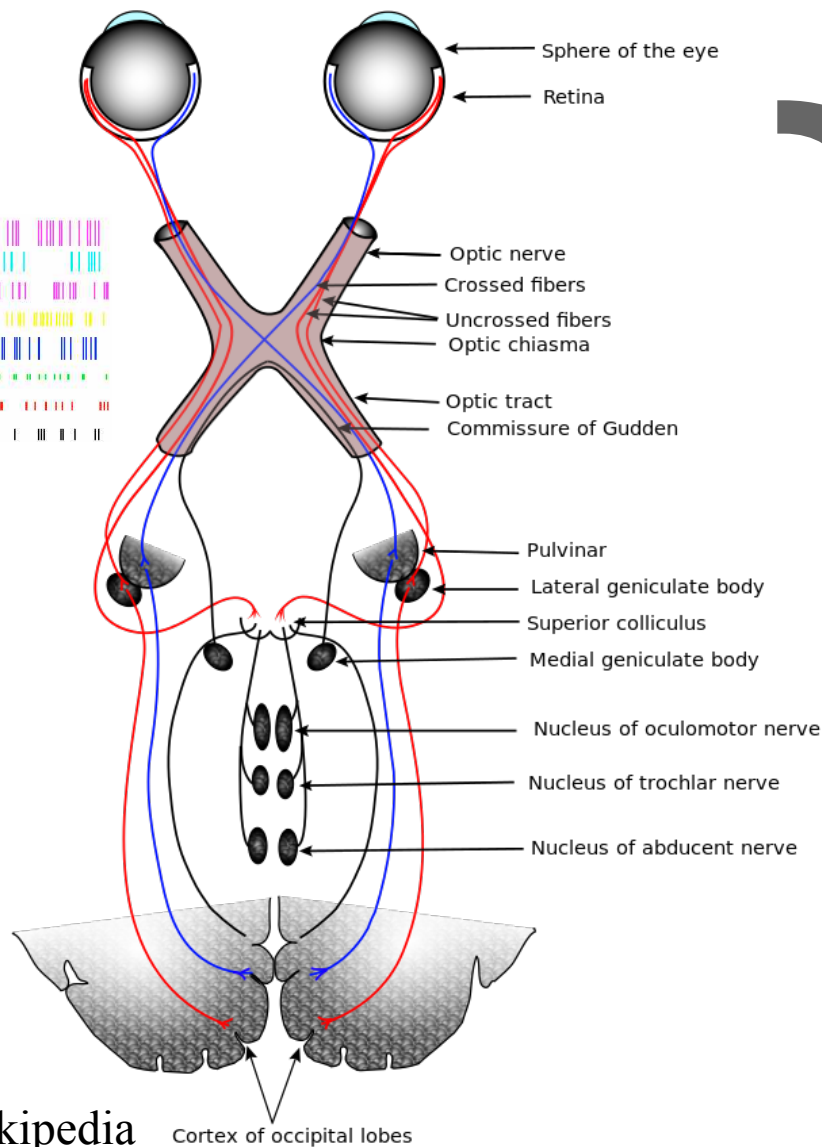
# The visual flow



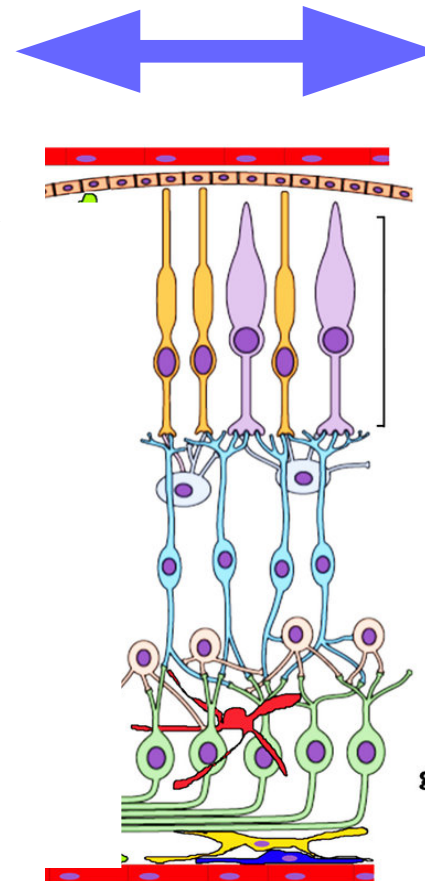
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Upcoming light

# The visual flow



Source : Wikipedia

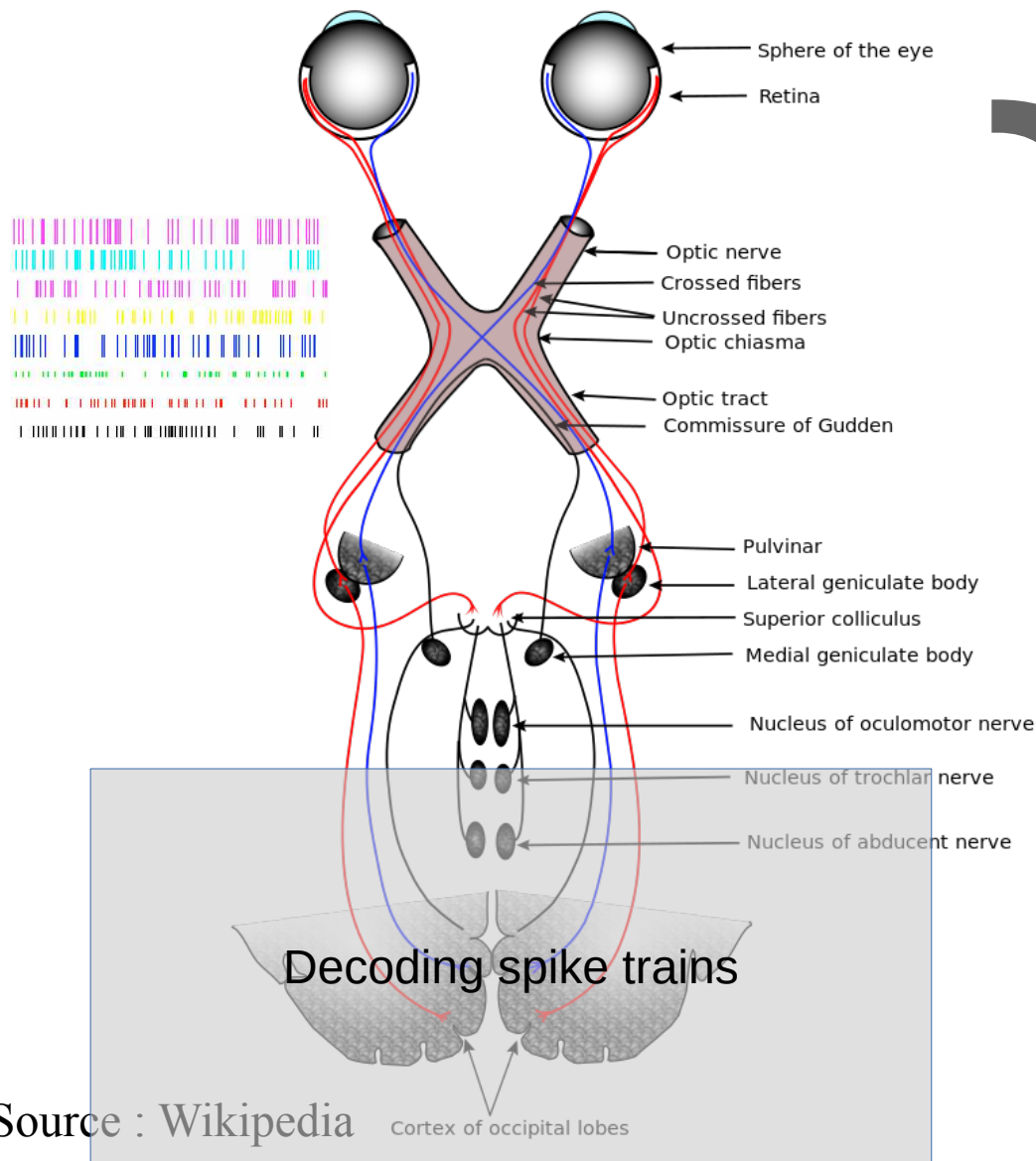


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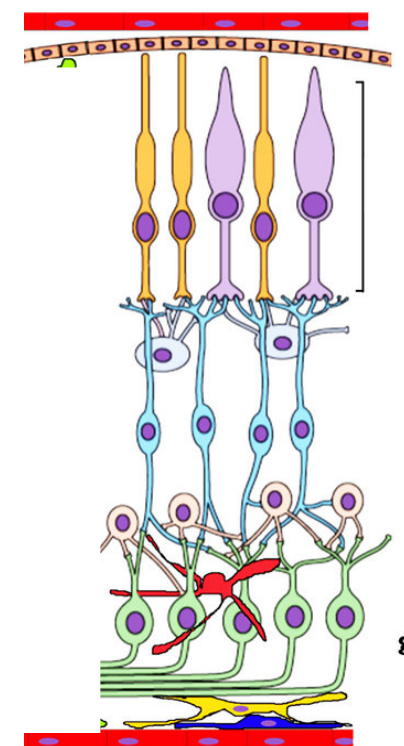
Upcoming light



# The visual flow



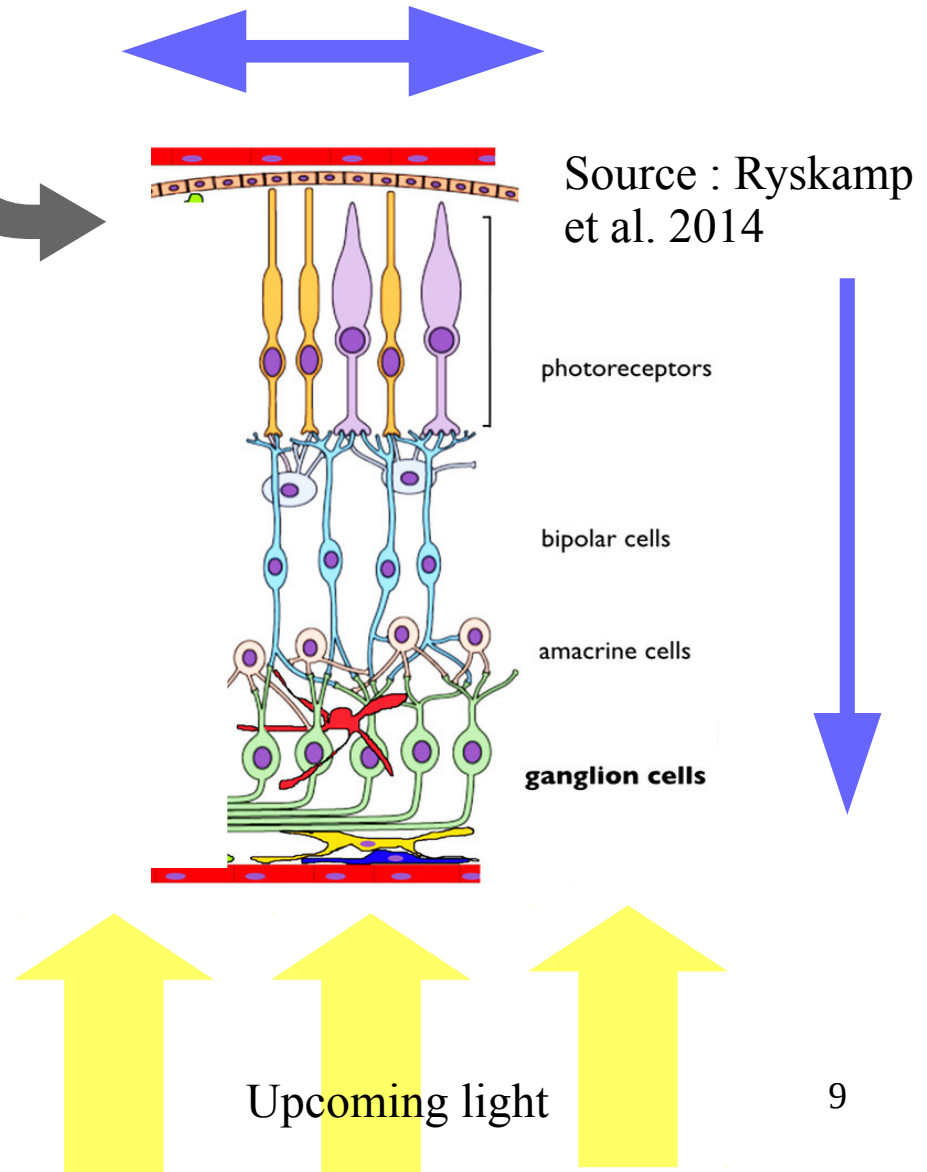
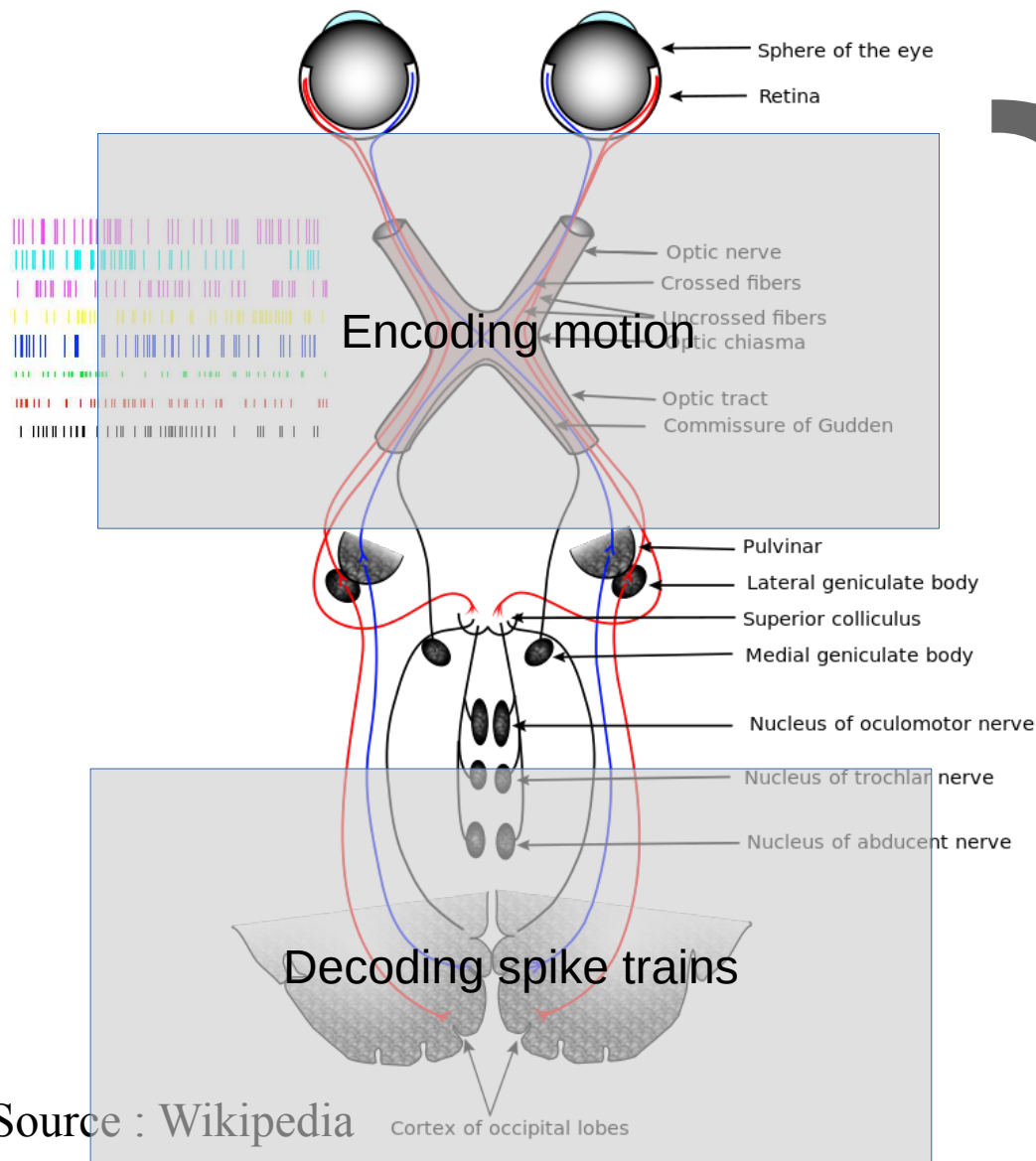
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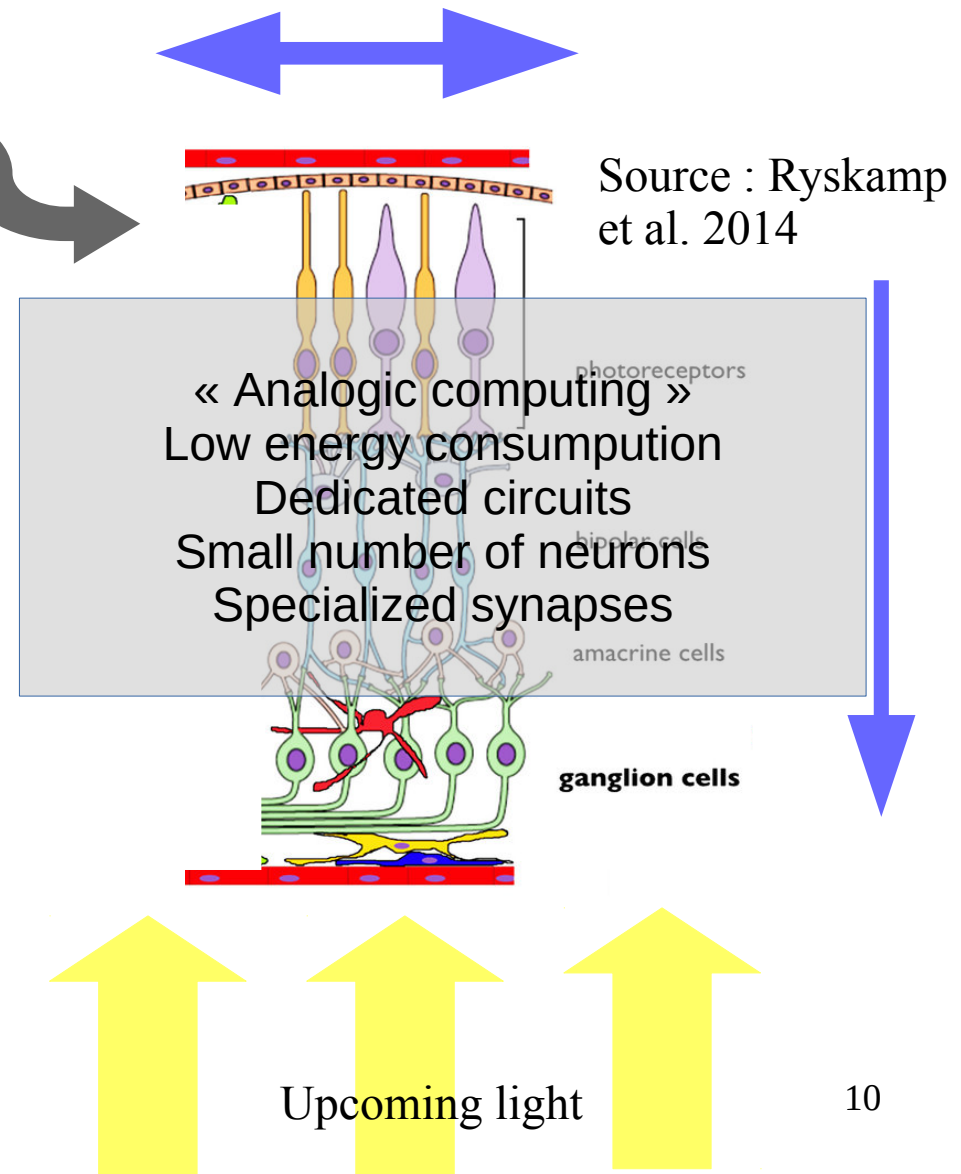
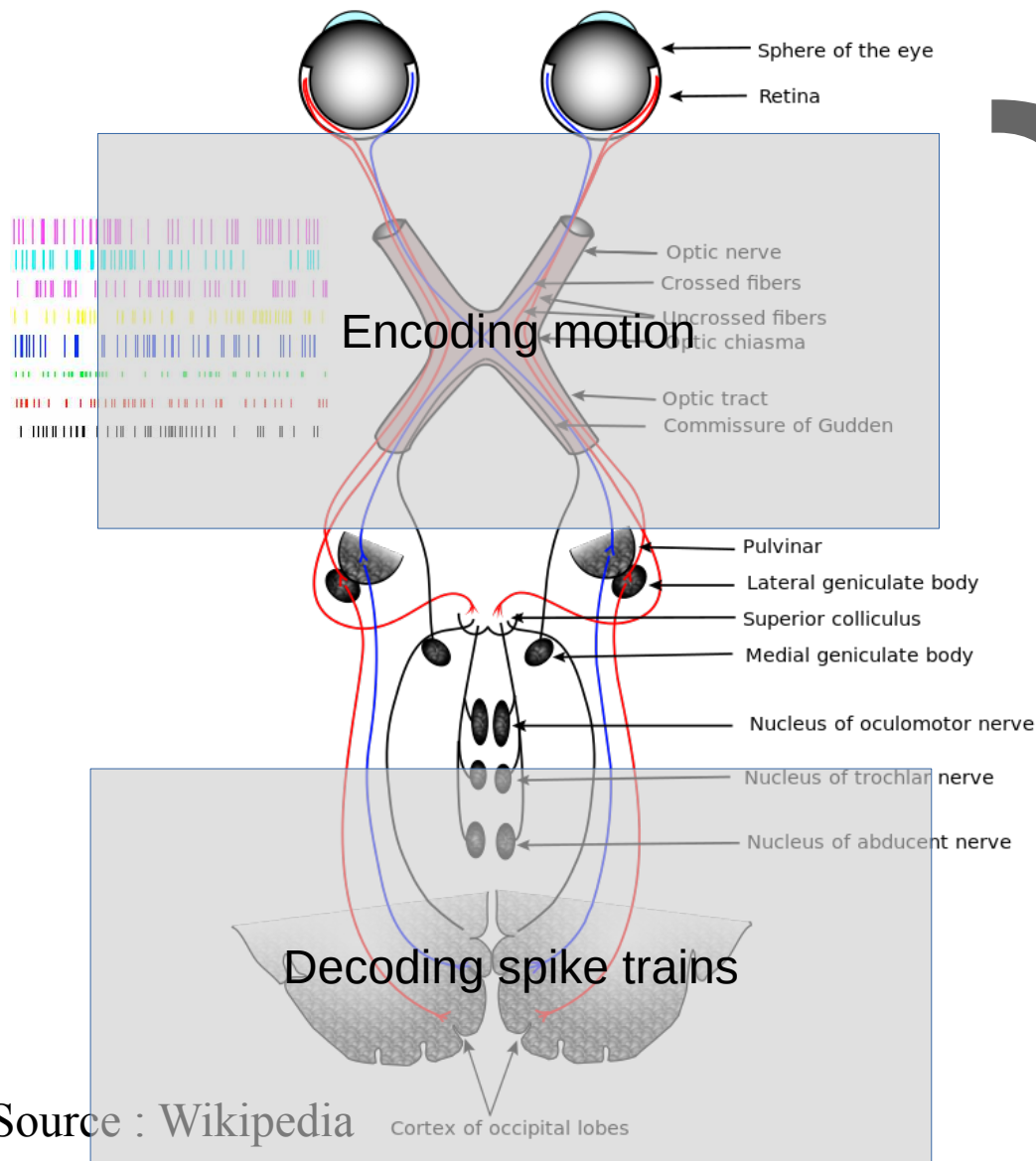
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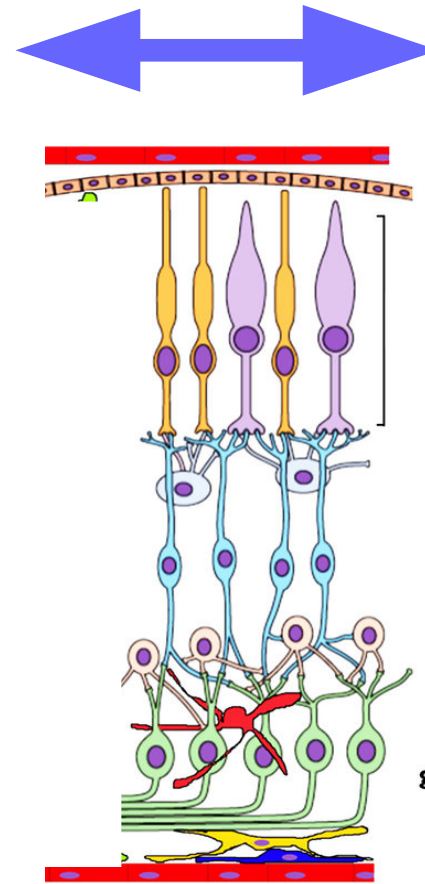
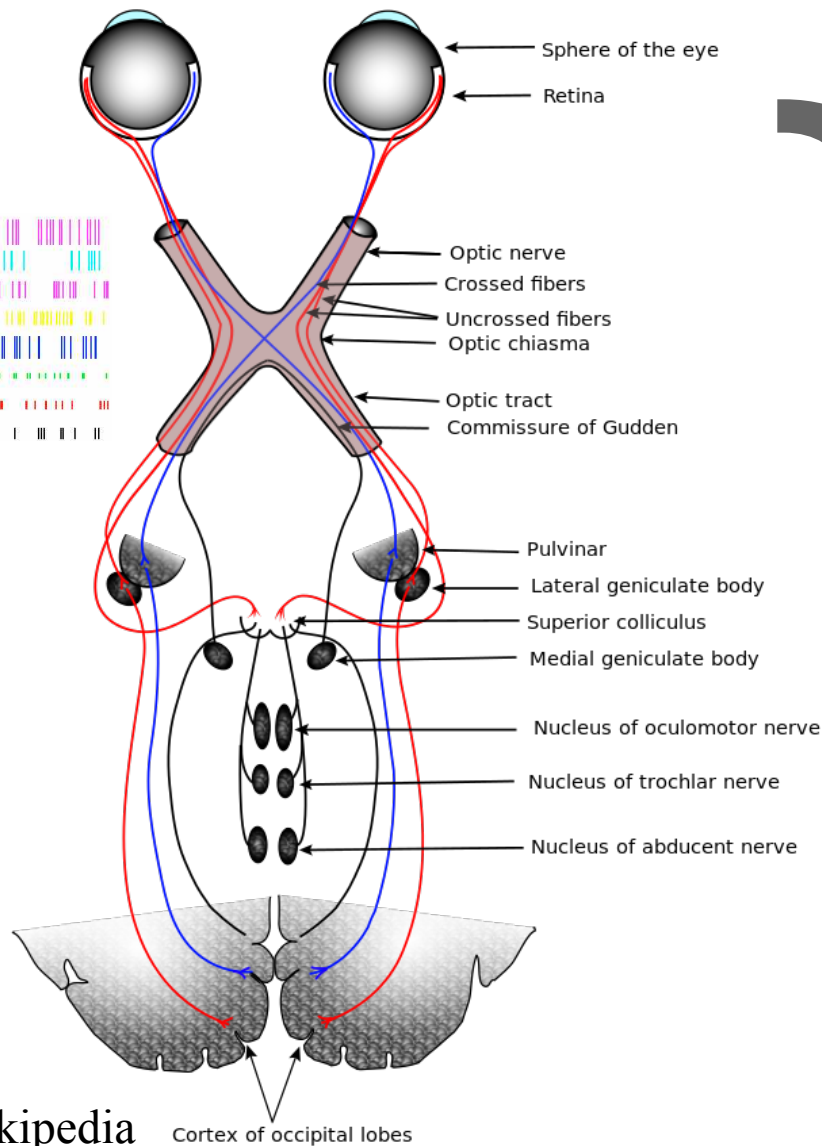
# The visual flow



# The visual flow



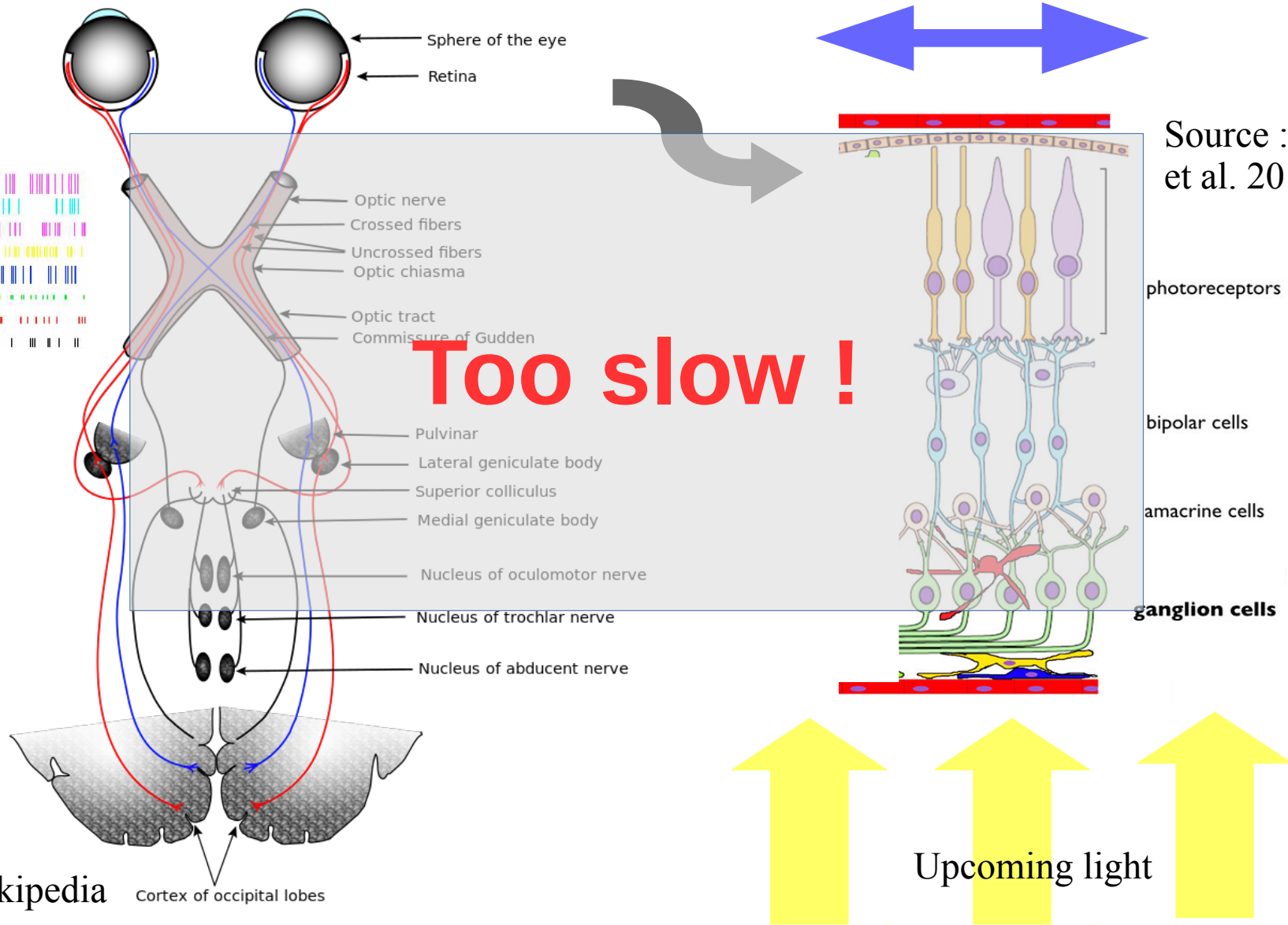
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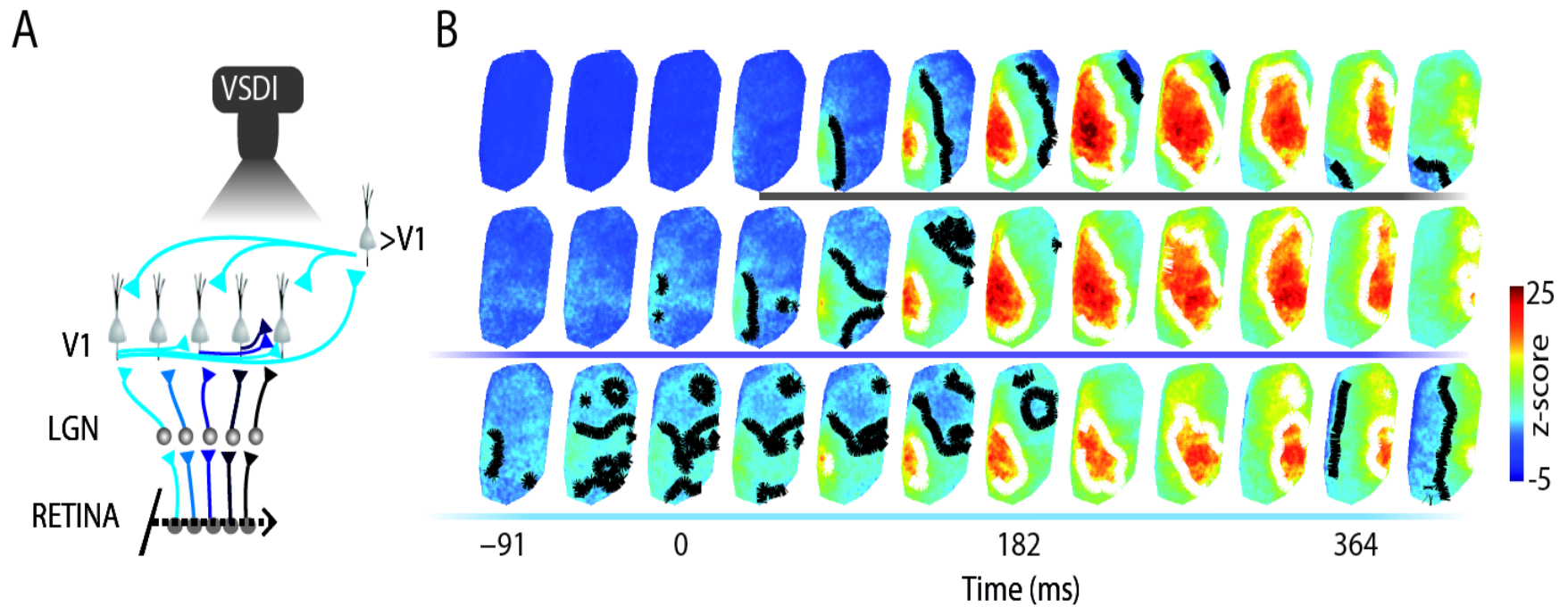
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Upcoming light

# The visual flow



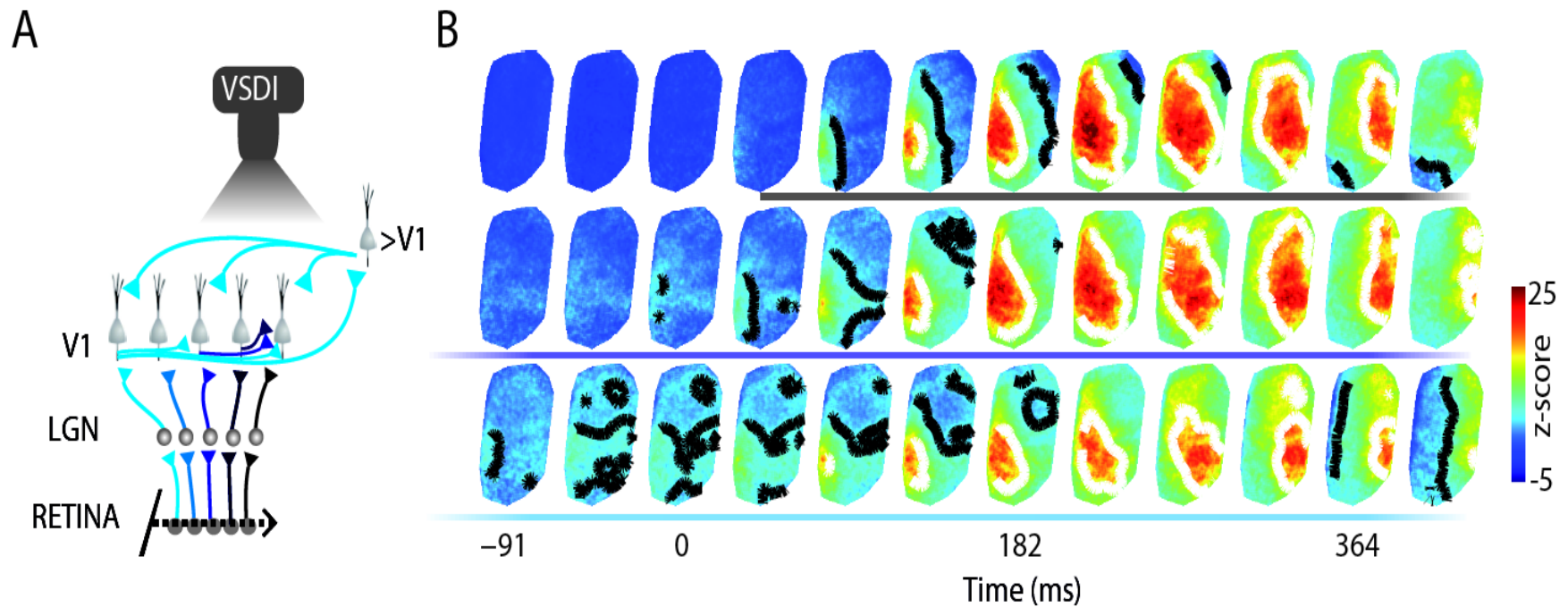
# Visual Anticipation



Source : Benvenuti et al. 2015

# Visual Anticipation

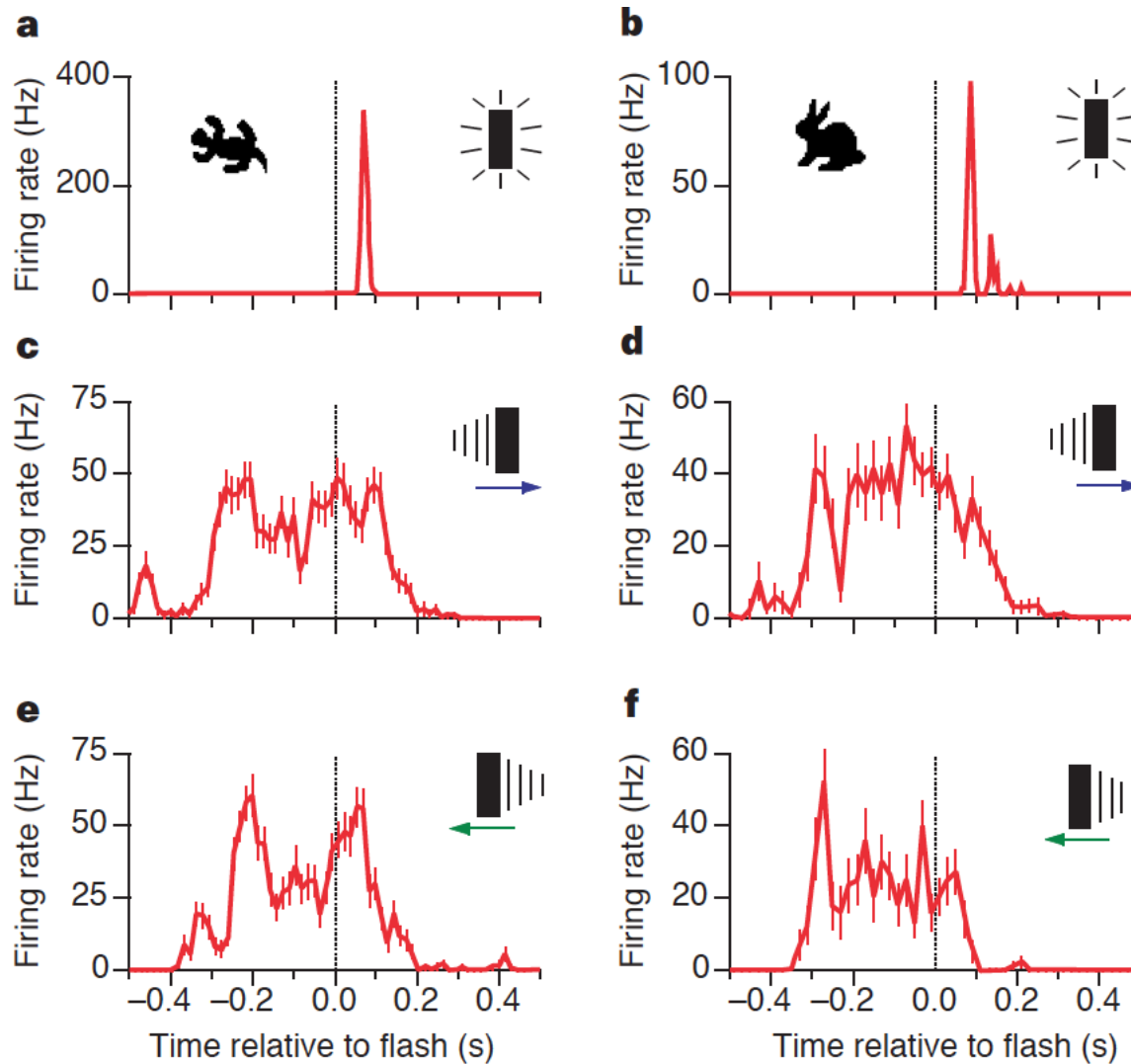
**Anticipation** is carried out by the primary visual cortex (V1) through an activation wave



Source : Benvenuti et al. 2015

# Visual Anticipation

**Anticipation** also takes place in the retina



Source :  
Berry et al.  
1999



# Visual Anticipation

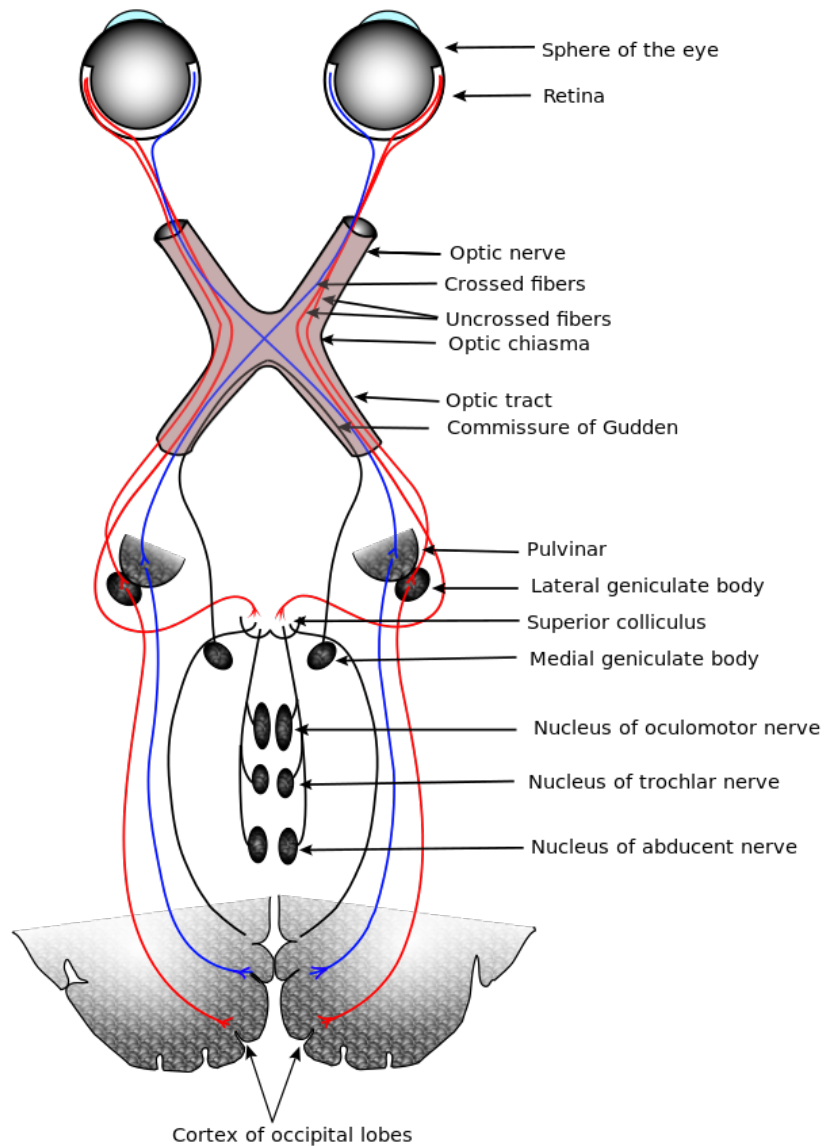


## Trajectory

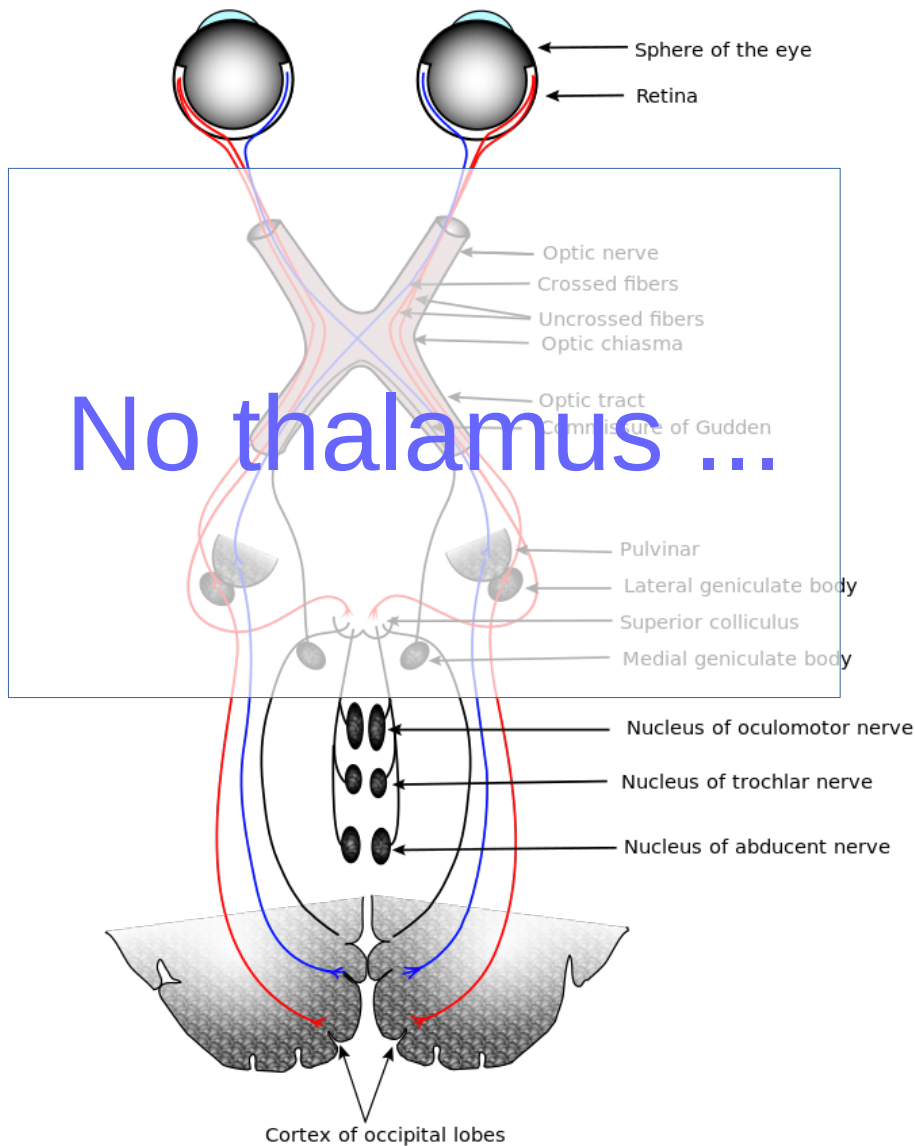
**What are the respective :**

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

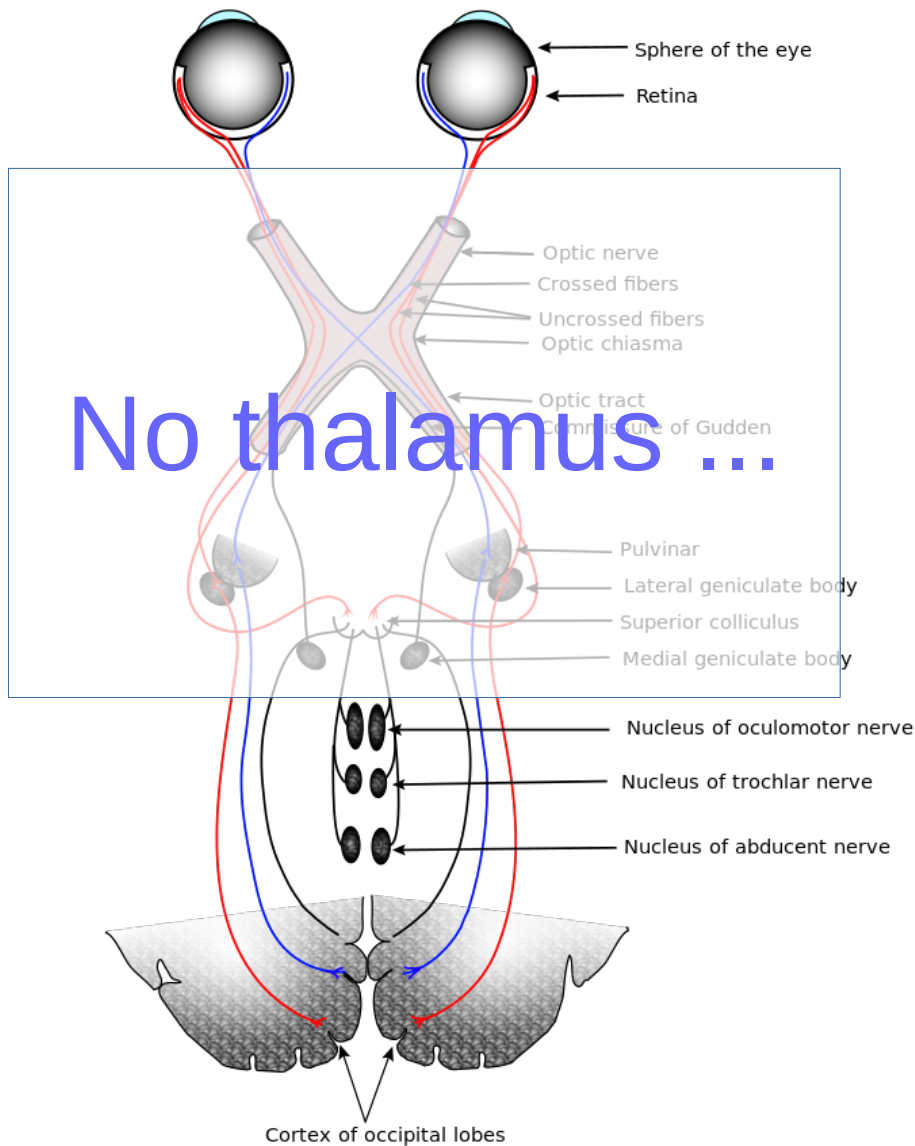
# Visual Anticipation



# Visual Anticipation

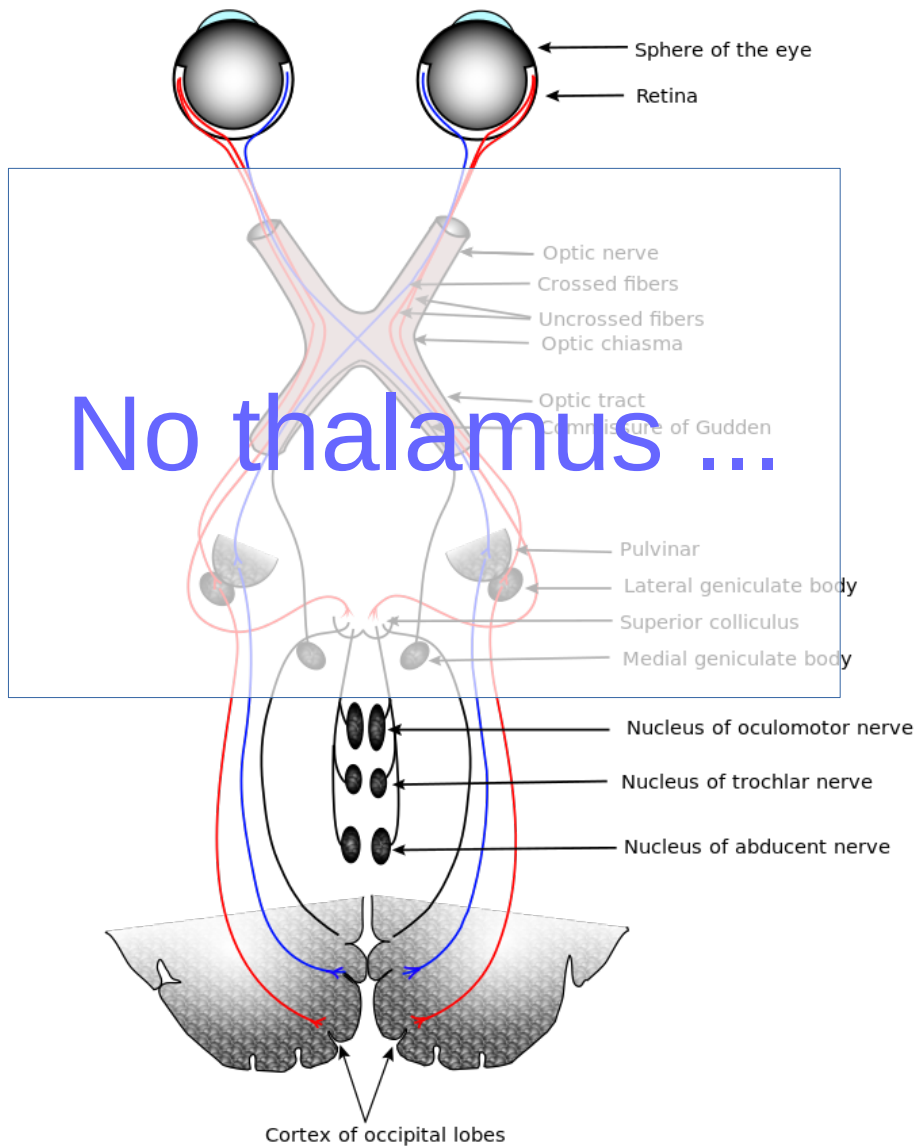


# Visual Anticipation



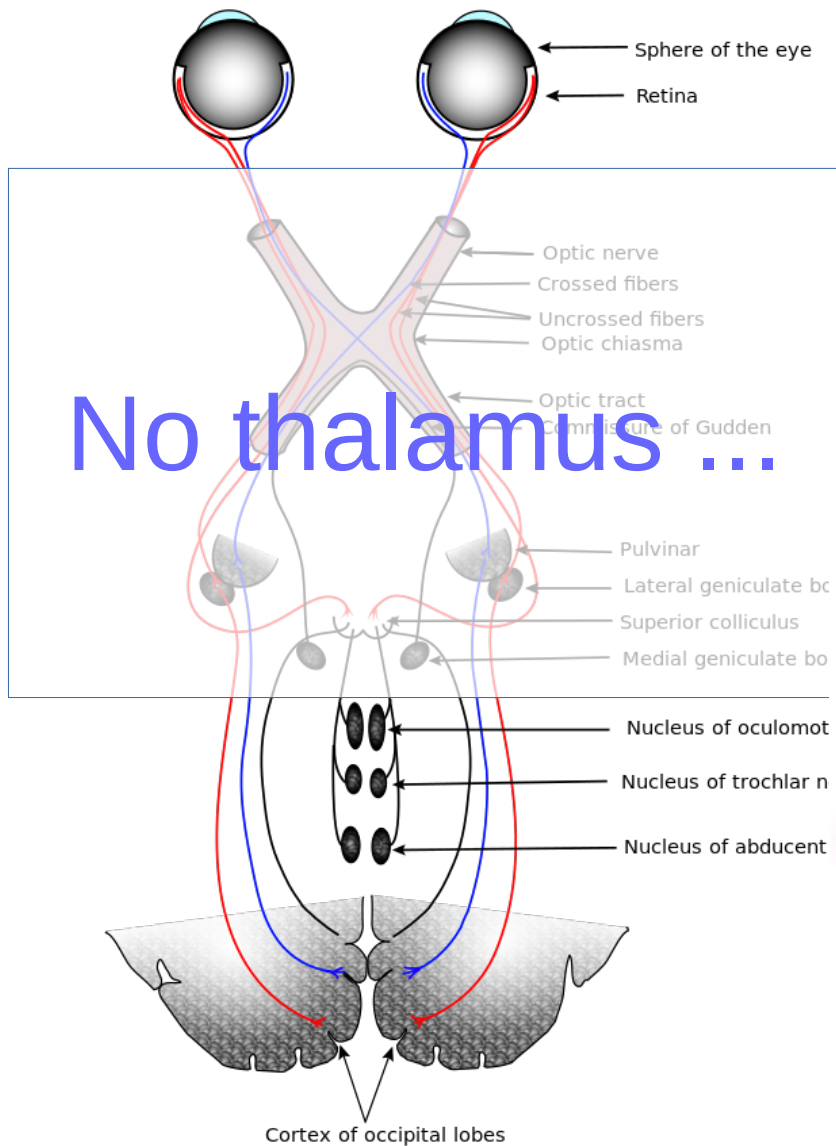
Which animal ?

# Visual Anticipation



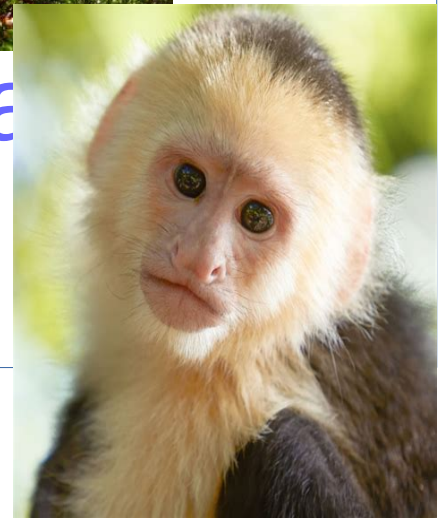
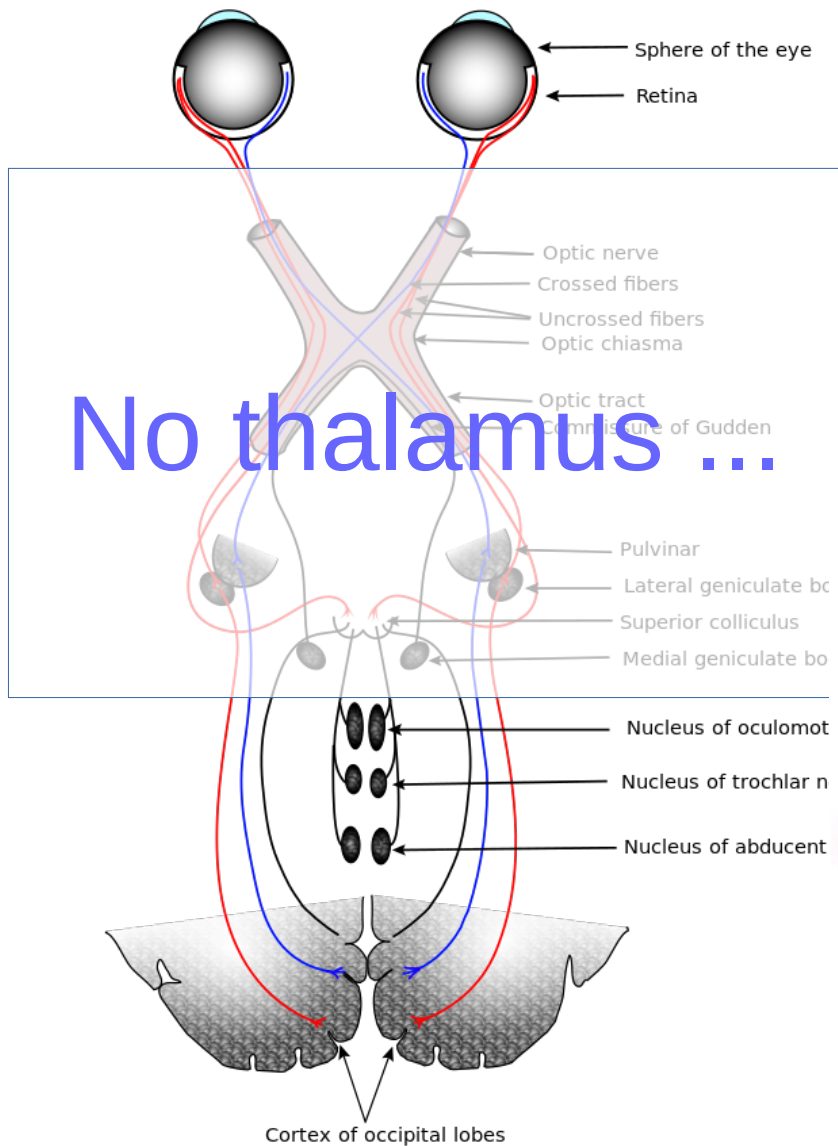
Which animal ?

# Visual Anticipation

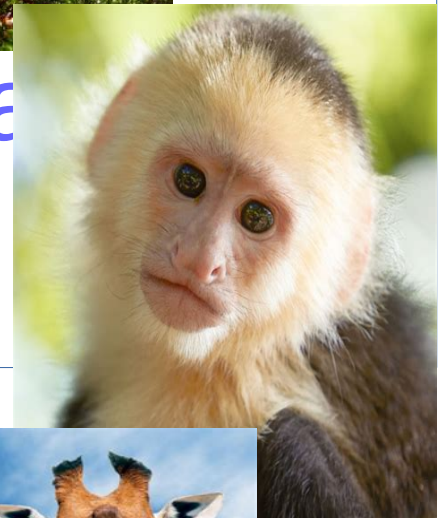
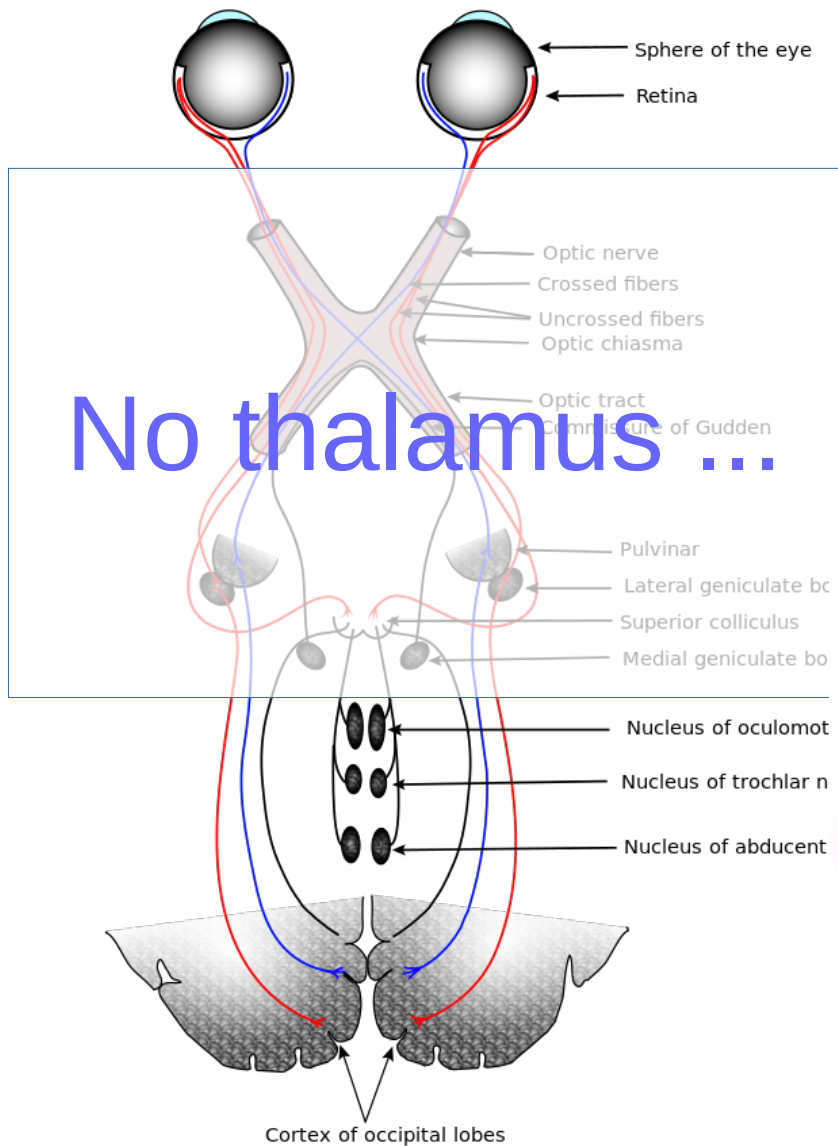


ch animal ?

# Visual Anticipation

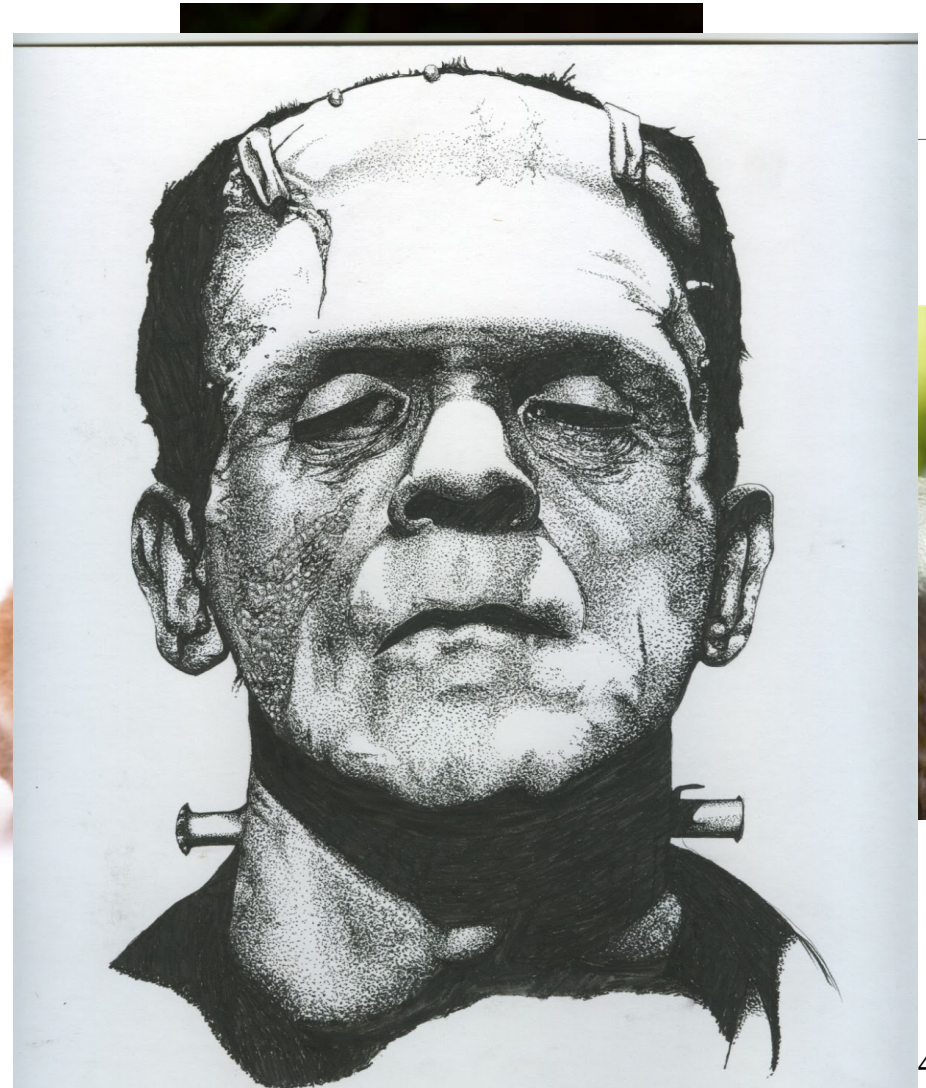
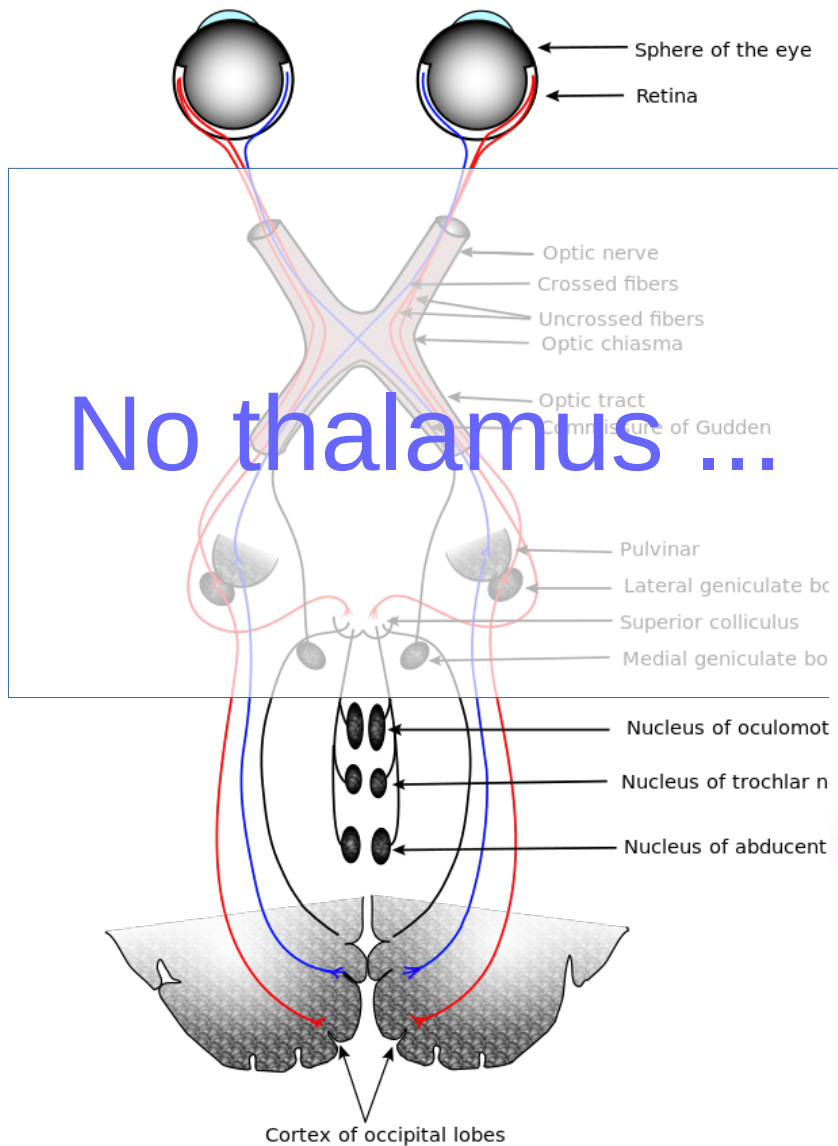


# Visual Anticipation





# Visual Anticipation



# Visual Anticipation

Developing a retino-cortical model of anticipation so as to

understand / propose

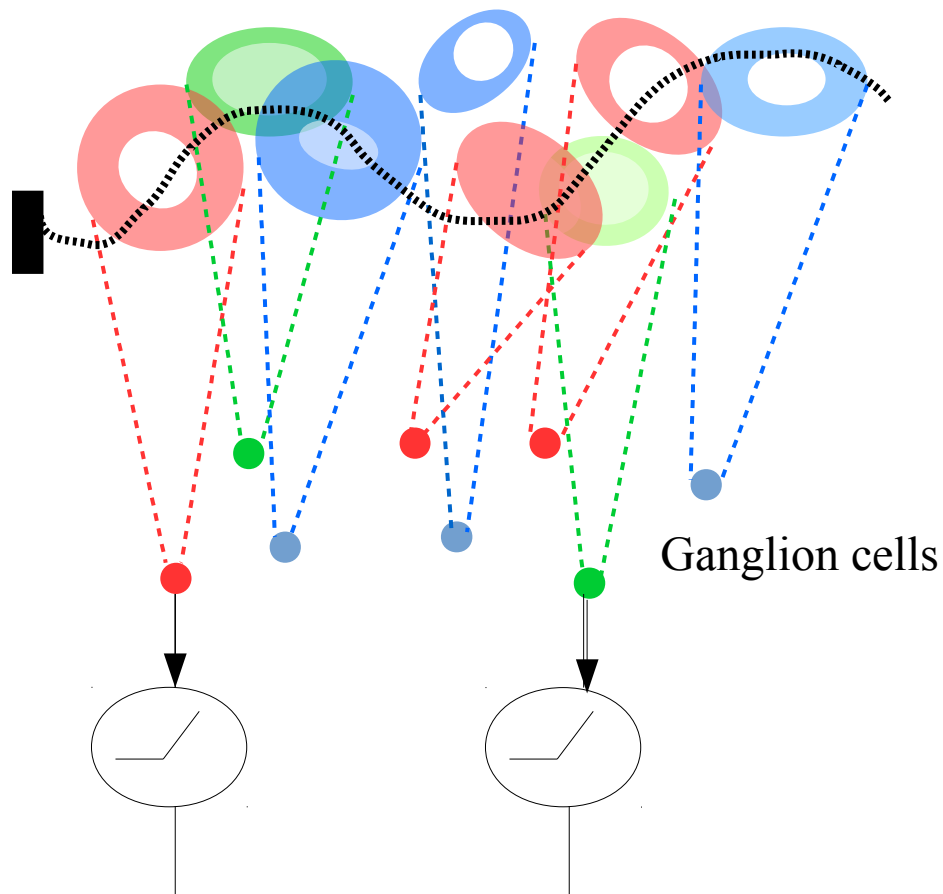
possible mechanisms for anticipation in the retina and in the cortex.

# Anticipation in the retina

# The Hubel-Wiesel view of vision

Nobel prize 1981

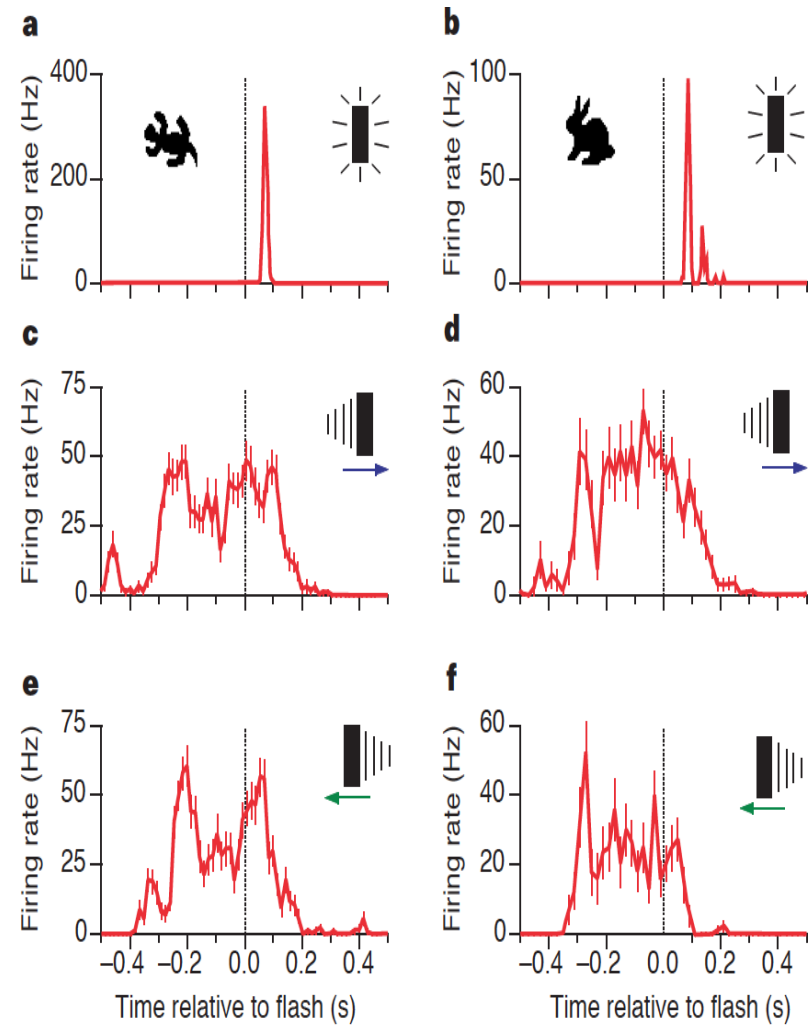
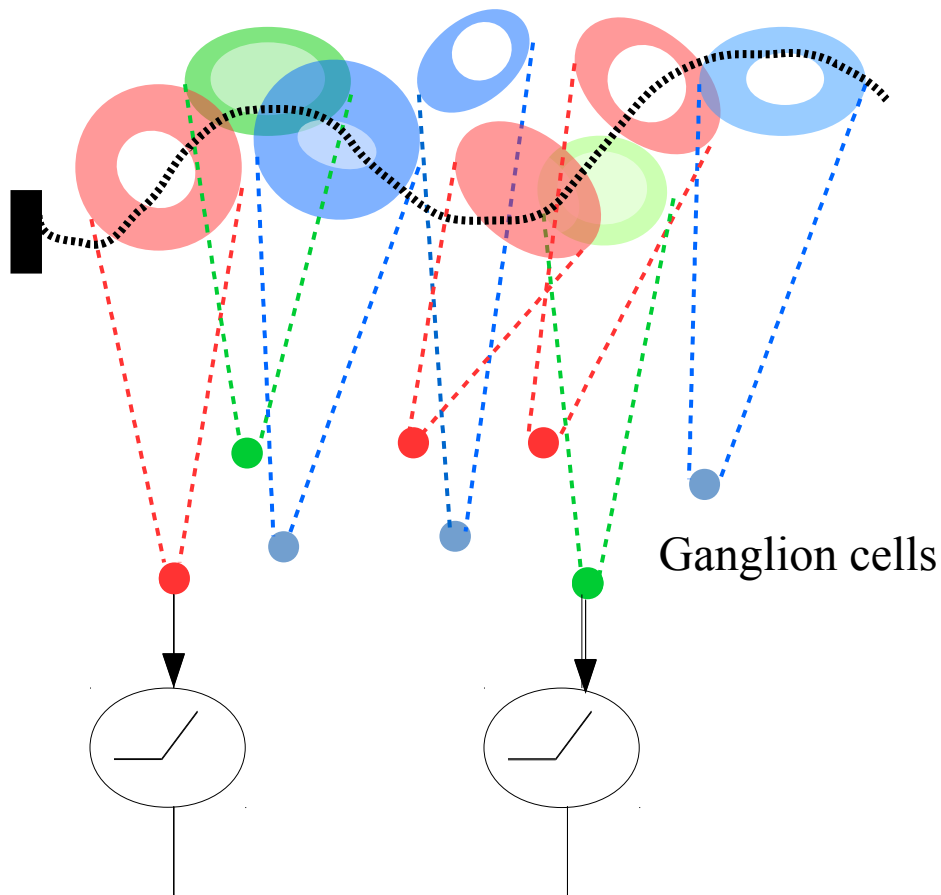
Ganglion cells response is the convolution of the stimulus with a spatio-temporal receptive field followed by a non linearity



Ganglion cells are independent encoders

# The Hubel-Wiesel view of vision

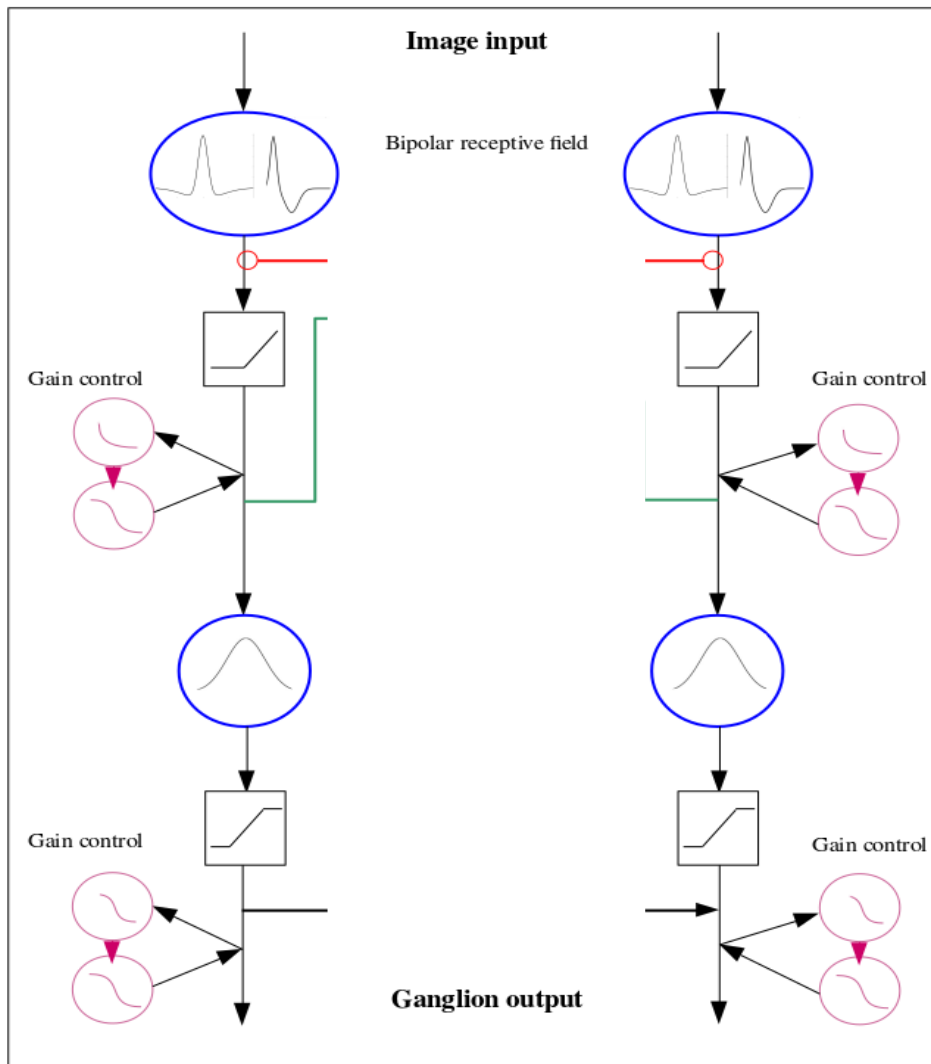
Nobel prize 1981



Source : Berry et al. 1999

# Building a 2D retina model for motion anticipation

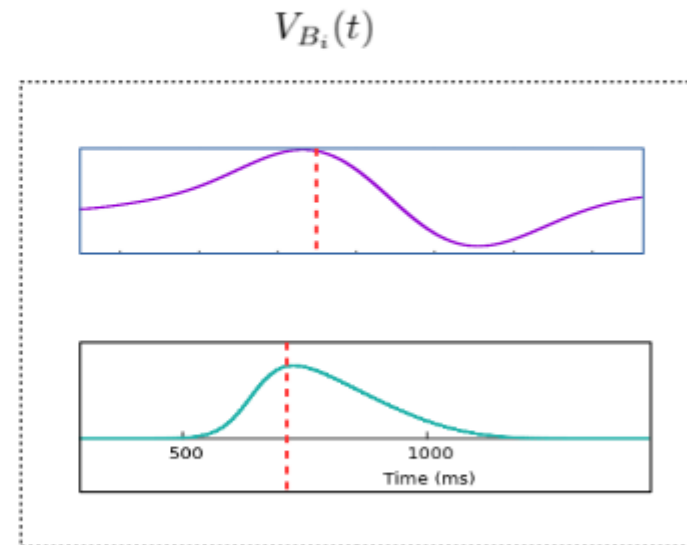
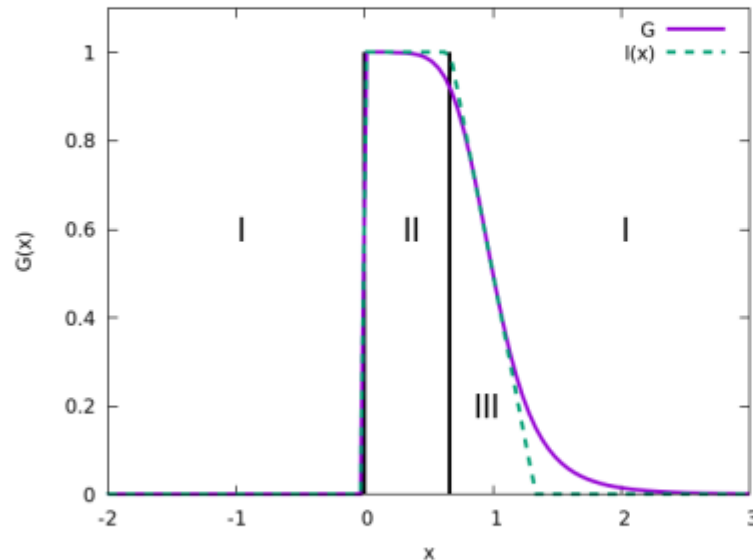
## Gain control (Chen et al. 2013)



# Building a 2D retina model for motion anticipation

## 1) Gain control

How does it work ?

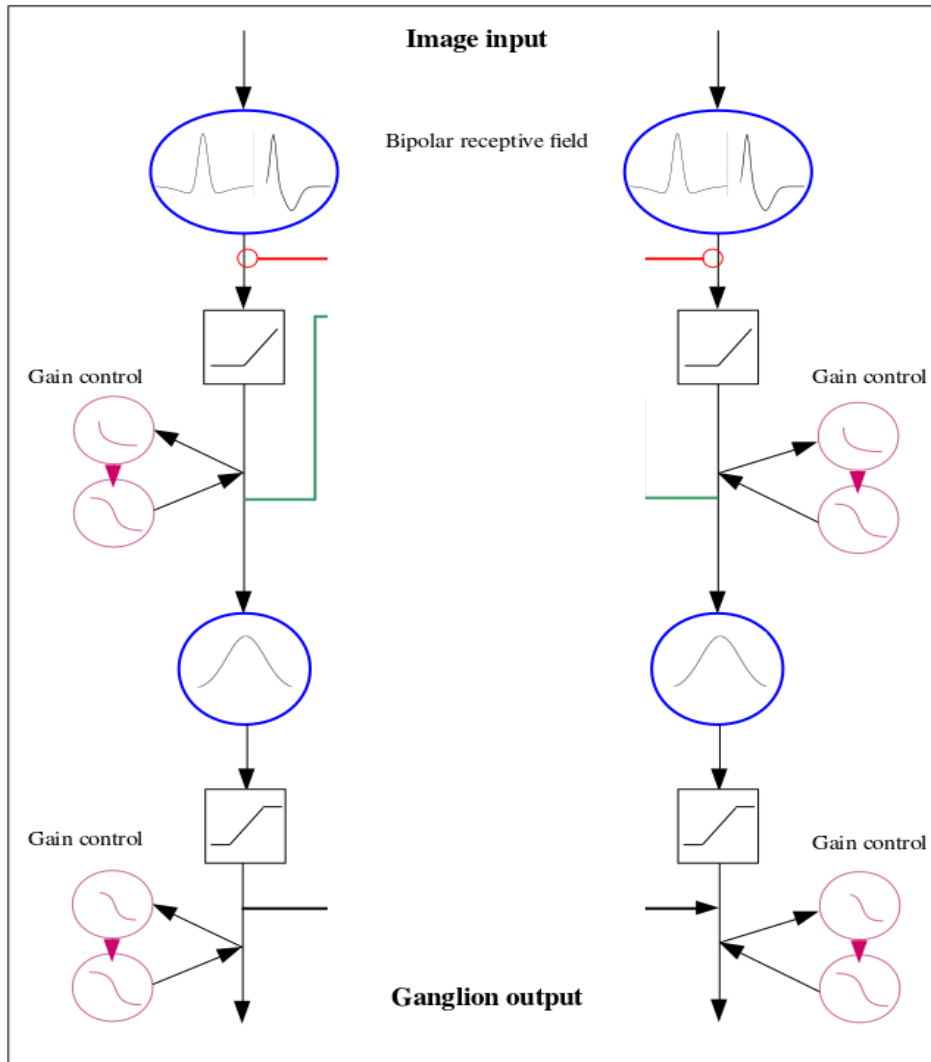


$$\mathcal{G}_B(A) = \begin{cases} 0, & \text{if } A \leq 0; \\ \frac{1}{1+A^6}, & \text{else.} \end{cases}$$

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

# Building a 2D retina model for motion anticipation

## Gain control (Chen et al. 2013)



- 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 :

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

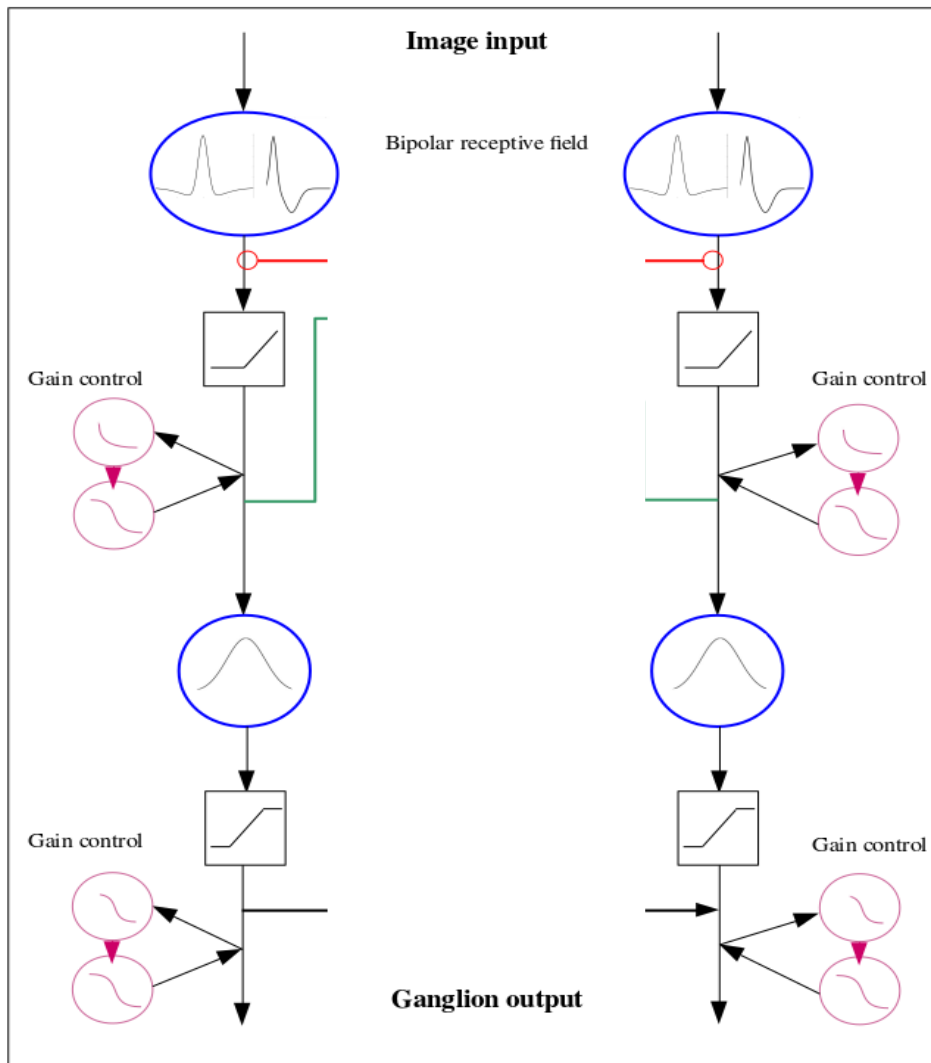
- Output :

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



# 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 :

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

- Activation function :

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

- Gain Control function :

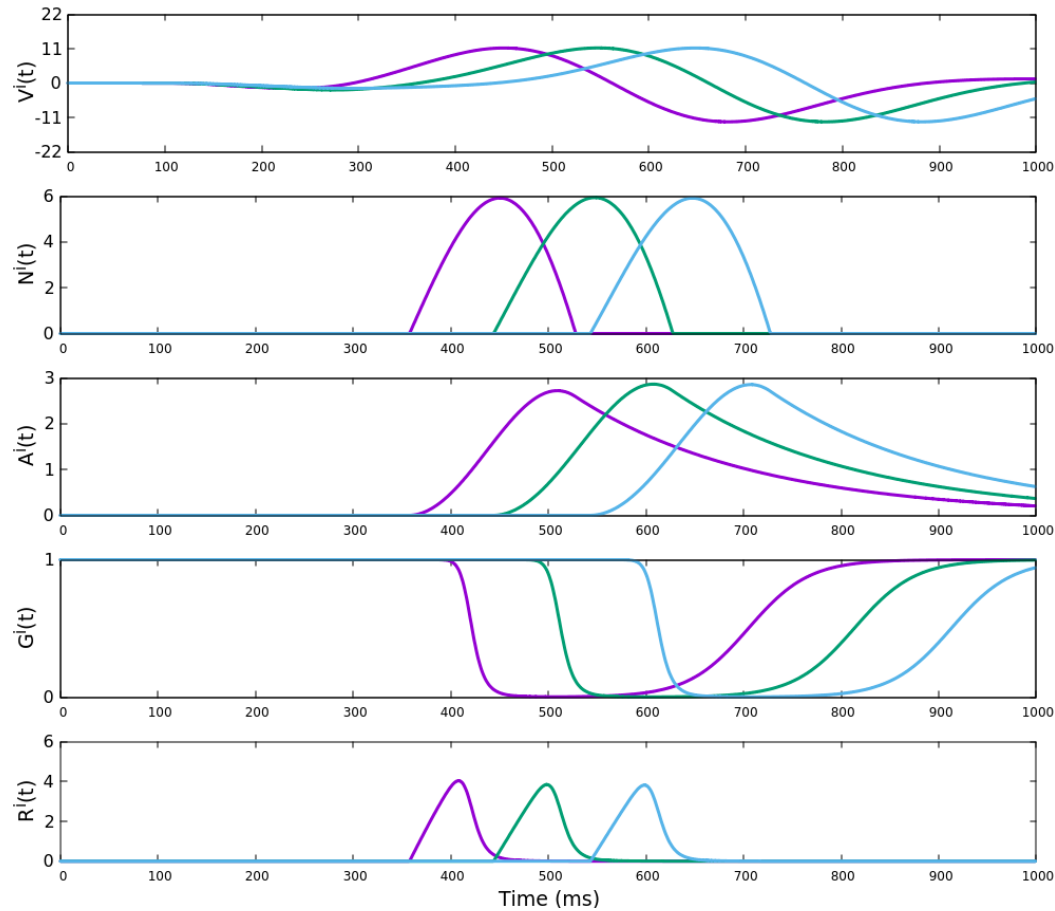
$$G_{G_F}(A) = \begin{cases} 0, & \text{if } A \leq 0; \\ \frac{1}{1+A}, & \text{else.} \end{cases}$$

- Output :

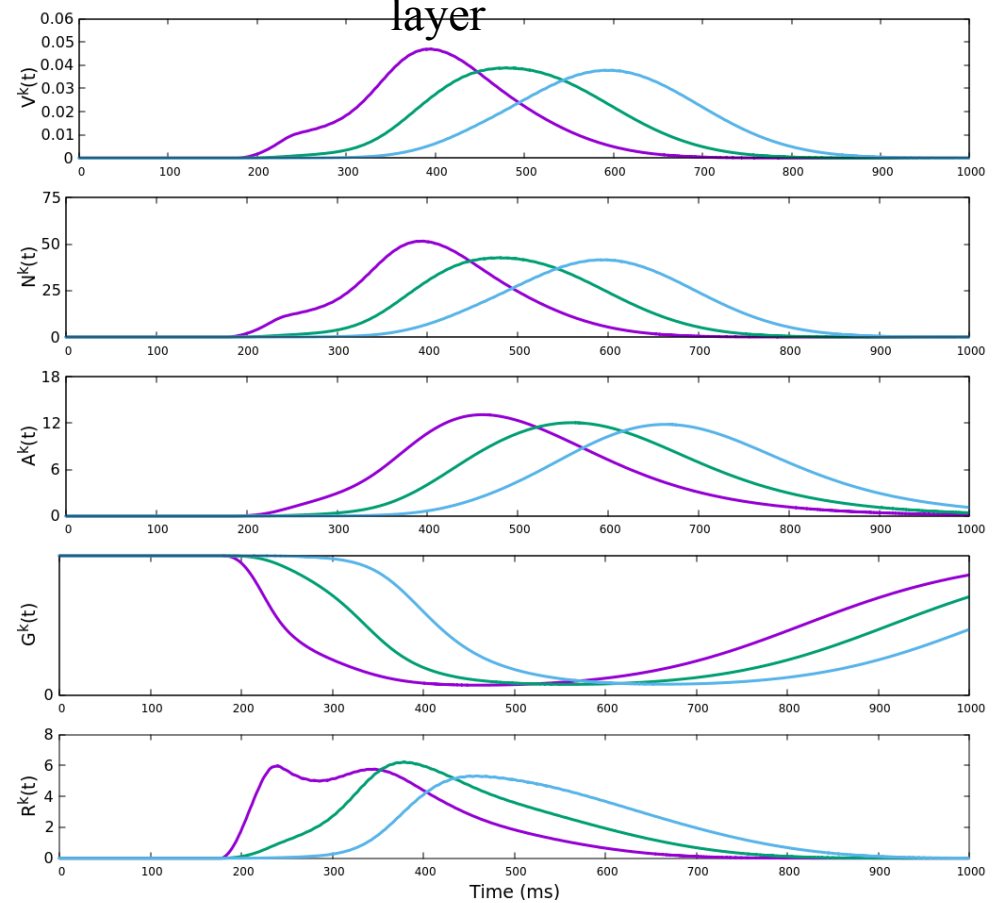
$$R_{G_F k_F}(V_{G_F k_F}, A_{G_F k_F}) = N_{G_F}(V_{G_F k_F}) G_{G_F}(A_{G_F k_F}).$$

# 1D results : smooth motion anticipation with gain control

Bipolar layer

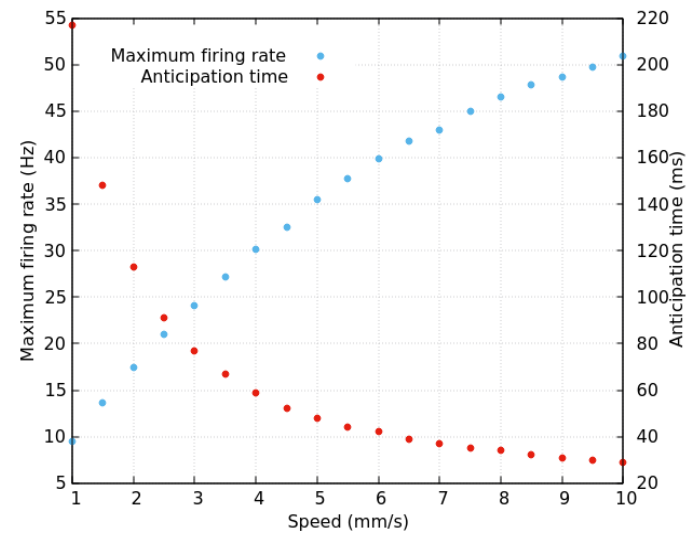
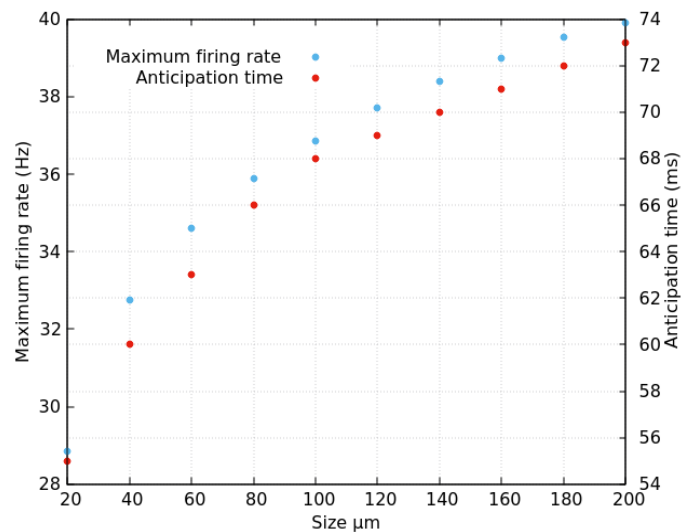
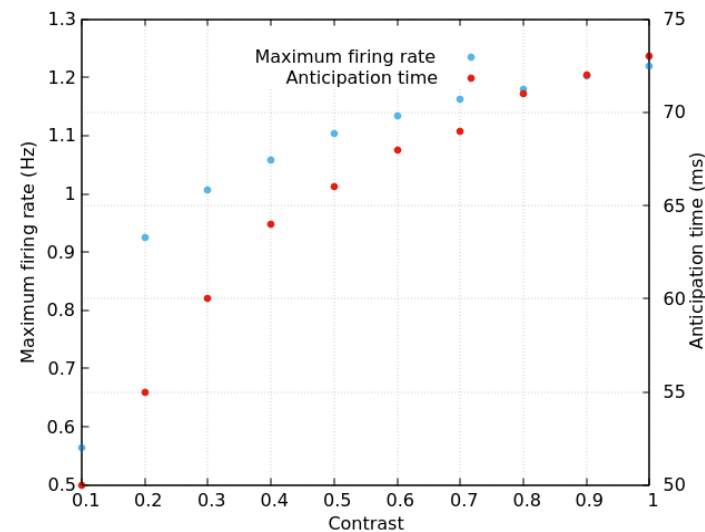


Ganglion layer

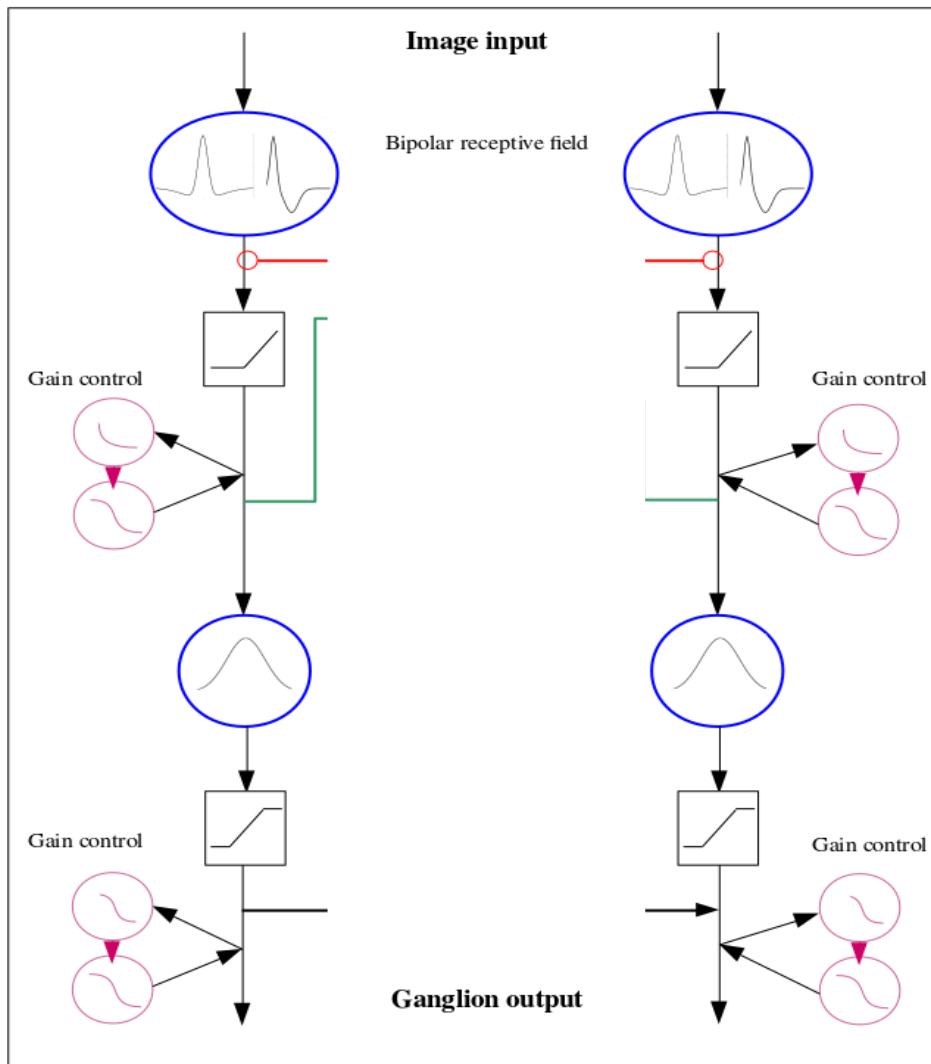


# 1D results : smooth motion anticipation with gain control

Anticipation variability with stimulus  
parameters



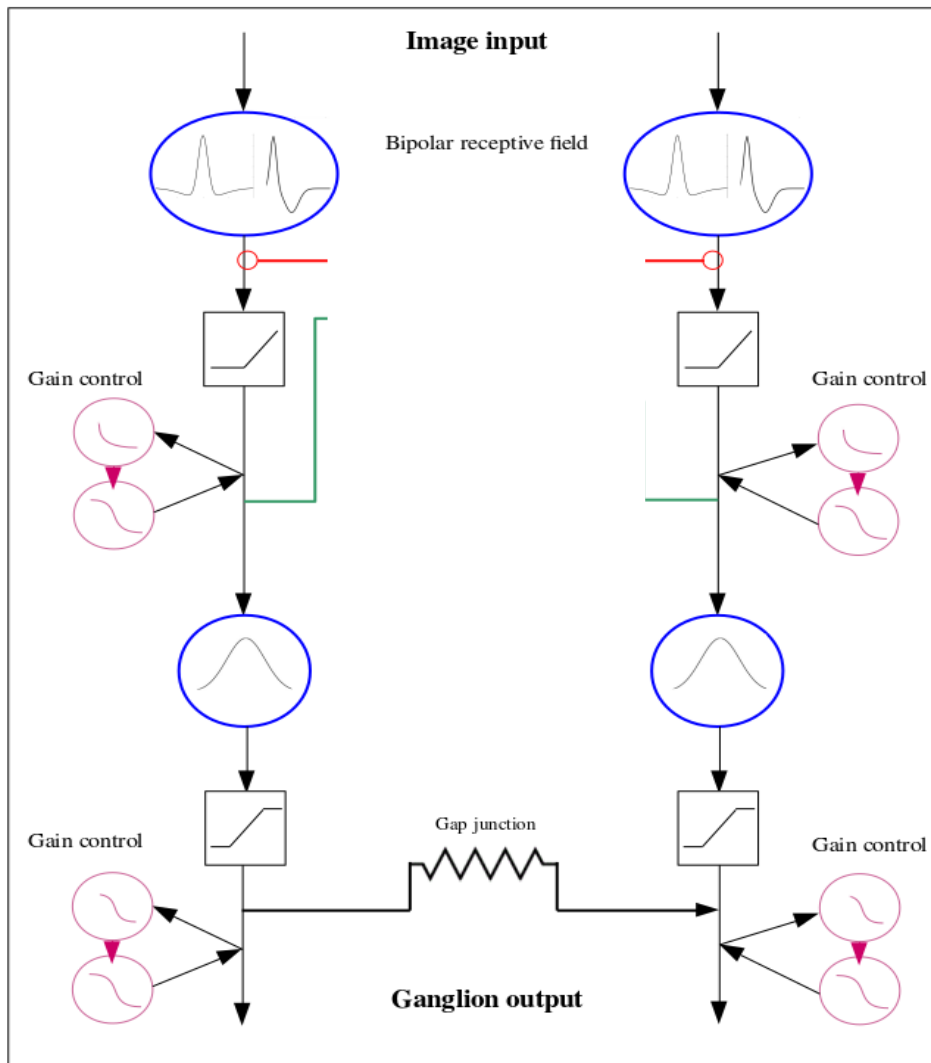
# Building a 2D retina model for motion anticipation



Ganglion cells are independent encoders

# Building a 2D retina model for motion anticipation

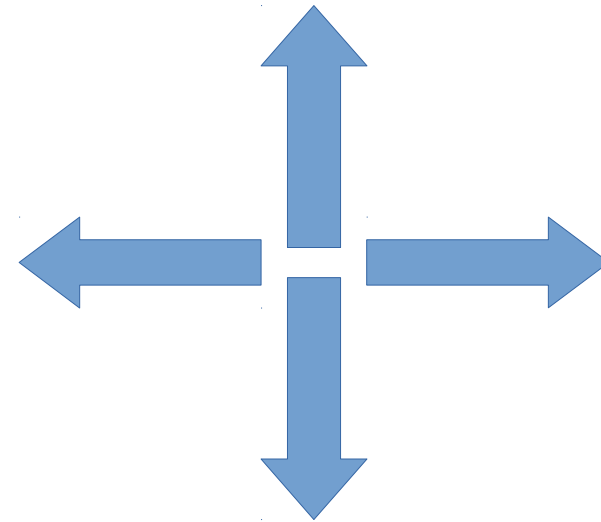
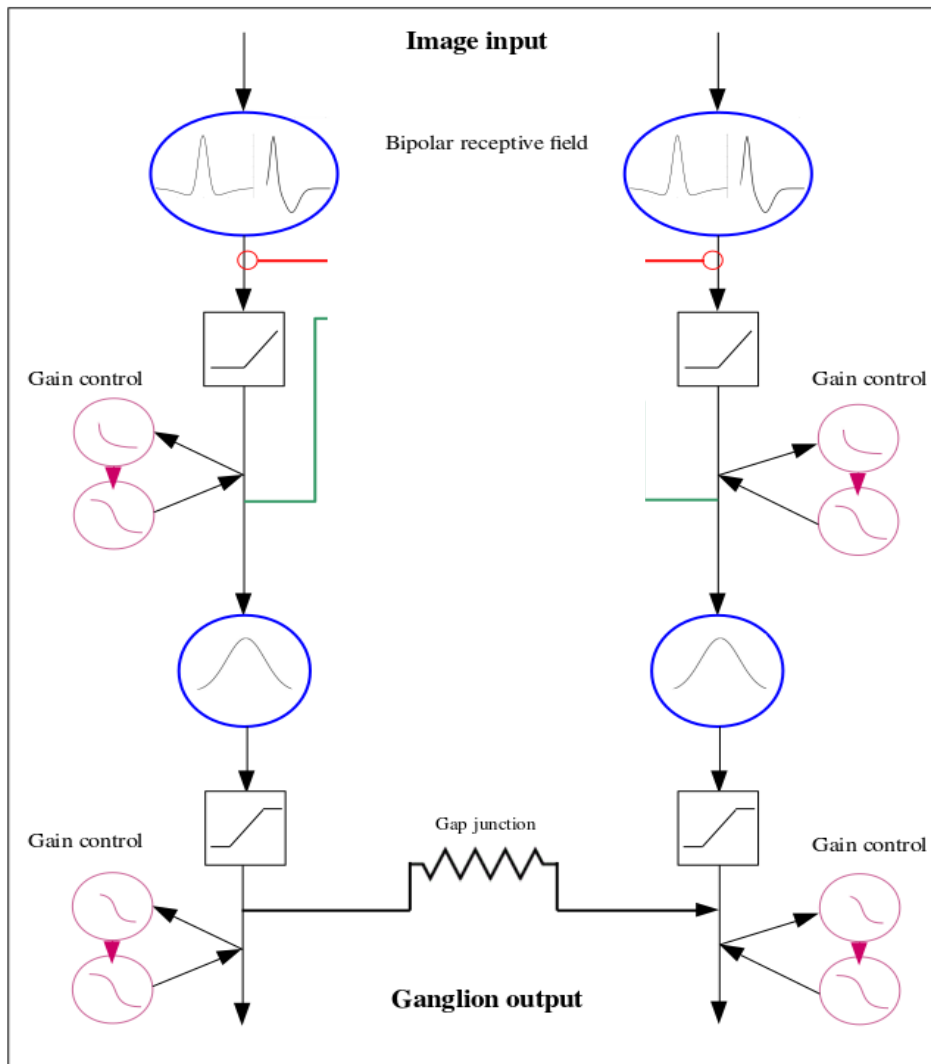
## Gap junctions connectivity



Ganglion cells are **not** independent encoders

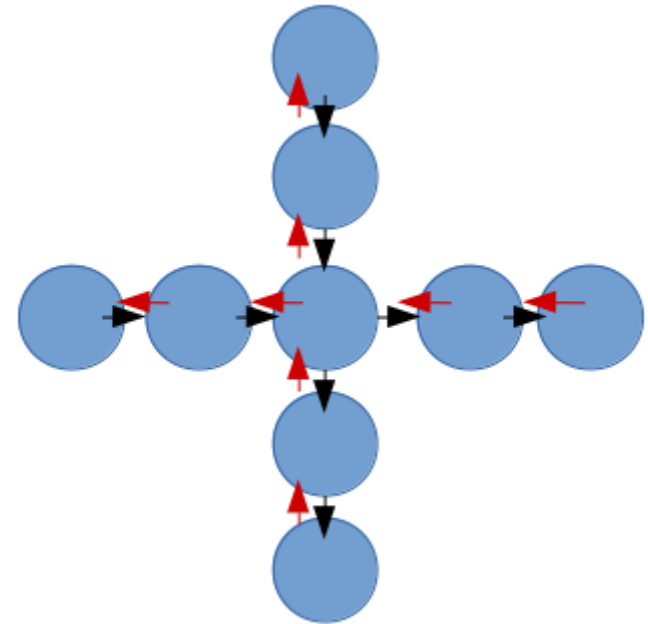
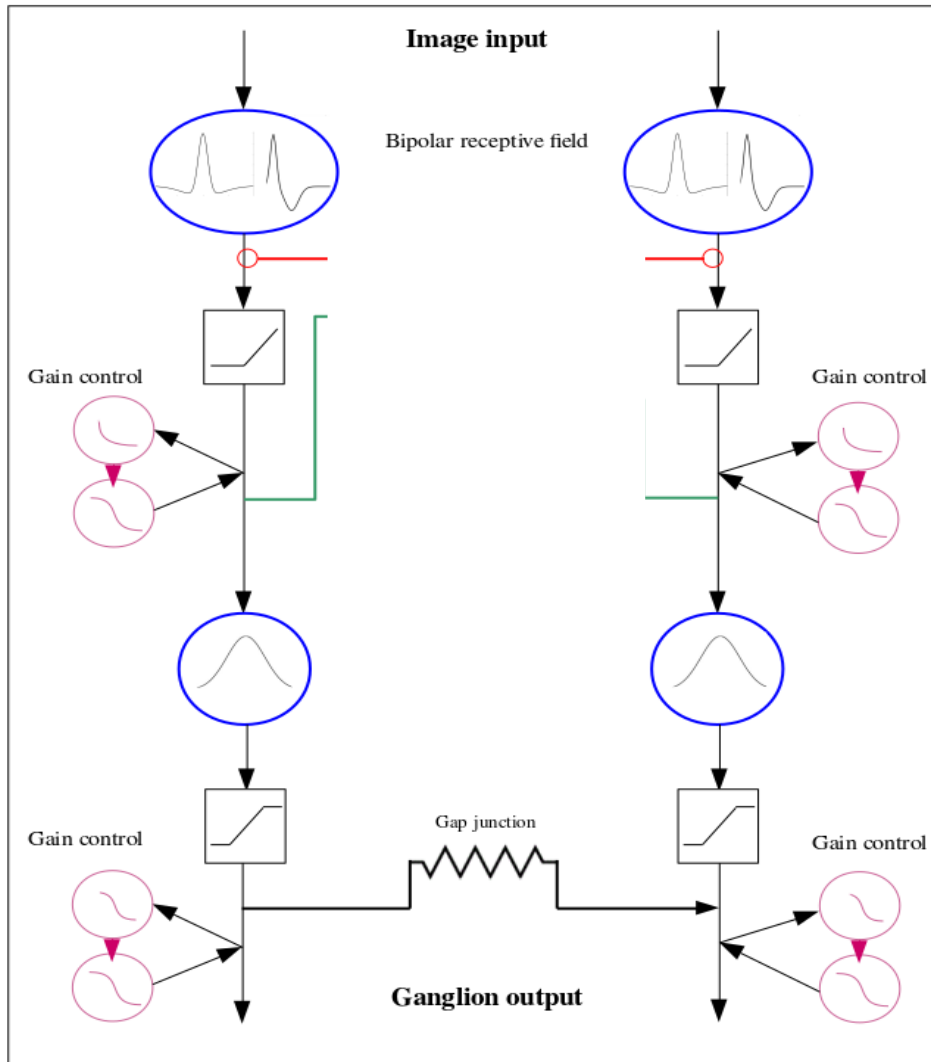
# Building a 2D retina model for motion anticipation

## Gap junctions connectivity



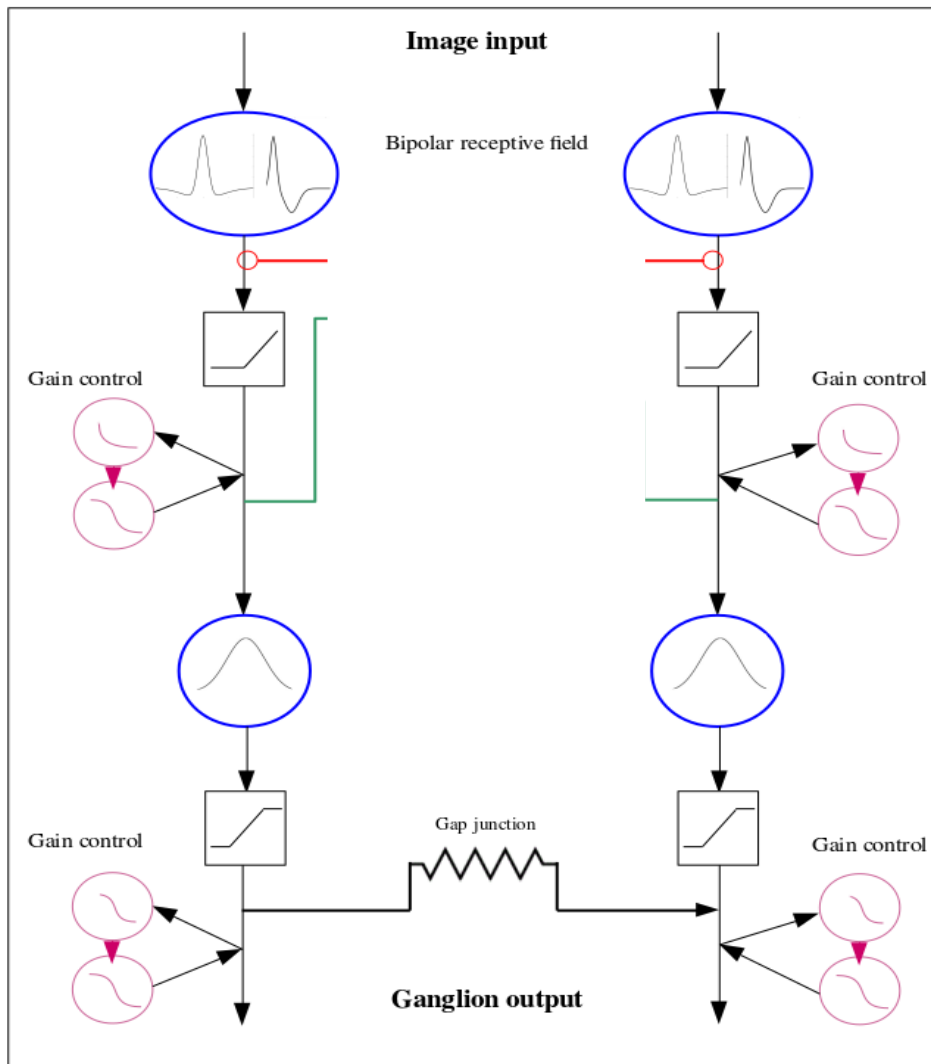
# Building a 2D retina model for motion anticipation

## Gap junctions connectivity

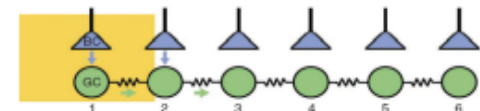


# Building a 2D retina model for motion anticipation

## 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

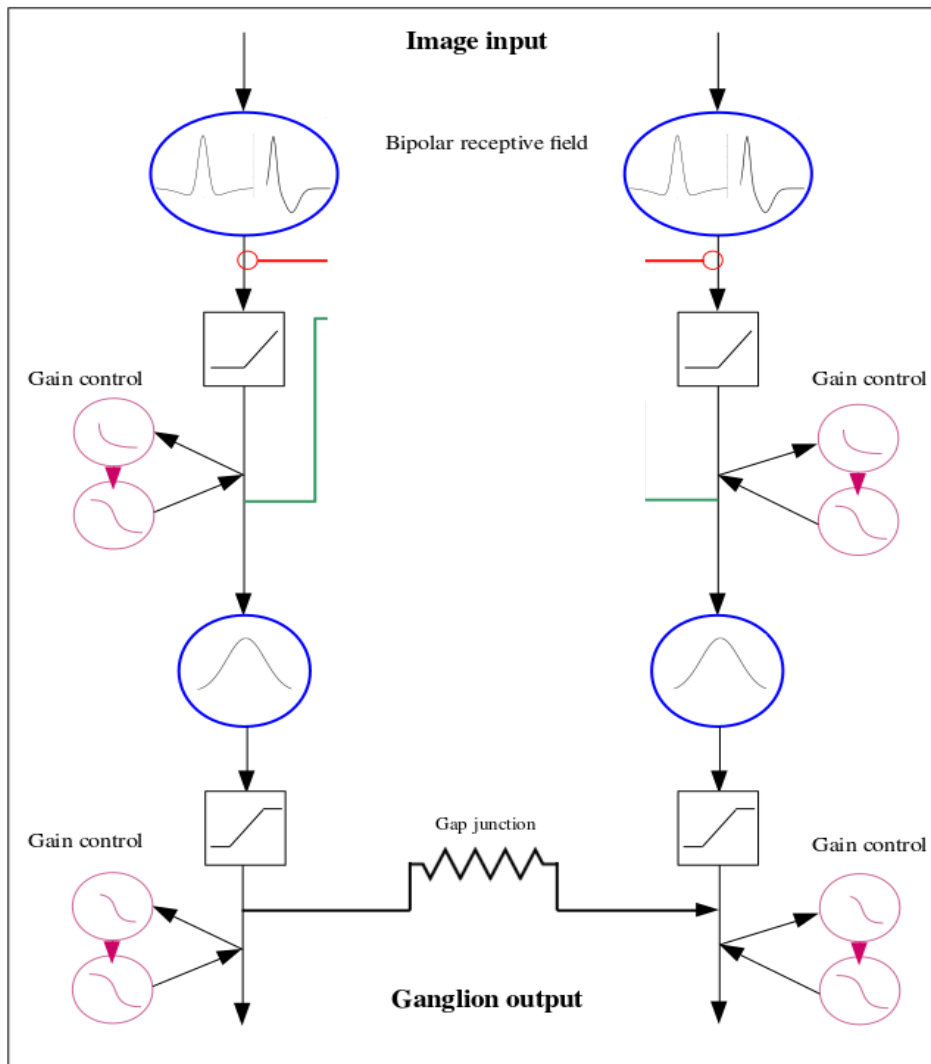


$$R_{GDkD} = V_{GDkD} + \beta R_{GDkD-1}$$



# Building a 2D retina model for motion anticipation

## Gap junctions connectivity

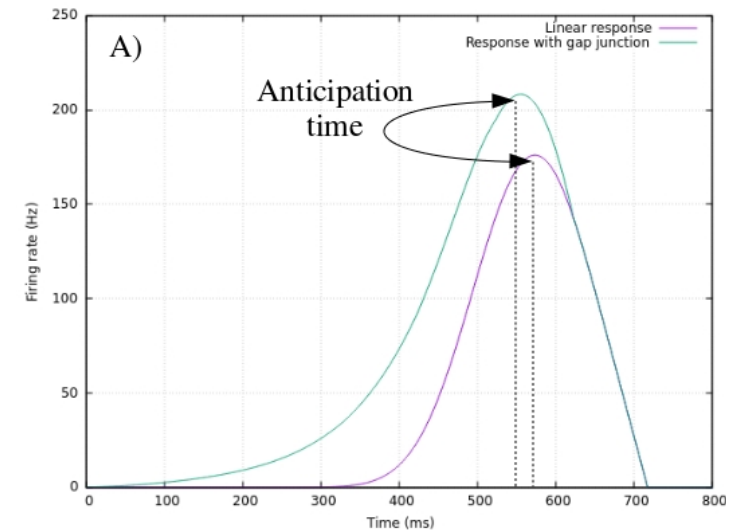
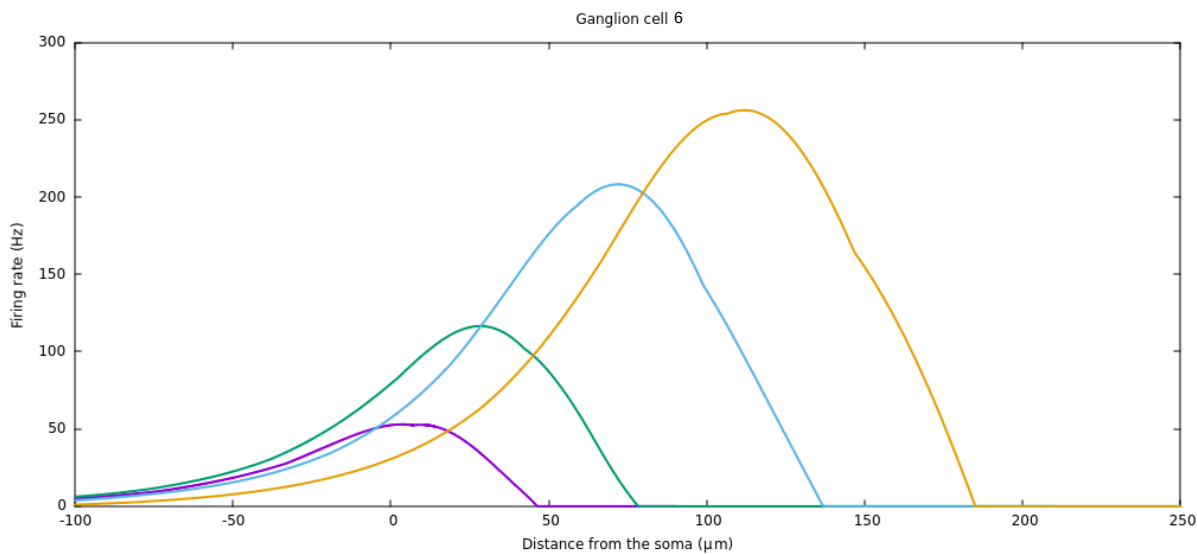
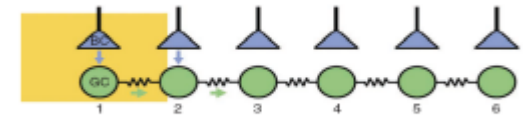


- A class of direction selective RGCs are connected through gap junctions
- Their activity comprises the activity pooled from bipolar cells and the activity coming from the downstream RGCs, in the direction of motion

Diffusive wave of activity  
ahead of the motion

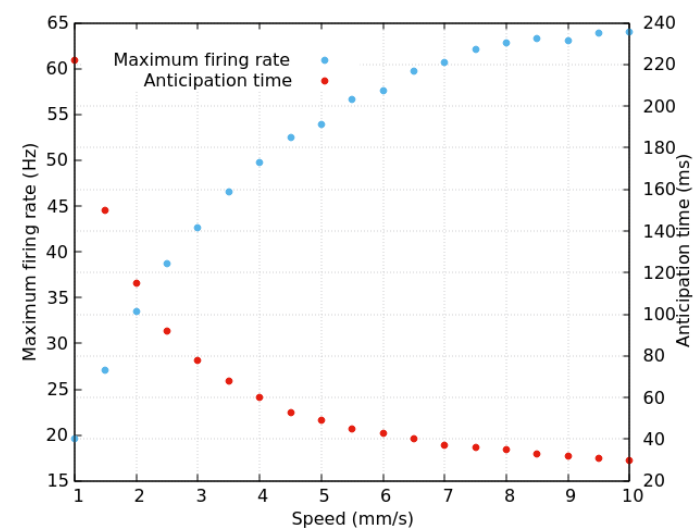
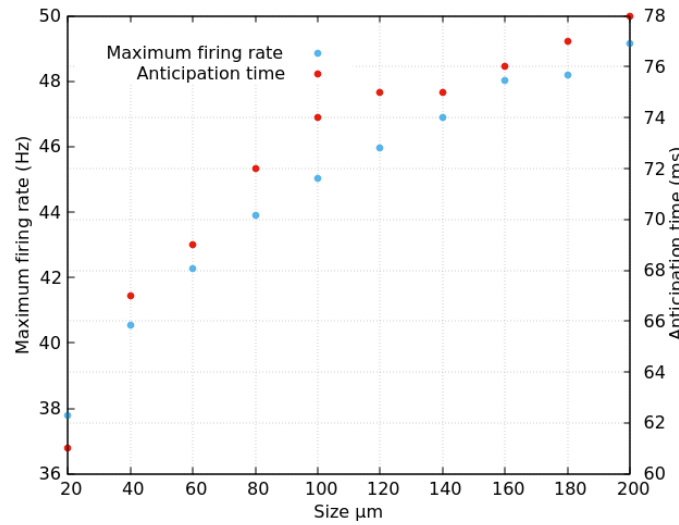
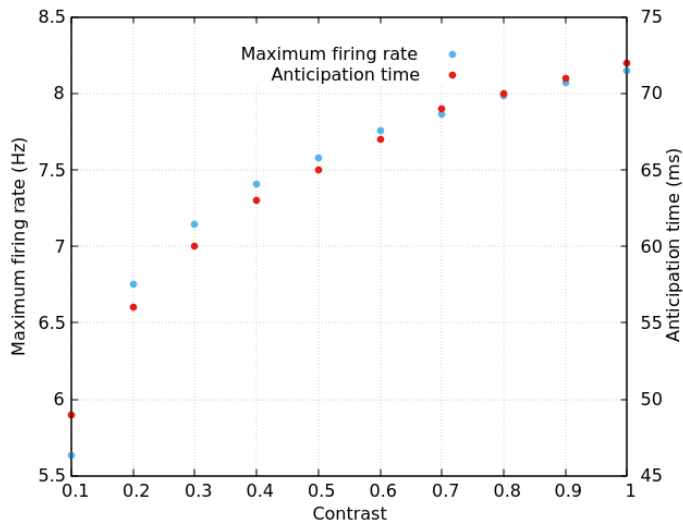
$$R_{GDkD} = V_{GDkD} + \beta R_{GDkD-1}$$

# 1D results : smooth motion anticipation with gap junctions

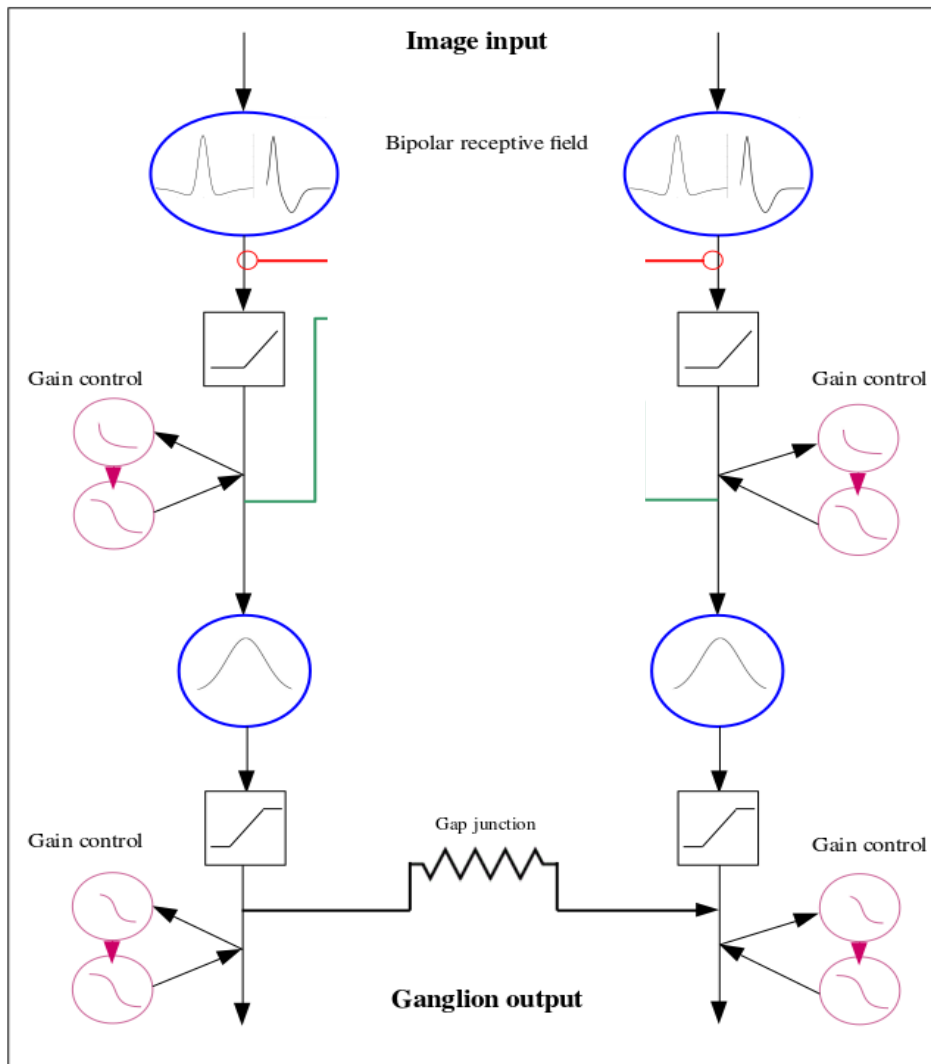


# 1D results : smooth motion anticipation with gap junctions

Anticipation variability with stimulus  
parameters

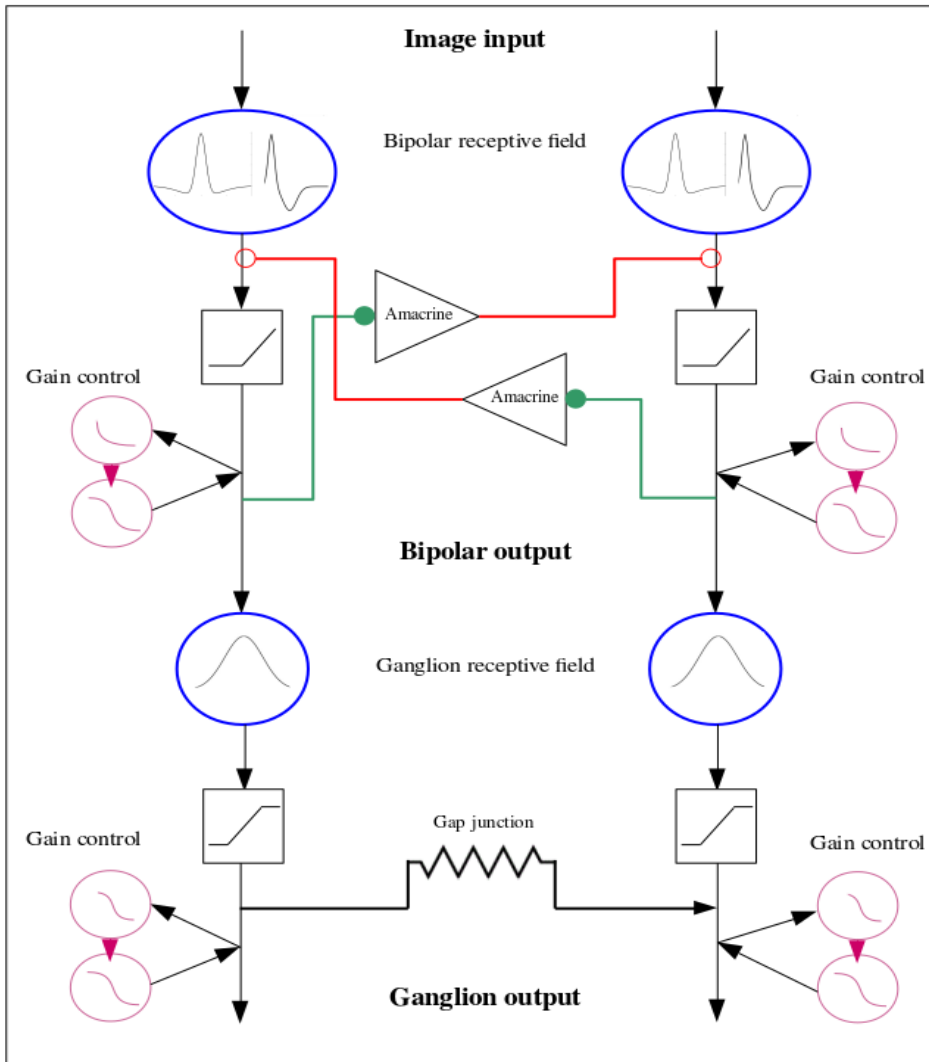


# Building a 2D retina model for motion anticipation



# 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

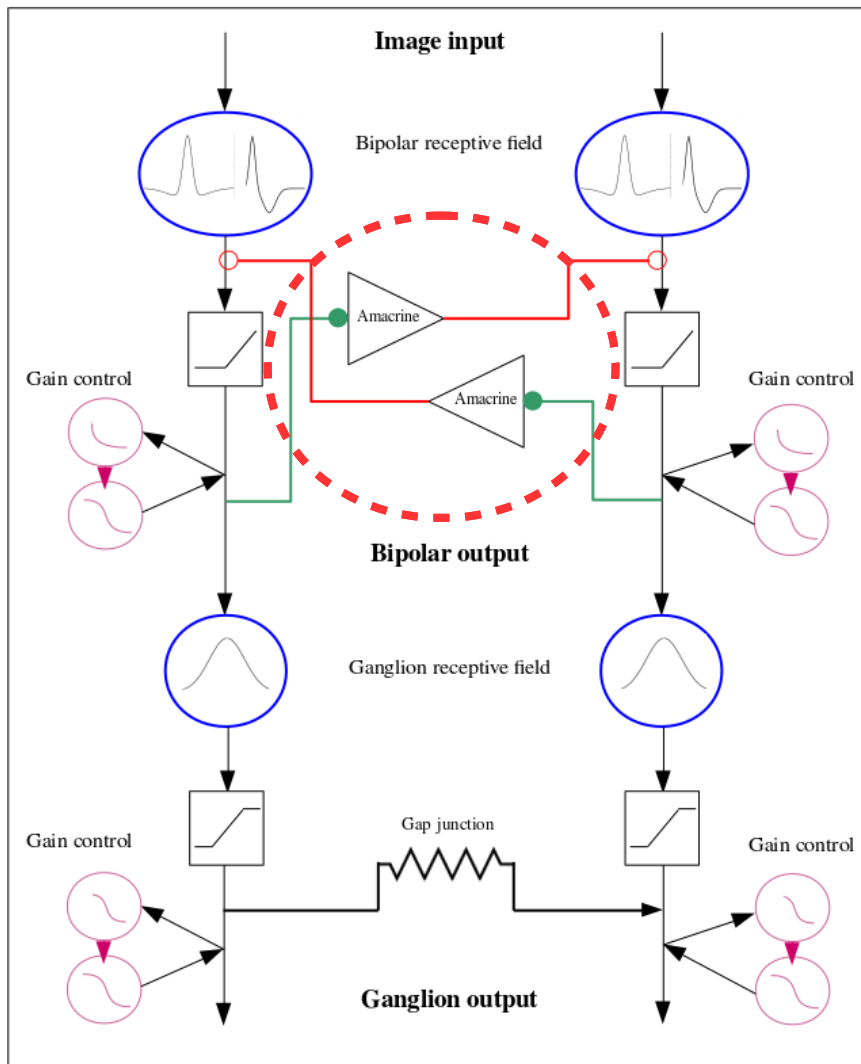
- A class of RGCs are selective to differential motion



- The circuitry involves amacrine cells connectivity upstream of ganglion cells

# Connectivity pathways

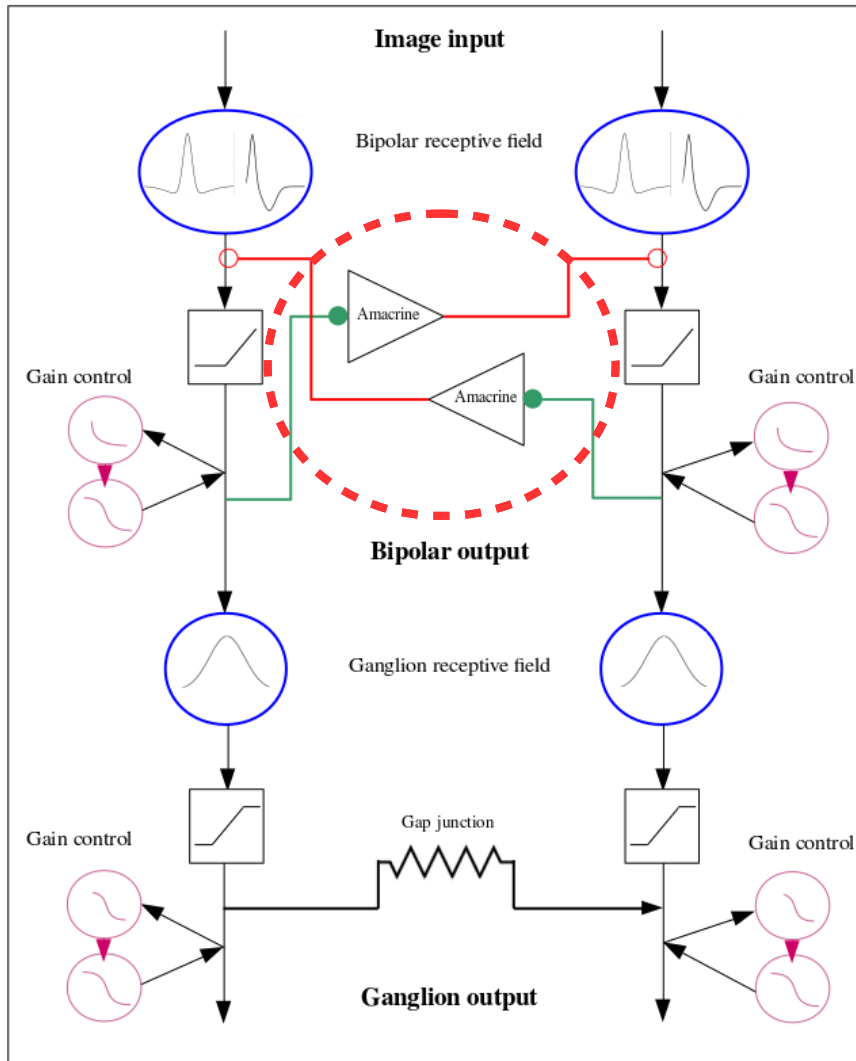
## Amacrine cells connectivity





# 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 :

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

- Amacrine voltage :

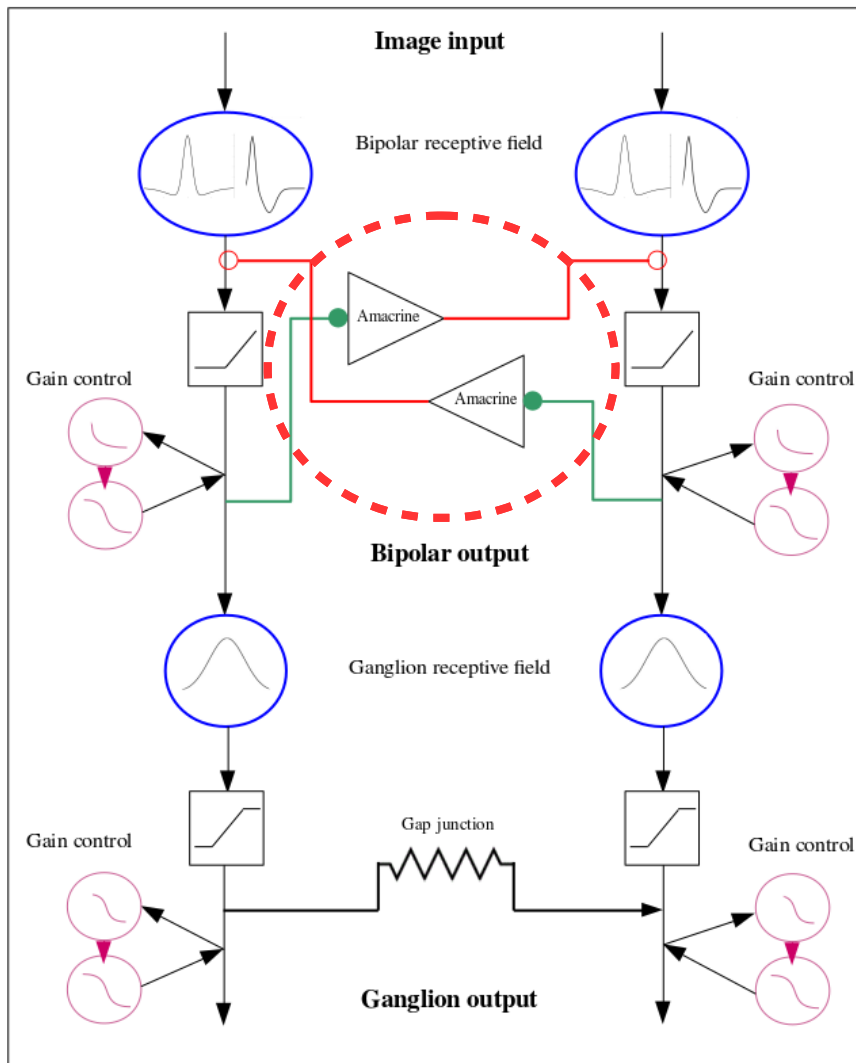
$$\frac{dV_{A_j}}{dt} = -\frac{1}{\tau_A} V_{A_j}(t) + \sum_{i=1}^{N_A} W_{A_j}^{B_i} R_{B_i}(t).$$

- Coupled dynamics :

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

# 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 :

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

- Amacrine voltage :

Anti diffusive wave of activity ahead of the bar

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

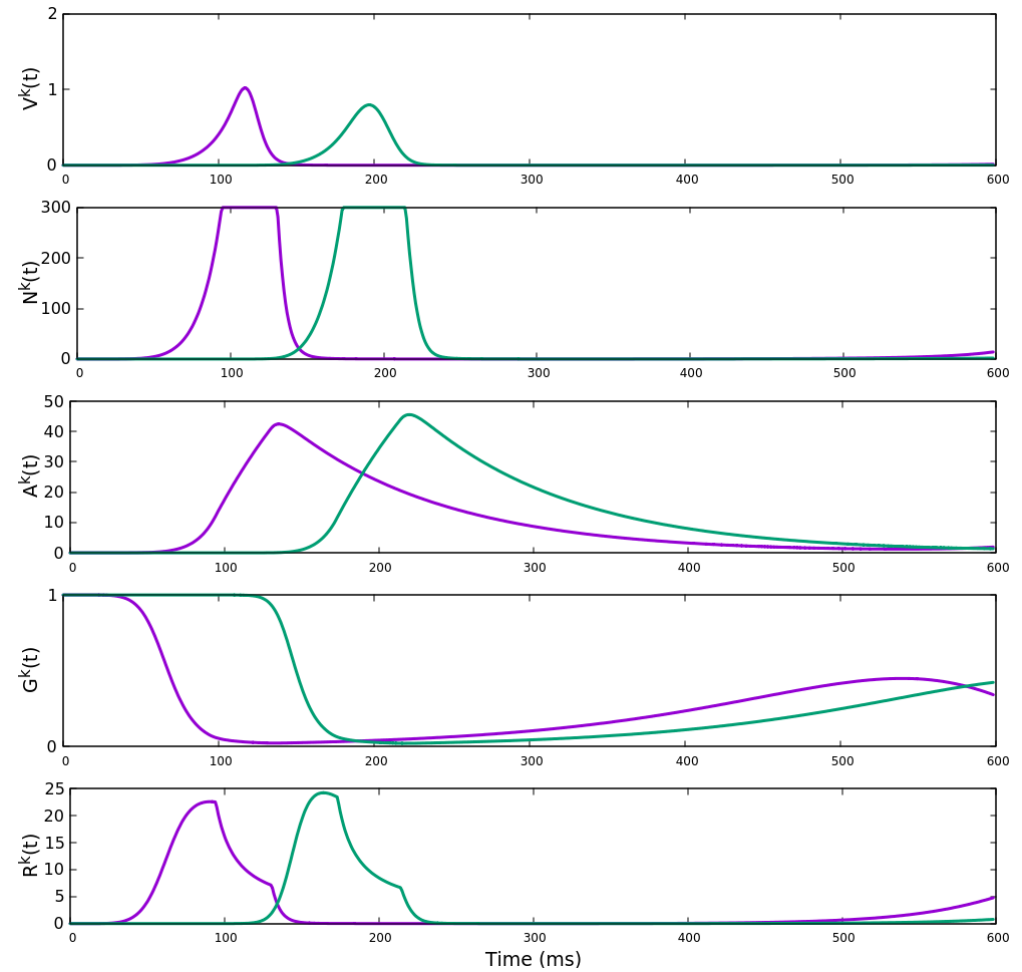
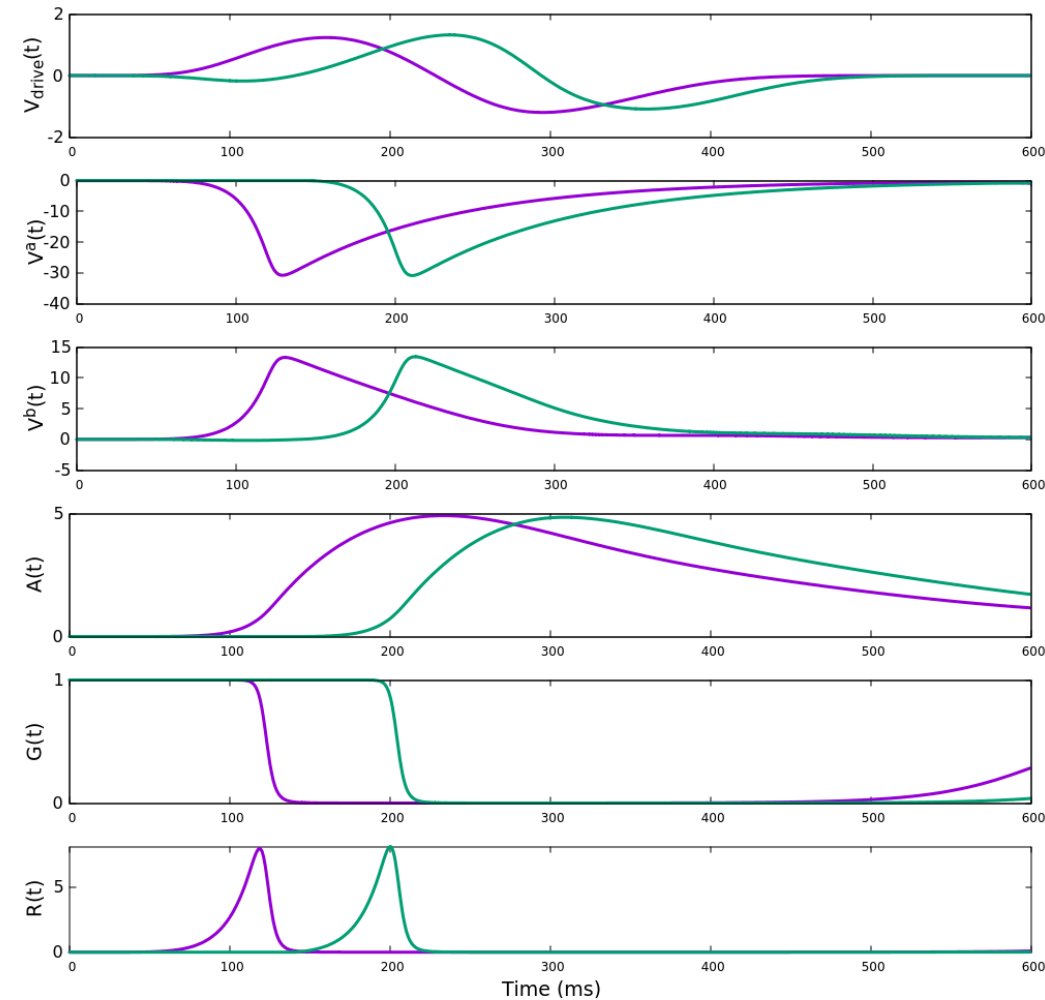
- Coupled dynamics :

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

# 1D results : smooth motion anticipation with amacrine connectivity

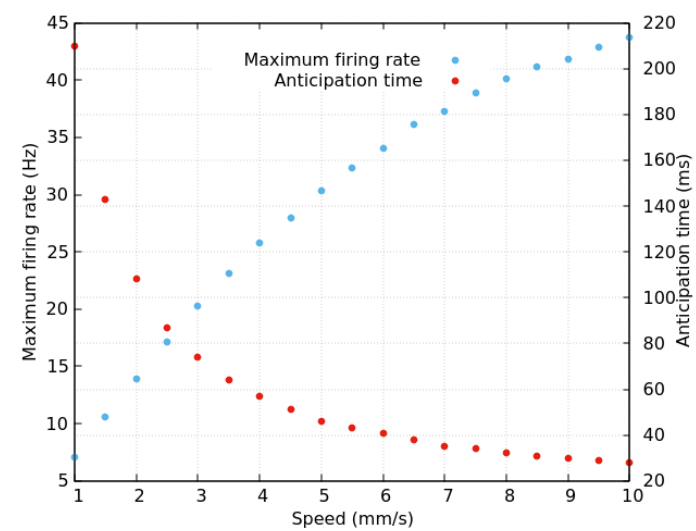
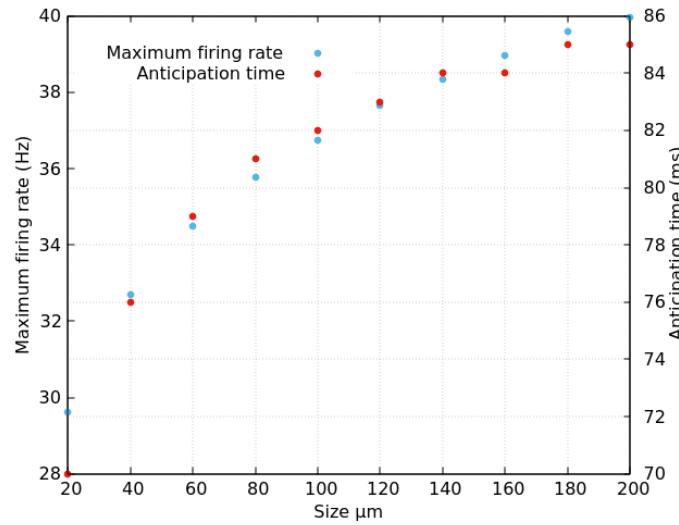
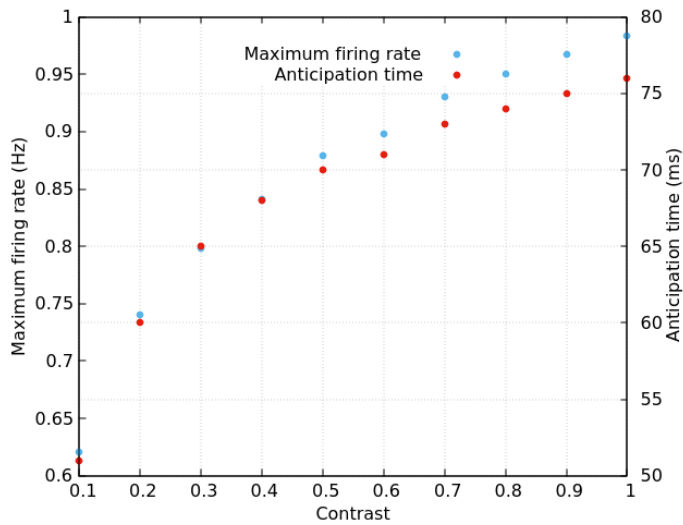
Bipolar layer

Ganglion layer

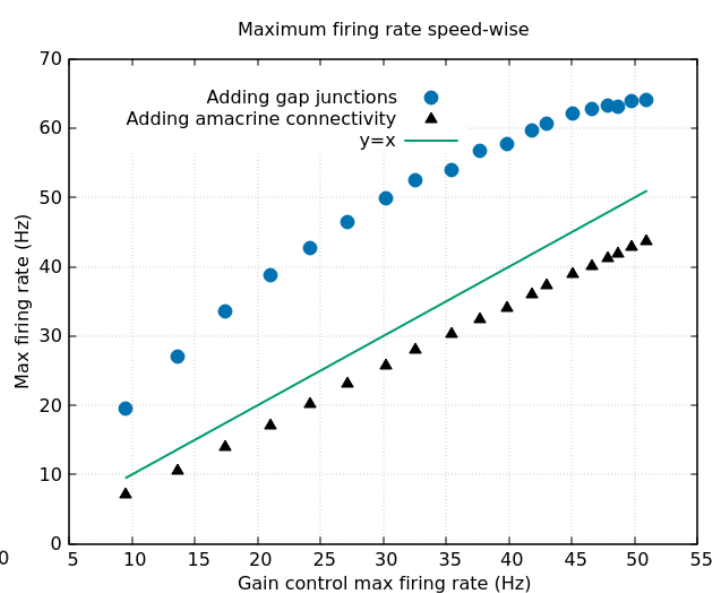
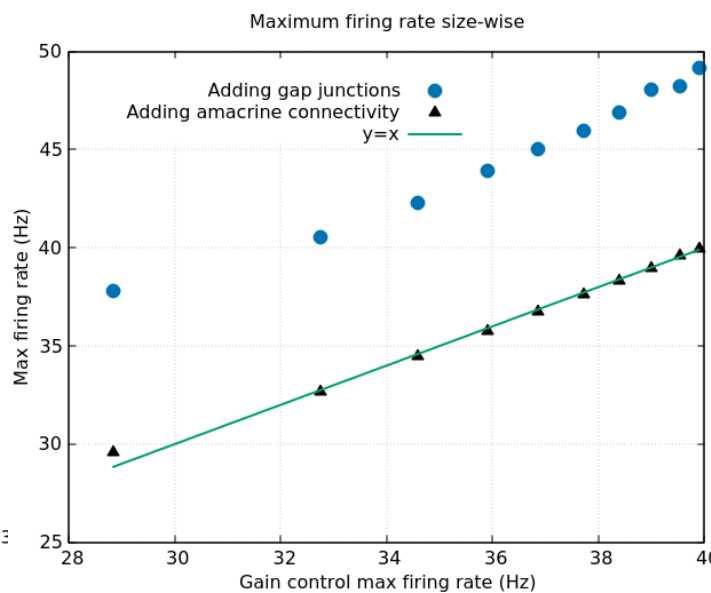
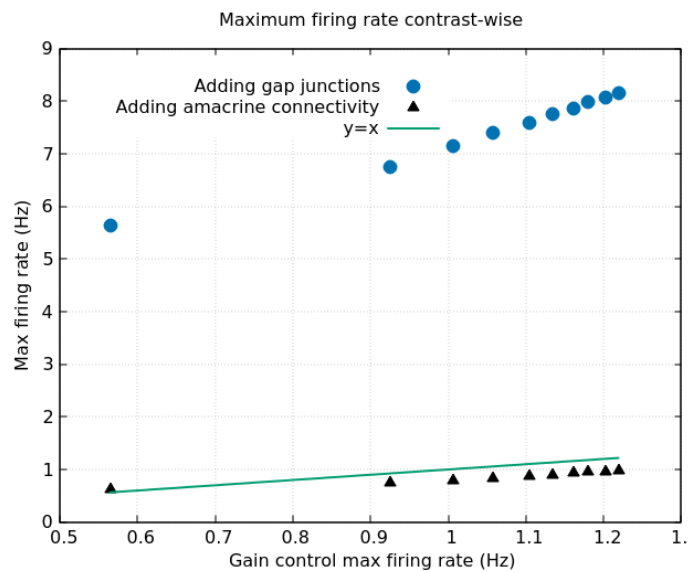
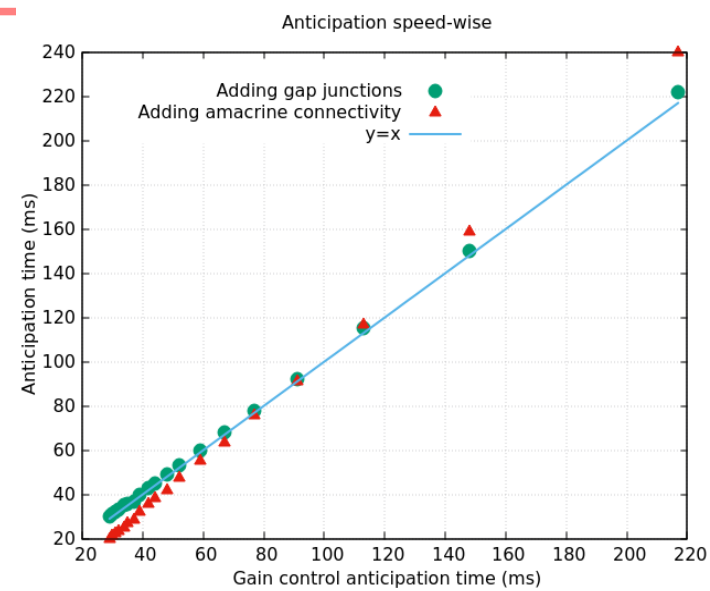
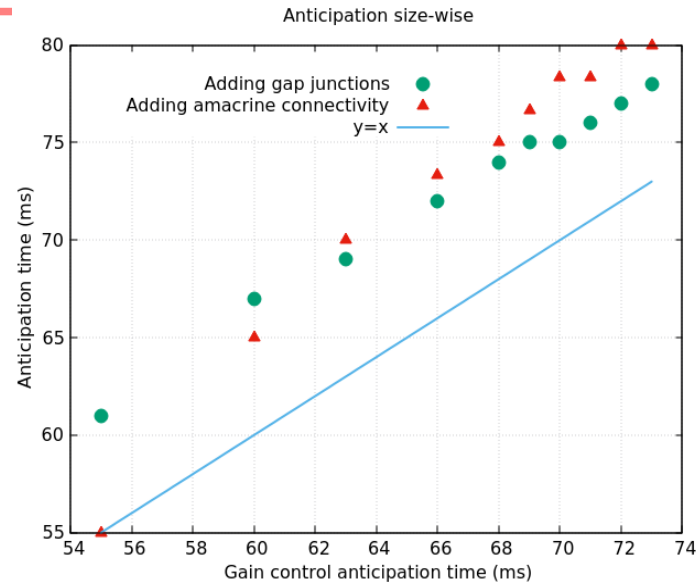
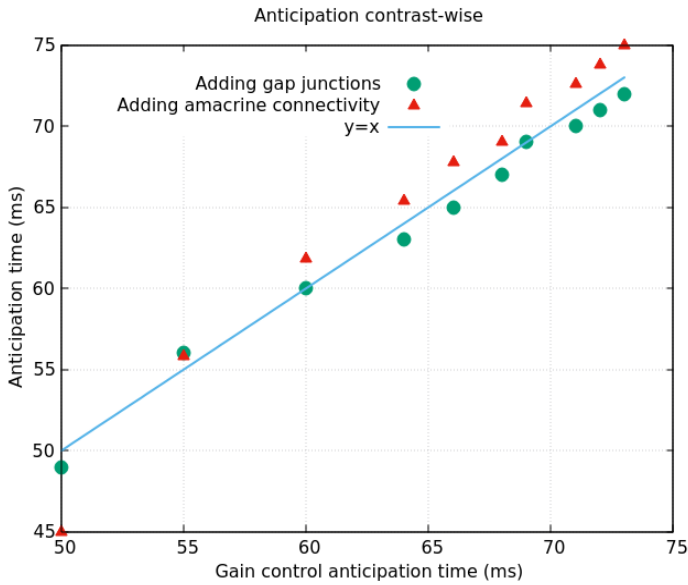


# 1D results : smooth motion anticipation with amacrine connectivity

Anticipation variability with stimulus  
parameters

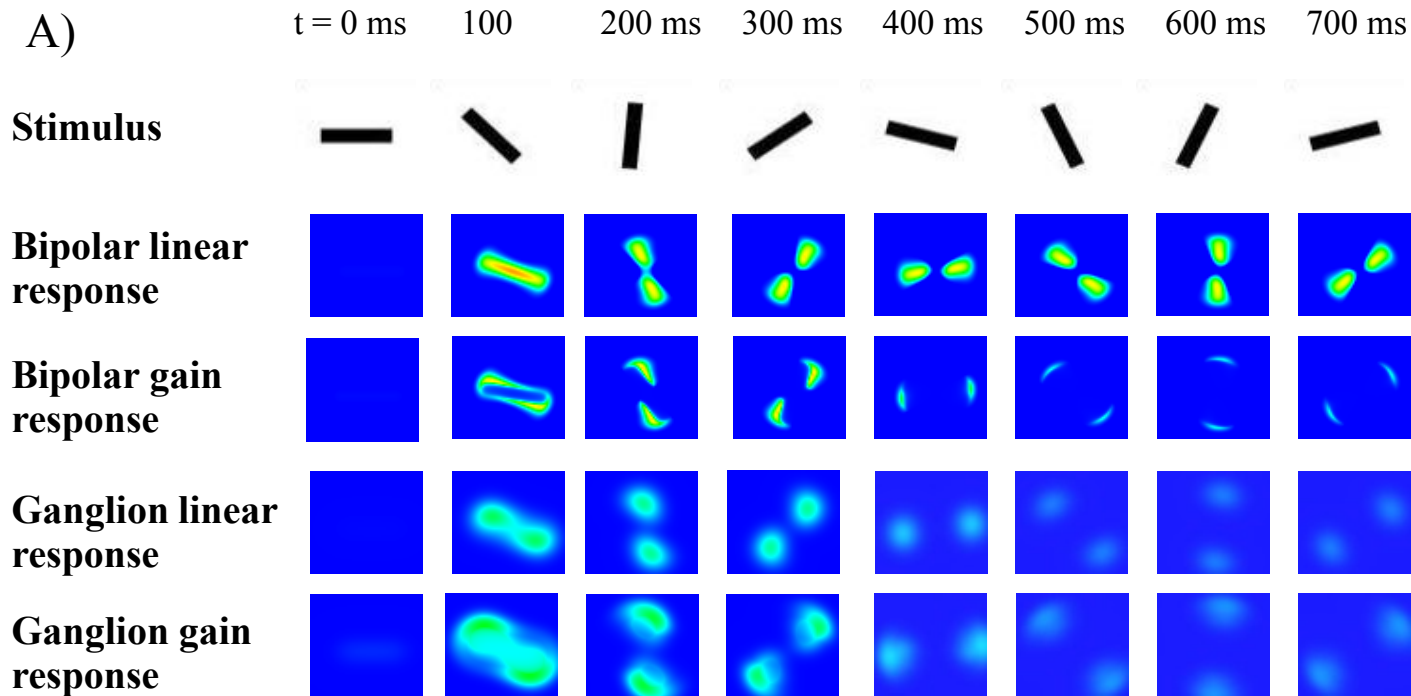


# Comparing the performance of the three layers

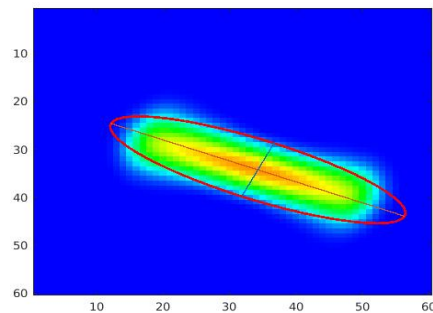


# Suggesting new experiments : 2D results

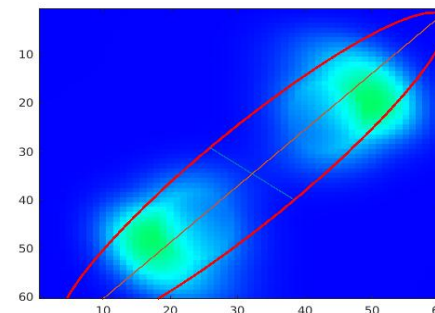
## 1) Angular anticipation



B)

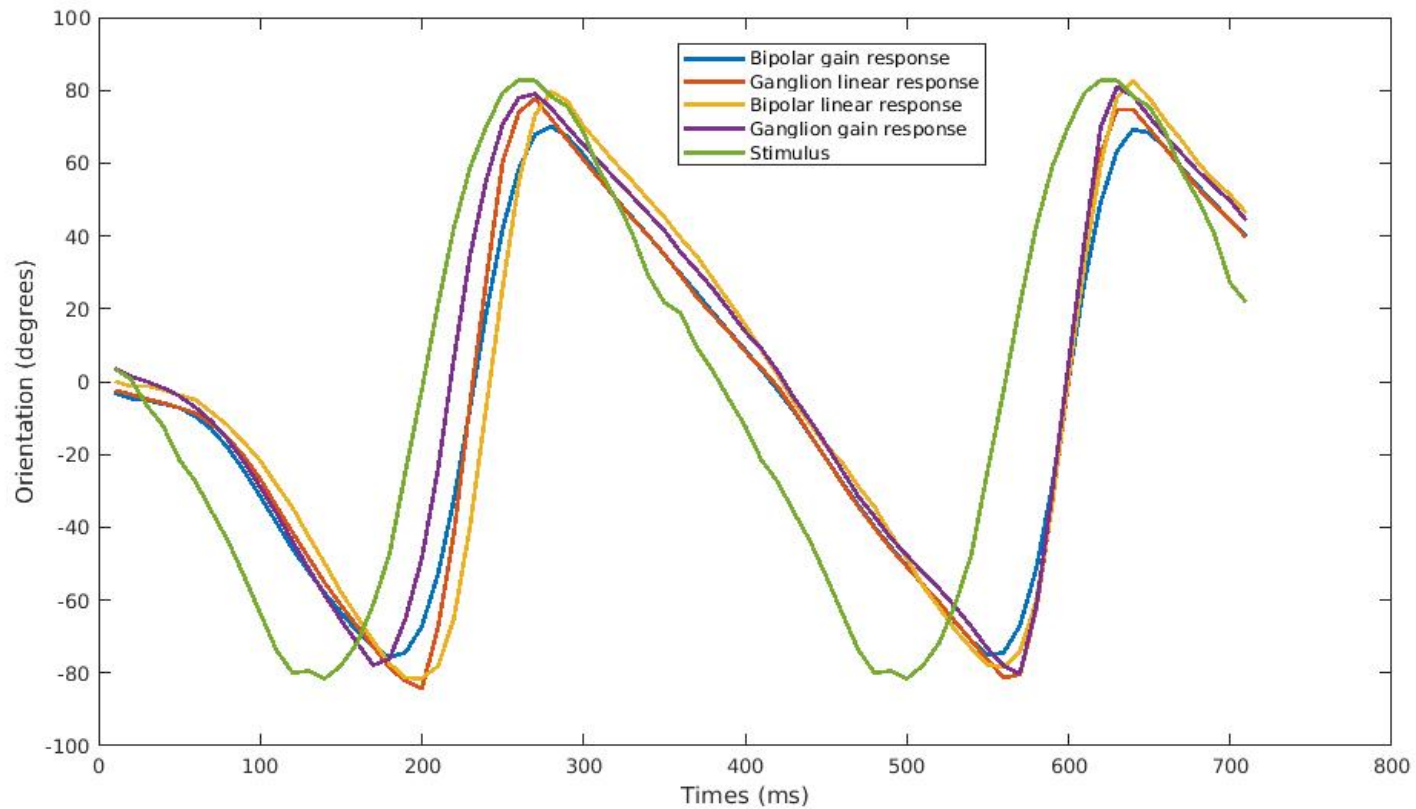


C)



# Suggesting new experiments : 2D results

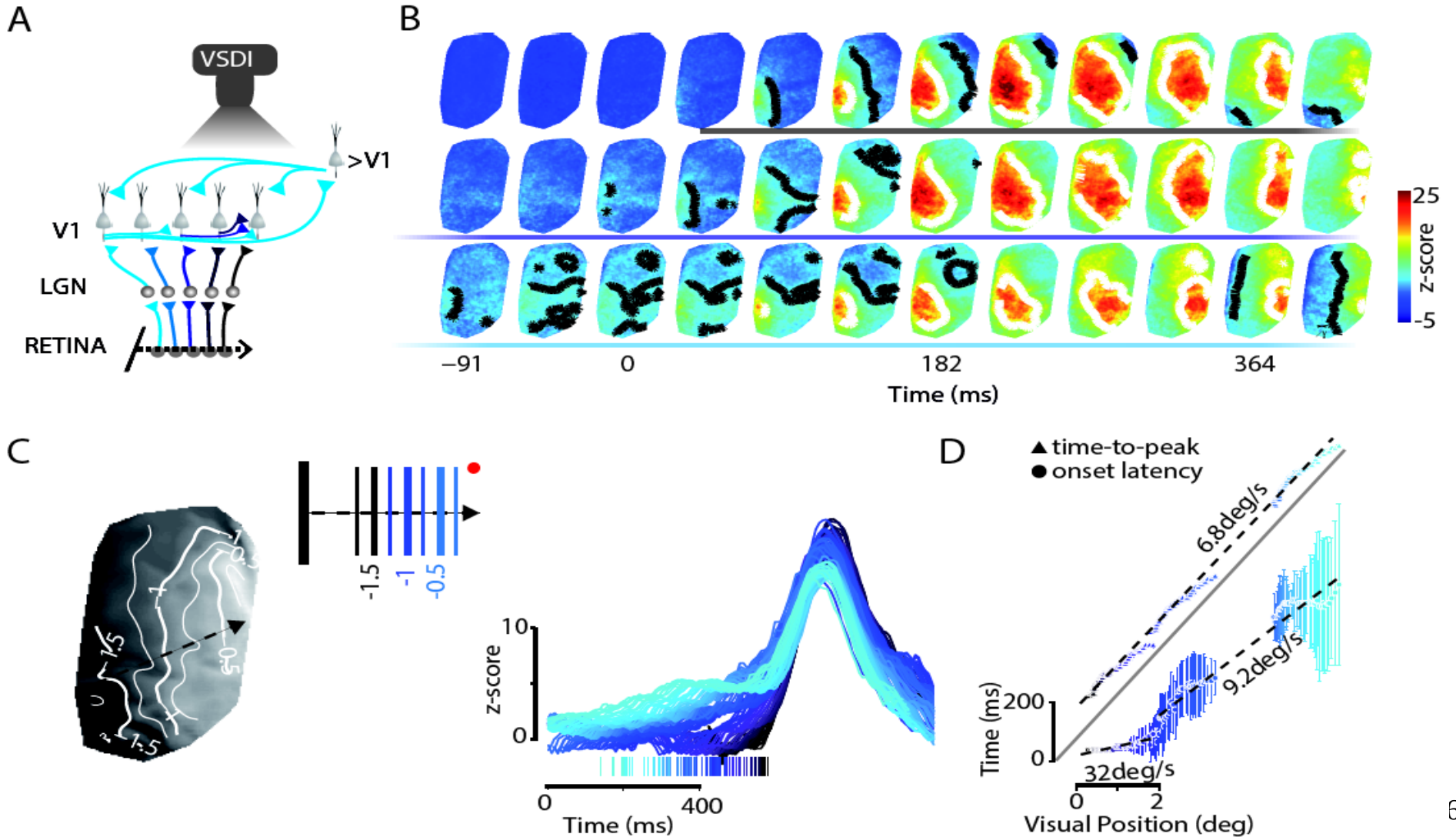
## 1) Angular anticipation



# Anticipation in V1

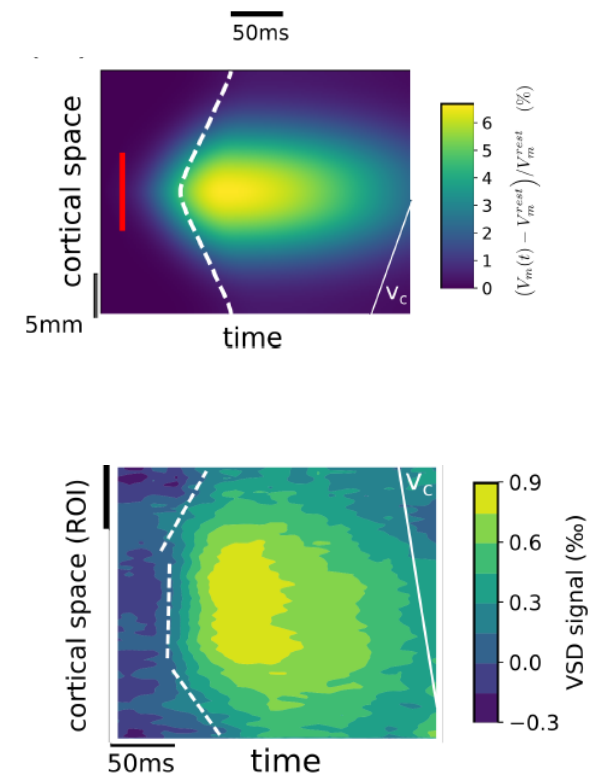
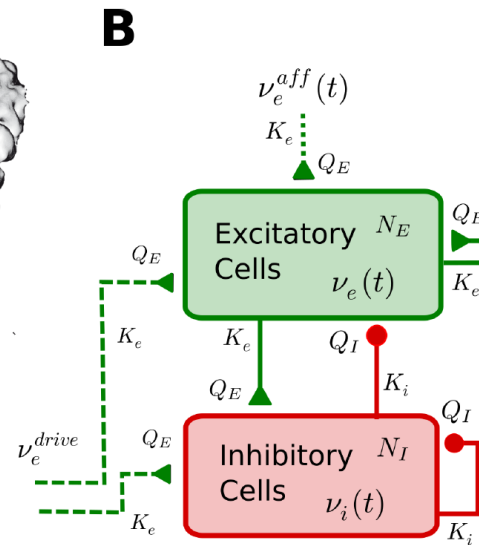
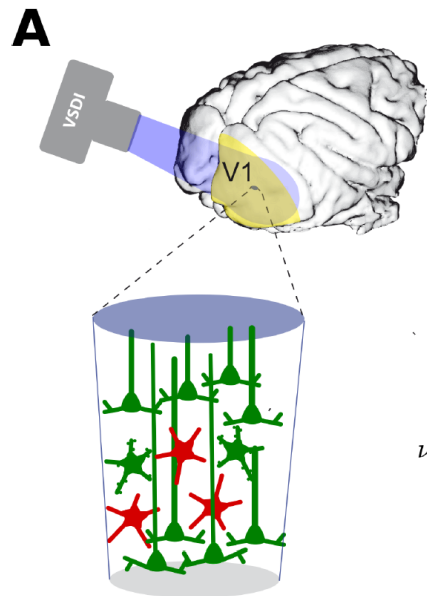


# Anticipation in V1



# 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 :

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

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

# A mean field model to reproduce VSDI recordings

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Affords a retino thalamic input

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

# 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 )

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

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 :

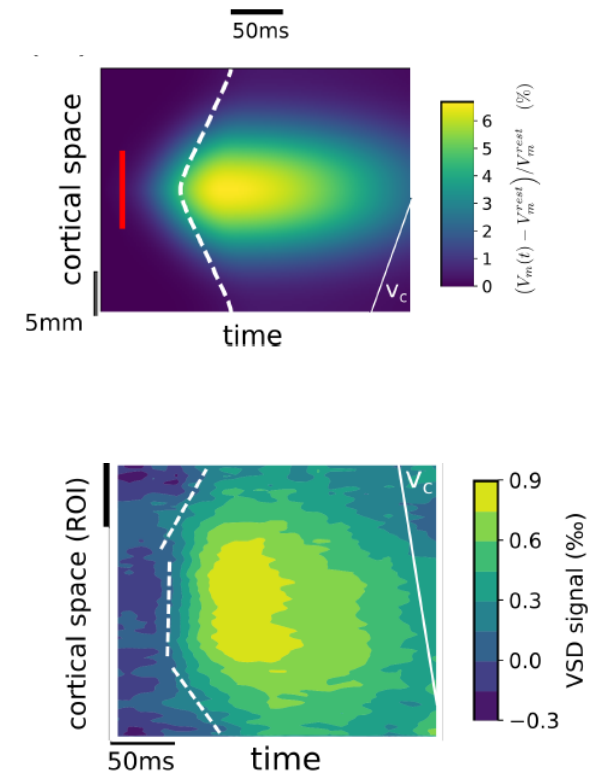
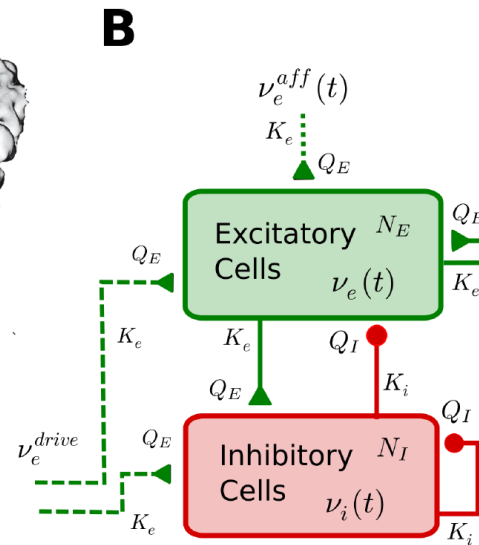
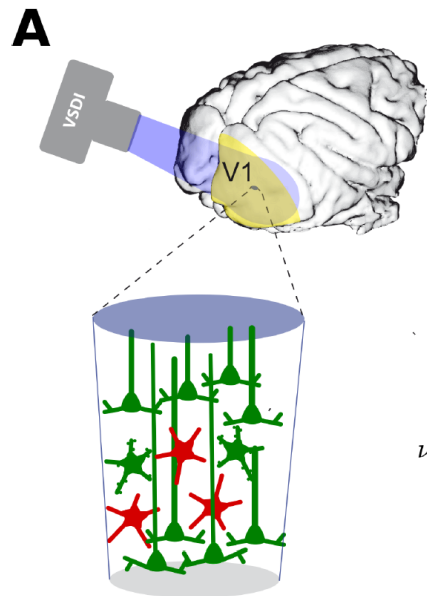
$$\begin{array}{l}
 \mu_{G_e}(\nu_e, \nu_i) = \nu_e K_e \tau_e Q_e \\
 \sigma_{G_e}(\nu_e, \nu_i) = \sqrt{\frac{\nu_e K_e \tau_e}{2}} Q_e \\
 \mu_{G_i}(\nu_e, \nu_i) = \nu_i K_i \tau_i Q_i \\
 \sigma_{G_i}(\nu_e, \nu_i) = \sqrt{\frac{\nu_i K_i \tau_i}{2}} Q_i
 \end{array}
 \longrightarrow
 \begin{array}{l}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

Finally, the transfer function reads :

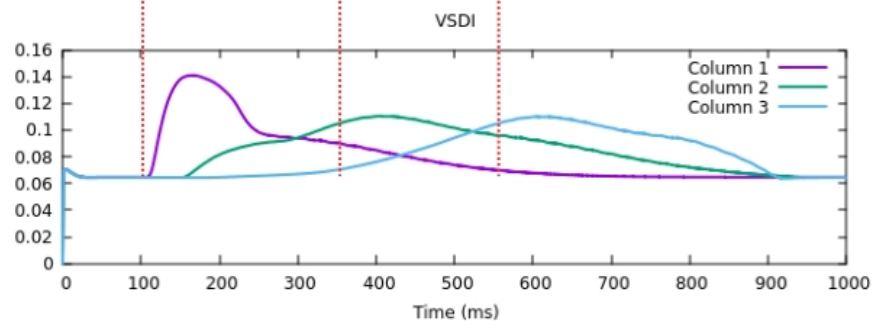
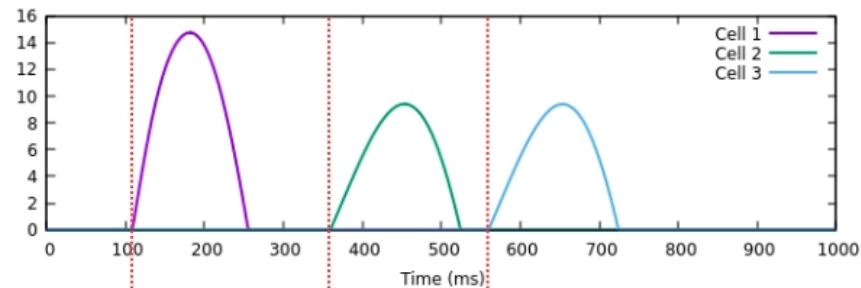
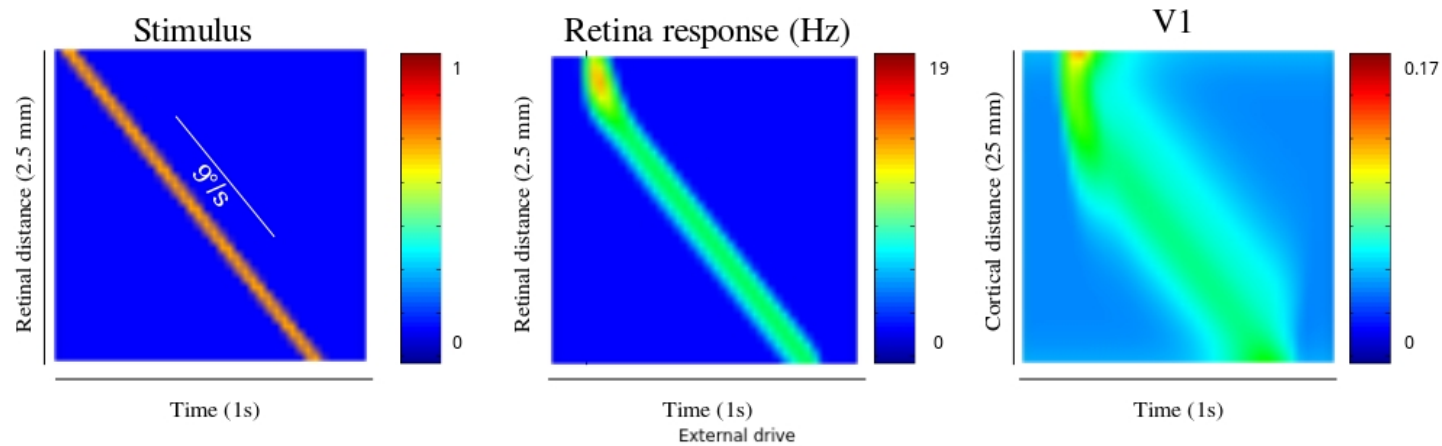
$$\nu_{out} = \mathcal{F}(\nu_e, \nu_i) = \frac{1}{2\tau_V} \cdot \text{Erfc}\left(\frac{V_{thre}^{eff} - \mu_V}{\sqrt{2}\sigma_V}\right)$$

# A mean field model to reproduce VSDI recordings

Zerlaut et al 2016  
Chemla et al 2018

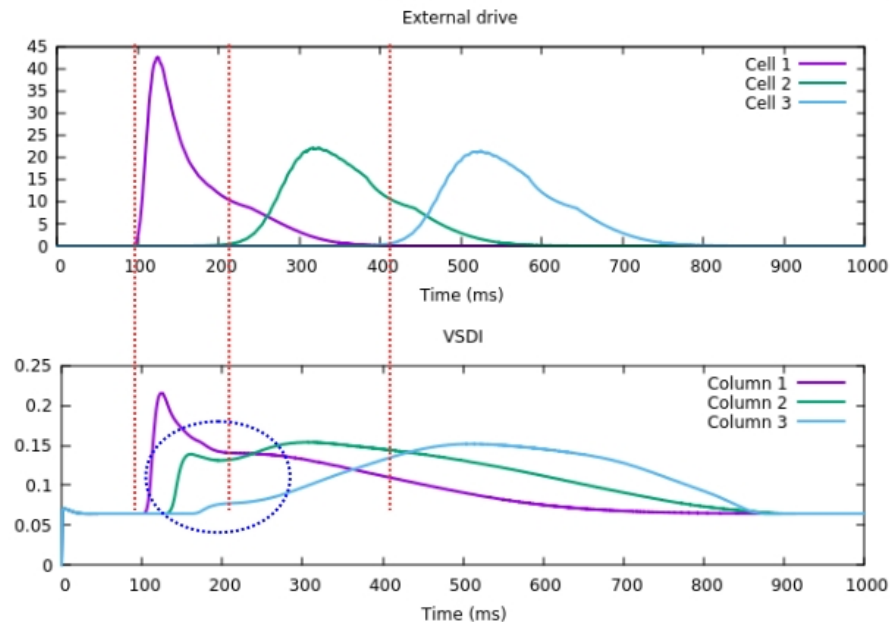
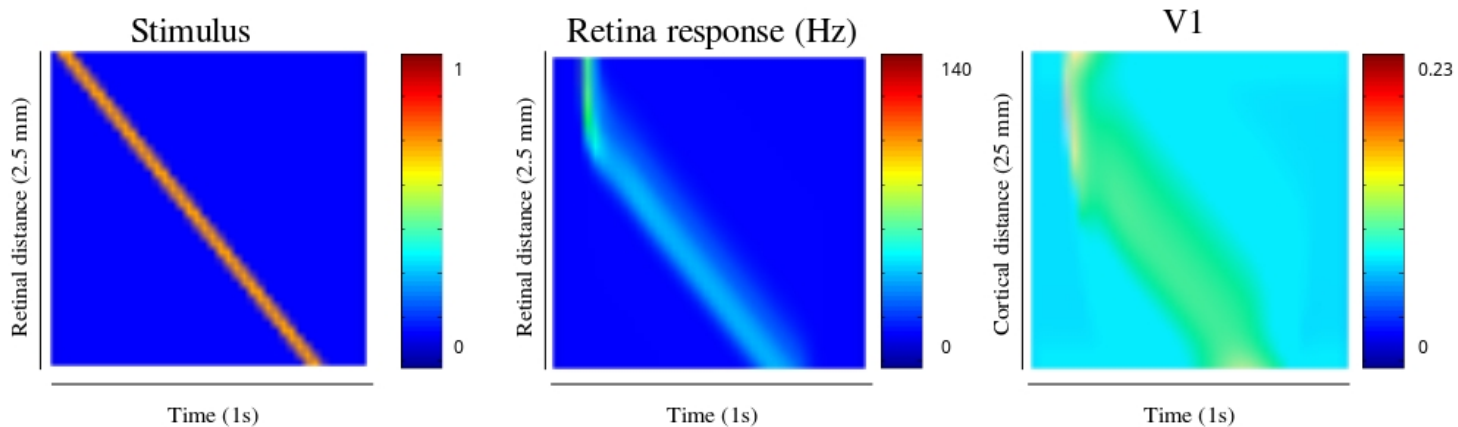


# Response of the cortical model to a LN retina drive



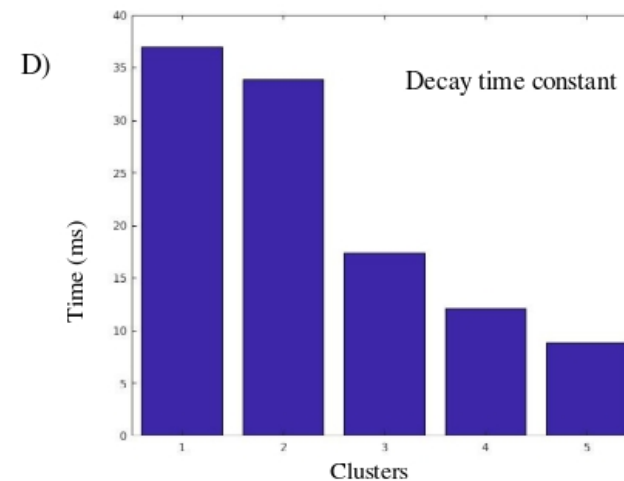
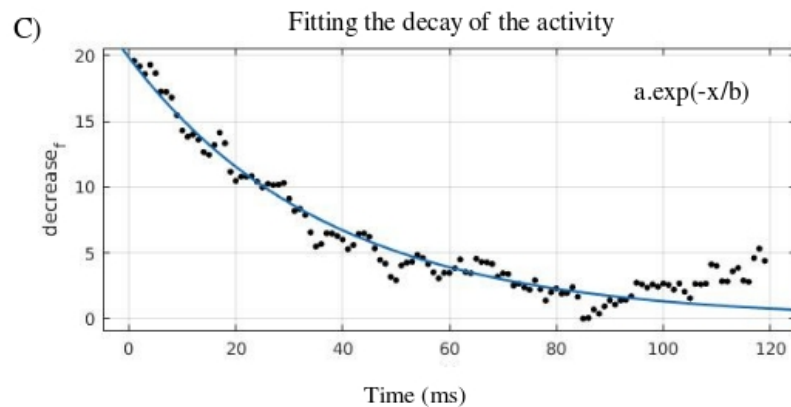
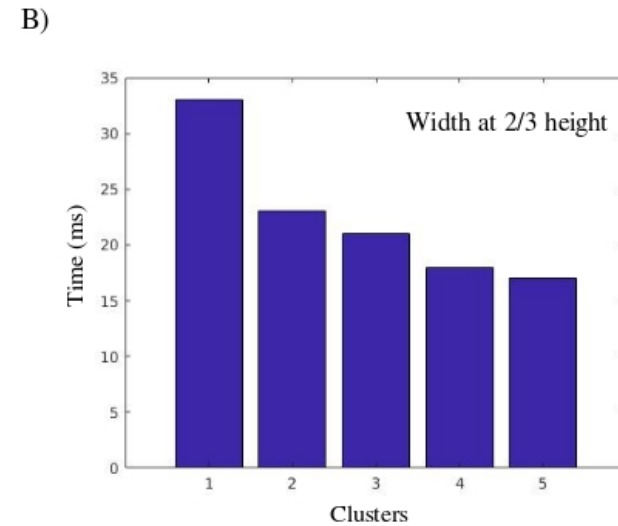
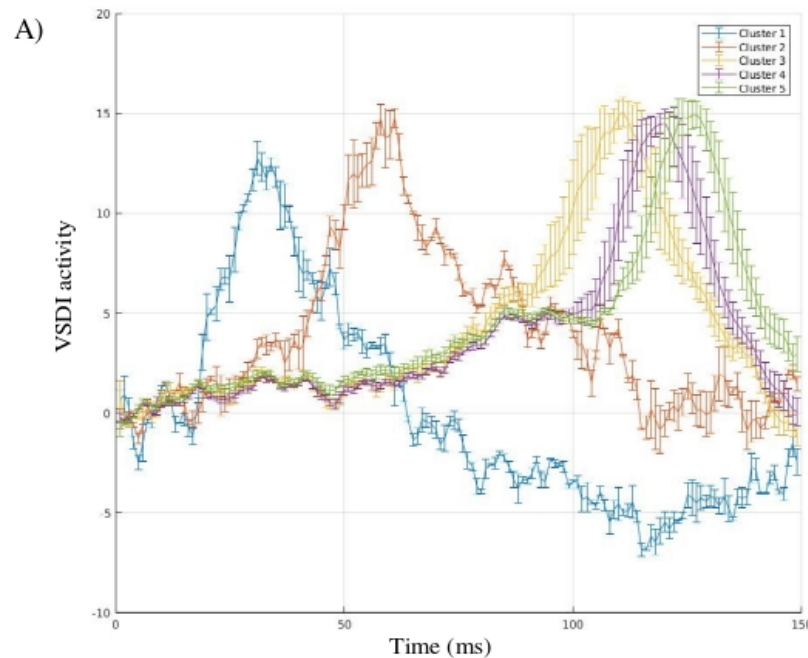


# Response of the cortical model to a retina drive with gain control



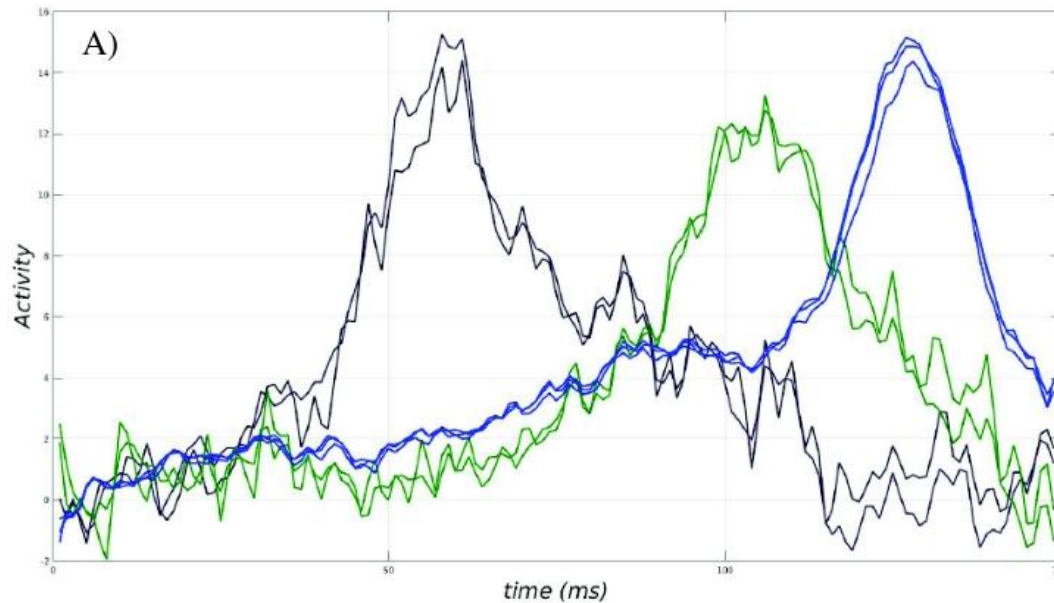
# Anticipation in the cortex : VSDI data analysis

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

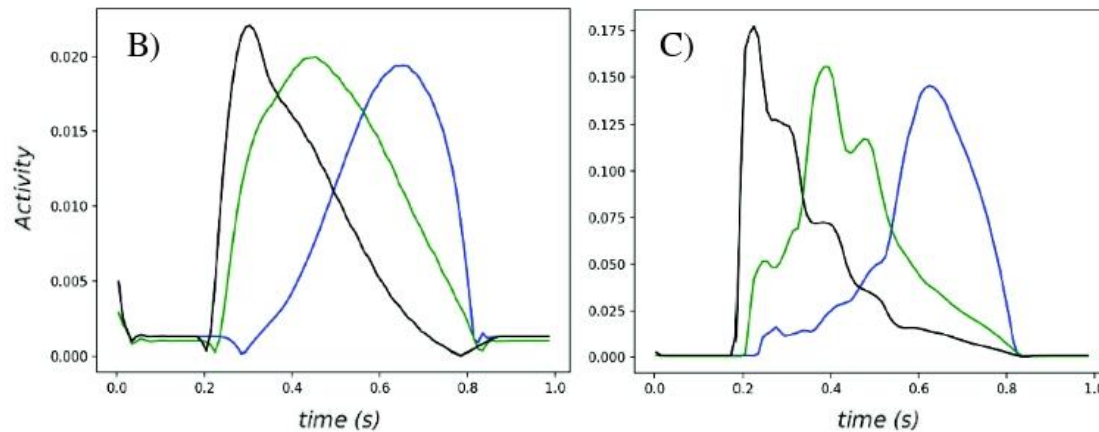


# Comparing simulation results to VSDI recordings

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 !