## **Effects of Time-Dependent Stimuli in a Competitive Neural Network Model of Perceptual Rivalry**

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 $\mathcal{R}_{\text{max}} = \mathbf{Y}_{\text{max}} = \sqrt{\mathbf{A}\mathbf{Y}_{\text{max}}} \mathbf{0}_{\text{max}} = \mathbf{0}_{\text{max}}$ © Society for Mathematical Biology 2012



 $T$ <sub>ime</sub> $\sum_{i=1}^n a_i$ 

 $t_{\rm eff} = \frac{1}{2} \sqrt{(\frac{1}{2} \pi \sqrt$  $\mathbf{a}$  in  $\mathbf{v}$  in the contrast of both stimuli increases the rivalry alternation rate. The rivalry alternation rate  $\mathbf{a}$  $P_1 \cap \mathcal{P}_1$  in  $\mathcal{P}_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$  in that is stimulus will define extensive extensive one extends the contrast of one extends of one extends the contrast of one extends the contrast of one extends  $\mathcal{C}_{\mathcal{A}}$ chease the dominance time of the other. Recent evidence suggests proposition (iii) may be defined by  $\overline{m}$  hold for  $\overline{m}$   $\overline{m}$  and  $\overline{m}$  increasing  $\overline{m}$  and  $\overline{m}$  increasing one stimulus  $\overline{m}$  $c_{\rm tot}$  affects the dominance time of the stronger stimulus (Brascamp et al. [2006](#page-29-2))  $c_{\rm tot}$  $\begin{array}{l} \mathcal{R}_{\rm int} = \frac{1}{2} \mathcal{R}_{\rm int} \left[ \begin{array}{ccc} \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} \\ \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} \end{array} \right] \mathcal{R}_{\rm int} \left[ \begin{array}{ccc} \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} \\ \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} & \mathcal{R}_{\rm int} \end{array} \right] \mathcal{R}_{\rm int$  $\arctan x$ e time dominance time dependence upon international stimuli (see timuli (see timul  $\overline{\mathbf{F}}_k = \nabla \left( \overline{\mathbf{F}}_k \right)$  intervals intervals intervals intervals in the same perceived in the same p  $r_{\rm m}$  ,  $r_{\rm m}$  et al. 2003  $r_{\rm m}$  row (Orbital et al. 2003; Leopold et al. 2003; Leopold et al. 2003; Leopold et al. [2002](#page-29-4); Leopold et al. 2003; Leopold et al. 2003; Leopold et al. 2003; Leopold et al. 2002; Leopold  $\mathbb{R}$ .  $\mathbb{R}$  et al. [2003;](#page-29-5) Pearson and Brascamp [2008\)](#page-30-3), possibly due to recovery of adaptation of adaptation of adaptation  $\mathbb{R}$ .  $\tau_{\rm eff}$ tive processes in the intervals in the intervals of  $\sigma_{\rm eff}$  et al. [2009\)](#page-29-6). Switching seems in the intervals seems in the intervals of  $\sigma_{\rm eff}$  $\tau_{\rm min}$  to  $\tau_{\rm min}$  be not be  $\tau_{\rm min}$  . The mass  $\tau_{\rm max}$  of  $\tau_{\rm max}$  and  $\tau_{\rm min}$  is to have memory up to  $\tau_{\rm min}$  $s_{\rm{max}} = \frac{1}{200} \left( \frac{0.200 \text{ m}}{100 \text{ s}} \right)$ .  $\frac{1}{200} \left( \frac{0.200 \text{ m}}{100 \text{ s}} \right)$ . In addition, the  $\frac{1}{200}$  $\bar{Q}$  in  $\bar{\nabla}$  then strengthening of alternating executive alternation  $Q_1$  and  $\bar{Q}$  $\mathbb{Z}_{m^2}$  and  $\mathbb{R}$  by  $\mathbb{Z}_{2}$  by  $\mathbb{Z}_{m}$  ,  $\mathbb{Z}_{2}$  to the time course of  $\sum_{n=1}^{\infty}$ intensifications (Kang et al. [2009\)](#page-29-7). Understanding the neural processes under processes under processes under  $\int_{\mathbb{R}^d} \mathbb{E}_{\mathbf{r}} \cdot \mathbf{r} \cdot \mathbf{r} = \int_{\mathbb{R}^d} \mathbb{E}_{\mathbf{r}} \cdot \mathbf{r} = \int_{\mathbb{R}^d} \math$  $\frac{1}{2}$ 



<span id="page-5-0"></span>
$$
\frac{4\pi}{4} \int_{\frac{1}{2}}^{0} \frac{1}{2} \int_{\frac{1}{2}}^{\frac{1}{2}} \frac{1}{2} \int_{\frac{1}{2}}^{\frac{1}{2}} \frac{1}{2} \int_{0}^{\frac{1}{2}} \frac{1}{2} \
$$







<span id="page-10-0"></span>**Fig. 6**









+  $I > a_L(t)$  **and**  $-$  +  $I_R < a_R(t)$ , t (, T

 $T_{10}$ 

 $N$  in the similar inequality of the second part of the second part of the oscillation, when  $\mathbb{R}^n$  $I_L(t) = -1$  At  $\int_{0}^{t} \int_{0}^{t} \rho \phi(t) dt$ ,  $\int_{0}^{t} \rho \phi(t) dt$  and  $\int_{0}^{t} \rho \phi(t) dt$  $a_L(T_I) = -a_L(0) e^{-T_I/7}$ and the right population should show that the right population should show that  $\mathbf{r}$  $I_R > a_R(T_I) = a_R(0)e^{-T_I/2}$ .  $F_{1}$  to  $F_{2}$  to  $t=T_I$  to  $T_I$  , the states of  $\mathbb{R}$  of  $\mathbb{R}$  and  $\mathbb{R}$  of  $\mathbb{R}$  and  $\mathbb{R}$  $\mathbf{r}_{\text{mean}}$  and  $\mathbf{r}_{\text{norm}}$  population with  $\mathbf{r}_{\text{norm}}$  $-$  < < a<sub>L</sub>(t), t (T<sub>I</sub>, T<sub>I</sub>),  $\frac{a}{\sqrt{a}}$  is always true, and the right population must not release the right population must not release the right population  $\frac{a}{\sqrt{a}}$ 





**Fig. 8** Cycle skipping generates 1 : *n* mode-locked solutions in network ([1a](#page-4-0))–([1d\)](#page-4-1) with left input intera 2 for rupted in time where (**a** *n* = 2 for



## **5 Time-Variation in Both Inputs**

 $S_{\rm eff}$  several authors have examined the effect of simultaneously switching both inputs  $\sqrt{2}$ and  $\mathbf{r}_1$  in  $\mathbf{v}_2$  in a competitive network ( $\mathbf{v}_1$ ,  $\mathbf{v}_2$ ,  $\mathbf{v}_3$ ,  $\mathbf{v}_4$ ,  $\mathbf{v}_5$ ,  $\mathbf{v}_6$ ,  $\mathbf{v}_7$ ,  $\mathbf{v}_8$ ,  $\mathbf{v}_9$ ,  $\math$  $\mathbf{F}_{\text{eff}}$  and  $\mathbf{F}_{\text{eff}}$  in an attempt to understand how intervals  $\mathbf{F}_{\text{eff}}$  $s_n$ single percept to remain in dominance for longing  $\mathcal{F}_n$  in  $\mathcal{F}_n$  .  $\mathcal{F}_n$  is a length of the set al. [1963](#page-30-2); Leopold et al. 1963; Leopold et al. 1963; Leopold et al. 1963; Leopold et al. 1963; Leopold et al. al. [2002](#page-29-4); Blake et al. [2003](#page-29-5); Chen and He [2004](#page-29-10)). They did not probe more complex more comple  $d_{\rm max}$  denote the study here. Exploiting a fast  $\frac{d}{dt}$  fast  $\frac{d}{dt}$  fast  $\frac{d}{dt}$  fast  $\frac{d}{dt}$ rameter space, in a single input varied case of  $\mathcal{R}_i$  to the single input varied case of Sect. , into different case of Sect. , in the single varied case of Sect. , in the single varied case of Sect. , in the single v  $\mathbf{d} = \sum_{i=1}^{n} \sum_{i=1}^{n} \mathbf{d}_{i} \mathbf{d}_{i} + \sum_{i=1}^{n} \mathbf{$  $s_{\mu}$  0  $s_{\mu}$   $\alpha$  or  $\alpha$ .  $\mathbf{s}$ . 1 Phase-Locked Online  $\mathbb{R}$  $T_1 = 0$  one simplest possible periodic solution is one where  $T_1$  $\overline{C}$ Frequencies  $\overline{C}$  to  $\overline{C}$   $\overline{C}$  and  $\overline{C}$ . Activity variables should then be in  $c_{\alpha}$  , as shown as shown as shown as shown and a fast  $\alpha$  fast  $\alpha$  fast  $\alpha$  fast  $\alpha$  and at arrive at arrive at a fast  $\alpha$  the same expression for both adaptation  $\mathbf{r}_i$  and  $\mathbf{r}_i$  and  $\mathbf{r}_i$  as in the phase-locked case for  $\mathbf{r}_i$  $\frac{1}{2}$ the single varied  $\frac{0}{2}$  $a_j$  ( ) =  $a_j$  (  $T_I$ ) =  $\frac{a_j}{T_I}$  ag  $a_j$  ( $T_I$ ) =  $\frac{a_{j+1}}{T_I}$ , j = L, R.  $\mathbf{N}_i \in \mathbb{R}^{n_i}$  we require that neither population  $\mathbf{N}_i \in \mathbb{R}^{n_i}$  and they are only are only are only as the theorem in the that the second secon switched  $\mathbf{v}$  and  $\mathbf{v}$  by changes in the input of input  $\mathbf{v}$  $\mathbf{t} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$  $\mathfrak{so}_1$  for  $\mathfrak{so}_{n+1}$  $(P^{-})$   $\longrightarrow$   $\longrightarrow$   $\frac{1}{t}$  +  $\longrightarrow$   $\frac{1}{t}$   $\longrightarrow$   $\frac{1}{t}$   $\longrightarrow$   $\frac{1}{t}$ *(*OF-ii*)* Switching OFF: − *β <* <sup>+</sup> *<sup>e</sup>*−*TI /τ ,*

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 $\hat{Z}$ 

 $\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$   $\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$   $\begin{pmatrix} 0 & \mathbf{1} \\ \mathbf{1} & \mathbf{1} \end{pmatrix}$ 

<span id="page-19-0"></span>**Fig. 11**  $\bullet$  Partition

 $\sum_{i=1}^n a_i$  $\Gamma$ <sup>i</sup>)  $\Gamma$ <sup>2</sup> $\Gamma$ <sup>2</sup>  $I > \frac{e^{-T_I / 2} (1 - e^{-T_I / 2} + e^{-T_I / 2})}{\frac{1}{1 - 2} + 1}$ ,  $\Gamma$ <sup>ii</sup>) R (2)  $\mathbf{F}$   $\mathbf{g}^2$ − + *∆I >*  $\frac{+}{-}$   $\frac{+}{-}$   $\frac{-}{I}$   $\int_0^1 (e^{-T_I x})^f e^{-T_I x} dx$  +  $\int_0^1 e^{-T_I x} dx$  $+$  − − *I* + *e*<sup>−</sup> *T<sub>I</sub> /* 

$$
\Gamma \qquad \qquad + \quad \frac{1}{I} \leq \frac{(1 - \frac{1}{I}) (1 + e^{-T_I / 2}) + (e^{-T_I / 2}) + (e^{-T_I / 2})}{1 - e^{-T_I / 2} + e^{-T_I / 2}},
$$

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 $\begin{picture}(180,10) \put(0,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}} \put(10,0){\vector(1,0){100}}$ 

Finally, the right population switches OFF after *TR*, its sole dominance time  $I(T_U + T_L + T_R - T) + = a_R(T_U + T_L + T_R - T).$ 

 $\mathbb{D}_{\mathbf{m}}$  solving for the adaptation variables and  $\mathbb{D}_{\mathbf{m}}$  in  $\mathbb{D}_{\mathbf{m}}$ tion ( [\)](#page-5-0), we arrive at the following for the following for the associated durations for the associated durations of  $\mathbb{R}^n$  $p_{\alpha}$  phase of the behavior of the behavior

$$
\frac{I}{I_{T}} - \frac{I}{I_{T}} = \frac{e^{(-T_I + T_L + T_U)/} - e^{-T_I}}{-e^{-T_I}}.
$$
\n
$$
\frac{I}{I_{T}} - \frac{(T_L - T)}{T_I} + \frac{e^{(-T_I + T_R + T_U)/} - e^{-T_I}}{-e^{-T_I}}.
$$
\n
$$
\frac{I}{I_{T}} - \frac{(T_U + T)}{T_I} = \frac{e^{(-T_I + T_R + T_U)/} - e^{-T_I}}{-e^{-T_I}}.
$$

 $\sum_{i=1}^{n} 0_i$ er  $\frac{1}{n}$  modell $\sum_{i=1}^{n} 0_i$ 

 $\mathbf{a}_k \in \mathbb{R}^{d-1}$  at  $\mathbb{R}^{d-1}$  and an  $\mathbb{R}^{d-1}$  on  $\mathbb{R}^{d-1}$  and a host of novellation of novellation  $\mathbb{R}^{d-1}$  $\mathbb{P}$ oscillatory behaviors in competitive networks can arise when it constant and input is constant and inpu  $e^{2\theta}$ especially time-dependent. We believe the provide a rich avenue for study in the  $e$  $\overline{\mathbf{v}}_i = \mathbf{v}_i$  models of  $\overline{\mathbf{v}}_i = \overline{\mathbf{0}}_i$  and  $\overline{\mathbf{v}}_i = \overline{\mathbf{0}}_i$  and  $\overline{\mathbf{v}}_i = \overline{\mathbf{0}}_i$ Noest et al. [2007\)](#page-30-4) as well as experimental studies of perceptual rivalry (Blake and Logothetis [2002;](#page-29-8)  $\mathbb{E}[\mathbf{z}]$ 

Perceptual rivalry has long provided a noninvasive way of uncovering neural sub- $\begin{array}{l} \left\{ \begin{array}{ll} \circ & \bullet & \circ \\ \circ & \circ & \circ \\ \bullet & \bullet & \circ \end{array} \right. \end{array}$  strates of visual experience (Eq. [2002\)](#page-29-8). Our results suggest supply to the model of the supply of the model of the supply of the model of the model of the supply  $\mu_{\rm c}$ eral directions for gauging contrast dependent mechanisms in binocular vision and  $\sigma_{\rm c}$  $\mathcal{F}_1 = \mathbf{Q}$  models of perceptual rivalry to potential data sets. The periodic inter $r_{\rm L}$ <sup>0</sup>ruption  $\sim$   $\sqrt{2}$  in a binocular rivalry enacted in  $\sqrt{2}$  rivalry enacted in a binocular rivalry experiment.  $F_{\rm eff}$  high contrasts, our analysis predicts the subject should immediately perceive the subject should immediately perceive the subject should immediately perceive the subject should be subject should be subject to the  $\frac{1}{2}$  intervals, once it is turned on  $\frac{1}{2}$  is the off period is long enough. This is long enough is long enough. This is long enough is long enough in the OFF period is a second to the OFF period is a second to t  $\sum_{i=1}^n \sum_{i=1}^n \sum_{j=1}^n c_{ij}^2$  and  $\sum_{i=1}^n c_{ij}^2$  or the claim that dominance support in percep- $\frac{1}{\sqrt{2}}$  rivalent are mainly governed by a slow adaptive process (Laing and Chow [2002](#page-29-0))  $L = 200$   $R_{\rm eff} = 200$   $R_{\rm eff} = 200$   $R_{\rm eff} = 200$   $R_{\rm eff} = 200$ 

et al. [2007](#page-30-7)). As the length of the stimulus ON period is increased, it would be increased, it would be in $t_{\rm eff,0}$ teresting to see when subjects locking of the phase of  $\sum_{i=1}^{\infty} \frac{1}{n_i} \sum_{i=1}^{\infty} \sum_{i=1}^{\infty} \frac{1}{n_i} \sum_{i=1}^$  $\mathbf{q} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$  $\frac{1}{16}$ tude. It is interesting that the dominance time of a perception of a perception increases with increases w  $\vec{r}_\text{max}$ ing contrast, as shown in our analysis in  $\vec{r}_\text{max}$  in Sect. . This reverse the contrast dependent of  $\vec{r}_\text{max}$  $d_{\mathbf{r}}(\mathbf{x}) = \mathbf{r} + \mathbf$ time decreases as contrast increases according to Levelt proposition (iv) (Levelt [1965](#page-30-0)  $\mathbf{S} = \begin{bmatrix} \mathbf{S} & \mathbf{$  $\begin{array}{cccccccccccccccccc} \mathbf{c}_{1} & \mathbf{c}_{2} & \mathbf{c}_{3} & \mathbf{c}_{4} & \mathbf{c}_{5} & \mathbf{c}_{6} & \mathbf{c}_{7} & \mathbf{c}_{8} & \mathbf{c}_{9} & \mathbf{c}_{1} & \math$ analysis. This may relate to existing evidence of hysteresis between function  $\mathbf{r}$ values of previous experiments (Buckthought et al. [2008\)](#page-29-12). Rather than simply record- $\lim_{n\to\infty} \frac{1}{n} \int_{-\infty}^{\infty} \frac{1}{n} e^{-n} \frac{1}{n} \lim_{n\to\infty} \frac{1}{n} \int_{-\infty}^{\infty} \frac{1}{n} e^{-n} \frac{1}{n} \int_{-\infty$  $\frac{1}{\sqrt{m}}$ 

Our results also suggest several interesting directions for future theoretical work  $\alpha$ ,  $\mathbf{u} = \mathbf{u} \cdot \mathbf{u}$  $\frac{1}{2}$ 0, we have found not behaviors such as mixed mode oscillations such as  $\frac{1}{2}$  $(\mathcal{M}, \mathcal{L})$ . This is not surprising, since  $\mathcal{L}$  is not surprising, since  $\mathcal{L}$  is not surprising, since  $\mathcal{L}$  $\mathbf{v}_1$  and compute neural neural network model where adaptation depends linearly upon  $\mathbf{v}_1$  $r_{\rm{max}} = \frac{1}{2}$  rate (Curtus). However, studying such behavior in a non-mous system in a nonmay offer  $\mathbf{v}_i$  and  $\mathbf{v}_i$   $\mathbf{v}_i$  of  $\mathbf{v}_i$  and  $\mathbf{v}_i$   $\mathbf{v}_i$   $\mathbf{v}_i$   $\mathbf{v}_i$   $\mathbf{v}_i$   $\mathbf{v}_i$  $\alpha$  and  $\alpha$  into our model, we could examine how robust the boundaries particles particle  $t_{\text{t}}$  in parameters are in the face of perturbation. In particular, the particular, the particular, the particular, the parameters  $\frac{1}{2}$ region in  $\mathbb{R}$  by  $\begin{array}{c} \n\mathbb{R} \n\end{array}$  of  $\begin{array}{c} \n\mathbb{R} \n\end{array}$  in pure  $\begin{array}{c} \n\mathbb{R} \n\end{array}$  in pure  $\mathbb{R}$ 

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