Role of Interneuron Diversity in the Cortical Microcircuit for Attention

Calin I. Buia and Paul H. Tiesinga

Computational Neurophysics Laboratory, Physics and Astronomy Department, University of North Carolina, Chapel Hill, North Carolina

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Buia CI, Tiesinga PH. Role of interneuron diversity in the cortical microcircuit for attention. J Neurophysiol 99: 2158–2182, 2008. First published February 20, 2008; doi:10.1152/jn.01004.2007. Receptive fields of neurons in cortical area V4 are large enough to fit multiple stimuli, making V4 the ideal place to study the effects of selective attention at the single-neuron level. Experiments have revealed evidence for stimulus competition and have characterized the effect thereon of spatial and feature-based attention. We developed a biophysical model with spiking neurons and conductance-based synapses. To account for the comprehensive set of experimental results, it was necessary to include in the model, in addition to regular spiking excitatory neurons (E) cells, two types of interneurons: feedforward interneurons (FFI) and top-down interneurons (TDI). Feature-based attention was mediated by a projection of the TDI to the FFI stimulus competition was mediated by a cross-columnar excitatory connection to the FFI, whereas spatial attention was mediated by an increase in activity of the feedforward inputs from cortical area V2. The model predicts that spatial attention increases the FFI firing rate, whereas feature-based attention decreases the FFI firing rate and increases the TDI firing rate. During strong stimulus competition, the E cells were synchronous in the beta frequency range (15–35 Hz), but with feature-based attention, they became synchronous in the gamma frequency range (35–50 Hz). We propose that the FFI correspond to fast-spiking, parvalbumin-positive basket cells and that the TDI correspond to cells with a double-bouquet morphology that are immunoactive to calbindin or calretinin. Taken together, the model results provide an experimentally testable hypothesis for the behavior of two interneuron types under attentional modulation.

INTRODUCTION

Only a small part of the visual information that enters the brain through the eyes can be consciously processed (Desimone and Duncan 1995). Selective attention is the process by which stimuli are selected based on current behavioral goals. For instance, when you are looking for a friend at the airport, and you know that she will be wearing a red shirt, red objects will be processed preferentially (Saenz et al. 2002; Serences and Boynton 2007). Experiments conducted to determine the single neuron correlate of selective attention have revealed attention-induced changes in the firing rate (Moran and Desimone 1985; Reynolds and Chelazzi 2004; Maunsell and Treue 2006) and in the gamma-frequency-range (35–50 Hz) coherence (Bichot et al. 2005; Fries et al. 2001; Taylor et al. 2005). Pathologies in the selection and processing of visual information underlie diseases such as attention-deficit disorder and schizophrenia. Patients suffering from these conditions show differences in gamma and beta (15–35 Hz) frequency oscillatory activity (Uhlhaas and Singer 2006; Uhlhaas et al. 2006) as well as postmortem abnormalities in interneuron densities (Benes and Berretta 2001). These results suggest a causal link between cognitive processing in the healthy human and the oscillations generated by interneurons.

Cortical area V4 is one of the best places to start the investigation of this link. The receptive field (RF) of a V4 neuron is large enough so that it fits multiple stimuli, only one of which may be behaviorally relevant at a given time. Stimulus selection by selective attention should therefore cause changes at the level of V4, both in terms of firing rate as well as coherence. The response of V4 neurons is the outcome of a competition between bottom-up salience, interaction with other neurons in V4 responding to the same stimuli, and the effect of top-down projections mediating selective attention (Ogawa and Komatsu 2004; Reynolds and Desimone 2003). Experiments have provided an extensive, yet incomplete, quantitative characterization of response modulation for a variety of stimulus configurations and attention conditions. Phenomenological models have been constructed to account quantitatively for these results (Boynont 2005; Reynolds et al. 1999). However, a mechanistic understanding of how these changes are achieved at the circuit level is still lacking. With the advent of experimental techniques to record from multiple neurons simultaneously during a behavioral task, this lack of understanding is rapidly becoming a serious impediment to further progress.

We study the mechanism for attentional modulation in a biophysical network of spiking neurons based on the hypothesis that attention effects are mediated by interneurons (Tiesinga and Sejnowski 2004; Tiesinga et al. 2004a,b). Our goal is to determine what types of interneurons are involved in attention and predict their behavior under various tasks and stimulus conditions.

Our model simulations suggest that at least two types of interneurons are involved in attention, referred to as feedforward interneurons (FFI) and top-down interneurons (TDI). They are differentially modulated by attention as follows. The firing rate of the FFI increases with spatial attention (SA) and decreases with feature-based attention (FBA), whereas the TDI increase their firing rate with FBA and shift the network synchrony from the beta to the gamma frequency range. The phase lag between interneurons and excitatory cells also increases with FBA.

METHODS

The network was comprised of two columns, 1 and 2, each containing three types of neurons: regular spiking excitatory neurons (E), FFI, and TDI. The identification of the FFI and TDI with an anatomical/physiological interneuron type is given in the DISCUSSION.

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There were 500 E, 75 FFI, and 50 TDI cells per column, yielding in total 1,250 neurons.

To keep the model simple, only the necessary synaptic connections were simulated. These were as follows (see Fig. 1).

First, the TDI within one column were connected among themselves with fast GABAergic (GABA_A) synapses to facilitate the generation of gamma rhythms.

Second, there were cross-columnar excitatory projections to the FFI: E1 to FFI2 and E2 to FFI1; and there was local feedforward (FF) inhibition: FFI1 to E1 and FFI2 to E2. The label E1 stands for the E cells in the first column, the rest of the labels, E2, FFI1 and FFI2, are defined accordingly. These two projections together, E1 to FFI2 and E2 to FFI1, mediated stimulus competition. The excitatory projection activated a mixture of AMPA and N-methyl-D-aspartate (NMDA) receptors, whereas the inhibition was mediated by GABA_A receptors (Shepherd 1998).

Last, the TDI projected fast GABAergic inhibition to the FFI and the E cells in their column. The combination of the direct pathway, TDI1 to E1 (TDI2 to E2) and the indirect pathway, TDI1 to FFI1 to E1 (TDI2 to FFI2 to E2) mediated FBA on the preferred feature of column 1 (column 2).

Sensory information entered the columns via a FF projection implemented as a driving current to the E and FFI neurons (the TDI did not receive direct stimulus-related inputs). The expression for this current is (using the same convention for subscripts as in the preceding paragraph)

\[
\begin{align*}
I_{E1} &= I_{0,E1} + A_E [\beta_1 c_1 + (1 - \beta_2) c_2] \\
I_{FFI1} &= I_{0,FFI1} + A_{FFI} [\beta_{FFI} c_1 + (1 - \beta_{FFI}) c_2] \\
I_{E2} &= I_{0,E2} + A_E [(1 - \beta_1) c_1 + \beta_2 c_2] \\
I_{FFI2} &= I_{0,FFI2} + A_{FFI} [(1 - \beta_{FFI}) c_1 + \beta_{FFI} c_2] 
\end{align*}
\]

Here \(I_0\) is a constant offset current and \(A\) is an overall scaling factor.

\(\text{FIG. 1. The model circuit. The model network was organized into 2 identical columns and contained 3 cell types: excitatory (pyramidal) cells (triangles, E1 and E2), feedforward interneurons (diamonds, FFI1 and FFI2) and top-down interneurons (pentagons, TDI1 and TDI2). The cell groups are connected by excitatory synapses (lines ending with arrow heads) and inhibitory synapses (lines ending with filled circles). The network model is driven by 2 sources of input external to the columns: FF inputs to the E cells and FFI (1) and top-down inputs to the TDI (7, 8). There is local FF inhibition (2) inside the column that is activated by a cross columnar excitatory projection (3) and inhibited by the TDI (4). There also is a direct inhibitory connection from the TDI to E cells (5). In addition, the TDI are connected among themselves via mutual inhibition (6).}

Stimulus 1 is the preferred (P) stimulus of column 1 and a nonpreferred (NP) stimulus of column 2, its contrast is denoted by \(c_1\). Likewise, stimulus 2 is the P stimulus of column 2 and a NP stimulus of column 1, its contrast is denoted by \(c_2\). In RESULTS, we will label the contrast by the stimulus preference of the first column: P contrast is \(c_1\) and NP contrast is \(c_2\). The degree of stimulus selectivity is given by \(\beta\), which takes values between 0.5 and 1, with higher values yielding higher selectivity. The parameter settings are in Table 1. The current is linear in the contrast, but the contrast response functions (CRF) of neurons in upstream areas (V1 and V2) that generate these FF inputs are not (Albrecht and Hamilton 1982). We made the current linear in contrast so that we could sample the entire dynamical range of the network responses at a uniform density. Presynaptic activity varying non-linearly with contrast can be incorporated by plotting a rescaled \(\tau\) coordinate, \(c_{\text{new}} = f(c_{\tau})\), in our graphs. Spatial attention at the location of stimulus 1 is implemented by replacing, for both columns, \(c_1\) by \(\gamma c_1\) and \(\gamma_{FFI} c_1\) in Eq. 1 for the E and FFI neurons, respectively. This implements the contrast gain model (Reynolds and Desimone 2003; Reynolds et al. 2000) for spatial attention in V2, but for a linear current-contrast relationship, this is also consistent with the response gain model (Williford and Maunsell 2006).

To reproduce the experimental results, we needed to divide the E and FFI groups into two parts. Twenty-five of the FFI neurons in each column (the FFIb) were given a high baseline current (\(I_0\)) so that they fired at a high rate even when there was no stimulus, and their responses were made contrast-independent (\(A = 0\) in Eq. 1). This provided a baseline level of inhibition so that the activation of the TDI neurons always resulted in an increase in excitatory cell rate via disinhibition even when the stimuli were presented at low contrast. To prevent unrealistic synchronization of the network in the pair condition, it was necessary to include a significant NMDA component in the excitatory synapses (Wang 1999). In the default parameter setting, the AMPA component was zero, but simulations with a nonzero AMPA component are discussed in RESULTS. Because presynaptic firing rates exceeding 20 Hz saturated the current through the NMDA channels, an increase in E rate did not yield a sufficient increase in the drive to the FFI necessary for stimulus competition. This problem was solved by having a pool of 250 excitatory neurons in each column (E1b and E2b) that were made less excitable by injecting an additional hyperpolarizing current so that they were only active when there were two stimuli present at sufficient contrast. The number of synaptic connections made between the different groups are listed in Table 2.

Three sets of synaptic connections probably present in the cortical circuit were omitted (Binzegger et al. 2004; Douglas and Martin 2004): local recurrent excitation (E1 to E1 and E2 to E2), cross-columnar excitation (E1 to E2 and E2 to E1), and excitatory feedback onto the FFI (E1 to FFI1 and E2 to FFI2). The potential impact of these omissions is discussed in the DISCUSSION.

For the excitatory neurons, we used the model in (Golomb 1998; Golomb and Amitai 1997), whereas for the TDI and FFI, we used the model given in (Tiesinga and Jose 2000; Wang and Buzsaki 1996). Full details of the model setup and its implementation are given in the APPENDIX.

The simulation output was analyzed using custom-written programs in Matlab (The Mathwork, Natick, MA). Spike times were detected when the membrane potential crossed 0 and \(-20\) mV from below for the inhibitory and excitatory neurons, respectively. For each group, the firing rate was calculated as the spike count divided by the measurement period, and it was averaged across all neurons in the group. A typical simulation was 1,000 ms long, of which the first 200 ms was discarded as a transient. To determine coherence (see following text), longer runs with a duration of 10 s were sometimes used. The spike time histogram was the number of spikes in a time bin from all neurons in the group, normalized by the number of neurons and the bin width in seconds (typical value: 0.001 s). This yielded the mean firing rate of a single neuron as a function of time.
The local field potential (LFP) was modeled as the spike time histogram of the E cells. The multi-taper power spectrum of the E-cell, FFI, and TDI histogram was calculated using the Matlab routine *mtm* (with time-bandwidth product NW = 3.5). We extracted the power in the beta and gamma band by averaging the power spectrum in a 10-Hz interval around the strongest beta peak (this peak usually was between 15 and 30 Hz) and around either 40 or 45 Hz for the gamma band. To calculate the coherence, the spike train of each neuron was binned at a resolution of 1 ms. A pair of binned spike trains was passed to the Matlab routine *coherencep* which was part of the CHRONUX toolbox (parameters: NW = 3, the FFT padding parameter was 1, and we averaged across 5 tapers). The coherency between two groups, or within a group, was averaged across 10 pairs randomly picked from all possible distinct pairs. In addition, we determined the coherence between the spike time histograms of the respective cell groups. Significance was reached when the coherence exceeded the shift-predicted coherence by 3 SE. The shift predictor was obtained by calculating the coherence between histograms obtained from different simulation runs. The SE was estimated using ten independent simulation runs (which were started from different initial conditions and using different seeds for the white noise currents, see APPENDIX).

The strength of stimulus competition was measured using the parameter \( \alpha = \frac{R(c_p,c_{np}) - R(0,c_{np})}{R(c_p,0) - R(0,c_{np})} \). \( R(c_p,c_{np}) \) is the firing rate of the excitatory neurons in column 1 in response to stimulus 1 at P contrast \( c_p \) and stimulus 2 at NP contrast \( c_{np} \). Stimulus competition occurred when \( 0 \leq \alpha \leq 1 \), with lower values indicating stronger stimulus competition because then the NP stimulus had a stronger suppressive effect. Problems arise with this expression when the denominator is zero or when the response to the NP stimulus exceeds that to the P stimulus. These data points were not included in the analyses reported here.

### RESULTS

#### Overview of results section

Our goal is to construct a model that reproduces experimental results on the attentional modulation of the response of V4 neurons with one or two stimuli in their RFs; predicts the corresponding response of interneurons and the modulation of their coherence; and provides quantitative insight into what model features are responsible for the strength and frequency of emergent oscillations. To help the reader, the experimental data are summarized in two tables (Tables 3 and 4). They can also be summarized in words using phenomenological theories that have been proposed to account for these data (see also DISCUSSION).

For a single stimulus, spatial attention approximately results in a change in either the contrast gain or the response gain, whereas feature-based attention results in a response gain (also referred to as feature gain). A quantitative definition is given in Tables 3 and 4. For multiple stimuli, the biased competition framework predicts that the response to two stimuli is less than the response to the strongest single stimulus and that attention drives this response toward the response to the attended stimulus by itself. Rather than discuss the underlying experiments in RESULTS, we use the predictions of the phenomenological frameworks to constrain the model. To facilitate our description of the model results, we abbreviate several frequently appearing phrases: spatial attention (SA), feature-based attention (FBA), preferred (P), nonpreferred (NP), and feedforward (FF).

#### Stimulus and attention conditions represented in the model

The model is driven by two distinct stimuli. The P stimulus strongly activates the E cells in the first column. It is denoted by a rectangle in the lower right corner of the box that represents the neuron’s RF (Fig. 2Ac). The NP stimulus is less effective in driving the E cells in the first column, but it does strongly activate the ones in the second column. It is denoted by a circle in the upper-left corner of the RF square (Fig. 2b).

When these two stimuli are either presented at full contrast or not at all, there are four different stimulus conditions as shown in Fig. 2A, subpanels a–d. In the model, stimuli can be presented at various values for the contrast, denoted by P contrast and NP contrast, respectively. The NP-P contrast plane is spanned by a 9 × 9 grid (which corresponds to a contrast...
We list the predicted change in firing rate compared to the no-attention condition (also referred to as baseline in our model) together with the phenomenological model from which the prediction comes. Each column is an attention condition and each row is a stimulus condition. *Response gain: the attended firing rate is the attend-away firing rate multiplied by a constant factor (McAdams and Maunsell 1999; Williford and Maunsell 2006). †Contrast gain: the attended firing rate corresponds to the attend-away rate of a stimulus presented at a contrast that is higher by a constant factor (Martinez-Trujillo and Treue 2002; Reynolds et al. 2000). ‡Biased competition: the firing rate in response to both stimuli is in between the lowest and highest response to the component stimuli presented singly; the attended firing rate is shifted closer to the response to the attended stimulus presented singly (Desimone and Duncan 1995; Reynolds and Chelazzi 2004; Reynolds and Desimone 2003; Reynolds et al. 1999).

### TABLE 4. Predictions for firing rate changes induced by feature-based attention

<table>
<thead>
<tr>
<th>Stimulus in RF</th>
<th>FBA to P Feature</th>
<th>FBA to NP Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>P stimulus</td>
<td>Increase (feature gain*)</td>
<td>Decrease (feature gain*)</td>
</tr>
<tr>
<td>NP stimulus</td>
<td>Increase (feature gain*)</td>
<td>Decrease (feature gain*)</td>
</tr>
<tr>
<td>Both stimuli</td>
<td>Increase (feature gain,* biased competition†)</td>
<td>Decrease (feature gain,* biased competition†)</td>
</tr>
</tbody>
</table>

We list the predicted change in firing rate compared to the no-attention condition (also referred to as baseline in our model) together with the phenomenological model from which the prediction comes. Each column is an attention condition and each row is a stimulus condition. *Feature gain (response gain): the attended firing rate is the no-attention firing rate multiplied by a constant factor, which is less than one for the NP feature and more than one for the P feature (Boynton 2005; Martinez-Trujillo and Treue 2004; Treue and Martinez-Trujillo 1999). †Biased competition: the firing rate in response to both stimuli is in between the lowest and highest response to the component stimuli presented singly; the attended firing rate is shifted closer to the response to the attended stimulus presented singly (Chelazzi et al. 2001; Desimone and Duncan 1995; Reynolds and Chelazzi 2004).
FBA to a feature increases the response of a neuron when it is the P feature and decreases the response, otherwise (see summary in Table 4). In the model, we hypothesize that this is mediated by a top-down activation of all columns that prefer the attended feature (Fig. 3B). This increases the E-cell rate via disinhibition (TDI1 to FF1 to E1, projections 4 and 2), and the network will display an oscillation in the gamma frequency range. The suppressive effects of FBA to a NP feature originate in the second column and are mediated by the cross-columnar projection (not shown).

SA to a location within the RF is mediated by a change in contrast gain of the stimulus at the attended location, which changes the FF input to the E cells and the FFI (Fig. 3C). The quantitative results of these hypothesized mechanisms are illustrated using only one parameter setting of the model. Simulations conducted to test the robustness of the model and oscillation frequencies against parameter changes will also be summarized in RESULTS.

Stimulus competition

As the results will be presented from the point of view of column 1, unless stated otherwise, the column number (for instance, 1 in E1) will be suppressed for notational simplicity. Furthermore, unless stated otherwise, results are for the E and FFI subpopulation, without including the Eb and FF1b subpopulation (see METHODS).

Stimulus competition was mediated by cross-columnar activation of the FFI

The model was designed to display stimulus competition in the E-cell rate when both stimuli were presented at full contrast (Fig. 4). Here we determine how the interneurons behave under these conditions. When the P stimulus or NP stimulus was presented by itself, it activated the E cells, although the former did so more than the latter. However, when both were presented simultaneously, the E-cell rate was less than that in response to the P stimulus by itself (Fig. 4C) even though the FF inputs corresponding to the P and NP stimulus were added (Fig. 4D). By design, the firing rate of the TDI did not vary with stimulus condition (Fig. 4A); hence, their activity was not responsible for stimulus competition. The FFI were not activated by the NP stimulus presented by itself (compared with their rate without a stimulus, as indicated by the solid line in Fig. 4B), but they were activated by the P stimulus (Fig. 4B). When both the FF projection and the cross-columnar excitatory projection were fully activated, the FFI fired at their highest rate so that the resulting E-cell rate was suppressed, thus yielding stimulus competition. In the bar graph, Fig. 4B, the combined activity of the FFI and FF1b in a given column is shown. The FFI received cross-columnar excitatory inputs but were not spontaneously active. The FF1b were spontaneously active, irrespective of stimulus condition. Hence the FFI and FF1b population together had a nonzero firing rate even when

![FIG. 3. Summary of the model mechanisms.](http://jn.physiology.org/)

![FIG. 4. Stimulus competition was mediated by cross-columnar activation of the FFI.](http://jn.physiology.org/)

FIG. 3. Summary of the model mechanisms. The model is designed to reproduce 3 aspects of neural responses in V4: stimulus competition (A) and firing rate changes with feature-based attention (B) and spatial attention (C). A: the suppressive effect of stimulus competition is mediated by a cross-columnar excitatory connection (3) followed by FF inhibition (2); the projection numbers are the same as in Fig. 1. In the model, suppressive effects are present only when the FFI are sufficiently driven by the P stimulus. B: FBA on the P feature was mediated by increasing the top-down drive to the TDI (represented by the upward arrow near projection 7). The E-cell firing rate increases because the disinhibition mediated by projection 4 followed by 2 exceeds the direct inhibition via projection 5. C: SA was mediated by increasing the FF drive (represented by the arrow near projection 1) corresponding to the stimulus at the attended location.

**FIG. 4.** Stimulus competition was mediated by cross-columnar activation of the FFI. From top to bottom, we show the firing rate of the TDI (A), FFI (B), and E (C) cells in the 1st column and a representation of the FF inputs to the 1st (D) and 2nd (F) column. Here the firing rate of the FF1b is included in the FFI rate. The small error bars on top of each bar represent the SD across 10 independent simulation runs. In E, the icons of the neuron types as well as the relevant projections are shown in the same notation as Fig. 1. Below D we show icons for the following stimulus conditions (same notation as in Fig. 2), from left to right, NP stimulus, P stimulus, and the pair condition. The NP stimulus by itself was excitatory because it drove the E cells via the FF inputs. However, it did not increase the firing rate of the FFI (their baseline firing rate is indicated by the solid line in B). The P stimulus by itself was excitatory and it also activated the FFI. Even though the FF input corresponding to the pair condition was larger than the one corresponding to the P stimulus by itself, the E cell rate decreased because of the cross-columnar activation of the FFI (projections 2 and 3). The dashed horizontal line in A–C indicates the response to the pair stimulus.
there was no stimulus present. In the other figures (Fig. 5, 6, and 11), we show only the FFI rate because it varies as a function of contrast.

The model predicts that stimulus competition leads to an increase in FFI firing rate.

**E-cell firing rate varied nonmonotonously with stimulus contrast**

The cross-columnar excitatory projection, which mediates stimulus competition, is only effective when the P stimulus is presented at sufficient contrast, which has consequences for the behavior of the E-cell firing rate as a function of contrast. First, consider the response to a single stimulus. The E-cell firing rate increased with NP contrast (Fig. 5A), without any sign of saturation because the FFI were not activated (the FFI activity is plotted in Fig. 5C). By contrast, for the P stimulus by itself, the E-cell firing rate increased rapidly with contrast (Fig. 5B) but saturated for larger contrast because the FF projection activated the FFI (Fig. 5D). Second, consider the response to a pair of stimuli. When the P stimulus was present at full contrast and the NP contrast was varied, the E-cell firing rate decreased with NP contrast (Fig. 5A), showing that the NP stimulus was suppressive in that case. When the NP stimulus was at full contrast and the P contrast was varied instead, there was a switch from facilitatory to suppressive effects. For low P contrast, adding the NP stimulus increased the E-cell firing rate (Fig. 5B, †), whereas, when the P contrast was sufficiently high, adding it decreased the rate (Fig. 5B, ‡).

The model predicts that stimulus interactions switch from facilitatory for low P contrasts to suppressive for high contrast values. The biased competition framework predicts only suppressive effects.

**During stimulus competition the model response was dominated by FFI activity**

The FFI mediate suppressive interactions, which would imply a correlation between FFI activity and the degree of stimulus competition. The strength of suppressive interaction is measured by α (see METHODS). For stimulus competition, the response to the pair is higher than the response to the NP stimulus and lower than the response to the P stimulus. This range of firing rates is mapped to α values between 0 and 1, respectively. Thus 0 corresponds to the strongest competition and 1 to the weakest competition in which case the response is equal to the maximum of the individual responses. For given values of the contrast, it is possible that the response to the NP stimulus was larger than that to the P stimulus, yielding a negative value for α. However, in that case, the stimulus interaction in the model was facilitatory, and it was not included in our analysis. It is possible that α is not defined because the terms in the denominator are equal, but this did not occur in our simulations except for the no-stimulus condition.

The strongest suppression of E-cell rate was obtained when both stimuli were present at high contrast (indicated by the arrow in Fig. 6A), which corresponded to the highest level of FFI activity (arrow in Fig. 6B). We therefore analyzed how the strength of suppression increased with FFI rate for all contrast pairs satisfying 0 < α < 1. Indeed, α decreased linearly with FFI rate (Fig. 6C). The strength of competitive interactions could also be represented by a weighted contrast with more weight given to the P contrast than to the NP contrast. The FFI rate was strongly correlated with the weighted contrast (Fig. 6D, NP weight was 32%, P weight was 68%, and the correlation coefficient was 0.97). The E-cell rate decreased with a weighted contrast, but a linear relationship explained less of the variance than for the FFI (correlation coefficient: −0.72). For lower values of the weighted contrast, there were facilita-

![FIG. 5](https://example.com/fig5.png)
the analysis.

25 Hz; the correlation coefficient /H11002

DISINHIBITION. Our hypothesis is that FBA to the P feature of EXCITATORY FIRING RATE EFFECTS OF FBA WERE MEDIATED BY
tory interactions, such as those illustrated in Fig. 5

The model predicts a relationship between the strength of stimulus competition (α) and the FFI rate, which was approximately linear for the parameter settings used here.

Feature-based attention

EXCITATORY FIRING RATE EFFECTS OF FBA WERE MEDIATED BY DISINHIBITION. Our hypothesis is that FBA to the P feature of a column activates the TDI in that column (Fig. 3B). This means that FBA to the NP feature does not directly affect the TDI in the column, rather the effect on the E cells is indirect and involves the cross-columnar projection from the column for which the attended feature is preferred. The model (Fig. 7) reproduced the predictions of the biased competition framework as follows (Table 4). FBA to the P feature led to an increased TDI rate (Fig. 7A), which reduced the FFI rate (Fig. 7B), which in turn led to an increase in E-cell rate (Fig. 7C). The activity of the FF projection was not modified by FBA (Fig. 7D). FBA to the NP feature did not change the TDI rate in column 1 (Fig. 7A), rather the FFI rate was increased (Fig. 7B) by way of the cross-columnar projection, which resulted in a decreased E-cell rate.

The model predicts that for FBA, the firing rate changes of the FFI are opposite in sign compared with those of the E cells. SUPPRESSIVE EFFECTS OF FBA WERE ONLY PRESENT AT SUFFICIENTLY HIGH STIMULUS CONTRAST. The excitatory and suppressive effects of FBA both involved the FFI, which limits the contrast pairs for which these effects can be obtained. One prediction, common to both the contrast gain and the response gain model (Table 4), is that FBA to the P-feature does not decrease the E-cell firing rate. In the model this implies that in the single stimulus condition, for all values of the contrast, the disinhibition should be stronger than the direct inhibition (Fig. 3B). This required two subtypes of FFI in the model: those that were spontaneously active without any stimulus (FFIb) and those that required the presence of the P stimulus to be active (FFI). It is important to emphasize that the FFIb were not necessary to obtain the effects of biased competition for when the P stimulus was presented at full contrast. The CRF for a P stimulus presented by itself is shown in Fig. 8A for the baseline (—) and FBA to P condition (- - -). For low contrast, there is an approximately constant increase in firing rate due to a constant disinhibition mediated by the FFIb population. The strength depends primarily on the spontaneous firing rate of the FFIb and also on the strength of both the TDI to FFIb and FFIb to E projection. This dependence makes it possible to modulate the low-contrast response change via the spontaneous firing rate of the FFIb. For high contrasts, when the FFI were active and saturation was present in the baseline

FIG. 6. The degree of stimulus competition was directly related to the firing rate of the FFI. Firing rate of E cells (A) and FFI (B) as a function of contrast. The arrow in A and B indicates the pair condition for which both stimuli were presented at full contrast. C: the strength of stimulus competition, as measured by α, was proportional to the FFI firing rate (tangent: 0.019 s; the correlation coefficient –0.89 was significant at P = 5 × 10^-5). D: the FFI firing rate was more strongly correlated with a weighted contrast (black line, NP contrast contributed 32% to the weighted contrast and P contrast contributed 68%; tangent: 59 Hz; the correlation coefficient 0.97 was significant at P = 1 × 10^-13) than the E-cell rate (gray line, NP contrast contributed 38% and P contrast 62%; tangent: –25 Hz; the correlation coefficient –0.72 was significant at P = 2 × 10^-5). In C and D, only those points with an α value between 0 and 1 were included in the analysis.
To investigate the nature of the suppressive effects, we presented the NP stimulus at full contrast, while we varied the P contrast, and compared the response with FBA to the NP feature to the baseline response. For the pair stimulus, decreases in firing rate with FBA to the NP feature were only obtained for high P contrast, which is when the FFI were active (Fig. 8C). The difference between the attend and attend-away conditions as a function of contrast had a negative peak (Fig. 8C, ↓). This is still consistent with response gain because the attentional modulation was strongest when the firing rate was highest. There was no effect at low contrast because the FFI were not active, and the FFILb were not driven by the cross-columnar projection.

Overall, increases in E-cell rate with FBA to the P feature were obtained for all contrast values, but significant decreases with FBA to NP were only obtained for high enough contrasts (Fig. 8D). Significant means that the difference between means exceeds two SDs when calculated based on 10 independent simulation runs.

The model predicts that FBA is more similar to a response gain with an independent low and high contrast component. Furthermore, it predicts that suppressive interactions only occur for higher values of the contrast.

**Spatial attention**

SA WAS MEDIATED BY A CHANGE IN CONTRAST GAIN OF THE FF INPUT. Our hypothesis is that spatial attention at a resolution less than the size of the typical RF is mediated by an increase in the FF input corresponding to the stimulus at the locus of attention (Fig. 3C). The increase in FF input with SA was higher for the P stimulus than for the NP stimulus. The model reproduced the effects predicted by the biased competition framework (Table 3, Fig. 9C). The issue addressed here is how the FFI rate changes with SA.
the increases obtained with SA. By design, there were no changes in TDI activity (Fig. 9A).

The model predicts that the firing rate of the FFI increases with SA, irrespective of whether SA is directed to the location of the P or NP stimulus.

**IN THE SINGLE STIMULUS CONDITION, SA RESULTED APPROXIMATELY IN A CHANGE OF CONTRAST GAIN.** In the model, there was no saturation in the FF input and saturation arose because of the normalization provided by the FFI neurons (solid lines in Fig. 5, B and D). SA was implemented as a change in contrast gain for the stimulus at the attended location, for the FF input to both the E cells and the FFI. For the single stimulus condition, the contrast gain model (Table 3) suggests that the firing rate does not need to increase with SA at high contrast. Furthermore (Table 3), neither the response gain nor the contrast gain model predicts that the firing rate actually decreases with SA. In the model, the suppressive effects due to the FFI dominated during saturation. This implies that the change in contrast gain with attention should be less for the FFI than that for the E cells. The model therefore predicts that for low P contrast, and for all values of NP contrast, when the FFI are not active, the effects of attention are exactly that of a change in contrast gain (Fig. 10, A and C). For higher contrast, when the FFI are active, the effective contrast for the FFI is lower than that for the E cells, and the change is not exactly a contrast gain. Nevertheless, the largest change in rate occurred below the contrast value with the highest firing rate (Fig. 10A, ↓).

The model predicts that the effects of SA are similar to a contrast gain, especially for low values of the contrast.

**SUPPRESSIVE EFFECTS OF SA WERE ONLY PRESENT FOR A LIMITED NUMBER OF CONTRAST PAIRS.** In the model, suppressive effects on the E-cell rate were mediated through the cross-columnar projection, which involved the FFI, thus limiting the contrast pairs for which these effects can be obtained. The excitatory effects reflect a balance between the FF activation of the E cells

**FIG. 9.** SA was implemented as a contrast gain on the FF inputs. We show the firing rate of the TDI (A), FFI (B), and E (C) cells and the corresponding FF input to columns 1 (D) and 2 (F). There are 3 attention conditions indicated by the icons below D (notation is the same as in Fig. 2), from left to right: attend away (or baseline condition), SA to the location of the NP stimulus and SA to the location of the P stimulus. Although SA to the location of the NP stimulus led to increases in the FF inputs, these increases were small compared with the effect of the cross-columnar projection (2). The net result was an increase in FFI firing rate and a decrease in E-cell firing rate. SA to the location of the P stimulus led to a larger increase in the FF input, which did result in an increase of E-cell and FFI firing rate. In these simulations the P contrast was 0.75 and the NP contrast was 0.625.

With SA to the location of the P stimulus, the FF input to the E cells and FFI increased. The net result was that both the FFI and E-cell firing rate increased (Fig. 9, B and C). With SA directed to the location of the NP stimulus, the FF input increased but to a lesser extent than before. Nevertheless the increase in FFI firing rate was higher because of the activation of the cross-columnar excitatory projection. As a result, the E-cell rate decreased. The decrease in E-cell rate was less than
and the FFI, thereby also limiting the contrast pairs for which excitatory effects are present. To further investigate these issues, we determined how SA affected the pair response. When the NP stimulus was presented at full contrast and the P contrast was varied, the rate change with attention appeared to be nonmonotonic (Fig. 10B, ⋯). Specifically, the largest change was not obtained for the largest firing rate, implying that it was different from a simple response gain. Overall, SA to the P location increased firing rate for all contrast pairs (Fig. 10D, ⋄) except when there was no P stimulus present (that is, a NP stimulus by itself). In contrast, SA to the NP location decreased the firing rate only in a narrow band of contrast pairs (Fig. 10D, ⊙). For a single NP stimulus and as well as for some pair conditions, the firing rate even increased (results not shown), which is inconsistent with the predictions of the biased competition framework.

The model predicts that suppressive effects of SA are only obtained for a limited range of contrast values.

**Attention-induced changes in firing rate were sometimes correlated with the strength of stimulus competition.** Attention-induced changes in E-cell and FFI rate were correlated because of the FFI to E-cell projection. The coordinated changes in E-cell and FFI rate were studied for the case when there was stimulus competition, that is, $0 < \alpha < 1$ (Fig. 11, A and B). For FBA, the magnitude of the changes in the FFI and E-cell rate was correlated: an increased change in FFI rate was associated with an increased change in E-cell rate (Fig. 11A). The sign of the change in firing rate was opposite: FBA to the NP feature led to increases in the FFI rate and decreases in the E-cell rate. Likewise, for FBA to the P feature, the FFI rate decreased and E-cell rate increased. In both cases, the linear correlations were almost perfect, with correlation coefficients of $-0.99$ and $-1.00$, respectively. For SA, the FFI firing rate always increased with SA (Fig. 11B). The relationship between FFI and E-cell rate changes was noisier than compared with FBA (the correlation coefficients were $-0.46$ and $-0.77$ for SA to the NP and to the P stimulus, respectively).

A correlation between attention-induced firing rate changes and the degree of stimulus competition is also expected because both involve FFI activity. For FBA, the correlation coefficients between either the E-cell or the FFI rate changes and $\alpha$ were small and not significant (Fig. 11C). For SA, there was a strong and significant correlation: the E-cell rate change was highest for the strongest stimulus competition, whereas the opposite was true for FFI rate changes (Fig. 11D).

The biased competition framework (Table 3) makes predictions for how the pair response is related to the responses to component stimuli and how this response changes with atten-

![FIG. 11. The sign of attention-induced changes in the FFI rate depended on the type of attention. A and B: the change in FFI firing rate is plotted versus that of the E cells for all contrast pairs satisfying $0 < \alpha < 1$. A: for FBA, the FFI rate increased when the E cell rate decreased and vice versa. The larger the change in FFI rate was in absolute terms, the larger the change in E cell rate was. B: for SA, the FFI rate always increased, but the E-cell rate could increase or decrease. ⊙: FBA to the NP feature (A; tangent: $-0.51$; correlation coefficient $-1.00$ was significant at $P = 1 \times 10^{-23}$) and SA to the location of the NP stimulus (B; tangent: $-0.39$; correlation coefficient $-0.46$ was significant at $P = 0.03$). ⊠: FBA to the P feature (A; tangent: $-0.55$; correlation coefficient $-0.99$ was significant at $P = 5 \times 10^{-15}$) and SA to the location of the P stimulus (B; tangent: $-0.40$; correlation coefficient $-0.77$ was significant at $P = 4 \times 10^{-5}$). C and D: the linear relationship between the attention-induced rate change for (●) E-cells and (○) FFI and the strength of stimulus competition ($\alpha$) in the baseline condition was significant for SA (D; E cells, tangent: $-8.9$ Hz; correlation coefficient $-0.69$ was significant at $P = 4 \times 10^{-4}$; FFI, tangent: $4.4$ Hz; correlation coefficient $0.67$ was significant at $P = 1 \times 10^{-3}$), but was not significant for FBA (C; E cells, correlation coefficient $0.26$ with $P = 0.25$; FFI, correlation coefficient $-0.39$ with $P = 0.08$). E: grid of contrast pairs. We studied whether the following 3 predictions were satisfied for a given contrast pair: stimulus competition (SC, $0 < \alpha < 1$) and biased competition with FBA and SA. This was indicated by a ●, ⊙, and ⊠ placed at the corresponding point, respectively. These constraints were only satisfied for 5 points with predictions for the SA-induced changes being the most restrictive.
tion. We investigated how difficult it was within the context of the model to satisfy all the constraints implied by the framework. Contrast pairs satisfy the predictions of biased competition when FBA to the P feature increases the E-cell rate and when FBA to the NP feature decreases it. For SA, it means that SA to the P location increases the rate and SA to the NP location decreases the rate. In addition, the pair response should be in between the response to the NP and P stimulus when they are presented singly. In terms of the number of contrast pairs for which the predictions were satisfied, FBA was easiest to achieve (Fig. 11E, □), followed by stimulus competition (Fig. 11E, ●), with SA being the most difficult to achieve (Fig. 11E, ○). For the parameter settings used, there were only 5 of 81 pairs for which all conditions were satisfied.

The effect of attention on stimulus competition can be studied by determining how it affects the distribution of α values. Starting from all contrast pairs with 0 < α < 1 in the baseline condition, SA to the location of the P stimulus made the distribution sharper and shifted its mean to a higher value (results not shown). As a result, the few α values closest to one actually decreased. For FBA on the P-feature, the distribution broadened and α values larger than one were obtained (results not shown). For these contrast pairs, there was stimulus competition in the baseline condition, but with FBA, this had disappeared. Overall, SA to the location of the P stimulus or FBA to the P feature reduced the degree of stimulus competition.

The model predicts correlations between attention-induced rate changes and the degree of stimulus competition, which are different for FBA compared with SA. This makes it possible to distinguish the effects of FBA from those of SA based on these correlations.

Gamma and Beta Oscillations Emerged in the Network Model. The model network displayed two types of coherent oscillations: in the beta and gamma frequency range. The peak beta frequency ranged from ~15 to 30 Hz depending on the P and NP contrast values. The peak gamma frequency was either 40 or 45 Hz. We briefly describe how these two oscillations emerge. In the subsection that follows, we show how FBA changes the balance between the beta and gamma oscillations, which is followed by a description of how the various model parameters affect oscillation strength and frequency.

The TDI synchronize by way of mutual inhibition, commonly referred to as ING (Borgers and Kopell 2003, 2005; Whittington et al. 2000). Conditions for synchronization by mutual inhibition have been extensively studied theoretically and computationally (see Discussion). For a network with identical neurons and without noise currents, synchry can be obtained for any oscillation frequency. However, when there is heterogeneity so that the firing rate of uncoupled neurons varies (Tiesinga and Jose 2000) and when there is noise so that the spike train of an uncoupled neuron is not exactly periodic (Tiesinga 2002; Tiesinga and Jose 2000), the network will only robustly synchronize at specific oscillation frequencies related to the inhibitory time constant. This is reviewed in one of our previous publications (Tiesinga and Jose 2000). The key parameter is the driving current to the TDI neurons; only when the current is such that the firing rate of individual neurons matches a harmonic or subharmonic of these oscillation frequencies will synchrony be obtained. The parameter setting of the network was such that for the baseline state the current was too low. Hence only a weak and noisy gamma oscillation was obtained. The top-down activation of the TDI increased the driving current to a value where the network synchronized.

The beta oscillation emerged via different mechanism, which is related to the PING mechanism (PING stands for pyramidal-interneuron-gamma) (see Borgers and Kopell 2003). It starts when a synchronous volley from the E2 cells recruits a synchronous volley from the FFI1. This temporarily shuts down the E1 cells, but on recovering, they produce a synchronous volley that in turn recruits a synchronous FFI2 volley. This shuts down the E2 cells for a while, but on recovery of the E2 cells, the sequence starts over again. The oscillation is thus a consequence of a competition in which each stimulus tries to shut down the column for which it is not preferred.

FBA Shifted the Network Oscillation Frequency from Beta to Gamma. The beta oscillation was strongest in the pair condition, where two stimuli were presented at high and equal contrast. The beta oscillations led to spike alignments in the E-cell rastergrams (Fig. 12Aa, box) and were visible as peaks at the beta frequency in the E-cell spectral density (Ab, oblique arrow) and also in the coherence between E cells in the same column (results not shown). The spectrum of the FFI cells also had a small peak at the beta frequency (Fig. 12Ab). In addition, there were small peaks in the gamma frequency range, at 45 Hz, in the TDI and E spectra (Fig. 12Ab, vertical arrow) but not in the FFI spectrum (Ab).

When the TDI were activated by FBA to the P feature, they synchronized in the gamma frequency range. The FFI and E locked to the synchronous inhibitory inputs from the TDI network. This is visible as spike alignments in the E-cell rastergram (Fig. 12Ba, box) and peaks at the gamma frequency in the E-cell and FFI spectrum (Bb). The peak gamma frequency also shifted to 40 Hz from its value of 45 Hz in the baseline condition. In the spectrum, the width of the beta and gamma peaks appeared similar because they were calculated using 800-ms-long time intervals. When the spectrum was calculated based on 9.8-s-long intervals, the frequency resolution was higher. In these spectra, the gamma peak was much sharper and higher than the beta peak. This means that the gamma oscillation was more regular than the beta oscillation. The spike alignments in the E-cell rastergram were not pure gamma (that is, ~25 ms apart) but had alternating long and short intervals between spike alignments (Fig. 12Ba, box). The model thus showed competition between two oscillations. The relative strength of beta and gamma oscillations also depended critically on the nature of the excitatory synapses (see following text).

As there was no direct connection between TDI cells of different columns, the gamma synchrony could only reach the other column via the cross-columnar excitatory projection, which was only effective when the FFI were active. In that case, beta oscillations were also present.

TDI Synchronized the E Cells via the Direct and Indirect Pathway. During FBA to the P feature, the E cells received inhibitory inputs, synchronous in the gamma frequency range, from two sources, the FFI and TDI (Fig. 3B). Which of these two projections is most important to the synchronization of the E cells? To assess the contribution of each of these projections to the FBA-induced synchronization, we first introduced a
constant delay in the synaptic connection. This did not change the results appreciably. Then a jitter (SD 10 ms) was introduced in the delays for the TDI to E connection but not in the FFI to E connection. This abolished the gamma coherence in response to the P stimulus presented by itself at full contrast but only weakly reduced the coherence in the pair condition when both stimuli were at full contrast. Note that for the single stimulus condition, the FFI rate was low, so that it only contributed a small fraction of the total inhibitory conductance that the E cells received. Only when the FFI to E connection was also jittered by the same amount was the coherence completely abolished in the pair condition. Thus both projections, when active, contribute to the observed synchronization of the principal cells.

**Oscillation frequency and power of the gamma oscillations depended on the time scale of inhibitory synapses.** The mechanism for beta and gamma is different but both depend critically on the inhibitory time scale. As mentioned before, gamma is generated by activation of the TDI by way of the ING mechanism, which works through mutual inhibition. The other cell groups in the column lock to this rhythm. Slice experiments in hippocampus show that pharmacological manipulations that increase the time constant of inhibition, reduce the frequency of gamma oscillations, whereas those that decrease the time constant, increase the oscillation frequency (Whittington et al. 1995). We explored whether the same was true for the model network when activated by FBA to the P feature. We covaried the time constant \( \tau_{\text{GABA}} \) and maximum conductance \( g_{\text{ii}} \) so that their product—an estimate of synaptic efficacy—remained constant. For time constants larger than the default, 8 ms, the oscillation frequency decreased as expected. For lower values of \( \tau_{\text{GABA}} \), the oscillation frequency jumped from 40 to \( \sim 60 \) Hz. The peak frequencies in that regime varied between 60 and 65 Hz with \( \tau_{\text{GABA}} \). The low-synchrony baseline state (no FBA) was stable against small changes in synaptic time scale. However, for large \( \tau_{\text{GABA}} > 10 \) ms, a synchronized oscillation at beta frequencies (30 Hz) appeared.

Taken together, the results show that the network can support FBA-mediated transitions to oscillations in the gamma frequency range for a range of parameter values.

**Oscillation frequency and power of the beta oscillations depended on the time scale of inhibitory synapses.** In the model, beta oscillations were generated in a loop with four synaptic steps: E1 to FFI2 to E2 to FFI1 to E1. When excitation was mediated by NMDA only, effectively there were only two time scales: the time constant of inhibition and the delay
between the emission of the inhibitory volley by the FFI and the arrival of the excitatory volley at the FFI. The latter involves both the level of depolarization of the FFI and axonal delays (with a default value of 0.05 ms). In the default parameter setting, the synaptic time scale for inhibition generated by the FFI was the same as for the TDI. Nevertheless, the beta oscillation had a longer period (lower frequency) because of the additional delays associated with the synaptic steps. We explored how the oscillation frequency obtained in response to both stimuli at full contrast was affected by manipulation of synaptic time scales and axonal delays. First, when \( \tau_G \) was varied, the frequency of the beta oscillation did not change but the power did. The peak height at the oscillation frequency in the spectral density was maximal for \( \tau_G \) values of \(-10 \) ms. Second, the level of depolarization of the FFI and E (varied via \( A_{\text{FFI}} \) and \( A_E \), respectively, see Methods) can affect the frequency by altering the delay between inhibitory spike emission and the arrival of excitatory inputs or by lengthening the interval after the inhibitory volley during which the E cells do not spike. The power as a function of \( A_{\text{FFI}} \) was peaked with the strongest oscillation occurring at \( 30 \) Hz for \( A_{\text{FFI}} = 0.7 \mu \text{A/cm}^2 \) (the default value). The oscillation frequency did not vary much for \( A_E \) values between 2 and \( 4 \mu \text{A/cm}^2 \), but the height of the beta peak did, reaching a maximum for the default value of the current, \( A_E = 3 \mu \text{A/cm}^2 \). Third, when the axonal delays were varied, the oscillation frequency did not change significantly.

Thus the frequency of the beta oscillation in the pair condition was related to the time scale of inhibitory synapses and was robust against parameter variation.

**STRENGTH AND FREQUENCY OF THE OSCILLATIONS DEPENDED ON STIMULUS CONTRAST.** We investigated the behavior of the oscillation for all contrast pairs, by determining the fraction of power in a 10-Hz interval around gamma and beta frequencies. Because the frequency of the beta oscillation did vary with contrast, we picked the power in an interval around the highest peak present in the spectrum \(<35 \) Hz. For gamma, we calculated the fraction of power in the 40- to 50-Hz frequency range for the baseline condition and between 35 and 45 Hz in the FBA condition. With FBA to the P feature, gamma power increased and beta power decreased for all contrast pairs (results not shown). An interesting structure becomes visible when the power is plotted as a function of firing rate (Fig. 12, C and D). The structure arises because the same E-cell firing rate is obtained in response to multiple different stimulus conditions (Fig. 6A). For instance, the response to a P stimulus at medium contrast can be the same as the response to the P and NP stimulus together at high contrast. For FBA to the P feature, the former stimulus condition has more gamma power than the latter. In the graph, this shows up as a general increase of gamma power with firing rate, but the curve then curls over to give two different gamma powers for the same firing rate. The high power branch is for the case with weak NP stimuli and the low power branch is for when the NP stimulus is stronger (box in Fig. 12D). The opposite happens for the beta power plotted as a function of the firing rate, there the high power branch of the curve corresponds to the “strong NP” pairs (Fig. 12C, box indicated by horizontal arrow).

In the baseline, or attend-away, condition there are two interesting features. First, gamma power increases with firing rate. Because, for the single stimulus condition and for low to medium contrasts in the pair condition, firing rate increases with contrast, this means that gamma power also increases with stimulus contrast. Second, beta power has a peak as a function of firing rate (Fig. 12C, box indicated by oblique arrow). The position of this peak corresponds to the firing rate obtained when two stimuli are present at high contrast, resulting in stimulus competition, with a firing rate less than that obtained in response to the P-stimulus at full contrast. There is a corresponding dip the gamma power as indicated by the oblique arrow in Fig. 12D.

We investigated the behavior of the coherence in the gamma frequency range between spike trains of individual E cells, averaged across 10 pairs. For a single P stimulus (results not shown), the coherence for FBA to the P feature exceeded the attend-away coherence when the contrast was \( >0.5 \). This difference increased with higher contrast values. This shows that behavior predicted by the model should be visible in the coherence between spike trains of two simultaneously recorded E cells when they are both in the same column. The coherence was increased even more when the NP stimulus was presented in addition to the P stimulus (with a P contrast equal to 1 and FBA to the P feature). This behavior is different from that of the gamma power shown in Fig. 12D, which decreased when the NP stimulus was added.

The model predicts that FBA to the P feature introduces a gamma oscillation that competes with the beta oscillation generated by two high contrast stimuli. Both in the baseline condition and the FBA to P condition, gamma power generally increased with contrast, but it decreased with stimulus competition. The latter was indicated by an increase in the beta power.
ented at full contrast, the FFI and E-cell responses were coherent in the beta frequency range (Fig. 13Aa), with the FFI lagging the E cells by ~90° (for a frequency of 30 Hz, this is equivalent to about a 8.3-ms delay, Fig. 13Ab). For the same situation, the coherence between E cells and TDI was significantly lower, although there were small peaks in both the beta and gamma frequency range (Fig. 13Ba).

We determined how the coherence changed when FBA was directed toward the P feature of the column. For the E with FFI coherence, a peak appeared at gamma frequencies (Fig. 13Aa, vertical arrow) and the peak coherence at beta frequencies shifted to lower frequencies (Aa, horizontal arrow). Concomitantly, the phase lag between FFI and E cells had increased in both the beta and gamma frequency range. For the E-TDI coherence, a peak in the gamma frequency range appeared (Fig. 13Ba) and the phase lag increased as well (Bb).

The model thus predicts that FBA increases both the coherence and the phase lag between interneurons and E cells.

**STRONGER STIMULUS COMPETITION LED TO A REDUCED PHASE-LAG OF THE FFI.** We also analyzed the change in phase lag between FFI and E cells when stimulus contrast was varied. First, we presented the P stimulus at full contrast and varied NP contrast. In this case the E-cell firing rate decreased with NP contrast (Fig. 5A) and the FFI firing rate increased (Fig. 5C). The coherence between FFI and E also increased (black line, Fig. 14C), whereas the magnitude of the phase lag decreased (gray line, Fig. 14C). The result that the phase lag decreased with increasing contrast seems unexpected because usually contrast increases are associated with firing rate increases and, given the preceding subsection, increasing phase lags. However, here there was stimulus competition, which actually reduced the E-cell rate.

Second, we presented a NP stimulus at full contrast and varied P contrast. For this case, the E cell rate varied nonmonotonously (Fig. 5B) and the FFI were only active for a P contrast >0.4. There can only be coherence between the E cells and FFI when the FFI are active. Hence there was a rapid increase from zero coherence at a P contrast of 0.375 to full coherence at a P contrast of one (black line, Fig. 14D) and a concomitant decrease in the magnitude of the phase lag (gray line, Fig. 14D). The TDI were active for all values of P contrast, their phase lag first increased when the E-cell rate increased, and for large contrast, the phase lag decreased when the E-cell rate also decreased (results not shown).

The model predicts that stronger stimulus competition is indicated by a reduced phase lag between the FFI and E cells.

**STRENGTH AND FREQUENCY OF COHERENT OSCILLATIONS DEPENDED ON THE TYPE OF EXCITATORY SYNAPSES.** It is not exactly known how much of the excitatory current is mediated by AMPA receptors compared with that mediated by NMDA receptors. In the default parameter setting, all the current was mediated by NMDA. We explored the effect of AMPA, by varying the percentage AMPA conductance from 0 to 100% in steps of 25% (while keeping the total maximum conductance constant). There were moderate effects on the E-cell firing rate but only when the FFI were active. The following results were obtained for the pair condition with the P and NP stimulus both at full contrast. With a nonzero AMPA component, the beta oscillations obtained for the pair condition led to sharper and higher peaks in the spectrum at a frequency lower by a few hertz. The coherence between E cells within the same column increased, and a significant coherence developed between E cells in different columns. For FBA to the P feature, the presence of an AMPA component led to a decrease of the power in the gamma peak, whereas the power in the beta frequency range increased. Note that the gamma oscillations in the TDI network were not affected by the strength of the AMPA conductance, whereas gamma oscillations in the E cells were indirectly affected via the change in FFI activity.

In addition, for an AMPA-mediated component, the oscillation frequency changed more with the parameter manipulations discussed in the preceding text. For instance, when $A_{FFI}$ and $A_{E}$ were varied, beta oscillations were obtained with frequencies ranging from 20 to 35 Hz. When axonal delays were increased from their default values of 0.05 ms, the rhythm slowed as expected. It did not matter whether these delays were in one synaptic connection or whether they were spread out among the two projections (E to FFI and FFI to E). When the delay became too long, 10 ms for our parameter settings, the oscillation had a “doublet” characteristic with two E-cell spikes per oscillation cycle. The oscillation frequency was less sensitive to the value of $\tau_{GABA}$: it ranged from 27 to 30 Hz for $\tau_{GABA}$ values between 4 and 24 ms.
These results show that beta and gamma oscillations were robust against small parameter changes but that a stronger AMPA component led to stronger beta oscillations at a frequency that was less robust to parameter changes.

**DISCUSSION**

In the canonical cortical computation, feedforward inputs merge with top-down inputs and are processed by a recurrent cortical network after which the activity is transmitted to a downstream area (Tiesinga et al. 2008). Cortical area V4 is a prime example because it receives feature-selective bottom-up inputs from V2 (Felleman and Van Essen 1991) and is modulated top-down by selective attention (Moore and Armstrong 2003). Experiments conducted in V4 over the past two decades have provided a set of quantitative constraints (Tables 3 and 4), which have been incorporated in phenomenological models (Boynton 2005; Reynolds et al. 1999). However, a mechanistic understanding at the spiking neuron level has so far been lacking. Only in spiking models can firing rate changes be linked to coherence modulations (Bichot et al. 2005; Fries et al. 2001; Womelsdorf et al. 2007). We have developed, for the first time, a model circuit that satisfies, for a large number of stimulus contrast values, all these experimental constraints with one set of parameter values.

We briefly summarize the main predictions of the model and the corresponding figures where these predictions are documented.

First, the model reproduces the predictions of the biased competition framework, but the circuit required two types of interneurons and a cross-columnar excitatory projection. It predicts the corresponding response of interneurons in the attend-away condition (Fig. 4), and their firing rate changes with FBA (Fig. 7) and SA (Fig. 9).

Second, the model predicts that for a single stimulus, SA acts more like a change in contrast gain (Fig. 10), whereas FBA acts more like a change in response gain (Fig. 8).

Third, the model predicts the responses when the stimuli are presented at intermediate contrasts. It shows that stimulus competition is not always present (Fig. 5). Specifically, it predicts a contrast-dependent switch from facilitatory to suppressive stimulus interaction. It further shows that the predictions for attention-induced changes in firing rate based on the biased competition framework are not satisfied for all contrast values (Figs. 8 and 10).

Fourth, the model predicts whether there are correlations between the magnitude of the attention-induced firing rate changes and the degree of stimulus competition (Figs. 11).

Fifth, the model predicts that FBA shifts the network oscillation from the beta to the gamma frequency range (Fig. 12). It
further predicts that the gamma power is highest in response to the P stimulus by itself, whereas the gamma coherence is highest in the pair condition with the P stimulus at full contrast.

And, sixth, the model predicts that the phase lag between the interneurons and the pyramidal cells increases with FBA (Figs. 13), whereas the phase lag decreases with the degree of stimulus competition (Figs. 14).

The discussion section is rather long; to guide the reader, we offer an outline. First, we present our conjecture on the physiological type of the interneurons in the model. Second, we highlight, motivate, and discuss the specific model assumptions. Third, we discuss some of the specific predictions the model makes. Fourth, we compare our model to other models. Fifth, we suggest specific experiments based on the model predictions and review methods with which it is possible to test the model hypothesis regarding interneuron identity. Sixth, we list the simplifications made in the model and discuss how these can be addressed in future work.

Conjecture on the physiological type of the interneurons in the model

We referred to the two interneuron types in the model as FFI and TDI to distinguish our hypothesis about the role of each interneuron in the circuit for attention from our conjecture about their anatomical/physiological type. Studies in layer 4 (L4) of rodent somatosensory cortex indicate that fast-spiking (FS) interneurons with a basket cell morphology provide FF inhibition to spiny stellate cells (Beierlein et al. 2003; Cruikshank et al. 2007). These cells target the soma and perisomatic dendrites (Markram et al. 2004), which makes them effective in sculpting the spike times of the postsynaptic cells (Cobb et al. 1995). The connectivity pattern of basket cells in L2/3 is similar, suggesting that these basket cells provide FF inhibition to L2/3 pyramidal cells (Binzegger et al. 2004; Douglas and Martin 2004). Basket cells typically express parvalbumin (PV), but they do not express somaantistatin (SOM), calbindin (CB) or calretinin (CR). Our conjecture is that the FFI in the model correspond to PV-expressing FS basket cells in L2/3.

The identification of TDI is more complex given the large number of possible candidates with the double bouquet cell (DBC) and martinozzi cells (MC) being the more prominent. Our conjecture is that the TDI correspond to DBC for the reasons outlined in the following text. DBC have vertical axons with a shape reminiscent of a horse tail, which target the dendrites of the postsynaptic neurons (DeFelipe et al. 2006; Markram et al. 2004). DBC can express CB and are unique in that they sometimes coexpress CB and CR, but they do not express SOM or PV (Markram et al. 2004). First, in the rodent, most cell bodies of CR-expressing interneurons were located in the supragranular layers (L1, L2/3), and within L2/3 they projected predominantly to other inhibitory interneurons, half of which also expressed CR (Gonchak and Burkhalter 1999). The remainder of the synapses was on the dendrites of L2/3 pyramidal cells. Second, feedback connections terminating in L1 specifically targeted CR-expressing interneurons, in the sense that the number of synapses was higher than expected based on the number of CR cells relative to other targets (Gonchak and Burkhalter 2003). Similar results were obtained in other brain areas where CB-expressing interneurons were preferentially targeted by top-down projections (Barbas et al. 2005). Third, anatomical studies in rat visual cortex show that FS interneurons and pyramidal cells share common FF inputs, but low-threshold spike (LTS) interneurons do so to a lesser extent (Yoshimura and Callaway 2005; Yoshimura et al. 2005). Interpreted within the context of the model, it supports the notion that FFI and E cells are stimulus-tuned and that the TDI are not. These three anatomical results support our conjecture that the TDI correspond to the DBCs.

There is evidence to suggest that Martinotti cells (Markram et al. 2004), projecting primarily to the tuft of pyramidal cells in L1 and usually containing SOM, are involved in attention. In vitro studies indicate that these neurons could mediate a highly nonlinear mechanism for gain modulation (Kapfer et al. 2007). Freund and Meskenaite report that the GABAergic projection from the basal forebrain synapses preferentially onto interneurons containing SOM (as well as those containing PV) (Freund and Meskenaite 1992). Because this projection is not fine grained enough to mediate FBA, it might serve as a general arousal mechanism that works via disinhibition, which might in turn also enhance gamma oscillations (Buia and Tiesinga 2006). Support for this idea comes from data obtained from simultaneous recordings in the basal forebrain and the prefrontal cortex in rats (Lin et al. 2006).

Model assumptions

We made a number of assumptions that need further discussion. First, we assumed that there were two groups of FFI, one group (FFI) that was stimulus tuned and another (FFIb) that was not. Second, there were two groups of E cells, one group (E) that responded to all stimuli and one group (Eb) that only responded to high contrast stimuli. Third, the model had broad excitation (example: E1 to FFI2), but no broad inhibition (example: FFI1 to E2). Fourth, the FFI and TDI were modeled to have the same spiking dynamics. Fifth, we conjectured that two populations of interneurons were necessary to satisfy the model constraints (Tables 3 and 4).

As shown in results (Fig. 8 and the corresponding text), the FFib were necessary to achieve the firing rate increases for low contrast stimuli with FBA to the P feature. They were not necessary to achieve the FBA effects at high contrast. The basic component of normalization models (Carandini et al. 1997; Heeger 1992), proposed to account for saturation in the CRFs, is untuned inhibition, presumably produced by FS basket cells. Untuned inhibition can come from untuned interneurons or can be generated from inputs from a group of tuned interneurons, each selective for a different stimulus/feature. Intracellular recordings reveal that the inhibition received by cat V1 cortical cells can be tuned (Monier et al. 2003). In some recordings from cat V1 (Hirsch et al. 2003; Nowak et al. 2007), complex interneurons were found that were not orientation selective, whereas another set of experiments revealed that interneurons were only slightly less orientation-tuned than principal cells (Cardin et al. 2007). Taken at face value, experiments in V1 support the existence of tuned (FFI) and untuned (FFIb) interneurons.

In the model, stimulus competition required an effective cross-columnar excitatory projection. The NMDA-mediated projection in the model was not effective because the postsynaptic current saturated when the presynaptic rates exceeded 20 Hz. Because typical firing rates in response to full-contrast
single stimuli exceeded 20 Hz, the increases in E-cell firing rate going from the single stimulus to the pair condition did not sufficiently increase the current to the FFI to lead to an adequate suppressive effect. The model therefore contained a pool of less excitable E cells (E1b and E2b), which would increase their firing rate from close to 0 to ~10 Hz going from the single stimulus to the pair condition. In vivo (Olshausen and Field 2005) a wide range of firing rates of visual cells is observed in response to visual stimulation. In the model, the two pools of E cells represent the extremes of this experimentally documented range.

The suppressive effects of stimulus competition could, in principle, also be mediated by cross-columnar (broad) inhibition. In that case, FFI1 would project to E1 and E2. Because, in the model, FBA to the P feature decreased the firing rate of the FFI in column 1, the E cells in both columns would be disinhibited. The resulting increase in firing rate of the E2 cells is inconsistent with experimental observations (Table 4). The axonal arborization of small and medium basket cells is less widespread than that of pyramidal cells (Douglas and Martin 2004; Markram et al. 2004), which means that an excitatory projection will have a longer range than an inhibitory projection. Therefore on anatomical grounds, a cross-columnar excitatory connection, as used here, is more likely than a cross-columnar inhibitory connection. However, the validity of this argument depends on the distance between the two columns on the cortical surface. This distance is determined by the retinotopy and the structure of the feature map(s) in V4, neither of which is known to sufficient detail.

The TDI were modeled using a model developed for FS interneurons (Tiesinga and Jose 2000; Wang and Buzsaki 1996), which may not be appropriate when, as is hypothesized in this paper, the TDI correspond to CR-expressing DBCs, possibly with an LTS spiking dynamics (Markram et al. 2004). This raises the issue of whether networks of such cells can actually synchronize in the same way as shown in the model. Synchrony by mutual inhibition has almost exclusively been studied for interneuron models with a continuous firing rate versus current (f-I) characteristic (Tiesinga and Jose 2000; Wang and Buzsaki 1996; White et al. 1998), such as the interneurons used here. This means that the model neuron can fire periodic spike trains at arbitrarily low frequencies in response to a constant depolarizing current. Some types of interneurons have an f-I with a step (Izhikevich 2006), which means they transition directly from subthreshold activity to firing at a finite frequency. We studied whether a network composed of these interneurons could also synchronize in response to a current step. A network consisting of the model neurons for CR-expressing cells developed by (Wang et al. 2004), could synchronize and increase firing rate in response to a depolarizing step. The network required some level of noise and was robust against heterogeneity in neural properties (results not shown). This shows that the dynamics of the TDI network hypothesized to underlie FBA can be obtained for a number of different types of model neurons. Furthermore, just as in the model used in this paper, the key properties determining the degree of synchronization and the oscillation frequency were the level of depolarizing current and the timescale of inhibition (results not shown).

We assume the presence of two types of interneurons in the model. Their projection pattern, based on the hypothesized identification of the TDI with DBC and the FFI with FS basket cells, is consistent with the published anatomy. Hence there is no reason not to include the TDI in the model. However, are both types necessary to account for the constraints provided by the phenomenological models (Tables 3 and 4)? First, as explained in the following text, in some circumstances, the models predict that FBA and SA have opposite effects on the E-cell firing rate. Second, FBA corresponds to a top-down effect (Fig. 3B) and SA to a bottom-up effect (Fig. 3C). For these two reasons, it was easiest to achieve their effects via different inhibitory neurons. Because we did not try all possible model configurations with only the FFI, we have not explicitly shown that the same results cannot be obtained without the TDI.

Model predictions

The network model makes a number of predictions that will be discussed in the context of phenomenological models (Tables 3 and 4) and recent experimental results. First, how do the model predictions relate to the ongoing discussion of whether attentional modulation is better described by either a response or a contrast gain model? Second, how do the predictions for changes in interneuron firing rate with SA compare with recent experimental results (Mitchell et al. 2007)? Third, is the synchrony observed in the model functionally relevant and is it consistent with experiment? Fourth, how do the model predictions relate to those made by the biased competition framework.

RESPONSE VERSUS CONTRAST GAIN. In experiment, SA to the location of a stimulus increased the firing rate, but the exact mathematical form of this transformation as a function of contrast remains unclear. Researchers have argued for contrast gain models (Martinez-Trujillo and Treue 2002; Reynolds and Desimone 2003; Reynolds et al. 2000), where the attended response corresponds to the attend-away response to the same stimulus but presented at a higher contrast and also for response gain models (Lee et al. 2007; Martinez-Trujillo and Treue 2004; Williford and Maunsell 2006), where the attended firing rate is increased by a constant gain factor compared with the attend-away firing rate. Our model does not make an assumption regarding the quantitative nature of the attentional effects in area V2, which projects to V4, the area modeled in this paper. Attention was implemented as an increase in contrast by a constant factor (see Methods), which, in the model, was the same as increasing the input (the V2 response) by a constant factor. However, in the general case, for which the FF input varies nonlinearly with contrast, this would not correspond to a response gain.

The model makes predictions about how attention modulates the output firing rate, as shown in Fig. 10. A large number of cells recorded in the visual system display signs of contrast saturation (Albrecht and Hamilton 1982). For high contrast, the firing rate does not increase anymore with contrast and can even decrease (Williford and Maunsell 2006). This means that an attention-induced change in contrast gain would yield the highest changes at intermediate contrast because the tangent of the CRF is highest there. For response gain, the largest change would occur at high contrast because there the firing rate is highest. Thus for this characteristic shape of the CRF, response
gain can be heuristically distinguished from contrast gain. In the model, we find that the rate changes are neither exactly described by a change in contrast gain nor by a change in response gain. However, in the single stimulus condition, using the above-established criterion, SA acts more like a contrast gain and FBA more like a response gain.

In some sense it is not surprising that SA results in a contrast gain because that is how it is implemented. However, there is a contrast gain for both the FFI and E, which we chose to be different. Therefore SA results only approximately in a contrast gain. This approximation is likely to be less good when the FFI are active for lower contrasts. In experiment (Fig. 5C in Williford and Maunsell 2006 as well as in Sundberg et al. 2005), there are peaked CRFs, which are suggestive of strong inhibition. Hence for those cases, the model predicts that contrast gain might not be able to fully account for the changes in firing rate with SA.

The E-cell firing rate depends on the balance between the drive to the E cells and FFI because the FFI project to the E cells. FBA changes this balance by inhibiting the FFI. Computational models can explain how this could lead to a response gain. When the FFI are asynchronous, they produce uncorrelated inhibitory Poisson spike trains that drive the E cell. Simulations show that changing the rate of inhibitory Poisson processes can change the response of the E cell to an FF input by a multiplicative gain factor (Chance et al. 2002; Doiron et al. 2001; Mitchell and Silver 2003; Prescott and De Koninck 2003; Tiesinga et al. 2000), that is, a change in response gain. In the model, the FFI are not completely asynchronous because there is power in the beta and gamma frequency bands, so the effect of a rate change does not correspond exactly to a response gain (Tiesinga et al. 2004a).

For both SA and FBA, the characterization as a change in contrast gain or in response gain, respectively, is only approximate. It is also fair to say that experimental response will have both a top-down (here FBA) and bottom-up (here SA) component, given the averaging interval (~200 ms) used to estimate firing rates. Hence for this situation, the model would predict neither a pure response nor a pure contrast gain. This is consistent with experiment because either phenomenological model can only explain part of the attention-induced variability (Williford and Maunsell 2006).

EXPERIMENTS ON ATTENTIONAL MODULATION OF INTERNEURONS. For the current parameter settings, the FFI fire at a lower rate than the E cells. This appears to contradict recent experiments (Mitchell et al. 2007), where it was reported that the FFI fired at a higher rate and had higher absolute changes in firing rate. We ran the model for the case where the FFI received stronger FF input but with weaker unitary inhibitory synapses (results not shown). The results were similar to those shown in this paper but with about double the inhibitory firing rate. This shows that the hypothesized mechanism for SA (Fig. 3C) is consistent with the experimental results.

FUNCTIONAL ROLE OF COHERENT OSCILLATIONS. Two types of oscillations emerged in the model network. Beta oscillations are predicted to occur in response to two high-contrast stimuli. Gamma oscillations are predicted to occur with FBA to the P feature. Furthermore, because of these oscillations, the phase lag between interneurons and E cells could be extracted from the model. The phase lag increased with FBA but decreased with increasing stimulus competition. This raises the question of whether the synchrony that emerged in the model is actually necessary for the firing rate effects and whether it is useful downstream. In our model, the effects of FBA could also be obtained with rate changes of an asynchronous TDI network because the E-cell firing rate increased mainly because of disinhibition rather than an increase in synchrony. In fact, simulations using synchronous inhibitory inputs show that too much synchrony will reduce or completely abolish stimulus competition (results not shown) (an alternative mechanism is described in Tiesinga 2005). In terms of downstream effects, because of gamma synchrony the impact of attended stimuli will be stronger as reviewed in (Salinas and Sejnowski 2001). Furthermore, the attention-induced phase lag would also increase the impact on neurons that receive excitatory and inhibitory inputs from this network as shown by us (Buia and Tiesinga 2006) and others (Mishra et al. 2006). A recent re-analysis of in vivo data suggests that modulation of phase relationships may form the basis of selective communication between brain areas (Womelsdorf et al. 2007).

The model predicts that for FBA to the P feature, gamma power in the E-cell histogram and the coherence between individual E-cell spike trains generally increases with contrast. It further predicts that gamma power is highest for the P stimulus by itself, whereas the coherence is highest for the pair condition as long as the P stimulus is in the RF at full contrast. Both of these predictions are consistent with experiment. In a FBA task, attending to the P feature of a V4 cell led to the highest coherence when the P stimulus was also in the RF (Bichot et al. 2005). In V1, it was shown that gamma power in the LFP increased with stimulus contrast (Henrie and Shapley 2005).

BIASED COMPETITION IN THE MODEL. A theoretical framework—biased competition—was formulated to account for experiments during which multiple stimuli were presented in the neuron’s RF. The basic premises were as follows. First, the response to the P and NP stimulus presented together is higher than the response to the NP stimulus and less than the response to P stimulus. This can be expressed in terms of the quantity α, which measures where the pair response falls in between the NP and P response. There are two aspects of the stimulus pairs, the relative preferredness of the features, which could be shape, stimulus orientation, color or location within RF (Desimone and Schein 1987; Gallant et al. 1993; Pasupathy and Connor 2001, 2002; Pollen et al. 2002; Schein and Desimone 1990), and the strength at which these features are present: contrast. The firing rate in response to a single stimulus depends on both of these factors. Specifically, a P stimulus at low contrast could yield a lower firing rate than a NP stimulus at high contrast. It is not clear whether biased competition predicts a response in between the P and NP response in this case. More generally, it raises the question of on what α depends. Does it depend on the relative preferredness, on the relative contrast, or only on the single stimulus firing rates? Our model sheds light on this issue because the contrast is varied independently of the relative stimulus preferredness. It shows that for low contrast, stimuli interact facilitatorily.

Second, the framework predicts how the pair response changes with attention. Overall, the firing rate should change so as to make the response more similar to the response when
the attended stimulus is presented alone. Hence SA to the location of the P stimulus or FBA to the P feature of the neuron would increase the response, closer to the response to the P stimulus alone. In other words, the effective driving force of the P stimulus is increased. Likewise SA to the location of the NP stimulus or FBA to a NP feature of the neuron would reduce the response, so that it is closer to the response to the NP stimulus presented alone. In other words, the suppressive effect of the NP stimulus is increased.

It was not trivial to design a model satisfying these constraints (Tables 3 and 4). One challenge is that the same stimulus can have two opposite effects. When the NP stimulus is presented by itself, it increases the neuron’s firing rate compared with when there is no stimulus. Hence it has an excitatory effect. When the NP stimulus is presented in addition to a P stimulus, it decreases the firing rate of the neuron compared with when the P stimulus is presented by itself. Hence in that case, it has a suppressive effect. The proposed circuit thus needs to contain a way of switching between an excitatory and suppressive effect of the NP stimulus. In our model, the switch came in the form of the excitability of the FFI. Only when these were driven sufficiently by the P stimulus were there suppressive interactions. This limited the range of contrast values for which suppressive effects were obtained (Fig. 11E).

A similar challenge exists for SA. SA to the location of the NP stimulus, when it is presented by itself increases the firing rate, but when both stimuli are presented simultaneously, SA should decrease the rate. We hypothesized that the context-dependent effect of SA was mediated by the same switch that mediates stimulus competition. This hypothesis explicitly links the strength of stimulus competition to the magnitude of the attentional effect, thus providing an experimentally testable hypothesis. The experimentally obtained rate changes can be plotted versus α just as shown in Fig. 11, C and D.

The change in response also depends on the type of attention. When the NP stimulus is presented by itself, SA to its location increases the firing rate, but when FBA is directed to the NP feature, the firing rate decreases. There are a number of other distinctions between FBA and SA. For FBA, the sign of the FFI rate change is opposite to that of the E cells. When the FFI increase their rate, the E cells decrease theirs and vice versa. For SA, the FFI rate always increased, but the E-cell rate could increase or decrease.

**Comparison to other models**

A significant number of models have been developed to study the mechanisms for stimulus competition and the attentional modulation thereof. Phenomenological models predict the firing rate as a function of contrast and attention condition and are capable to reproduce experimental results (Boynton 2005; Reynolds et al. 1999). Their main value lies in providing a concise summary of the experimental results and a benchmark with which to compare the results of more detailed biophysical models. The firing rate models proposed by Spratling and Johnson go one step further because for each set of experiments, a model architecture is proposed that reproduces the temporal dynamics of the response (Spratling and Johnson 2004). However, firing rate models cannot be used directly to study the effect of spike-time correlations, which recent experiments indicate are an integral part of attentional modulation (Bichot et al. 2005; Fries et al. 2001). Both Deco and Rolls as well as Usher and Niebur have used model networks of spiking neurons to account for biased competition (Usher and Niebur 1996; Deco and Rolls 2005). There are two main differences between these models and the model studied in this paper. First, they use a single inhibitory pool that projects to all the feature-selective excitatory pools. Second, FBA was mediated by a projection to the excitatory neurons.

The potential link between attention and neural correlations or synchrony in the gamma band was established in early models by Niebur and colleagues (Niebur and Koch 1994; Niebur et al. 1993). Gamma oscillations also emerged in a large-scale model of the visual cortex with a retinotopic map and feature-selective neurons (Kirkland and Gerstein 1999). A key feature of the large-scale model was feature-selective inhibitory pools, which, in contrast to our model, were connected by inhibition. It was shown, using single-neuron models, that modulation of the relative phase between excitatory and inhibitory inputs, synchronous in the gamma frequency range, could reproduce attentional modulation of stimulus competition (Mishra et al. 2006; Tiesinga 2005). Archie and Mel took it one step further and investigated whether dendritic nonlinearities alone could account for biased competition (Archie and Mel 2000). In their model, biased competition was achieved by spatial segregation on the neuron’s dendritic tree of inhibitory and excitatory synapses with the same feature selectivity. In a very recent model (Ardid et al. 2007), attentional modulation of stimulus competition was studied in a circuit representing the medio-temporal and prefrontal cortex. Two authors did not quantify the attentional modulation as a function of contrast, nor did they study the effect of attention on gamma synchrony. Oscillations related to the beta oscillations in our model network, but with a lower frequency, have been observed experimentally in area IT (Rollenhagen and Olson 2005) and were reproduced in a model sharing features with the one used here (Moldakarimov et al. 2005).

The value of these models lies in the diversity of mechanisms and the different predictions that they make, so that they can be validated or disproved by experiment. Our contribution lies in proposing a role for different types of interneurons and predicting their differential modulation by spatial and feature-based attention.

**Testing the model predictions**

The model predicts that FFI cells behave differently for SA compared with FBA. To test these predictions, monkeys need to be trained on a task that switches between SA and FBA during the same recording session, preferably using the same stimulus configuration. In addition, FFI—FS basket cells—should be identified as such in the recordings. Monkeys have been trained on a SA task (McAdams and Maunsell 1999; Reynolds et al. 1999), on a FBA task (Bichot et al. 2005; Chelazzi et al. 2001), and a task that yielded information on either type of attention (Hayden and Gallant 2005). Therefore a single task involving both SA and FBA is possible. In a recent experiment (Mitchell et al. 2007), recorded cells were classified as narrow- and broad-spike cells. The former corresponded to putative FS interneurons and formed a minority of
the recorded neurons. With multi-electrode recordings, the yield of thin-spike neurons can be increased. Furthermore the classification as an inhibitory neuron can be validated using cross-correlation functions (Bartho et al. 2004; Henze et al. 2000; Kara and Reid 2003), which is necessary because not all interneurons have thin spikes; instead some of them are classified as regular spiking nonpyramidal neurons (Markram et al. 2004). Interneuron classification can also be achieved by genetic means, but it would require two-photon microscopy imaging of calcium dynamics in the awake primate (Stettler et al. 2006). Interneurons express specific proteins, such as, PV, CR, and CB. The regulatory gene sequences that drive the expression of these proteins could be used to drive expression of a green fluorescent dye (GFP) (Knopfel et al. 2006). For example, transgenic mice have been made where the expression of GFP is coupled to GAD-67, which is only present in cells that release GABA from their synaptic terminals (Tomioka et al. 2005). In these mice, all inhibitory cells light up and can thus be easily distinguished from excitatory cells. The difficulty lies in training mice on a behavioral task, which is likely to be resolved in the near future (Huber et al. 2008). There are no transgenic monkeys yet, but there GFP labeling could be achieved by viral transfection (Callaway 2005). Furthermore, it is only a matter of time before these techniques are extended to CB- or CR-expressing cells by linking GFP expression to a promoter for CB or CR.

Our hypothesis suggests that if the TDI are activated, it would locally have the same effects as FBA, for instance, changing the neurons’ CRF and tuning functions. This could change the perceived contrast of stimuli (Carrasco et al. 2004), which could be tested in monkeys using, for instance, a standard two-alternatives, forced-choice task (Green and Swets 1988). New technology makes it possible, by linking the expression of a light-activated channel or pump to the presence of a promoter for CR or CB, to activate specific groups of cells in a noninvasive way (Han and Boyden 2007; Zhang et al. 2007) and test for possible changes in perception (Huber et al. 2008). Taken together, multi-electrode recordings, imaging techniques and genetic methods, make feasible a direct test of our hypothesis and corresponding predictions.

The hypothesized model mechanisms also make quantitative predictions that can be tested experimentally. For instance, the results shown in Fig. 5B suggest the following experiment. First, present the P stimulus by itself for different values of the contrast. Second, repeat this but with the NP stimulus also present at full contrast. In the pair condition, the model predicts that the firing rate will vary nonmonotonically with contrast: increasing for low contrast and decreasing for high contrast. Specifically, there will be a contrast value at which the firing rate is maximal (1st asterisk in Fig. 5B). The effect of adding the NP stimulus is obtained by comparing the firing rate in the pair condition to that of the single stimulus condition. In the model, for low P contrast, the NP stimulus has an excitatory effect, whereas for high P contrast, it has a suppressive effect (Fig. 5B). The transition from an excitatory to suppressive effect occurs at a particular value for the contrast (2nd asterisk in Fig. 5B) — generally different from the contrast value for which the firing rate in the pair condition is maximal. The two values will depend on the relative preferredness of the stimulus features and whether the relevant features are the same or different. To be specific, the P and NP stimuli could be oriented bars and have different orientations (“same feature”). Or the P stimulus could have a P color and the NP stimulus could be black and white and have a NP orientation (“different feature”). In the model, we varied the relative preferredness (β) in such a way as to keep the firing rate in the pair condition the same (results not shown). A β equal to a half means that both stimuli are equally preferred, and a β of one means that the cell is not driven by the NP stimulus. As β increases from just above a half to just below one, the firing rate peak moves to higher contrast, whereas the excitatory-to-suppressive transition moves to lower contrast, thus reducing the distance between those points.

**Limitations of the model**

The model was designed to be as simple as possible but with spiking neurons and conductance-based synapses. The model therefore does not include some experimentally well-documented features, the absence of which might affect the results. The potential consequences and future studies necessary to address these are discussed in the following.

Experimental studies (Galarreta and Hestrin 1999; Gibson et al. 1999) have shown that there are gap-junctions between groups of interneurons of the same type. In L4 of rodent cortex, LTS interneurons synchronize in response to activation by glutamatergic and cholinergic agonists, even when the GABA_A receptors are blocked by picrotoxin, suggesting the direct involvement of gap-junctions. This interpretation is supported by simulations of network synchronization by way of gap junctions (Chow and Kopell 2000; Lewis and Rinzel 2003; Nomura et al. 2003). The DBC (TDI) synchronization dynamics might similarly rely on gap junctions. Hence to compare with anatomical and physiological data, gap junctions as well as the appropriate spiking dynamics for DBC should be incorporated in the model. Analysis based on so-called phase-response curves could also be helpful in this regard (Mancilla et al. 2007).

Only the changes in gamma power and coherence with FBA were studied in the model. Because the effects of SA are inherited from the upstream cortical areas, they likely also influence changes in the gamma power (Taylor et al. 2005). Hence during SA, the FF inputs may be synchronous in the gamma range. This was not accounted for in the model because FF inputs were modeled as a constant driving current. Future studies will therefore need to incorporate coherent FF synaptic inputs. This will also allow issues related to how SA modulates response latencies to be addressed (Lee et al. 2007).

The simulations have focused mostly on the inhibitory projections: the model included only one type of excitatory projection (from E1 to FFI2 and from E2 to FFI1). We have performed simulations where there was excitation to excitatory neurons in the other column and where there was excitation to the FFI in the same column. We found parameter settings for which stimulus competition and the attention effects listed in Tables 3 and 4 were observed. Nevertheless, more quantitative studies need to be conducted to assess the impact of these additional excitatory connections.

The model was constructed to account for attentional modulation in visual area V4, for stimulus conditions where SA is bottom-up and FBA is top-down. To what extent do these
results apply to V1, where, for the same conditions, SA is top-down? A key feature of the model, which was necessary to obtain stimulus competition, was the direct excitatory projection between the columns. Because in V1 the two stimuli fall in nonoverlapping RFs, the columns are further apart on the cortical surface, reducing the strength of the direct excitatory connection. Hence at the level of V1, the model predicts that the competition effects are weaker. In the single-stimulus condition, the model predicts that SA synchronizes the TDI and increases the E-cell firing rate. By contrast, in experiment, the effects of attention on the firing rate of V1 cells are small and increases the E-cell firing rate. By contrast, in experiment, condition, the model predicts that SA synchronizes the TDI

TABLE A1. Standard parameter values for the excitatory and inhibitory model neurons

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Pyramidal Neurons</th>
<th>Interneurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_L$, mV</td>
<td>−70</td>
<td>−65</td>
</tr>
<tr>
<td>$E_{Nar}$, mV</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>$E_K$, mV</td>
<td>−90</td>
<td>−90</td>
</tr>
<tr>
<td>$E_{AMPA}$, mV</td>
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<td>0</td>
</tr>
<tr>
<td>$E_{NMDA}$, mV</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$g_{L}$, mS/cm^2</td>
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<td>0.1</td>
</tr>
<tr>
<td>$g_{Na}$, mS/cm^2</td>
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<td>35</td>
</tr>
<tr>
<td>$g_{K}$, mS/cm^2</td>
<td>0.07</td>
<td>—</td>
</tr>
<tr>
<td>$g_{Kl}$, mS/cm^2</td>
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<td>—</td>
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<tr>
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<td>1.4</td>
</tr>
<tr>
<td>$g_{KB}$, mS/cm^2</td>
<td>0.2</td>
<td>1.4</td>
</tr>
<tr>
<td>$C_m$, μF/cm^2</td>
<td>9</td>
<td>9</td>
</tr>
</tbody>
</table>

Here the label $x$ stands for the kinetic variable, and $\zeta = 5$ is a dimensionless time scale that can be used to tune the temperature dependent speed with which the channels open or close. The rate constants are

$\alpha_m = \frac{-0.1(V + 35)}{\exp[-0.1(V + 35)] - 1}, \quad \beta_m = 4 \exp[-(V + 60)/18]$

$\alpha_n = 0.07 \exp[-(V + 58)/20], \quad \beta_n = \frac{1}{\exp[-0.1(V + 28)] + 1}$

$\alpha_h = \frac{-0.01(V + 34)}{\exp[-0.1(V + 34)] - 1}, \quad \beta_h = 0.125 \exp[-(V + 44)/80]$

and the asymptotic values of the gating variables are

$x_+(V) = \frac{\alpha_x}{\alpha_x + \beta_x}$

where $x$ stands for $m, n,$ and $h$.

We made the approximation that $m$ follows the asymptotic value $m_+(V)$ instantaneously (Wang and Buzsaki 1996).

Pyramidal neuron model

A different single compartment Hodgkin-Huxley-type model (Golomb 1998; Golomb and Amitai 1997) was used for the dynamics of the pyramidal neuron (groups E1, E1b, E2, and E2b). The membrane potential obeys the following differential equation

$C_m \frac{dV}{dt} = -I_{Na} - I_{Nar} - I_{Kd} - I_{KA} - I_{Ks} - I_L - I_{GABA} - I_{AMPA}$

$- I_{NMDA} + I + C_m \xi$

for the membrane potential of the model neuron is where $I_L = g_L(V - E_L)$ is the leak current, $I_{Na} = g_{Na}m^3h(V - E_{Na})$ is the sodium current, $I_{Nar} = g_{Nar}p_{Na}(V - E_{Na})$ is the persistent sodium current, $I_{KA} = g_{Kd}n^4(V - E_K)$ is the delayed rectifier potassium current, $I_{Ks} = g_{Ks}m^2(V - E_K)$ is the slow potassium current, $I_{GABA} = g_{GABA}m^2(V - E_{GABA})$ is the inhibitory GABA current, and $I_{AMPA} = g_{AMPA}m^2(V - E_{AMPA})$ is the AMPA current.

APPENDIX: THE MODEL EQUATIONS

Interneuron model

The interneuron (groups FFI1, FFI1b, FF12, FF12b, TD11, and TD12) was modeled as a single compartment with Hodgkin-Huxley-type voltage-gated sodium and potassium currents and a passive leak current (Tiesinga and Jose 2000; Wang and Buzsaki 1996). The equation for the membrane potential of the model neuron is

$C_m \frac{dV}{dt} = -I_{Na} - I_K - I_L - I_{GABA} - I_{AMPA} - I_{NMDA} + I + C_m \xi$

Characterization of neocortical principal cells where $I_L = g_L(V - E_L)$ is the leak current, $I_{Na} = g_{Na}m^3h(V - E_{Na})$ is the sodium current, $I_K = g_Kn^4(V - E_K)$ is the potassium current, $I_{GABA}$ is the inhibitory synaptic current and $I_{AMPA}$ and $I_{NMDA}$ are the excitatory synaptic currents. The Gaussian noise variable is denoted by $\xi$ while $I$ is the tonic drive (see following text). The gating variables are $m, n, h$ and they satisfy the equation

$\frac{dx}{dt} = \zeta(\alpha_x(1 - x) - \beta_x x)$

TABLE A2. Strength of the synapses in mS/cm^2

<table>
<thead>
<tr>
<th></th>
<th>To E</th>
<th>To FFI/TDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>From E</td>
<td>0.0 (0.0)</td>
<td>0.004 (0.0)</td>
</tr>
<tr>
<td>From FFI/TDI</td>
<td>0.0085</td>
<td>0.005</td>
</tr>
</tbody>
</table>

For excitatory synapses, the strength of AMPA is listed between parentheses.
The rate constants are
\[
m_a = \frac{[\exp(-(V + 30)/9.5) + 1]^{-1}}{[\exp((V + 53)/7) + 1]^{-1}},
\]
\[
h_a = \frac{[\exp((V + 40)/5) + 1]^{-1}}{\tau_s = 0.37 + 2.78 \times [\exp((V + 40.5)/6) + 1]^{-1}}
\]
\[
p_a = \frac{[\exp(-(V + 40)/5) + 1]^{-1}}{\tau_n = 0.37 + 1.85 \times [\exp((V + 27)/15) + 1]^{-1}}
\]
\[
a_a = \frac{[\exp(-(V + 50)/20) + 1]^{-1}}{\tau_t = 15 \text{ ms}}
\]
\[
b_a = \frac{[\exp((V + 80)/6) + 1]^{-1}}{\tau_z = 75 \text{ ms}}
\]

The tonic drive, \(I\), for the neurons, was the sum of a common component \(I_b(x, c, x')\) (here \(x\) stands for the excitatory neurons E1, E1b, E2, E2b, or inhibitory neurons FF11, FF1b, FF12, FF12b, TD11, TD12, \(c_1\) and \(c_2\) are the contrast of stimulus 1 and 2, respectively) and a heterogeneous component that varied across neurons and was drawn from a uniform distribution between \(-\Delta_c\) and \(\Delta_c\). The equations for \(I_b\) as a function of stimulus contrast are given in the main text and the parameter values are listed in Table 1.

The noise \(\xi\) in the current of neuron \(i\) is chosen such that \(\langle \xi(t) \rangle = 0\) and \(\langle \xi(t) \xi(t') \rangle = 2\Delta \delta(t - t')\delta_{ij}\). On each integration time step, the noise was drawn independently from a uniform distribution between \(-12\Delta/\text{dr}\) and \(12\Delta/\text{dr}\), where \(\text{dr}\) was the time step. \((\lambda_{\text{inh}}, \lambda_{\text{exc}})\) takes the value \((0.02, 0.5)\) (expressed in mV²/ms). The differential equations were integrated using a second-order Runge-Kutta method with a time step of \(\text{dr} = 0.05 \text{ ms}\) (Gerald and Wheatley 1999; Press et al. 1992).

### Synaptic models

Each synapse is modeled using a gating variable \(s_j\), with \(j\) being the index of the postsynaptic neuron and \(i\) being the index of the presynaptic neuron. Because the gating variable is independent of the postsynaptic neuron, except for the effects of axonal conduction delays, we write \(s_j = s_j\). Thus \(s_j^{\text{GABA}}, s_j^{\text{AMPA}}, s_j^{\text{NMDA}}\) are the gating variables for the GABA inhibitory and AMPA and NMDA excitatory synapses, respectively. The synapses were labeled by the presynaptic neuron \(i\). The synaptic gating variables obey the following equation

\[
\frac{ds_{j}^{\text{GABA}}}{dt} = \frac{1}{\tau_{s_{j}^{\text{GABA}}}} (k_{s_{j}^{\text{GABA}}} \sum s_j(t - \tau_j - t') - s_{j}^{\text{GABA}})
\]

\[
\frac{ds_{j}^{\text{AMPA}}}{dt} = \frac{1}{\tau_{s_{j}^{\text{AMPA}}}} (k_{s_{j}^{\text{AMPA}}} \sum s_j(t - \tau_j - t') - s_{j}^{\text{AMPA}})
\]

\[
\frac{ds_{j}^{\text{NMDA}}}{dt} = \frac{1}{\tau_{s_{j}^{\text{NMDA}}}} (k_{s_{j}^{\text{NMDA}}} \sum s_j(t - \tau_j - t') - s_{j}^{\text{NMDA}})
\]

where \(\tau_j\) is the \(\text{th}\) spike time generated by the \(\text{th}\) neuron, the constants are \(k_{s_{j}^{\text{GABA}}} = 0.44, k_{s_{j}^{\text{NMDA}}} = 0.48, k_{s_{j}^{\text{AMPA}}} = 1\); \(\tau_{s_{j}^{\text{GABA}}} = 2\text{ ms}, \tau_{s_{j}^{\text{NMDA}}} = 149\text{ ms}, \tau_{s_{j}^{\text{AMPA}}} = 8\text{ ms}\) are the synaptic decay times for excitatory and inhibitory synapses, respectively. We used a sum of Dirac delta functions to account for the arrival of the spikes to the postsynaptic neuron because it was computationally less expensive than similar synapses in Golomb and Amitai (1997) and Wang and Buzsaki (1996).

The synaptic currents to the \(\text{th}\) neuron (membrane potential \(V_i\)) take the values

\[
E_i^{\text{GABA}} = g_{s}^{\text{GABA}} s_j(t - d_j)(V_i - E_i^{\text{GABA}})
\]

\[
I_{\text{AMPAn}} = g_{s}^{\text{AMPA}} s_j^{\text{AMPA}}(t - d_j)(V_i - E_i^{\text{AMPA}})
\]

\[
I_{\text{NMDAn}} = g_{s}^{\text{NMDA}} s_j^{\text{NMDA}}(t - d_j)(V_i - E_i^{\text{NMDA}})
\]

\[
I_{\text{inh}} = g_{s}^{\text{inh}} s_j^{\text{inh}}(t - d_j)(V_i - E_i^{\text{inh}})
\]

Here \(j(i)\) stands for all neurons \(j\) that project to neuron \(i\). \(g_{s}^{\text{NMDA}}\) is the NMDA component of the unitary conductance of the excitatory synapses onto the inhibitory neurons, with a similar notation for the other the synaptic couplings, their values are given in Table A2. \(d_j\) is the axonal delay with which a spike generated by neuron \(j\) arrives at the synapse on neuron \(i\). Unless stated otherwise this delay was one time step (0.05 ms). \(G(V) = 1/\left[1 + \exp(-(V - \theta)/\sigma)\right]\) is the nonlinearity of the NMDA current with parameter values \(\theta = -25\) mV and \(\sigma = 12.5\) mV.

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