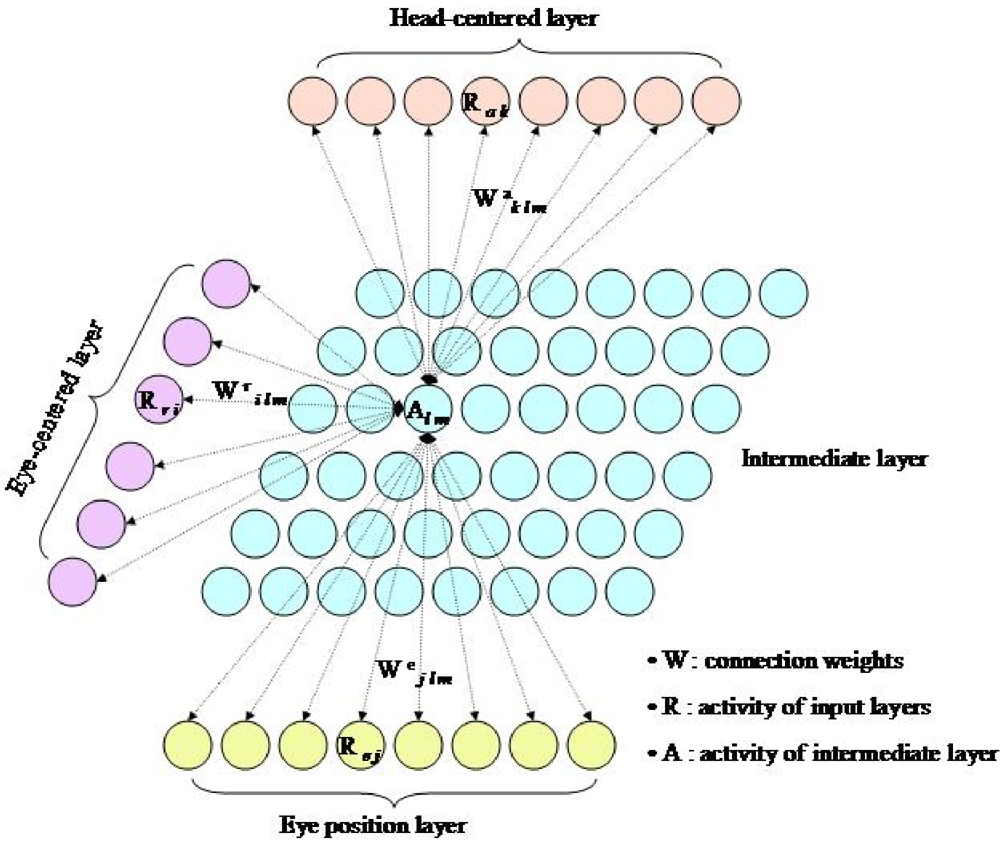

The network consists of three input layers and an intermediate layer. The three input layers – an eye-centered layer, an eye position layer and a head-centered layer – are also output layers; the final estimates of the network are read from these layers after relaxation. The three input layers consist of three topographic layers of N units indexed by their position, *i(*or *j,k)*, where *i(*or *j,k)* = 1…*N*. Similarly, the intermediate layer is a topographic 2D map of $N \times N$ units indexed by their position *l*, *m*, where *l* = 1…*N* and *m*=1…*N*.

1. Connection weights

The input layers are symmetrically interconnected with the intermediate layer (hidden layer), and the corresponding matrices of connection weights are denoted by W^r, W^e, W^a for, respectively, the eye-centered, eye position and head-centered layers. The connection strengths between unit *i* (*j*,*k*) in each input layer and unit (*l*,*m*) in the intermediate layer are given by

$$W_{ilm}^{r} = K_w \exp\left[\frac{\cos[(2\pi/N)(i-l)]-1}{\sigma_w^2}\right]$$

$$W_{jlm}^{e} = K_w \exp\left[\frac{\cos[(2\pi/N)(j-l)]-1}{\sigma_w^2}\right]$$

$$W_{klm}^{a} = K_w \exp\left[\frac{\cos[(2\pi/N)(k-l-m)]-1}{\sigma_w^2}\right]$$

The variable σ_w represents lateral spread: unit i is strongly connected if $|i-l|/N \le \sigma_w/2\pi$. Note that with these connection matrices, unit (*l*,*m*) in the intermediate layer is most strongly interconnected with unit *i*=*l* in the eye-centered layer, *j*=*m* in the eye position layer and *k*=*l*+*m* in the head-centered layer. Unit (*l*,*m*) is connected more weakly to neighboring units in each layers, with the spatial extent of these connections is controlled by σ_w .

2. Network initialization

$R_{ri}(t)$, $R_{ej}(t)$, and $R_{ak}(t)$ are denoted as the activity of unit *i* (*j*,*k*) in the eye-centered, eye-position and head-centered layer at time t.

For eye-centered position, the probability distribution for the initial activity, denoted $R_{ri}(0)$, is given by

$$P(R_{ri}(0)\,|\,x_r) = \frac{f_i(x_r)^{R_{ri}(0)} \cdot e^{-f_i(x_r)}}{\Gamma(R_{ri}(0))},$$

$$f_i(x_r) = C_r\left(K \exp\left[\frac{\cos[x_r - (2\pi/N)i]-1}{\sigma^2}\right] + \nu\right)$$

The expressions for $P(R_{ej}(0)|x_e)$ and $P(R_{ak}(0)|x_a)$ are identical to $P(R_{ri}(0)|x_r)$, except that *r* is replaced by *e* or *a*. The expressions for f (x_a) and f (x_e) are identical to $f_i(x_r)$ except that *r* is replaced by *a* or *e*.

The activity in the intermediate layer, $A_{lm}(0)$, is initialized to 0: $A_{lm}(0) = 0$ for all *l*,*m*.

3. Recurrent network evolution

The evolution of the activities in the recurrent network is described by a set of coupled nonlinear equations. Denoting $A_{lm}(t)$ as the activity of unit (*l*,*m*) in the intermediate layer at time t, the evolution equations are written

$$L_{lm}(t) = \sum_i W_{ilm}^{r} R_{ri}(t) + \sum_j W_{jlm}^{e} R_{ej}(t) + \sum_k W_{klm}^{a} R_{ak}(t)$$

$$A_{lm}(t+1) = \frac{L_{lm}(t)^2}{S + \mu \sum_l \sum_m L_{lm}(t)^2}$$

$$R_{ri}(t+1)=\frac{\left[\sum_l\sum_m W^r_{ilm}A_{lm}(t+1)\right]^2}{S+\mu\sum_i\left[\sum_l\sum_m W^r_{ilm}A_{lm}(t+1)\right]^2}$$

$$R_{ej}(t+1)=\frac{\left[\sum_l\sum_m W^e_{jlm}A_{lm}(t+1)\right]^2}{S+\mu\sum_j\left[\sum_l\sum_m W^e_{jlm}A_{lm}(t+1)\right]^2}$$

$$R_{ak}(t+1)=\frac{\left[\sum_l\sum_m W^a_{klm}A_{lm}(t+1)\right]^2}{S+\mu\sum_k\left[\sum_l\sum_m W^a_{ilm}A_{lm}(t+1)\right]^2}$$

where $L_{lm}(t)$ represents a linear pooling of activities from the three input layers. The activation functions A_{lm} or R_{ri}, R_{ej},R_{ak} implement a quadratic nonlinearity coupled with a divisive normalization.

4. Parameters used in the simulation

K = 20 Hz, ν = 1 Hz, σ = 0.40 radians, K_w = 1, μ = 0.002 s and S = 0.1 Hz.
σ_w = 0.37 radians, C_r=C_e=C_a=1 s.