Learning Coordinated Eye and Head Movements: Unifying Principles and Architectures

Sohrab Saeb[1], Cornelius Weber[2], Jochen Triesch[1]

1. Frankfurt Institute for Advanced Studies, Frankfurt am Main, Germany
2. University of Hamburg, Hamburg, Germany

Bernstein Conference on
Computational Neuroscience
Berlin, 2010

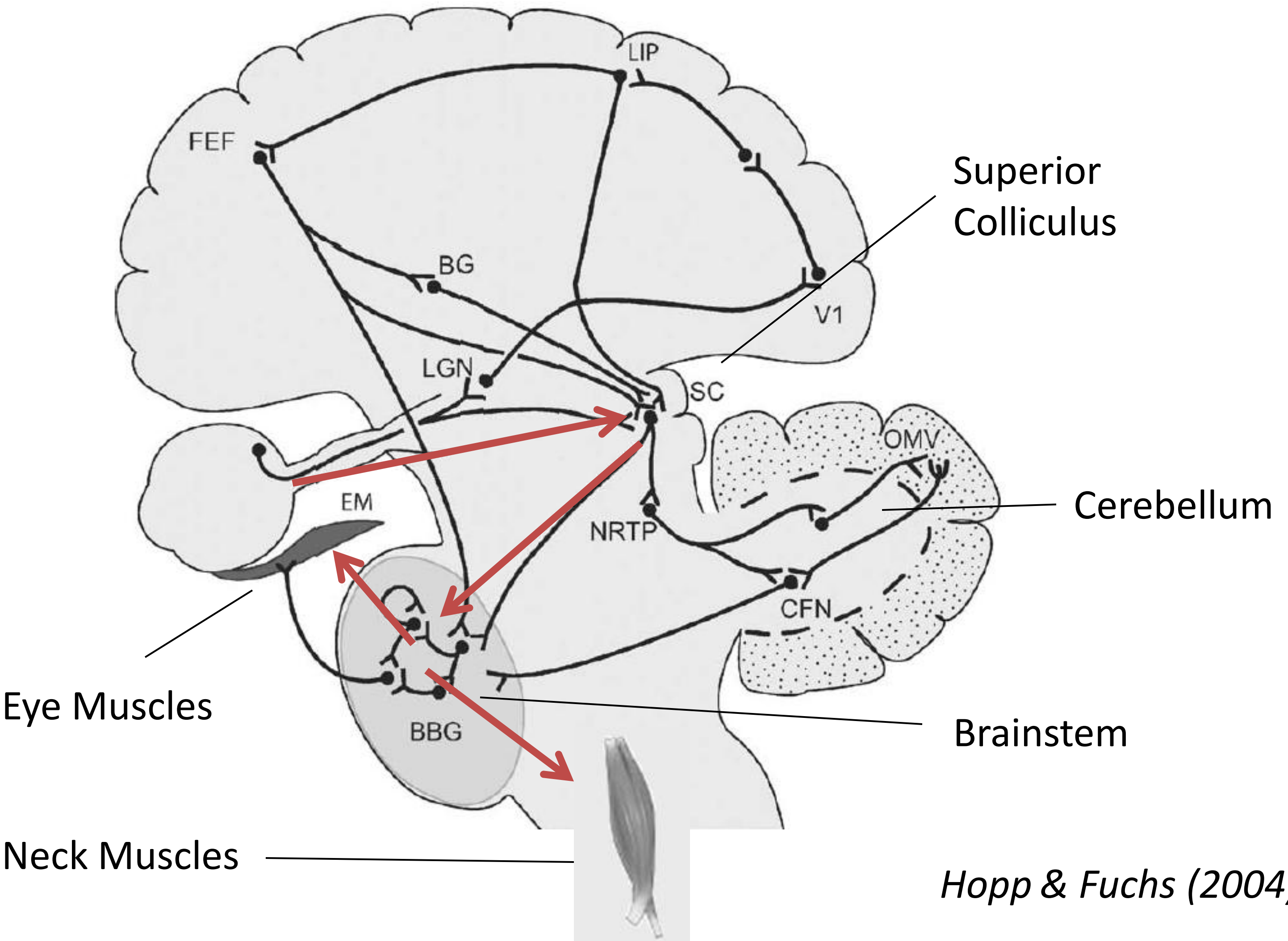
Coodinated Eye/Head Movements

- Saccade: Quick change of gaze direction
- Multi-segment control of different motor systems
- Saccades are ballistic movements (Leung et al. 2008)
- Head-restrained vs. Head-free

Open Questions

- Do saccade kinematics result from some optimality principle?
- How does the brain learn saccade kinematics?
- Is it possible to address both questions above using a single computational model?

Biological Basis of Saccadic Eye/Head Movements



Hopp & Fuchs (2004)

Eye/Head Plant Models

Eye Plant: Linear models sufficient for realistic saccades (Van Opstal et al, 1985)

$$T_1T_2T_3\dddot{r}_{\mathrm{e}}(t)+(T_1T_2+T_2T_3+T_3T_1)\ddot{r}_{\mathrm{e}}(t)+(T_1+T_2+T_3)\dot{r}_{\mathrm{e}}(t)+r_{\mathrm{e}}(t)=g_{\mathrm{e}}u_{\mathrm{e}}(t)$$

$$h_{\mathrm{e}}(t)=g_{\mathrm{e}}(k_1e^{-\frac{t}{T_1}}+k_2e^{-\frac{t}{T_2}}+k_3e^{-\frac{t}{T_3}})$$

$$r_{\mathrm{e}}(t)=\int_0^t u_{\mathrm{e}}(\tau)h_{\mathrm{e}}(t-\tau)d\tau$$

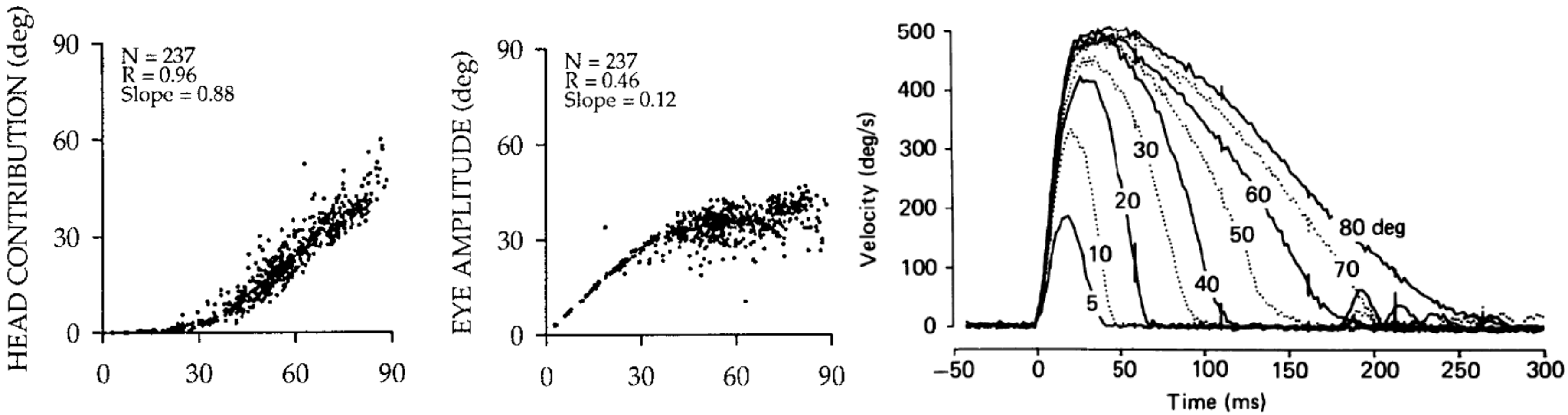
Head Plant

$$T_4T_5\ddot{r}_{\mathrm{h}}(t)+(T_4+T_5)\dot{r}_{\mathrm{h}}(t)+r_{\mathrm{h}}(t)=g_{\mathrm{h}}u_{\mathrm{h}}(t)$$

$$h_{\mathrm{h}}(t)=g_{\mathrm{h}}(k_4e^{-\frac{t}{T_4}}+k_5e^{-\frac{t}{T_5}})$$

$$r_{\mathrm{h}}(t)=\int_0^t u_{\mathrm{h}}(\tau)h_{\mathrm{h}}(t-\tau)d\tau$$

The Neural Control Signal: Optimization



$u_e(t) = ?$ → Eye Plant

$u_h(t) = ?$ → Head Plant

- Can we derive the control signals from some optimality principle?

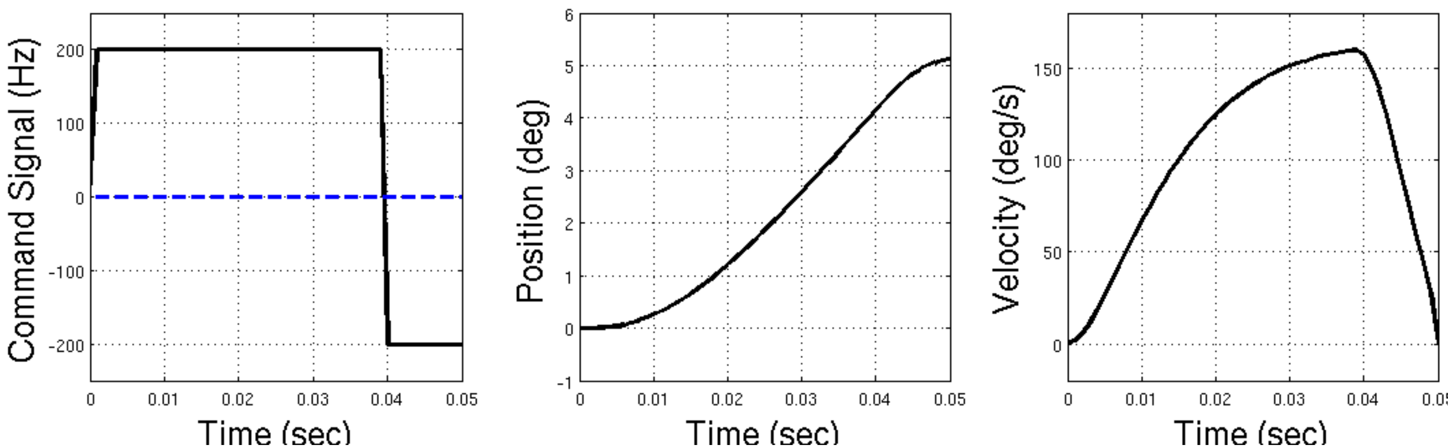
- How are the control signals optimized through learning?

Optimality Principles

➢ No proper vision during saccades due to **motion blur** or **neural suppression**.

➢ **Minimum Time**

The control signal instantateously switches between its maximum positive and negative values to accelerate and decelerate the eye (“bang-bang”).



Models: Optimality Principles

- **Minimum Variance:** (*Harris & Wolpert, 1998; 2006*)

$$\text{Cost} = \underbrace{\int_0^T \alpha \, \mathrm{d}t}_{\text{Movement cost}} + \underbrace{\int_T^{T+F} \beta \, e(t)^2 \, \mathrm{d}t}_{\text{Fixation cost}}$$

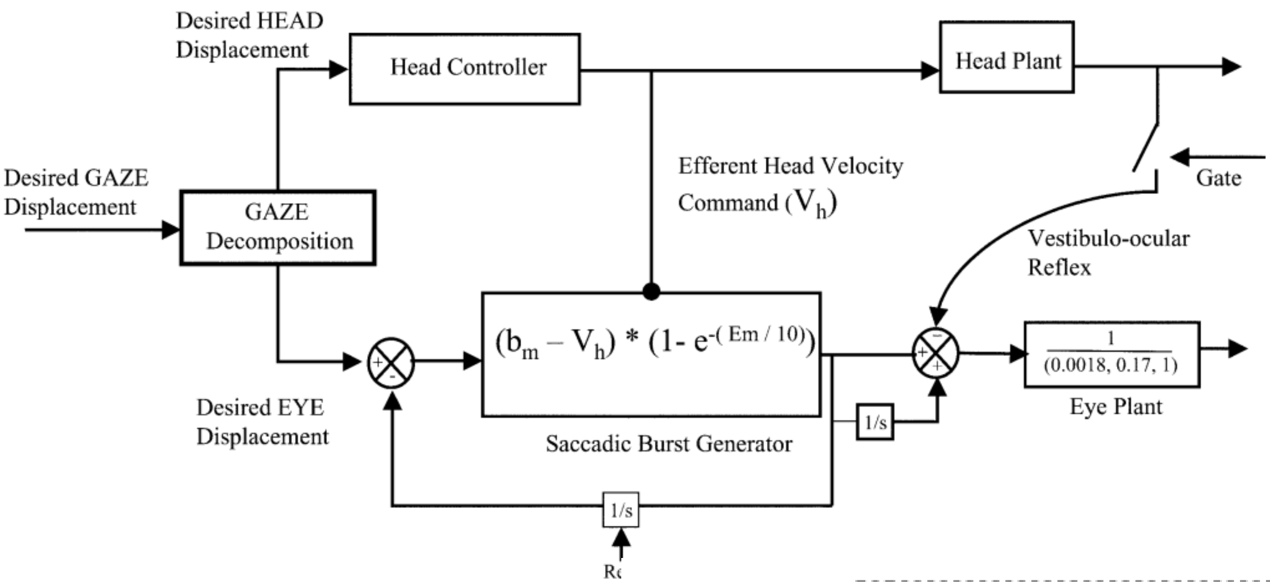
$$\sigma_u(t) = k|u(t)|$$

- **Minimum Effort** (*Kardamakis & Moschovakis, 2009*)

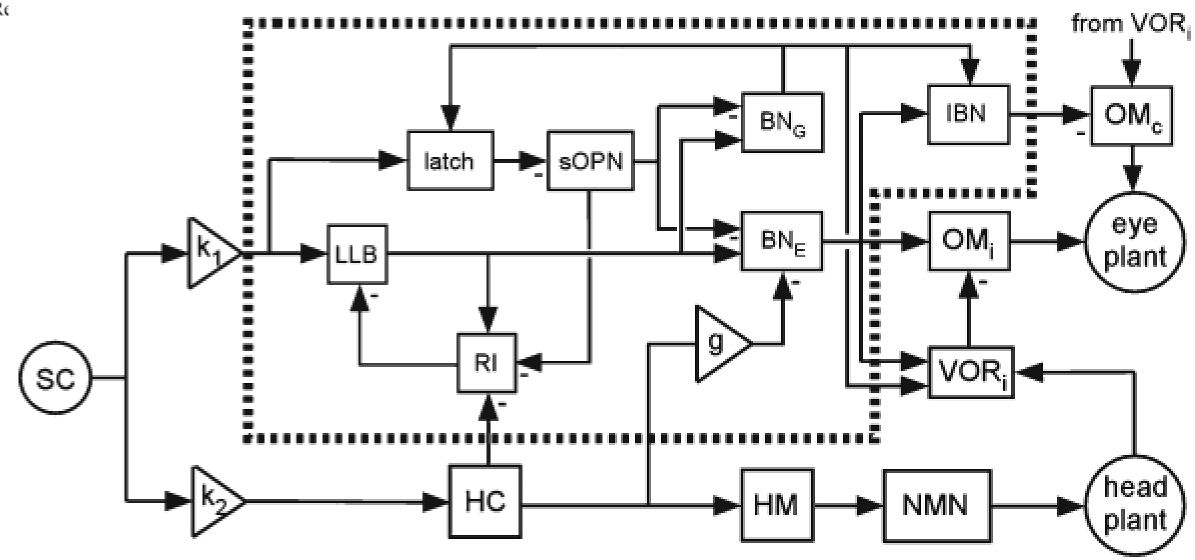
$$\text{Cost} = \int_0^T [\alpha(x_e)u_e^2 + \beta u_h^2]dt$$

$$\alpha(x_e) = \alpha_0 + \alpha_1 x_e + \alpha_2 x_e^2$$

Models: Neural Architectures



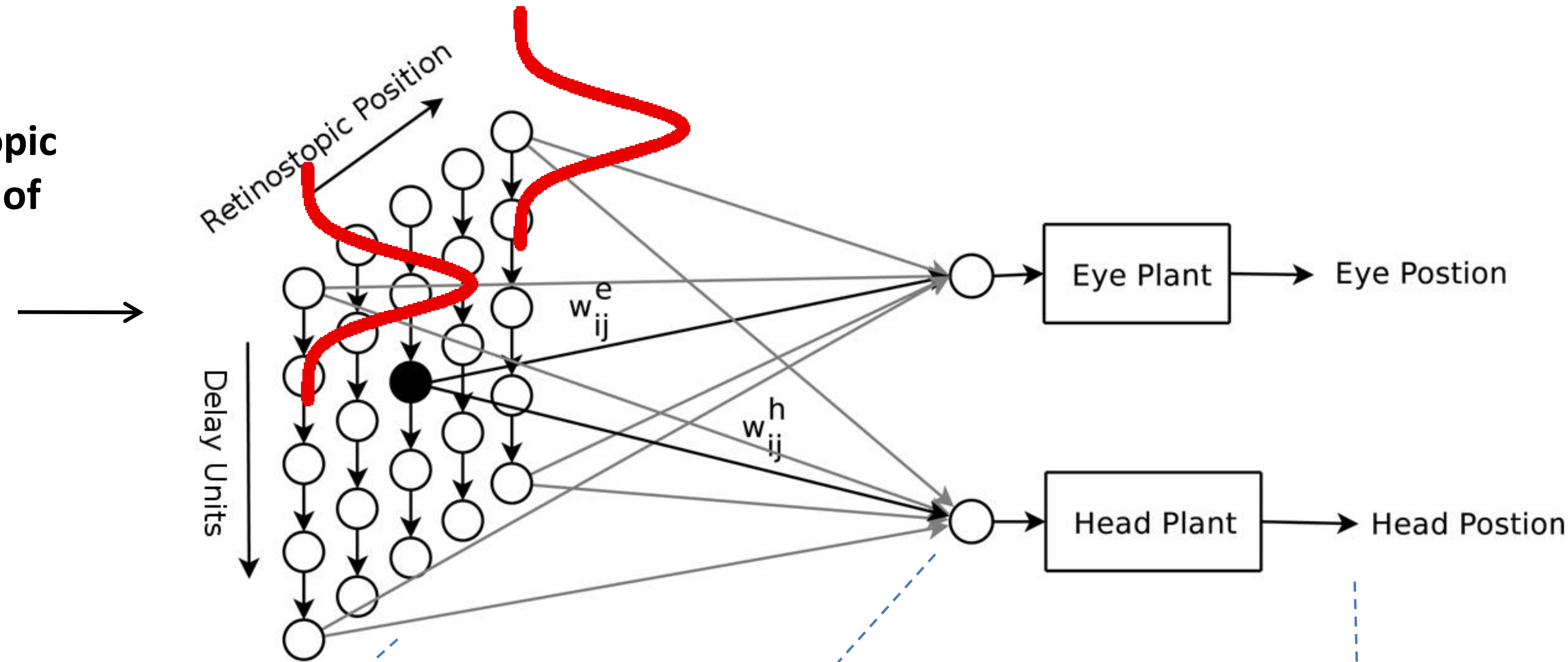
Freedman (2001)



Kardamakis et al. (2010)

The Open-loop Neural Controller

Retinotopic Position of Target



$$s_{ij}(t) = A \exp\left(-\frac{(i - \frac{t}{\Delta t})^2}{2\sigma^2}\right)$$

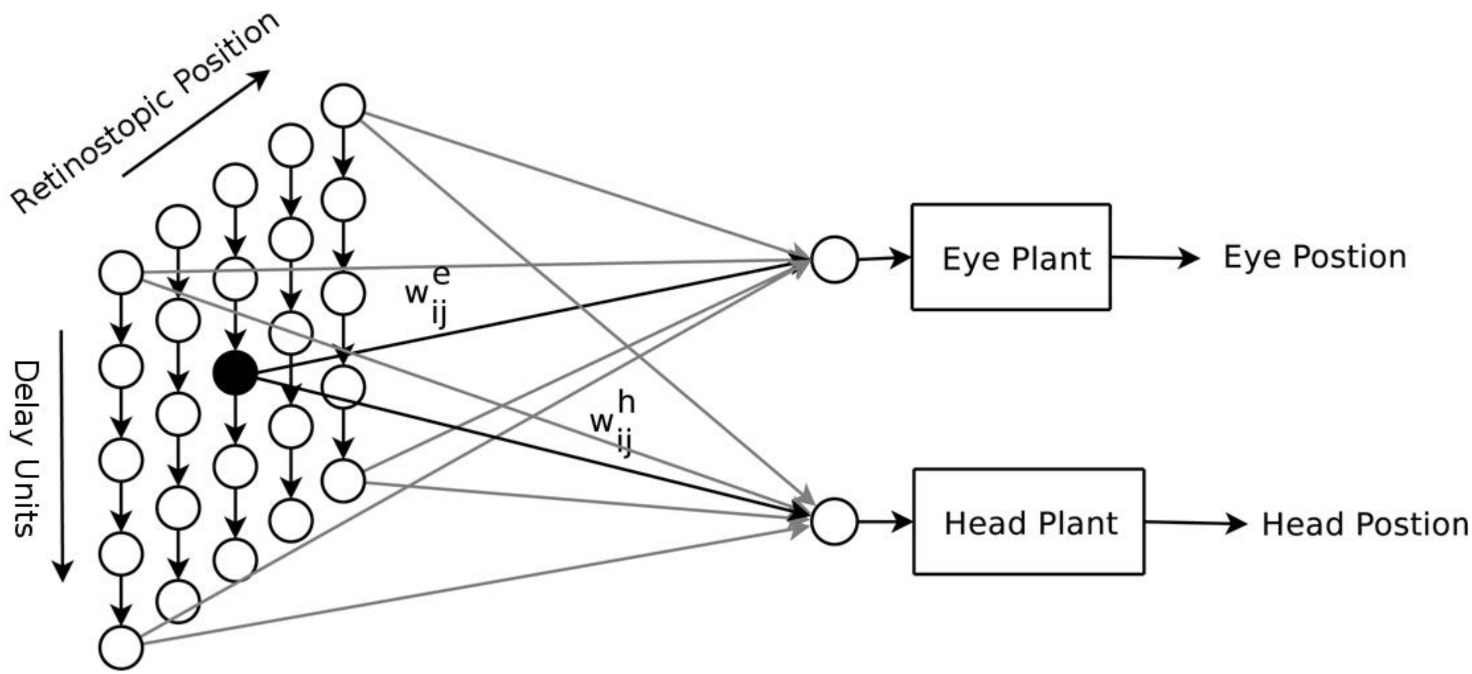
$$u_{\mathrm{e}}(t) = \sum_{j=1}^{N} \sum_{i=1}^{M} w_{ij}^{\mathrm{e}} s_{ij}(t)$$

$$u_{\mathrm{h}}(t) = \sum_{j=1}^{N} \sum_{i=1}^{M} w_{ij}^{\mathrm{h}} s_{ij}(t)$$

$$r_{\mathrm{e}}(t) = \int_0^t u_{\mathrm{e}}(\tau) h_{\mathrm{e}}(t-\tau) d\tau,$$

$$r_{\mathrm{h}}(t) = \int_0^t u_{\mathrm{h}}(\tau) h_{\mathrm{h}}(t-\tau) d\tau$$

The Cost Function



1. **The gaze should reach the target as soon as possible and then stand still on the target position.**

2. **The power of the neural command signal should be constrained**.

$$E = \boxed{\int_0^T |r_{\mathrm{vis}}(t)| dt} + \boxed{\sum_{j=1}^{N} \sum_{i=1}^{M} (\alpha_{\mathrm{e}} |w_{ij}^{\mathrm{e}}|^n + \alpha_{\mathrm{h}} |w_{ij}^{\mathrm{h}}|^n)}$$

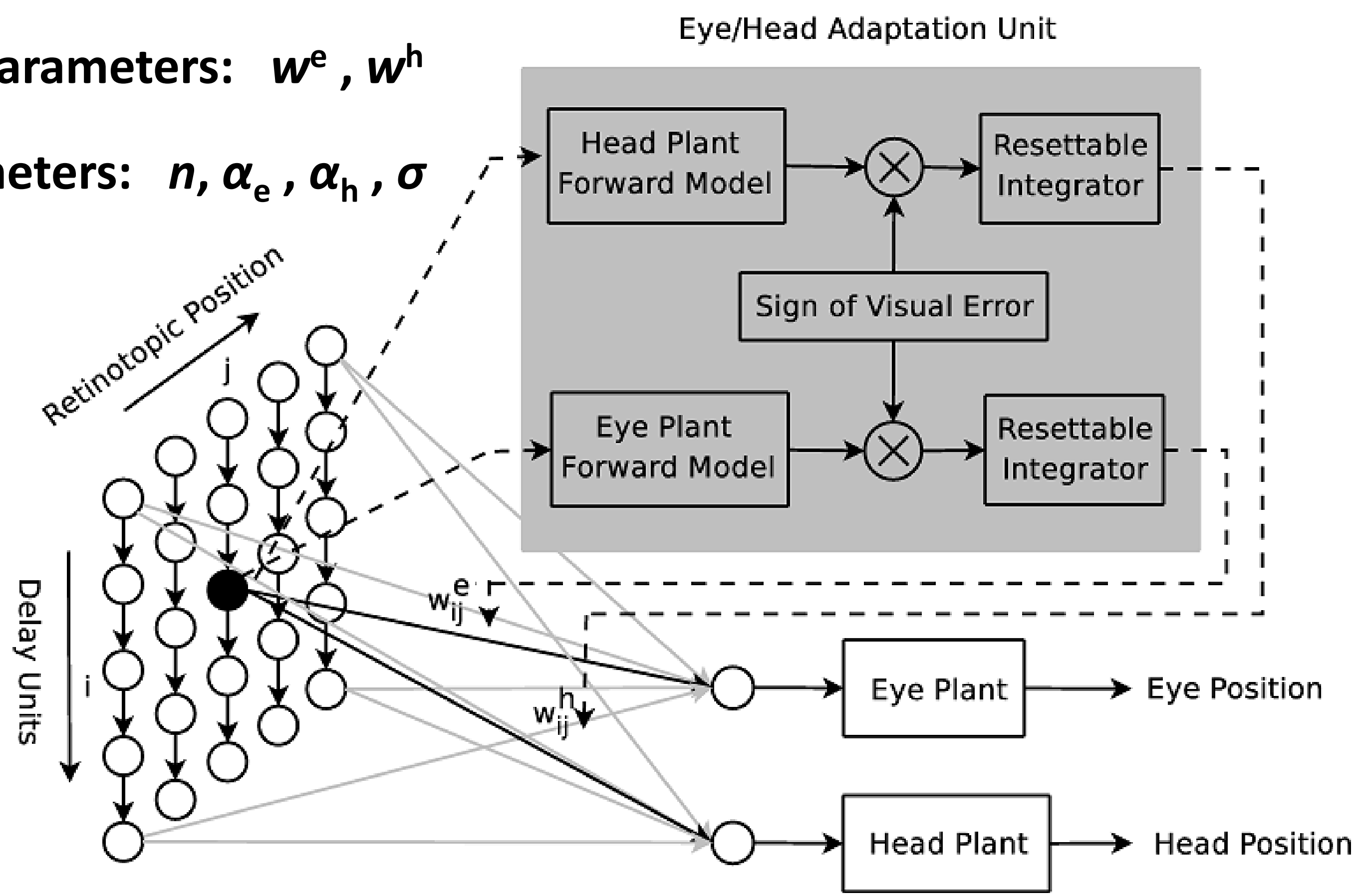
Adaptation: Gradient Descent on the Cost Function

$$\Delta w_{ij}^{\mathrm{e}} = \delta_{ij}^{\mathrm{e}} \int_0^T \mathrm{sign}(r_{\mathrm{vis}}(t)) \left(\int_0^t s_{ij}(\tau) h_{\mathrm{e}}(t-\tau) d\tau \right) dt - n\delta_{ij}^{\mathrm{e}} \alpha_{\mathrm{e}} (w_{ij}^{\mathrm{e}})^{(n-1)}$$

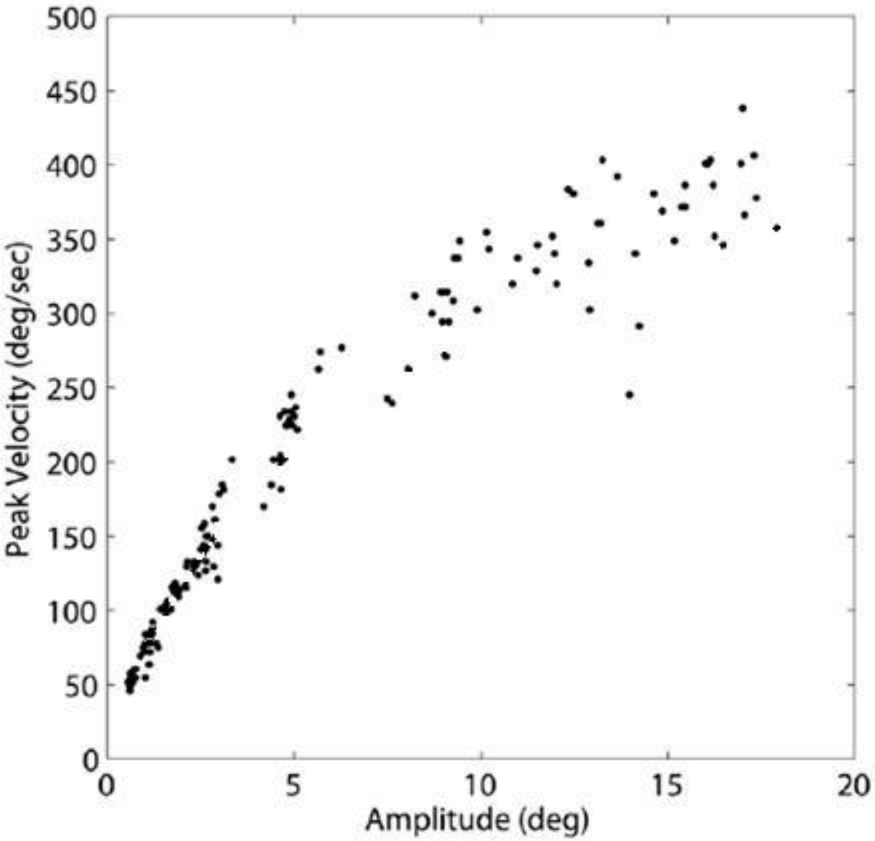
$$\Delta w_{ij}^{\mathrm{h}} = \delta_{ij}^{\mathrm{h}} \int_0^T \mathrm{sign}(r_{\mathrm{vis}}(t)) \left(\int_0^t s_{ij}(\tau) h_{\mathrm{h}}(t-\tau) d\tau \right) dt - n\delta_{ij}^{\mathrm{h}} \alpha_{\mathrm{h}} (w_{ij}^{\mathrm{h}})^{(n-1)}$$

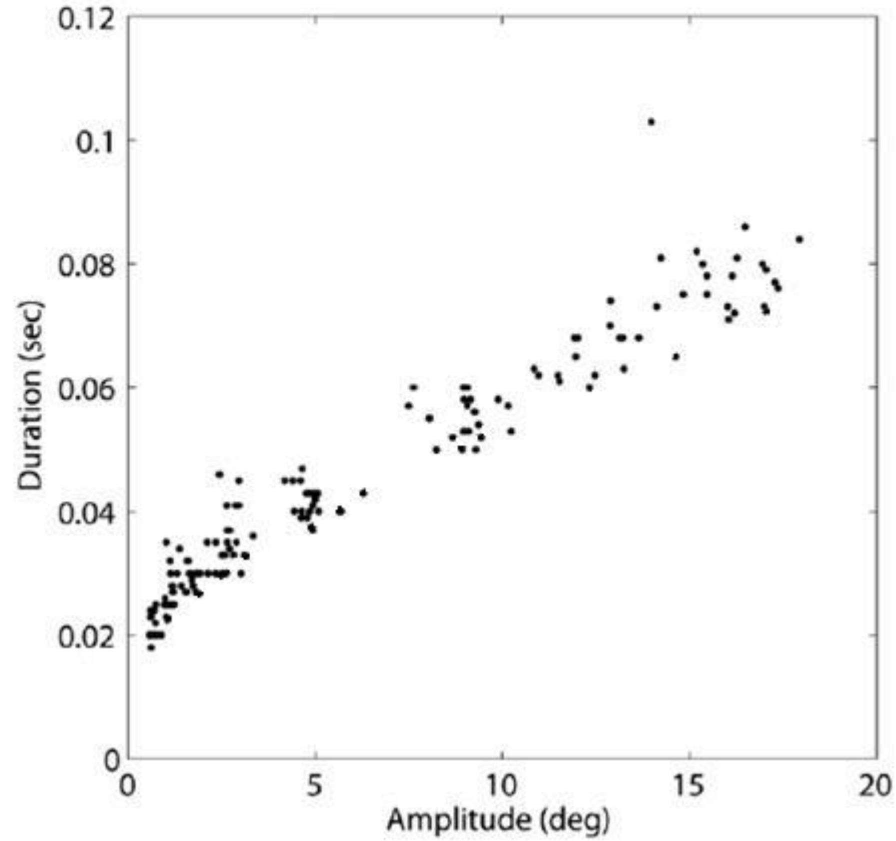
Adaptive Parameters: w^{e} , w^{h}

Free Parameters: $n, \alpha_e , \alpha_h , \sigma$



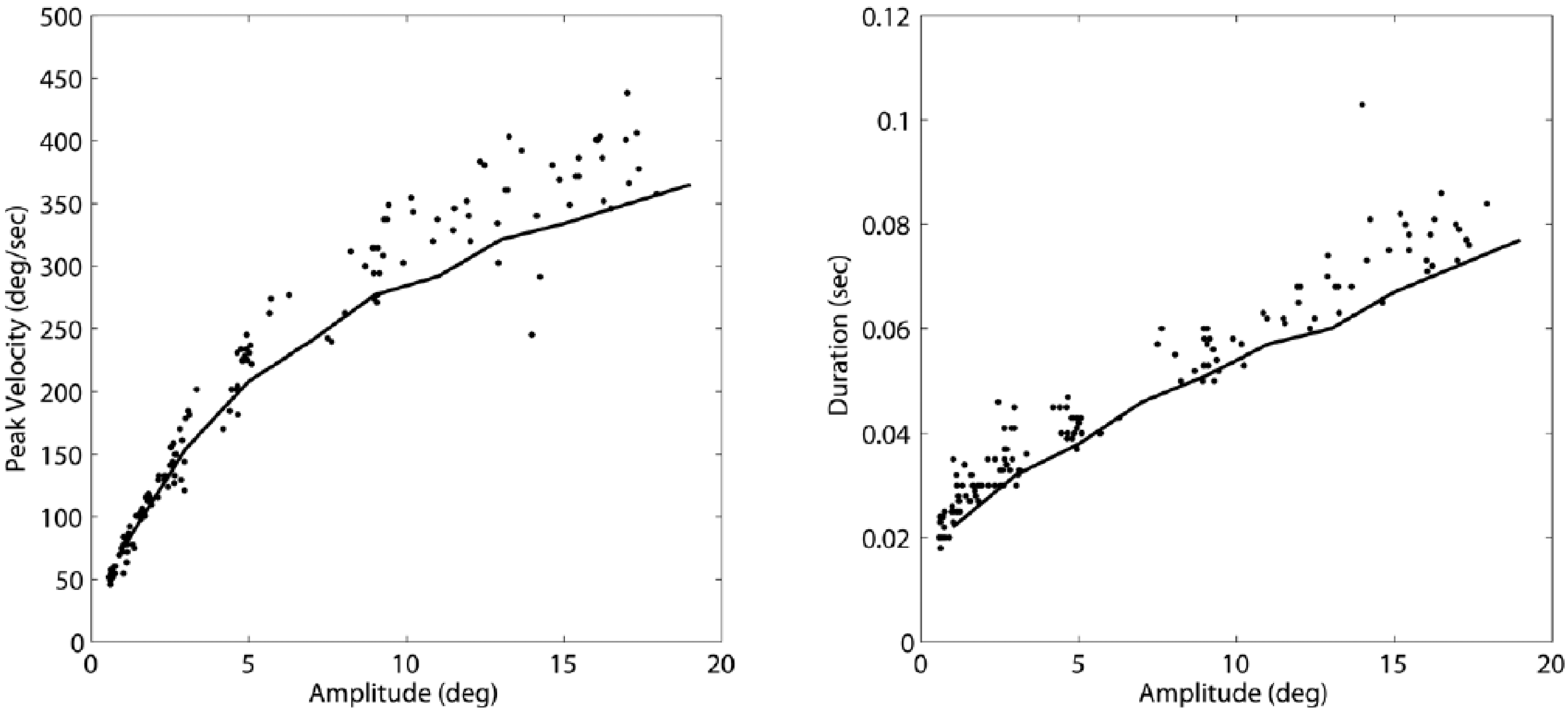
Results: Head-Restrained Saccades





.... Experimental Data (Harwood et al., 1999)

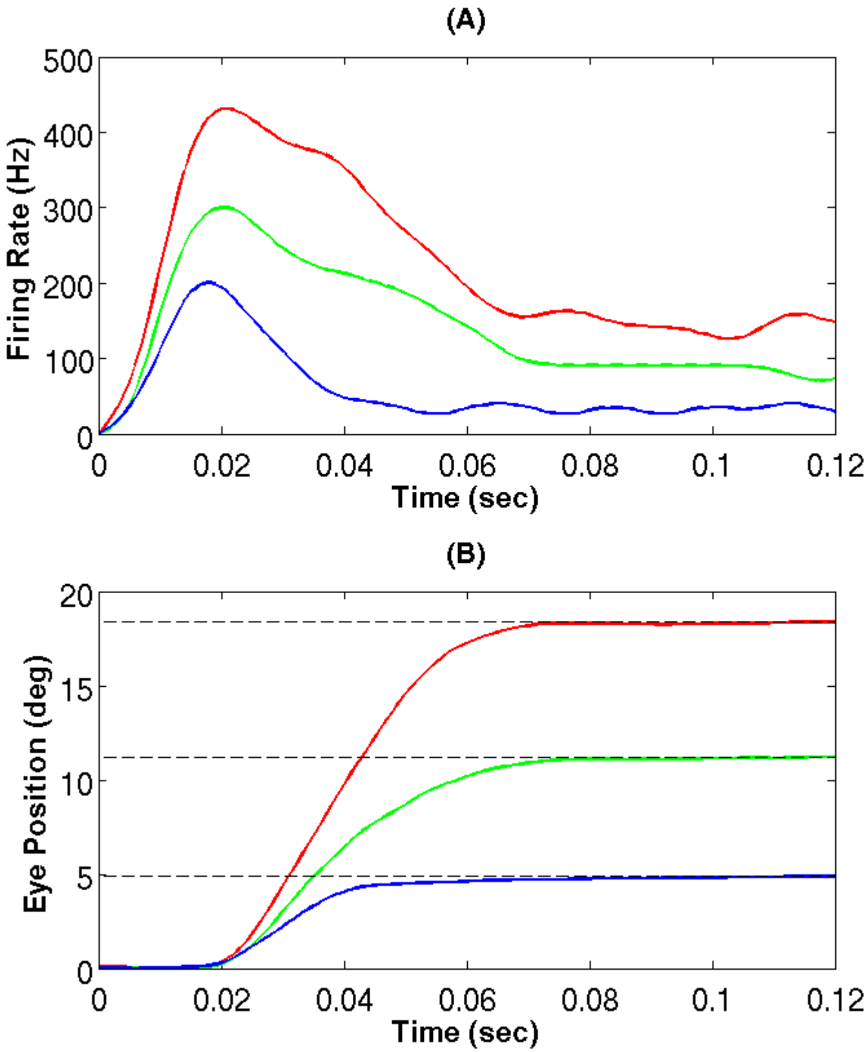
Results: Head-Restrained Saccades



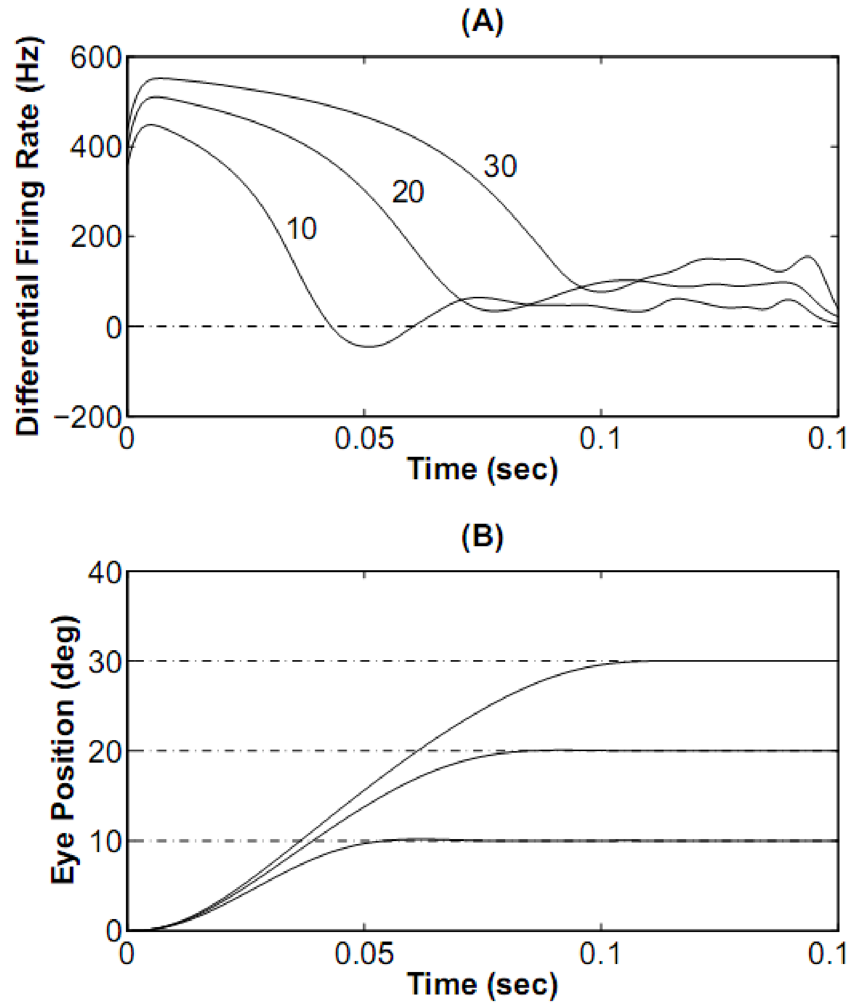
········ Experimental Data (Harwood et al., 1999)

—— Model Result (**σ = 0.002, α_e = 0.016, n=4**)

Results: Head-Restrained Saccades

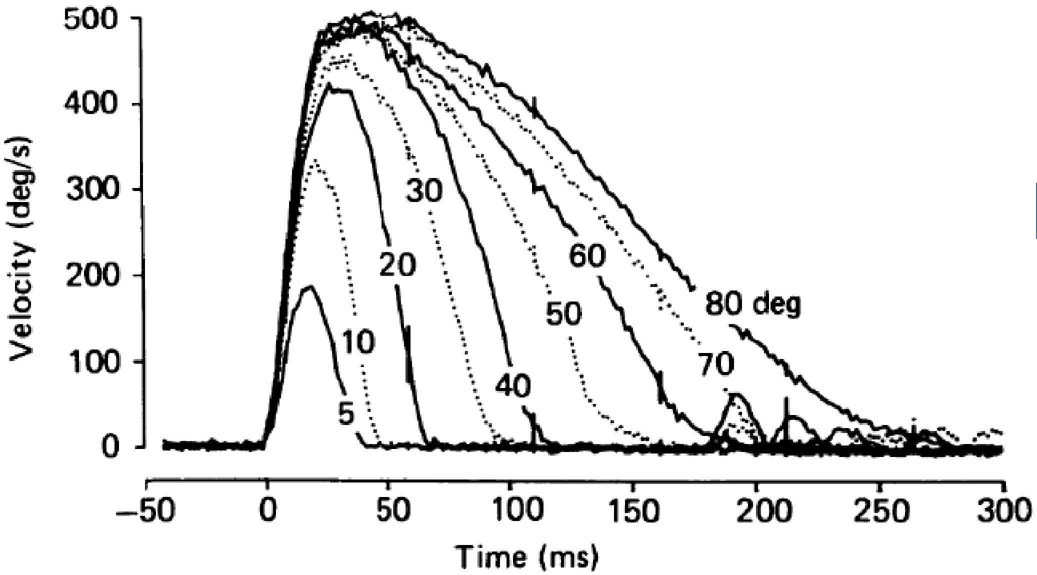


Experimental Results
(Sylvestre & Cullen, 1999)



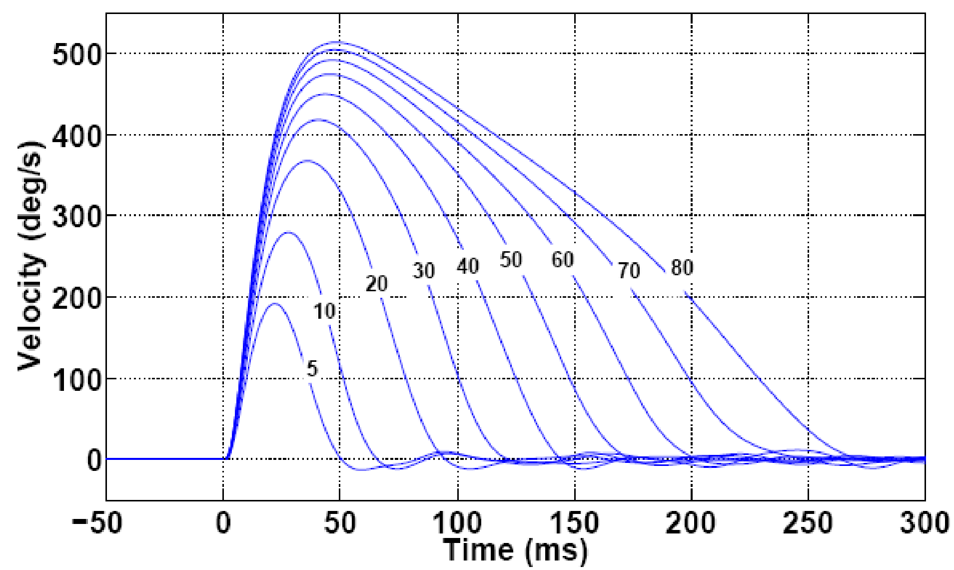
Model Simulation Results

Results: Head-Restrained Saccades

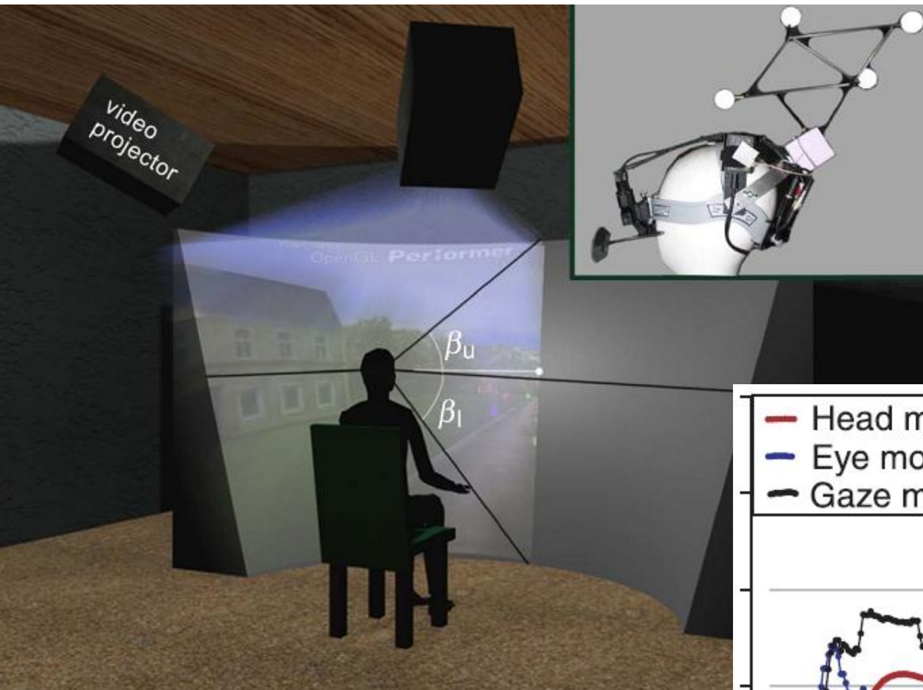


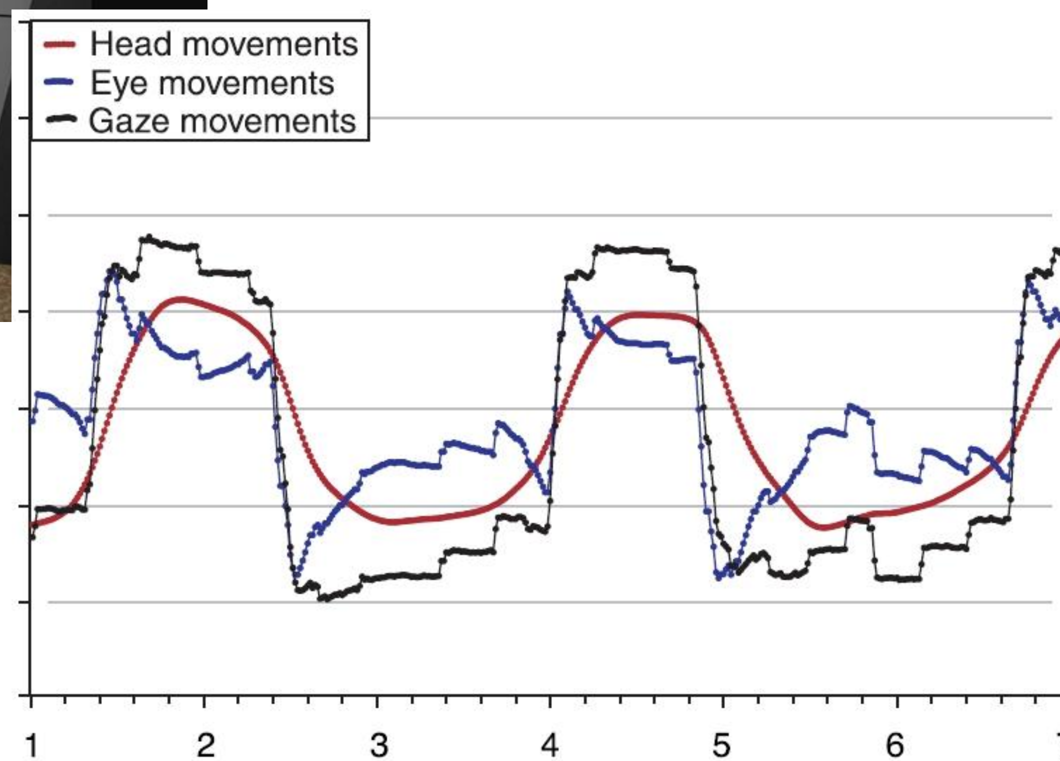
Experimental Results (Collewijn et al., 1988)

Model Simulation Results



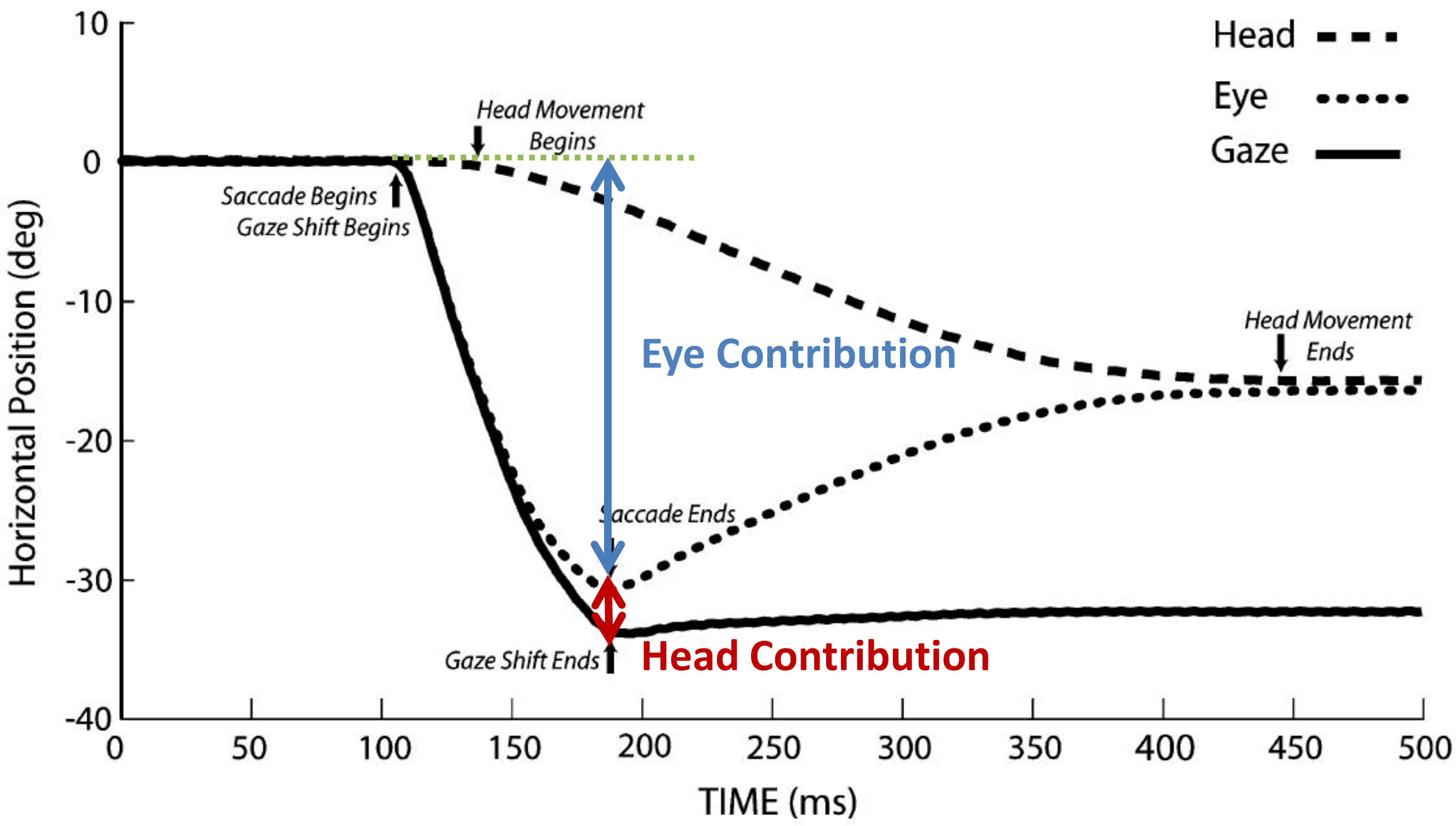
Results: Head-Free Saccades



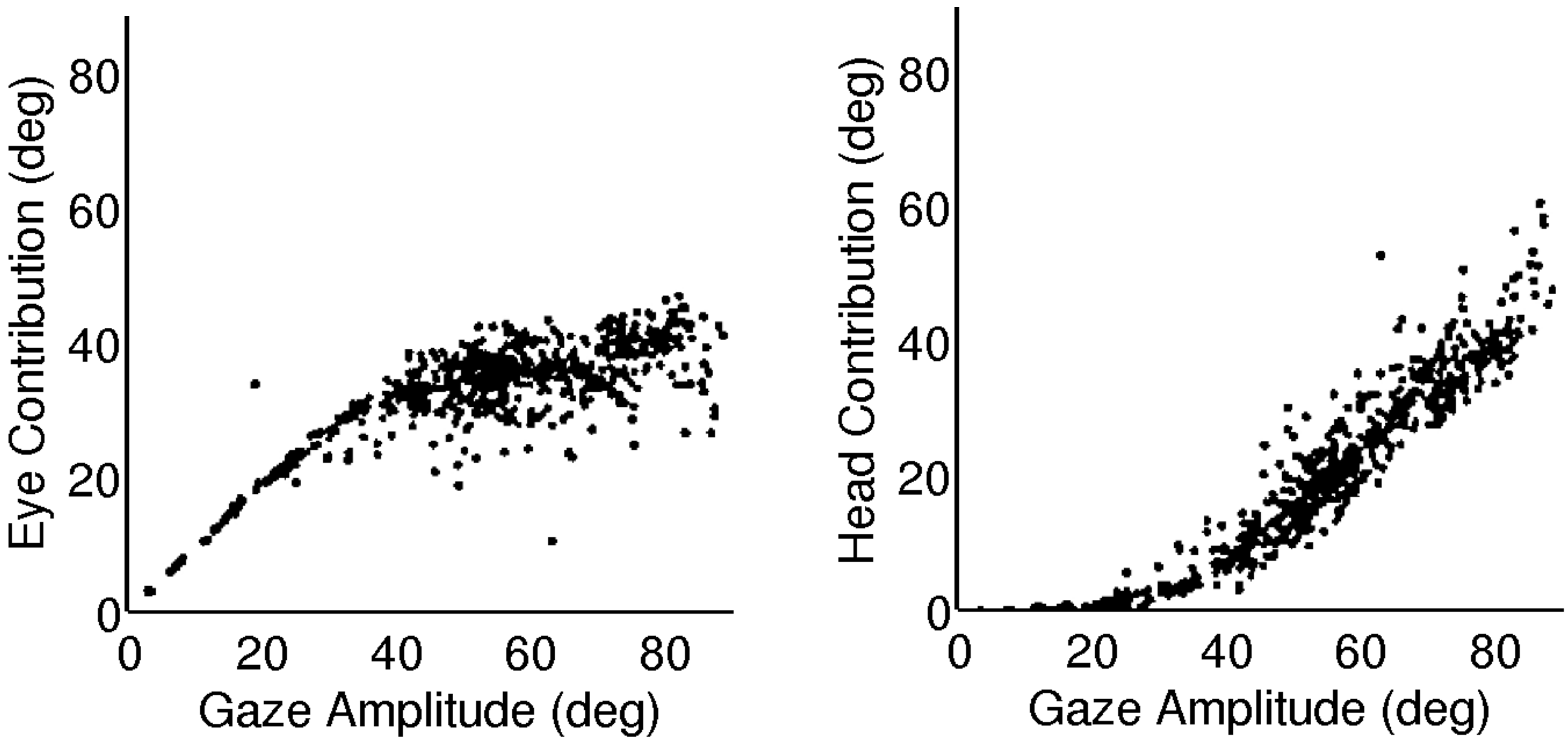


Head-free gaze shift of human subjects during a visual search paradigm (Hardiess et al, 2008)

Results: Head-Free Saccades

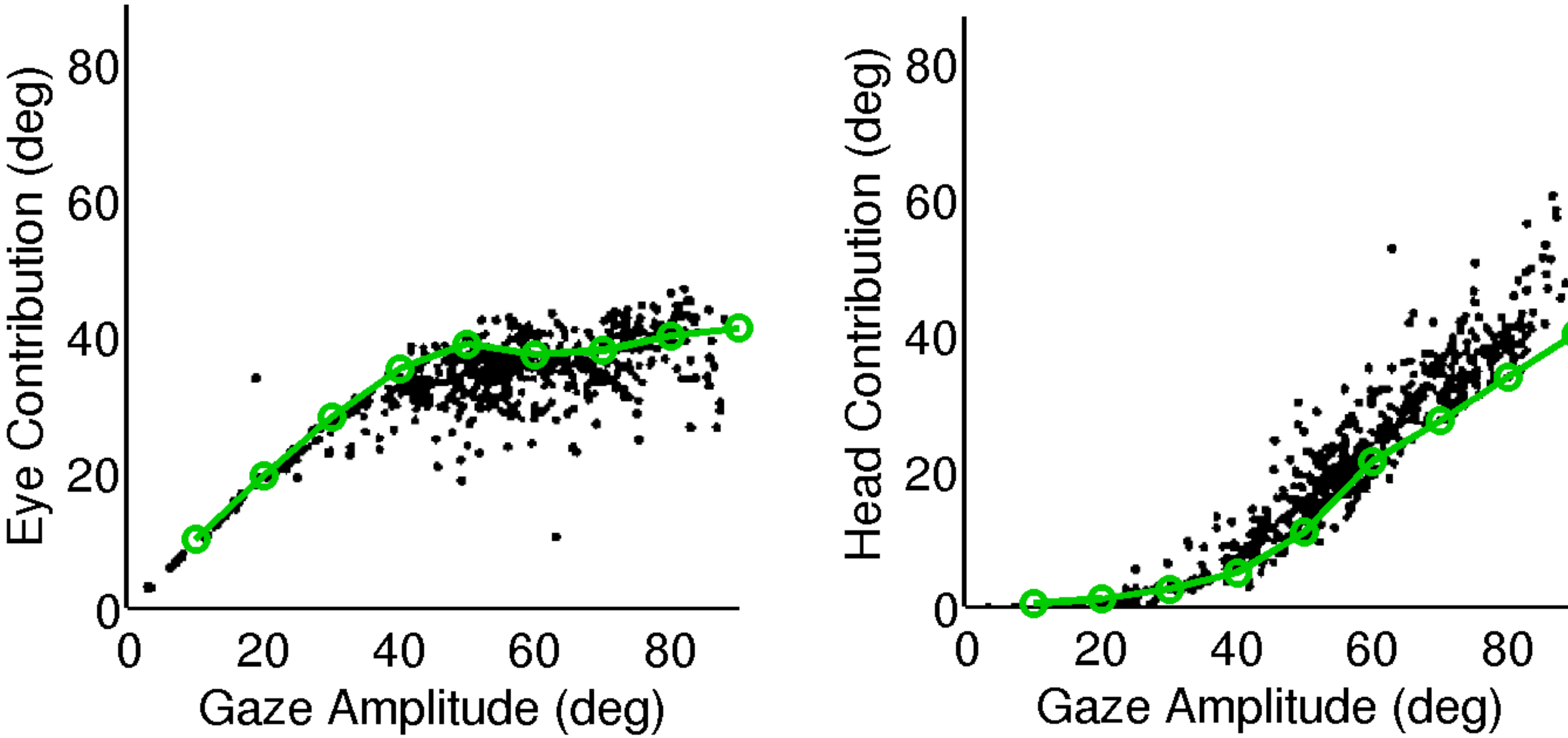


Results: Head-Free Saccades



▪▪▪▪▪▪ Experimental Data (Freedman and Sparks; 1997)

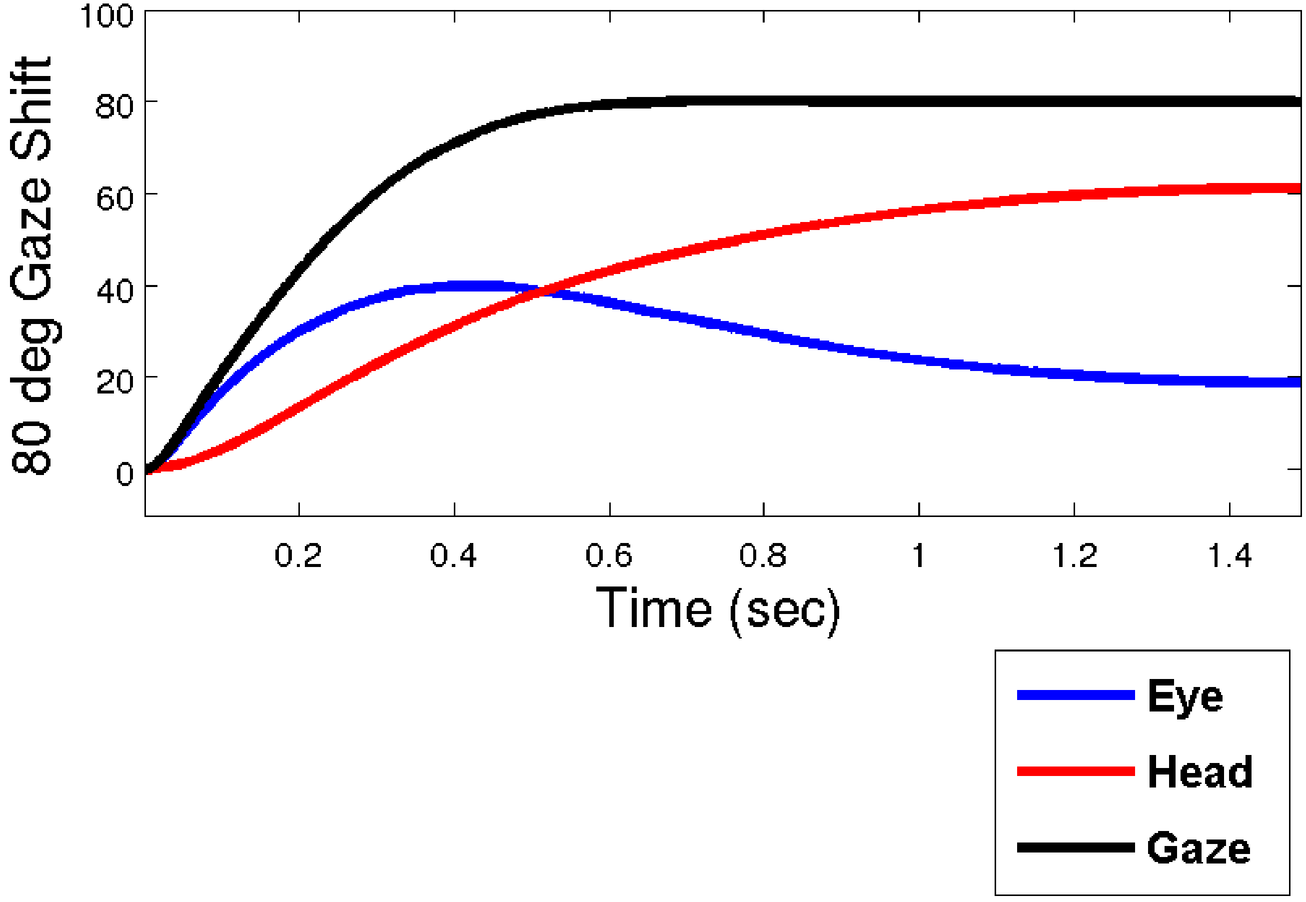
Results: Head-Free Saccades



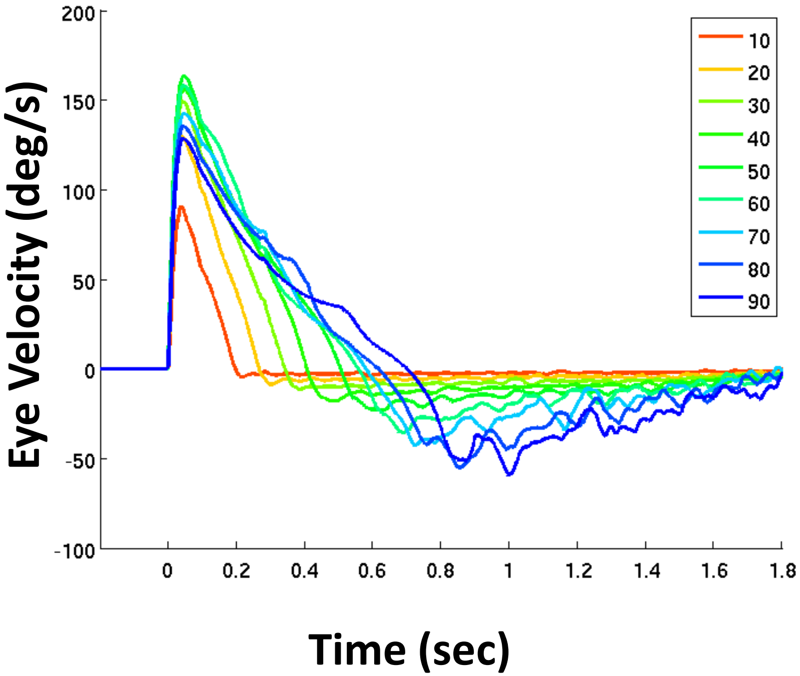
Experimental Data (Freedman and Sparks; 1997)

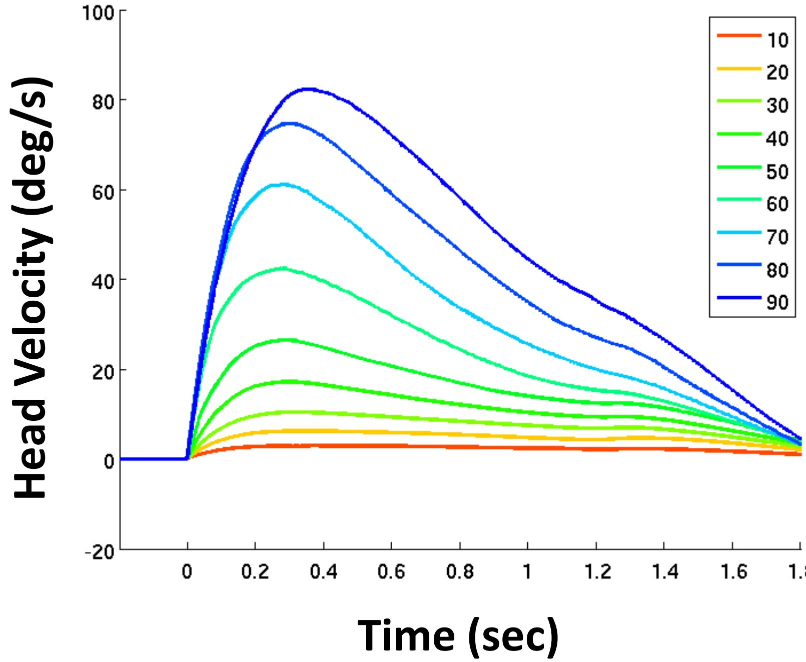
Model Result (**σ = 0.002, α_e = 1.0, α_h = 0.016, n=4**)

Results: Head-Free Saccades



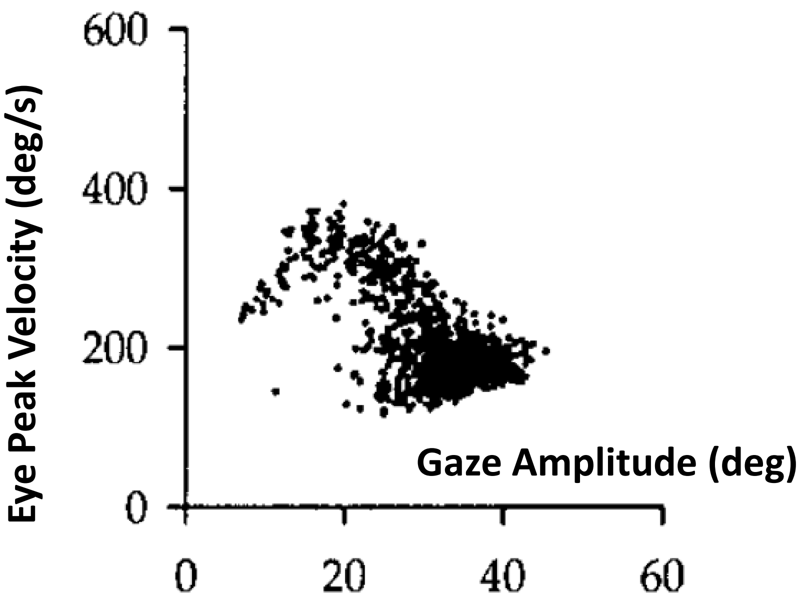
Results: Head-Free Saccades



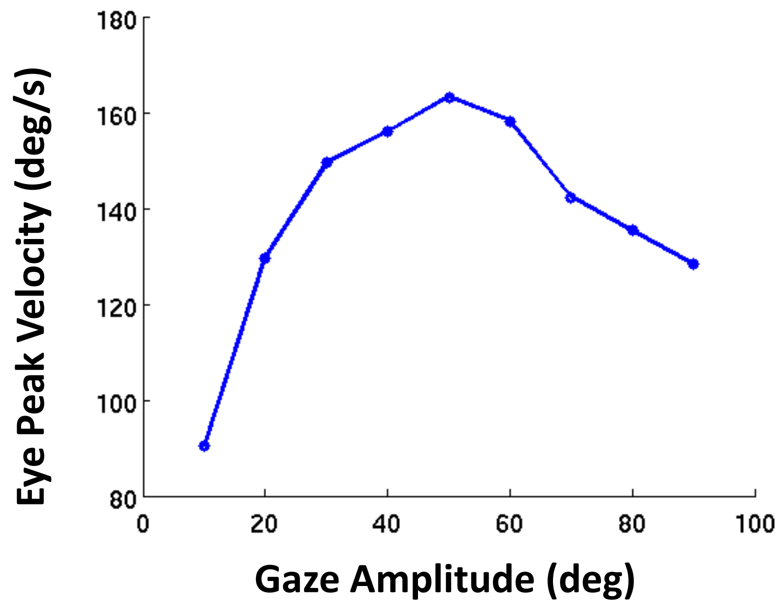


Model Result (**σ = 0.002, α_e = 1.0, α_h = 0.016, n=4**)

Results: Head-Free Saccades



Experimental Data
(Freedman and Sparks; 1997)



Model Result

Conclusion

- Simple open-loop neural controller capable of reproducing biologically realistic eye and head movements.

- The model is based on an adaptation mechanism that on one hand is local and biologically plausible and on the other hand minimizes a cost function, therefore it creates a bridge between **optimality principles** and **neural architectures**.

Future Directions:

- Different initial eye positions

- Forward model learning

- Other ballistic movements