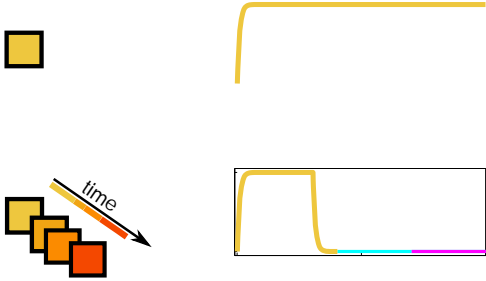


2012). In contrast, the temporal attributes of the stimuli -

Table 1 Variable and parameter with their default value

Symbol	Description
Variable	
I_j	Excitatory inhibitory efficacy of cell j
u_j	Normalized excitatory efficacy of cell j (initially $u_j = 1$)
v	Normalized excitatory efficacy of inhibitory cell (initially $v = 1$)
p_j	Learning rate of cell j (baseline $p_j = 1$)
w_{jk}, w	Strength of excitatory/inhibitory cell k to cell j
T_j, T	Decay time constant
Time scale (default value in the i)	
	Time scale of excitatory cell (10 ⁻⁶)
f	Time scale of synaptic facilitation (1 ⁻⁴)
w	Time scale of weight (150 ⁻¹)
a	Time scale of adaptation (400 ⁻⁵)
s	Time scale of synaptic depression (50 ⁻⁶)
T_{cue}	Decay time constant of trigger cue (50 ^{-2,3})
D	Decay time constant of excitatory effect on behavior (30 ⁻¹)
D'	Decay time constant of inhibitory effect on behavior (20 ⁻¹)
Other parameters (default value in the i)	
	Excitatory effect (Hebbian learning)
	Threshold of excitatory cell (0.5)
v	Threshold of inhibitory cell (0.5)
p_{max}	Maximum learning rate (2)
Z_k	Strength of excitatory/inhibitory cell k (0.3)
L	Weight of inhibition (0.6)
b	Strength of adaptation (1)
M	Learning rate of Hebbian (1)
w_{max}	Maximum synaptic weight on behavior (0.4852)
w'_{max}	Maximum synaptic weight on behavior (4.1312)
w_{min}	Minimum synaptic weight on behavior (1.3488)
d	Strength of LTD 6.4598999 194.03999328 369.368985f h hh

and ... ti ... i ... ified the a a ... i, b ... t ... a ... t ... ece ... a



2. \dots

Therefore, it is clear that the algorithm described above is correct. In fact, it is easy to see that the expected weight of the tree T is $w(T) = \sum_{i=1}^n w_i$. (6) To achieve the desired weight $w(T)$ of the tree T , it is necessary to choose the appropriate values of α and β . (9) This can be achieved by using the following theorem. (6) and (9), that

$$(1)$$

(Kerle et al. 1999; Pfeiffer and Gerstner 2006; Cuthbert et al. 2010).

The delay between the triggering event can be coded in the electrical architecture, e.g., with the delay (Fig. 2). During training, synapse 1 is activated for T_1 seconds followed by synapse 2 (Fig. 2a). The timing of the delay is determined by the delay of the synapse (Sect. 2). When the first synapse is active, synapse 1 is active and LTD is induced, decreasing the synaptic weight, w_{21} , from synapse 1 to synapse 2. After T_1 ends, the first synapse is deactivated, and the second synapse is activated. Hence, synapse 1 did not become inactive again, and therefore, the second synapse is active. During this period, LTP is induced again, increasing the synaptic weight w_{21} . Shortly after, synapse 1 becomes inactive, changing the weight w_{21} again, a cyclic process. Hence, the synaptic weight is active. The initial value of the synaptic weight (w_{21}^0 and w_{21}^1 , respectively) can be computed in closed form (Sect. 2). Repeated sequences of the training sequence lead to the synaptic weight of the synaptic weight, w_{21}^i (synaptic weight after i training), to a fixed value (Fig. 2b). On the other hand, the synaptic weight w_{12} is decreased during each training because the synaptic weight 2 is active after the first synaptic weight 1 (Sect. 2). In the case of N synapses, each synaptic weight $w_{k+1,k}$ is connected to a sequence associated with T_k , hence, each synaptic weight $w_{k+1,k}$ becomes negligible during training. Thus, the electrical architecture encodes the sequence of the sequence.

The delay between the first synapse 1, T_1 , determines the delay between the synaptic weight w_{21} (Sect. 2). For a given value of T_1 , LTD at the beginning of w_{21} (Fig. 2c). Hence,

is considered a mechanism for fine-tuning (Bassett et al. 2000; D'Esposito 2003; Reiter et al. 2004; Kaur et al. 2007; Gaerembois et al. 2009). With this change in connectivity, directed connectivity decreases as well as the strength of the bidirectional relationship. This might be due to

the first time the effect of the relationship, here activity of the first relationship is related to the second (Fig. 3). This is if the analysis is based on the fact that the eight are fixed digressions. This is a typical feature (Section 4.4). After the analysis is related with a brief case, it is also related to the second case (Section 2

(Fig. 20,000 iterations w^0). The attractor eight after the initial stage, w_{21}^i , is described by a basis of eight functions that converge in the initial stage. The eigenvalues of the distribution in the initial stage of the attractor eight after the initial stage are the eigenvalues of the attractor eight after the initial stage (Fig. 5c). The variance of the attractor eight, w_{21}^∞ ,

are; a ... ai, ca ... the; e fa ... ti et ac -
 ig; ce (Be da a d He; 2003), i tead f h; t; .
 faci itati . I c; t; att the ca e f h; t; . faci itati ,
 ada tai ca e the effecti ei t f; . e ... ai t
 dec; ea e; e ti e.

I thi ca e ... ai acti it; a ... de ed b

$$\frac{du_j}{dt} = -u_j + (w_{jj}u_j + s_j - Lv - a_j),$$

$$a \frac{da_j}{dt} = -a_j + bu_j,$$

$$s \frac{ds_j}{dt} = -s_j + \sum_{k \neq j}^N w_{jk}u_k,$$

$$v \frac{dv}{dt} = -v + \sum_{k=1}^N Z_k u_k - v,$$

he; e a_j de te the ada tai e e f; ai j , ai
 the ti e ca e fa da tai , a d bi the ada tai t; e gh.
 Feedbac be; ee ... ai ... a ... ed t be; e
 tha feedbac; ithi a ... ai ; th , the t ta i t
 f; ... ai j a ... it i t e f-e citati $(w_{jj}u_j)$, a d
 a tic i t f; the; ... ai (s_j) hich e ed
 the ti e ca e s. N t that i the i it $s \rightarrow 0$, a e
 a e i ta ta e .

F; a ... ilab e ch ice f; a a et; , g ba i hibiti
 t; ac acti it fa t; tha e citati be; ee ... ai .
 The; he a ... ai bec e i acti e d e t ada -
 tai , the e e f g ba i hibiti dec; ea e , a; i g
 be e t ... ai t bec e acti e. Thi; ea the
 eigh t f e f e citati ca e c de ti i g. Th , i thi
 et; e; e de ed g t; a tic i t; ithi a ... ai
 a; e . The ea; i g; e f; w_{jj} a a a g; t w_{jk} ith
 the additi a a ... ti that i ce w_{jj} e; e e ted the
 a tic eigh t; ithi a ... ai , it c; d t dec; ea e
 be; a cetai a e w_{min} . A , the a a et; f; g
 t; a tic i t; ithi a ... ai a e a; ed t be dif-
 f; e t f; the a a et; f; g t; a tic i t be; ee
 ... ai .

The ea; i g; e; a the

$$\frac{dw_{jj}}{dt} = - \frac{p}{d}(w_{jj} - w_{min})u_j(t - D')(1 - u_j(t)) - \frac{p}{d}(w_{jj} - w_{max})u_j(t - D')u_j(t).$$

Whe the ... ai ... a acti ated $(u_1(t) \approx 1)$ f; $t \in [0, T_1]$ (Fig. 7a), the cha ge i the; eigh t w_{11} e; e g; e d b the iec; i e diff; e tia e; ai

$$\frac{dw_{11}}{dt} = \begin{cases} 0, & t \notin [D', T_1 + D'] \\ \frac{p}{w_j}(w_{max} - w_{11}), & t \in [D', T_1] \\ -\frac{d}{w}(w_{11} - w_{min}), & t \in [T_1, T_1 + D']. \end{cases}$$

The f; i g; e; ai e; e the a tic; eigh t at the e d fa; e e tai , $w_{11}(T_{tot})$, t the a tic; eigh t at the begi i g f the e e tai , $w_{11}(0)$:

$$w_{11}(T_{tot}) = w_{11}(0)e^{-T_1 \frac{p}{d} \frac{1}{w}} e^{(\frac{p}{d} - \frac{d}{w})D' \frac{1}{w}} + w'_{max} e^{-D' \frac{1}{d} \frac{1}{w}} (1 - e^{-T})$$



This emerging evidence indicates that the architecture of the brain (Buckner and Gollman 2009; He et al. 2014), in particular the connectivity between the default mode network (DMN) and the task-positive network (TPN) is critical for cognitive performance.

4.1.1. The role of the DMN in cognitive performance

The DMN is a network of brain regions that are active when the individual is at rest and not engaged in any task.

to occur. This article therefore provides a rigorous and
calibrates the evidence base. For
instance, the authors have identified the following

- Friston, K.J., Harrison, N., Frith, C.D., Frith, C., & Frith, N. (2003). Hierarchical predictive coding: a theory of perception. *The Journal of Neuroscience*, *23*(37), 11,628–11,640.
- Gardner, C.W. (2004). *Handbook of stochastic methods*. Berlin: Springer.
- Gauthier, J.P., & Beauregard, M.F. (2014). Learning to read: a neural basis for reading. *Nature Neuroscience*, *17*(5), 732–737.
- Gauthier, J.P., Shallice, M.G.H., Leclercq, Y., Beauregard, M.F., & Shallice, H.Z. (2009). Learning to read: a neural basis for reading. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(16), 6826–6831.
- Gelman, W., & Kitano, W.M. (2002). *Mathematical modeling*.

- Morone, M.C., Rizzo, J., & Basso, D. (2005). Saccadic eye movements: A neural code for eye position. *Nature Neuroscience*, *8*(7), 950–954.
- Nabavi, S., Fong, R., Poon, C.D., Li, J.Y., Tiesi, R.Y., & Maiorini, R. (2014). Eye position: A neural code for eye position. *Nature*, *511*(7509), 348–352.
- Oh, M.C., DeAngelis, V.A., Gire, E.S., & Stryker, T.R. (2006). Eye position: A neural code for eye position. *The Journal of Biological Chemistry*, *281*(2), 752–758.
- Oja, E. (1982). Simplified algorithm for data clustering. *Journal of Mathematical Biology*, *15*(3), 267–273.
- Perrin, R., Berger, T.K., & Muzina, H. (2011). A neural code for eye position. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(13), 5419–5424.
- Pfister, J.P., & Geisler, W. (2006). The neural code for eye position. *The Journal of Neuroscience*, *26*(38), 9673–9682.
- Pfister, P.Q. (2003). A neural code for eye position. *Journal of Experimental Psychology: Human Perception and Performance*, *29*(5), 949.
- Phillips, B.D., Shadmehr, A.K., Shadmehr, H.Z., & Beierholm, M.F. (2001). Visual adaptation: A neural code for eye position. *Neuron*, *29*(1), 157–169.
- Poggio, C., Nardelli, R., Meier, S., & Geisler, W. (2013). The neural code for eye position. *Nature Neuroscience*, *16*(7), 942–948.
- Rao, R.P., & Sejnowski, T.J. (2001). Signal processing in the eye position. *Neural Computation*, *13*(10), 2221–2237.
- Reich, J., Yu, V., Fisi, S., & Stryker, W. (2004). The neural code for eye position. *The Journal of Neuroscience*, *24*(13), 3295–3303.
- Saiki, K., Hikosaka, O., Miachin, S., Tani, R., Sasaki, Y., & Poggio, B. (1998). The neural code for eye position. *The Journal of Neuroscience*, *18*(5), 1827–1840.
- Shea-Brown, E., Rife, J., Rife, B.C., & Maffei, C. (2006). A neural code for eye position. *Brain Research*, *1070*(1), 189–201.
- Shadmehr, M.G., & Beierholm, M.F. (2006). Reading the neural code. *Science*, *311*(5767), 1606–1609.
- Singer, P., Baccus, F., Chelazzi, J.D., & Hikosaka, P., et al. (2011). A neural code for eye position. *Philosophical Transactions of the Royal Society B*, *31*(25), 9238–9253.
- Sjostrom, P.J., Tiesi, G.G., & Newsome, S.B. (2001). Rate, timing, and adaptation in the eye position. *Neuron*, *32*(6), 1149–1164.
- Sing, S., Sjostrom, P.J., Reig, M., Newsome, S., & Chelazzi, D.B. (2005). High-speed feature extraction in the eye position. *PLoS Biology*, *3*(3), e68.
- Tanaka, T., D'Esposito, A.J., & Maffei, R.G. (2014). The neural code for eye position. *Neural Computation*, *26*(1), 1–15.