Travelling waves and EEG patterns during epileptic seizure: Analysis with an integrate-and-fire neural network

Mauro Ursino*, Giuseppe-Emiliano La Cara

Department of Electronics, Computer Science, and Systems, University of Bologna, viale Risorgimento 2, I-40136 Bologna, Cesena, Italy

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Abstract

Epilepsy is characterized by paradoxical patterns of neural activity. They may cause different types of electroencephalogram (EEG), which dynamically change in shape and frequency content during the temporal evolution of seizure. It is generally assumed that these epileptic patterns may originate in a network of strongly interconnected neurons, when excitation dominates over inhibition.

The aim of this work is to use a neural network composed of 50 x 50 integrate-and-fire neurons to analyze which parameter alterations, at the level of synapse topology, may induce network instability and epileptic-like discharges, and to study the corresponding spatio-temporal characteristics of electrical activity in the network. We assume that a small group of central neurons is stimulated by a depolarizing current (epileptic focus) and that neurons are connected via a Mexican-hat topology of synapses. A signal representative of cortical EEG (ECoG) is simulated by summing the membrane potential changes of all neurons.

A sensitivity analysis on the parameters describing the synapse topology shows that an increase in the strength and in spatial extension of excitatory vs. inhibitory synapses may cause the occurrence of travelling waves, which propagate along the network. These propagating waves may cause EEG patterns with different shape and frequency, depending on the particular parameter set used during the simulations. The resulting model EEG signals include irregular rhythms with large amplitude and a wide frequency content, low-amplitude high-frequency rapid discharges, isolated or repeated bursts, and low-frequency quasi-sinusoidal patterns. A slow progressive temporal variation in a single parameter may cause the transition from one pattern to another, thus generating a highly non-stationary signal which resembles that observed during ECoG measurements.

These results may help to elucidate the mechanisms at the basis of some epileptic discharges, and to relate rapid changes in EEG patterns with the underlying alterations at the network level.

Keywords: Epilepsy; EEG; Neural networks; Integrate-and-fire neurons; Mathematical modelling

1. Introduction

The electroencephalogram (EEG) plays an important diagnostic role in epilepsy today. It may help in the classification of seizures and may provide important prognostic information. However, understanding the mechanisms which relate EEG changes to patterns of neuronal activity in the cortex, and the neurophysiological and neurobiological factors involved, is still a difficult issue.

Epileptic seizures are characterized by various events of electrical activity (cortical EEG), which may rapidly change with time and may exhibit a different frequency content. Drake et al. (1998) reported that seizure patients have a decreased power at high frequencies (8.25–30 Hz) relative to lower frequencies (0.25–8 Hz). Inouye et al. observed a change of power spectrum in alpha frequency (Inouye et al., 1990) and structural changes in EEG frequency composition (Inouye et al., 1990) just before the occurrence of spike and wave complexes during seizure. Low-amplitude patterns at high frequencies (40–100 Hz), named electrodecremental events, appear as a key phenomenon at focal seizure onset (Fisher et al., 1992). These patterns are characterized by a decrease of signal voltage...
and a marked increase of signal frequency. It has been suggested that generalized electrodecremental events are one of the most common early ictal manifestation (Alarcon et al., 1995) and that they may provide important evidence for the localization of an epileptic focus (Allen et al., 1992; Gotman et al., 1995). The termination of seizure is often characterized by low-frequency rhythms (Gotman et al., 1995). As a matter of fact, EEGs measured with intracerebral or subdural electrodes during pre-operative assessment show a complex scenery, including electrodecremental events, high-frequency activity, irregular sharp waves intermixed with slow activity, spike-wave activity and rhythms (Alarcon et al., 1995; Wendling et al., 2002).

It is well recognized that the individual patterns of EEG, and their temporal evolution during seizure (or even before seizure onset), may provide important information to characterize the epileptic phenomenon and to gain a deeper insight into the underlying physiological mechanisms. Although many studies using signal processing methods have appeared recently to describe intracerebral EEG during epilepsy [see (Jerger et al., 2003) for a review], just a few works try to investigate the main mechanisms at neural network level.

A widespread idea is that epileptic seizures in a network of neurons originate from excessive mutual excitation, not sufficiently counterbalanced by interneuron inhibition (Dichter, 1997; Morimoto et al., 2004; Wendling et al., 2002). This assumption is at the basis of most recent neural models of epilepsy. Wendling et al. (2002), using a “neural mass model” of interactions among four neural groups, demonstrated that realistic EEG activities, similar to those observed during seizure, can be produced by modifying a few parameters which establish the strength of synaptic connections among excitatory and inhibitory populations. Giannakopoulos et al. (2001), using a model consisting of nonlinear delay differential equations, demonstrated that increasing excitation or decreasing inhibition induce spontaneous and stimulus-evoked rhythmic discharges. Other studies which investigated the effect of a change in the balance between excitation and inhibition are those by Antoniadis and Kostopoulos (1995); Brunel (2000); and Kudela et al. (2003). These works show that different activity states can be reached in a network of neurons by varying the synaptic balance.

An important aspect in networks of interacting neurons, moreover, is the strong integration of temporal and spatial aspects. Experimental studies demonstrated that networks of neurons can exhibit several spatio-temporal modes of activity: oscillations, synchronism, waves or avalanches (Beggs and Plenz, 2003; Chervin et al., 1988; Engel et al., 2001). Some of these patterns have been obtained via computer simulations too using mathematical models (Brunel, 2000; Jefferys et al., 1996; Kudela et al., 2003).

It is thought that these spatio-temporal modes correspond to different kinds of behaviour, either of physiological relevance [for instance synchronism may be involved with the binding and segmentation problem (Engel et al., 2001)] or occurring in pathological conditions (such as epilepsy). Chervin et al. (1988) observed that activity in epileptic cortical slices propagates in a wave-like manner. Milton et al. (1993) proposed that spiral waves may occur in cortical slices during a paradoxical activation, such as epilepsy.

The previous theoretical and experimental studies suggest that epileptic seizure may be characterized by various patterns of travelling electrical waves, which propagate along cortical slices in different modes, depending on a balance between excitation and inhibition. We may speculate that, in normal conditions, when inhibition is strong enough to avoid propagation of activity toward surrounding neurons, a focal activity remains confined in a small cortical zone, or becomes synchronized with activity in far functionally interconnected zones. However, in case of insufficient inhibition or stronger excitation, activity may propagate toward proximal neurons by originating different travelling waves, which may correspond to different voltage amplitude and frequency distribution detected via cortical EEG (ECoG).

The aim of this study is to investigate this problem, using a network of spiking neurons connected via reciprocal excitatory and inhibitory synapses. We wish to analyse how possible alterations in synaptic activity may induce uncontrolled travelling waves, and how these waves may be related with intracerebral EEG patterns observed during seizure. The final aim is to reach a deeper insight into the possible relationship between synaptic alterations, patterns of travelling waves in the cortex, and electrical activity recorded via ECoG.

We remark that our model aspires to simulate propagation from a central focus to proximal neurons in a cortical slice, and that the output signal (ECoG) is assumed to be measured by a local electrode. Simulation of seizures in different brain structures (such as the hippocampus) as well as simulation of scalp EEG will require other models, which differ from the present both concerning the synaptic connectivity and the anatomical arrangement of neurons, as well as concerning the presence of interposed tissues. Furthermore, our model does not intend to study biochemistry of the system, which is certainly important in the genesis of epilepsy.

2. Model description

The present model is based on equations describing the classical leaky integrate-and-fire (LIF) neuron. Moreover, each neuron includes excitatory and inhibitory synaptic conductances, and a hyperpolarizing conductance in order to provide a description for the refractoriness property and adaptation. In the present work, we consider an array of $50 \times 50$ interconnected neural units. For the sake of simplicity, we do not distinguish between excitatory (pyramidal) neurons and inhibitory interneurons. Hence, all inhibitory synapses in the model should be considered as representative of a by-synaptic connection, from an excitatory neuron to an inhibitory neuron, and then from
the inhibitory neuron to another excitatory unit. The output of the single neural unit is represented by the membrane potential, while the overall output network is represented by the mean membrane potential in order to obtain a quantity comparable with the clinical EEG signals commonly recorded.

The network input is represented by a constant depolarizing current injected in a little cluster of neurons. In this way the neurons in the depolarized group fire in synchrony emulating an epileptic focus. Moreover, all neurons receive input Gaussian noise.

We present the network model starting from the description of the single neural unit.

### 2.1. Single neural unit

Our model is a derivation of the classical LIF model, with a synaptic description following the formalism of cinematic models (Dayan and Abbott, 2001). The LIF model reduces drastically the complexity in the description of stereotyped behaviour of a single neuron, by replacing the exact dynamic description of the ionic channels involved in the generation of the action potential, with a mechanism threshold-like.

The classical equations for the LIF model, which provides the action potentials as stereotyped events, can be written as follows (see Fig. 1):

\[
\begin{align*}
\tau_m \frac{dV_m(t)}{dt} &= E_L - V_m(t) - R_L \sum_s g_s (V_m(t) - E_s) \\
&\quad - R_L g_{g_e}(V_m(t) - E_{g_e}) + R_L I \\
V_m(t) &= V_{m,\text{max}} \quad \text{if } V_m(t) < V_{\text{th}}, \\
V_m(t) &= V_m(0) \quad \text{if } t_k + T < t < t_k + T + T_r,
\end{align*}
\]

where \( V_m \) is the membrane potential, \( \tau_m = R_L C_m \) is the membrane time constant, \( R_L \) is the leakage resistance, \( I \) represents an external current, \( E_L \) is the membrane potential at equilibrium, in the absence of synaptic input (often named the leak reversal potential), \( V_{\text{th}} \) is a fixed threshold for the spike generation, \( t_k \) is the instant of the \( k \)th spike, \( T \) and \( T_r \) are the duration of the spike and the absolute refractoriness period. \( g_s \) and \( E_s \) represent synaptic conductances and their effective reversal potential, while \( g_{g_e} \) and \( E_{g_e} \) denote the after hyperpolarization conductance and its reversal potential. In this paper, two kinds of synaptic conductances are included, excitatory (subscript \( s = e \)), and inhibitory (\( s = i \)).

The previous equations can be explained as follows:

(i) The model behaves as a leaky integrator until the membrane potential reaches a threshold, then it generates a spike of duration \( T \). During the spike, membrane potential is maintained at a high value, \( V_{m,\text{max}} \).

(ii) After the spike generation, membrane potential is forced at the resting level, \( V_{m,0} \), to simulate the absolute refractory time (\( T_r \)). Afterwards, the membrane potential is again described by the input integration behaviour.

Moreover, in order to have a clear representation of spiking times, we considered a further quantity for each neuron:

\[
y(t) = \begin{cases} 
1 & \text{if } t_k < t < t_k + T, \\
0 & \text{otherwise},
\end{cases} 
\]

i.e. the quantity \( y \) is Boolean in type, and assumes value 1 only during the occurrence of a spike.

As specified above, in the model two different kinds of synaptic conductances are included; i.e. excitatory and inhibitory. The dynamic of excitatory and inhibitory conductances, \( g_s \) (\( s = e, i \)), is described according to a first-order kinetic scheme (Dayan and Abbott, 2001). Accordingly, we can write

\[
g_s = g_{s,\text{max}} P_s, \quad s = e, i,
\]

where \( g_{s,\text{max}} \) is the conductance when all ionic channels are open (maximal conductance) and \( P_s \) is the probability of having an open channel. \( P_s \) is described with the following well-known kinetic equation:

\[
\frac{dP_s(t)}{dt} = \alpha_s (1 - P_s) - \beta_s P_s, \quad s = e, i,
\]

where \( \alpha_s \) is the opening rate and \( \beta_s \) the closing rate of the channels.

In order to account for the effect of excitatory and inhibitory influences, coming from other neurons in the network, we assumed that the opening rate in Eq. (4) depends on a synaptic input (say \( S \) with \( S = E_x \) and \( S = I_n \) as to excitatory and inhibitory inputs, respectively). These latter describe the overall influence of other neurons in the network, as specified in the subsection “Synaptic connections” below. Eq. (4) can be rewritten as follows:

\[
\tau_s(S) \frac{dP_s(t)}{dt} = P_{s,\text{max}}(S) - P_s(t), \quad s = e, i,
\]

where \( \tau_s(S) \) and \( P_{s,\text{max}}(S) \) are the synaptic time constant and the maximal conductance, respectively, for inhibitory and excitatory synapses, respectively.
where
\[ \tau_s(S) = \frac{1}{x_s(S) + \beta_s}, \quad s = e, i, \]
\[ P_s^\infty(S) = \frac{x_s(S)}{x_s(S) + \beta_s}, \quad s = e, i \]
with \(0 \leq P_s^\infty(S) \leq 1\).

In order to describe the influence of synaptic input on the opening rate, we assumed that, in the absence of the synaptic input, the opening rate is zero. The higher the synaptic input, the higher the opening rate, up to a maximum saturation level. This is mimicked with the following equation:
\[ x_s(S) = x_{s, \text{max}}(1 - e^{-S/k_s}), \quad s = e, i, \]
where \(x_{s, \text{max}}\) is the saturation for the opening rate, and \(k_s\) is a constant which establishes the slope of the sigmoidal relationship.

A further aspect in the description of a single neuron concerns the presence of a hyperpolarization conductance, named \(g_{\text{h}}\), which simulates the relative refractoriness period and the phenomenon of “spike rate adaptation”. The conductance \(g_{\text{h}}\) assumes its maximum value \(g_{\text{h, high}}\) after the spike generation, maintains this value throughout the absolute refractory period (i.e. \(t^* < t < t_k + T + T_r\)) and then falls to zero according to the following equation:
\[ \tau_{g_{\text{h}}} \frac{dg_{\text{h}}(t)}{dt} = -g_{\text{h}}(t). \]

### 2.2. Synaptic connections

The previous description concerns a single neuron. However, in a network neurons communicate via the synaptic terms, \(S = E_x\) and \(I_n\) in Eqs. (4)–(8). In the following, we will consider a network of neurons, arranged in a regular lattice. Hence, each quantity will be represented using two subscripts, \(i\) and \(j\), which denote the row and column position of the neuron.

Of course, various different arrangements for the synapses are possible, depending on the particular network. In the present study, we assumed a classical Mexican-hat disposition for the synapses, i.e. one neuron receives excitatory and inhibitory synapses from a layer of proximal neurons, with excitation having narrower extension than inhibition. Moreover, we assumed that the synaptic lateral connections among neurons in the network decrease with the distance, named \(d\), between the pre- and post-synaptic units. Furthermore, in order to account for the intrinsic variability of synapses, we assumed that the synaptic strength follows a random uniform distribution between a minimum and a maximum value. This signifies that not all neurons receive the same excitation and the same inhibition. Hence, the following equations can be written for the terms \(E_x\) and \(I_n\) of the neuron \(ij\):
\[ E_{x_{ij}} = \sum_{l,m=1}^{N} W_{e_{ij}} p_{ij} e^{d_{ij}/\sigma_{e_{ij}}} y_{lm}, \]
\[ I_{n_{ij}} = \sum_{l,m=1}^{N} W_{i_{ij}} p_{ij} e^{d_{ij}/\sigma_{i_{ij}}} y_{lm}, \]
\[ d_{ij,m,n} = \sqrt{(i - i)^2 + (j - m)^2}, \]
where \(W_{e_{ij}}\) and \(W_{i_{ij}}\) are the strength of excitatory and inhibitory synapses, respectively; \(\sigma_{e_{ij}}, \sigma_{i_{ij}}\) are the standard deviations, which mimic the decrease of synaptic strength with distance, and \(p_{ij}\) represents a random variable with uniform distribution between 0.5 and 1.5. The quantity \(y_{lm}\) in Eq. (10) signifies that the synaptic input is different from zero only when a pre-synaptic neuron is spiking (see also Eq. (2)).

The contributions of excitatory and inhibitory synapses described above affect the dynamic of synaptic conductances, and then the currents crossing the membrane, with a consequent modulation in the membrane potential evolution.

Finally, the output from the overall network is computed as the mean value of membrane potential of all neural units in the network. In this way, it is possible to obtain a quantity comparable with the commonly recorded EEG clinical signal. By denoting \(V_{EEG}(t)\) this output, we have:
\[ V_{EEG}(t) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} V_{m_{ij}}(t)}{NN}. \]

### 3. Parameter assignment

Parameters that characterize the cellular membrane (i.e. the membrane capacity \(C_m\), the leak reversal potential, \(E_L\), the leakage resistance, \(R_l\), the reset potential \(V_{\text{reset}}\), the threshold for spike generation, \(V_{\text{th}}\), the duration of a spike, \(T\), and the absolute refractory period, \(T_r\)) have been given values in the range reported in the literature (Dayan and Abbott, 2001; McLaughlin et al., 2000; Somers et al., 1995; Troyer et al., 1998). In particular, a normal value for \(C_m\) is about 500 pF as to pyramidal neurons, whereas it is as low as 200 pF as to inhibitory neurons (Somers et al., 1995; Troyer et al., 1998). In our model, we do not distinguish between excitatory and inhibitory neurons, and we used the value 400 pF. Normal values for the leakage resistance range between 10 and 100 MΩ (Dayan and Abbott, 2001). In the present study we used a value at the higher limit of the physiological range. As it is shown in Eq. (1), the high value of this parameter enhances the effect of the synaptic conductances, thus favouring instability.

The values of the effective reversal potentials for the excitatory and inhibitory synapses (\(E_e\) and \(E_i\)) agree with values commonly used in the literature (Dayan and Abbott, 2001; Somers et al., 1995; Troyer et al., 1998). The reversal potential used to simulate a relative refractory
period and subsequent adaptation \( (E_r) \) has been taken equal to the reset potential.

A delicate question concerns the choice of parameters that describe the dynamic of the synapses. Let us consider first the excitatory synapse. It is worth noting that the use of Eqs. (5)–(8) implies that, after a pre-synaptic spike, the synapse rises (ON phase) with a time constant \( \tau_{\text{rise}} = 1/(\lambda_e + \beta_e) \) and, after 1 ms (at the end of the spike), it falls (OFF phase) with the time constant \( \tau_{\text{fall}} = 1/\beta_e \). A value for the constant parameter \( \beta_e \) has been given assuming that the time constant for excitatory synapses in the OFF phase is as high as 1.5 ms, which is close to values used by others (Somers et al., 1995; Troyer et al., 1998). The value of the rising time constant, however, depends on the excitatory input \( E_x \): the higher the excitation, the lower this time constant. The minimum value of \( \tau_{\text{rise}} \) is achieved when parameter \( \lambda_e \) reaches its saturation level, \( \lambda_{e,\text{max}} \). A value to the latter has been assigned assuming that, under maximal excitation, the rising time constant is as low as 0.3 ms. This warrants that, in case of strong excitation, the transient is exhausted within approximately 1 ms. When excitation is smaller (i.e. \( \lambda_e < \lambda_{e,\text{max}} \)), the synapse rises with a slower time constant.

A value for the maximal synaptic conductance, \( g_{e,\text{max}} \), a basal value for the synaptic strength, \( W_{\text{exc}} \), the synaptic spatial extension, \( \sigma_{e,y} \), and parameter \( k_e \) which establishes the rate of saturation of the synaptic conductance, have been given according to several considerations. First, Prinz et al. (2003), using LIF neurons, observed that the effect of a change in synaptic conductance is maximum in the range 10–100 nS, and then progressively saturates. Hence, the maximal synaptic conductance is assigned in this range (80 nS). Second, in normal conditions firing of a single pre-synaptic neuron may induce a maximal conductance change of the order of 3 nS in the post-synaptic neuron (Somers et al., 1995); finally, we assumed that the probability \( P_e \), and so the excitatory conductance, start to saturate when 50–60 pre-synaptic neurons are simultaneously spiking. The latter rule is not based on physiological consideration (the number of connections received by real neurons might be much higher) but simply reflects the topological organization of synapses in our network. The previous considerations leads to the value of parameters reported in Table 1.

![Table 1](art216f1.jpg)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_{m} )</td>
<td>400 pF</td>
</tr>
<tr>
<td>( g_L )</td>
<td>10 nS</td>
</tr>
<tr>
<td>( E_i )</td>
<td>−70 mV</td>
</tr>
<tr>
<td>( I )</td>
<td>6 nA</td>
</tr>
<tr>
<td>( V_{\text{thr},\text{max}} )</td>
<td>0 mV</td>
</tr>
<tr>
<td>( V_{\text{th}} )</td>
<td>−55 mV</td>
</tr>
<tr>
<td>( T )</td>
<td>1 ms</td>
</tr>
<tr>
<td>( \tau_m )</td>
<td>40 ms</td>
</tr>
<tr>
<td>( T_r )</td>
<td>3 ms</td>
</tr>
<tr>
<td>( V_{\text{inj}} )</td>
<td>−70 mV</td>
</tr>
<tr>
<td>( g_{i,\text{max}} )</td>
<td>80 nS</td>
</tr>
<tr>
<td>( g_{i} )</td>
<td>0 mV</td>
</tr>
<tr>
<td>( g_{e} )</td>
<td>120 nS</td>
</tr>
<tr>
<td>( E_i )</td>
<td>−70 mV</td>
</tr>
<tr>
<td>( \lambda_{e,\text{max}} )</td>
<td>2.667 ms(^{-1})</td>
</tr>
<tr>
<td>( \beta_e )</td>
<td>0.667 ms(^{-1})</td>
</tr>
<tr>
<td>( k_e )</td>
<td>5</td>
</tr>
<tr>
<td>( \sigma_{e,y} )</td>
<td>3.143 ms(^{-1})</td>
</tr>
<tr>
<td>( \lambda_{e} )</td>
<td>0.19 m/s(^{-1})</td>
</tr>
<tr>
<td>( k_i )</td>
<td>20</td>
</tr>
<tr>
<td>( g_{i,\text{thr},\text{high}} )</td>
<td>60 nS</td>
</tr>
<tr>
<td>( E_i )</td>
<td>−90 mV</td>
</tr>
<tr>
<td>( C_{0} )</td>
<td>15 ms</td>
</tr>
<tr>
<td>( W_{\text{exc}} )</td>
<td>0.1 (0.8)</td>
</tr>
<tr>
<td>( W_{\text{inj}} )</td>
<td>0.3 (0.7)</td>
</tr>
<tr>
<td>( \sigma_{e} )</td>
<td>2</td>
</tr>
<tr>
<td>( \sigma_{m} )</td>
<td>4</td>
</tr>
</tbody>
</table>

parameters \( \lambda_i \) and \( \beta_i \) have been given to have a time constant in the ON phase as low as 0.3 ms (as in the case of excitation) and a time constant in the OFF phase as great as 5.26 ms. The latter value agrees with Destexhe et al. (1994). Parameter \( W_{\text{inj}} \), which sets the inhibitory strength, has been chosen so that excitation of a single pre-synaptic synapse causes a change in the inhibitory conductance as great as about 5 nS (Somers et al., 1995).

Finally, the value of \( g_{i,\text{thr},\text{high}} \), which simulates the relative refractory period + the post-spike adaptation has been taken as great as 60 nS (i.e. a little less than excitatory synapse), while the time constant has been assumed equal to 15 ms.

4. Results

Throughout the present simulations we assumed that a cluster of \( 3 \times 3 \) neurons, located at the centre of the network, receives a constant depolarizing concurrent \( I = 6 \) nA. Moreover, all neurons in the network receive a constant but random noise current, chosen from a Gaussian random distribution with mean value equal to 1 pA and variance equal to 5 pA.

A first group of simulations (part I) has been performed to investigate the effect of changes in the distribution of synapses on the activity in the network and on the consequent epileptogenic patterns. Subsequently (part II), the role of all other parameters in the network is investigated, in order to illustrate how much the effects
observed in part I may be influenced by other parameter changes. Since the number of parameters is too high to consider all possible combinations, we consider the effect of each parameter individually. Only a few examples are shown, for the sake of brevity, whereas all other cases are discussed by considering a superimposition of effects.

4.1. Role of parameters describing the strength and distribution of synapses

The first simulations have been performed using the normal parameter values reported in Table 1. Results (not shown in figures since they are quite trivial) demonstrate that, in this condition, only the stimulated neurons exhibit spiking activity; this activity, however, does not propagate toward surrounding neurons, i.e. it remains confined in the central focus. In order to study possible epileptogenic conditions, we modified the parameters which describe the synaptic interactions among neurons, namely, \( W_{\text{exc}} \), \( W_{\text{inh}} \), \( \sigma_{\text{exc}} \) and \( \sigma_{\text{inh}} \). In the following, just a few examples of the possible variability of results are presented, for the sake of brevity. We remind that all these simulations have been performed starting from a random initial state, using random synapses and random input noise. Hence, the results are just exemplary. Profound differences in behaviour can sometimes be observed using the same parameter set, depending on randomness.

In the first example we examine the effect of an increase in the excitation strength, obtained by varying parameter \( W_{\text{exc}} \) in Eq. (10) from its basal value in Table 1, up to 1.5. However, in order to avoid excessive instability, during these simulations we also used a higher value for the inhibitory strength \( (W_{\text{inh}} = 0.7) \). When \( W_{\text{exc}} \) has a low value (about 0.1 or 0.2), the activity in the network remains confined within the small central focus, without propagating toward adjacent neurons. This results in a quite constant small-amplitude potential in Eq. (11). The effect of increasing parameter \( W_{\text{exc}} \) is depicted in Fig. 2. First, when \( W_{\text{exc}} = 0.45 \) (see panel a), one can observe the occurrence of small sporadic waves which propagate slowly along the network, and, at certain instants, may join together to form large wave fronts. This behaviour results in the appearance of some large amplitude waves, with a low-frequency content (mainly \(<15\text{Hz})\). When \( W_{\text{exc}} \) is

![Fig. 2. Sensitivity analysis on the role of strength of excitatory synapses (i.e. parameter \( W_{\text{exc}} \) in Eq. (10)). In each row the left panels represent the simulated EEG patterns, the middle panels show the amplitude spectra (normalized, to have a maximum equal to 1), the right panels represent a snapshot of network activity at different time steps in the numerical simulation. In row (b) two amplitude spectra are presented: the snapshots of network activity are enclosed in the relative spectrum panel. The parameter values used for the simulations shown in each row are: (a) \( W_{\text{exc}} = 0.45 \); (b) \( W_{\text{exc}} = 0.6 \); (c) \( W_{\text{exc}} = 1.2 \); (d) \( W_{\text{exc}} = 1.5 \). The average strength of inhibitory synapses has been given the value \( W_{\text{inh}} = 0.7 \) in all simulations. The other parameters have the same value as in Table 1.](image-url)
further increased up to 0.6 (panel b), we have the initial formation of circular waves, which propagate form the central focus to the periphery. This phase corresponds to the occurrence of small-amplitude high-frequency oscillations in the average potential. However, at certain instants (around 300 ms in panel b) these waves may break down into different separate waves. This corresponds to the appearance of larger oscillations in the EEG, in part similar to multiple spikes. The latter behaviour, however, is truly random, and does not always occur with the same parameter set. At higher values of $W_{\text{ex}0}$ (1.2, panel c), we have only circular regular waves, which propagate rapidly across the network. In this condition, the average potential exhibits small-amplitude high-frequency oscillations. Finally, if excitation is further raised ($W_{\text{ex}0} = 1.5$, panel d), circular waves may break down again, resulting in irregular waves, but with a wide frequency content. The previous examples show the great number of behaviours which may originate in the network even from changes in a single parameter only.

A second set of simulations has been performed by varying the standard deviation of the excitatory synapses (i.e. parameter $\sigma_{\text{ex}}$ in Eq. (10)) in the range 1.6–2.2, and using the values for excitation and inhibitory strength $W_{\text{ex}0} = 0.8$ and $W_{\text{in}0} = 0.7$. It is worth noting that, with these values, and $\sigma_{\text{ex}} = 2$, the network exhibits a circular wave propagating from the centre to the periphery. Fig. 3 shows that a smaller extension of synapses ($\sigma_{\text{ex}} = 1.6$, panel a) results in broken waves, which propagate along the network. With a higher value of $\sigma_{\text{ex}}$ (1.75, panel b) we can often observe the appearance of spiral waves. They tend to become more regular and assume a circular shape when $\sigma_{\text{ex}}$ is further raised (1.9, panel c). With higher values of $\sigma_{\text{ex}}$, circular waves become thicker and thicker. These changes correspond to a progressive shift of the spectrum from low frequencies ($<15$ Hz) to higher frequencies (up to 100 Hz).

An interesting behaviour can be seen by increasing the strength of the inhibitory synapses, starting from the oscillating condition $W_{\text{ex}0} = 0.8; W_{\text{in}0} = 0.7$ (see Fig. 4). A small increase of inhibition ($W_{\text{in}0} = 0.9–1.4$, see panels c and d) causes sometimes the rupture of the regular circular wave. This may induce a sudden change in the average potential, appearing as a spike. A further increase in inhibition causes more frequent ruptures of the circular

**Fig. 3.** Sensitivity analysis on the role of extension of excitatory synapses (i.e. parameter $\sigma_{\text{ex}}$ in Eq. (10)). In each row the left panels represent the simulated EEG patterns, the middle panels show the amplitude spectra (normalized, to have a maximum equal to 1), the right panels represent a snapshot of network activity at different time steps in the numerical simulation. The parameter values used for the simulations shown in each row are: (a) $\sigma_{\text{ex}} = 1.6$; (b) $\sigma_{\text{ex}} = 1.75$; (c) $\sigma_{\text{ex}} = 1.9$; (d) $\sigma_{\text{ex}} = 2.2$. The average strengths of excitatory and inhibitory synapses have been given the value $W_{\text{ex}0} = 0.8$ and $W_{\text{in}0} = 0.7$ in all simulations. The other parameters have the same value as in Table 1.
waves, and the alternation of periods with high-frequency activity and smaller oscillations in the EEG (circular waves), with periods of lower-frequency and larger-amplitude activity (ruptured waves).

Finally, varying the extension of inhibition (parameter $\sigma_{in}$) also has significant effects on the shape and frequency content of the average potential (see Fig. 5). A smaller value of $\sigma_{in}$ (1.7, panel a) causes thick circular waves, similar to those observed by increasing $\sigma_{ex}$. The use of larger values of $\sigma_{in}$ is associated with the propagation of small irregular wave fronts, i.e. a signal with small-amplitude and a large-frequency band, but with a predominance of low frequencies. Finally, the use of a very large value of $\sigma_{in}$ is again associated with the appearance of circular waves, but with lower frequency (in fact, in this condition most waves cannot propagate and abort).

All previous results have been obtained by maintaining the same set of parameters throughout an individual simulation, starting from different random condition for the initial state and synapses, and using a different random noise. It is now interesting to observe network behaviour when just a single parameter progressively shifts during the simulation. Examples are shown in Figs. 6–9, which refer to long simulations (5.5 s in duration each), with a ramp change in parameters $W_{ex0}$, $\sigma_{ex}$, $W_{in0}$, and $\sigma_{in}$, respectively. $\sigma_{ex}$ and $W_{ex0}$ are modified in the direction which causes greater activity in the network, $W_{in0}$ and $\sigma_{in}$ in the direction which reduces network activity. It is worth noting that the simulated EEGs show evident transitions from different patterns in the same tracing: for instance (see Fig. 6), low-frequency large-amplitude waves (instant $t_2$), irregular activity (instant $t_3$), and high-frequency small-amplitude activity (instant $t_4$) are observed by increasing $W_{ex0}$. An even more complex pattern occurs by progressively increasing $\sigma_{ex}$ (Fig. 7): we can observe irregular waves, spikes, small portions of low-frequency low-amplitude activity, and finally a high-frequency final activity. Large-amplitude activity with low frequency dominates after a progressive increase in $\sigma_{in}$ (Fig. 9), while an increase in $W_{in0}$ (Fig. 8) first induces irregular waves with a reduction in frequency, followed by regular quasi-sinusoidal waves interrupted by spikes.

4.2. Role of the other parameters

The role of the other parameters has been investigated in the conditions reported in panels b or c of Fig. 2. These
conditions have been chosen since they are characterized by a transition between irregular waves, sporadic waves and circular waves, hence are particularly suitable to point the role of additional parameter changes.

4.2.1. Other parameters affecting excitatory synapses

There are many parameters in the model which modulate the efficacy of excitatory synapses (see Eqs. (3)-(8)), and so have comparable effects in the model (although mediated via nonlinear interactions). In particular, an increase in parameter $g_{e,\text{max}}$ or $z_{e,\text{max}}$ or a decrease in $b_e$ or in $k_e$ cause an increase in excitatory strength (i.e. an effect quite similar to an increase in parameter $W_{e0}$, which has been investigated in Fig. 2). All these changes, in fact, have the effect of making excitatory synapses stronger by increasing the synaptic conductance. Another parameter related with the action of excitatory synapses is the reversal potential $E_e$. An increase in this parameter toward positive values reinforces the strengths of the excitatory synapses, since the synaptic current is proportional to the product $g_e(E_e-V_e)$.

In conclusion, results similar to those shown in Fig. 2 (obtained by increasing $W_{e0}$) are obtained by varying the following list of parameters: increase in $W_{e0}$, $g_{e,\text{max}}$, $z_{e,\text{max}}$, or $E_e$; decrease in $b_e$ or $k_e$.

4.2.2. Parameters affecting the inhibitory synapses

As in the previous point, the effect of an increase in the strength of inhibitory synapses (i.e. an increase in parameter $W_{i0}$, which has been investigated in Fig. 4) can be replicated by increasing parameter $g_{i,\text{max}}$, increasing $z_{i,\text{max}}$, decreasing $b_i$ or decreasing $k_i$. Similarly, reducing $E_i$ toward more negative values reinforces the inhibitory synaptic current.

4.2.3. Parameters describing the adaptation phenomenon

In the model we included an adaptation conductance, whose temporal changes are modulated by the parameters $g_{tr,\text{high}}$ (see Eq. (9)). Hence, we performed some simulations to investigate how the patterns observed in part I are affected by a change in this parameter. The results (obtained by repeating the simulations in Fig. 2b and c by varying $g_{tr,\text{high}}$ in the range 30–90 nS) show that a change in this parameter has no dramatic effect on the shape of the EEG signal or in the patterns of travelling waves, but it just modulates the frequency of waves. There are other two parameters related with the adaptation phenomenon, i.e. $\tau_{gi}$ and $E_{gi}$. An increase in the first reinforces the adaptation phenomenon since, according to Eq. (9), it prolongs the falling time of $g_{i}$ after a spike. Reducing the
reverse potential $E_r$ to a more negative value also reinforces the adaptation phenomenon, increasing the adaptation current. In both cases, however, we cannot observe significant effects on the patterns of travelling waves.

4.2.4. Leakage resistance of the membrane

An increase in parameter $R_L$ has the same effect as an increase in all parallel conductances in the model (see Eq. (1)), i.e. as a simultaneous increase in $g_{e,max}$, $g_{i,max}$ and $g_{thr,high}$, joined with an increase in the external current, $I$. Fig. 10 shows the effect of a change in parameter $g_L = 1/R_L$ in the range 5-15 nS, by maintaining all other parameters as in panel b of Fig. 2. Results show that an increase in the leakage conductance causes the appearance of small sporadic waves, which are reflected in an EEG with a low-frequency spectrum. By contrast, decreasing the leakage conductance causes the appearance of thick circular waves, which sometimes break down to form irregular patterns or suddenly change their frequency. This corresponds to the occurrence of a high-frequency wave, often interrupted by complexes with lower frequency (Fig. 10 panel b) or by spikes (Fig. 10 panel a). This is a very interesting behaviour, often encountered in epileptogenic tracings. If the changes in $g_L$ are performed starting from the conditions observed in panel c of Fig. 2 (regular circular waves), we can observe that increasing $g_L$ reduces the frequency of waves, while a decrease in $g_L$ increases the frequency and makes the circular waves thicker. The latter results are not shown for brevity.

4.2.5. Other parameters related with the membrane properties

Several other parameters in the model describe the properties of the cell, particularly of the membrane. An increase in the time constant of the membrane, $\tau_m$, augments the time required for the membrane potential to reach the threshold starting from its reset potential. Hence, an increase in this parameter reduces the frequency of spikes, with an effect similar to that of an increase in inhibitory synapses or in the leakage conductance. In this condition, circular waves are often transformed into sporadic waves with lower frequency (see Fig. 11, panels c and d). By contrast, a reduction in this parameter reinforces the excitation in the network, causing the appearance of thick high-frequency waves (Fig. 11 panels a and b). An increase in the threshold, $V_{th}$, or a decrease in the membrane resting potential $E_0$ (that we assumed equal to the reset potential $V_0$) have the effect of increasing the time required for spike generation, hence these changes are
Fig. 7. Simulated EEG signal obtained with the model when the synaptic excitatory extension $\sigma_{ex}$ varies as a function of time according to three ramps taking 250 ms each. The parameter values assumed by $\sigma_{ex}$ are: 1.6, 1.7, 1.9, 2.5. The average strengths of excitatory and inhibitory synapses have been given the value $W_{ex0} = 0.8$ and $W_{in0} = 0.7$ in all simulations. The other parameters have the same value as in Table 1. The disposition and the meaning of all panels are the same as in Fig. 5.

Fig. 8. Simulated EEG signal obtained with the model when the synaptic inhibitory gain $W_{in0}$ varies as a function of time according to five ramps taking 250 ms each. The parameter values assumed by $W_{in0}$ are: 0.3, 0.8, 1.25, 1.6, 1.9, 2.7. The average strength of excitatory synapses has been given the value $W_{ex0} = 0.8$ in all simulations. The other parameters have the same value as in Table 1. The disposition and the meaning of all panels are the same as in Fig. 5.
quite similar as an increase in $\tau_m$ (although the relationship among the parameters is logarithmic in type). An increase in the duration of the spike, $T$, reinforces the effect of all synapses in the model (both excitatory and inhibitory, as well as the adaptation conductance) by giving them more time to take action: this effect is similar to that simulated by an increase in parameter $R_L$ (see Fig. 10 above).

Finally, an important role is played by the input current $I$. We performed a few simulations by changing its value in the range 3–9 nA. The effect of these changes is to alter the frequency of spikes: increasing $I$ accentuates the high-frequency portion of the spectra (i.e. circular waves become more regular, rapid and thicker), whereas reducing $I$ lessens the frequency and often causes broken or sporadic waves, but without causing new kinds of behaviour.

5. Discussion

The purpose of the present study was to investigate the relationships among EEG patterns during seizure, wave propagation in cortical slices, and excitation/inhibition balance. To this end, we used a small network of LIF units, connected via local synapses. Although various models investigated the effect of an alteration in the inhibition/excitation balance in simulated neural networks (Beggs and Plenz, 2003; Brunel, 2000; Chervin et al., 1988; Engel et al., 2001; Jefferys et al., 1996; Kudela et al., 2003), and pointed out their putative role in epilepsy, the possible spatio-temporal patterns involved, and their relationships with cortical EEG frequency and shape are still insufficiently understood.

A first interesting result of our simulations is that different patterns of average potential may occur in the network, by changing just a few parameters, which describe the average topology of synapses. In particular, even a progressive derangement of a single parameter may induce multiple patterns of activity, which alternate rapidly. These patterns are characterized by different shapes in the time domain and by different frequency content. A second important point is that these patterns share some qualitative aspects with those observed with ECoG recordings ictally or interictally (Alarcon et al., 1995; Allen et al., 1992; Fisher et al., 1992; Gotman et al., 1995; Wendling et al., 2002). Although checking a perfect similarity between the patterns shown in Figs. 2–9 and real ones is not the objective of this work, we can classify different types of activity, on the basis of their shape and frequency content. Similar patterns have been observed in real epileptic seizures (see (Wendling et al., 2002) for some examples). Of course, this classification is just indicative, and one type may coalesce into another without a clear boundary.

(i) Low-frequency patterns with irregular shape and large amplitude often occur after a moderate increase in
excitatory synaptic strength, or a moderate reduction in inhibition. These correspond to the presence of small and broken wave fronts which propagate slowly along the network, and change their dimension; (ii) regular quasi-periodic patterns with higher frequency occur in the presence of strong excitation and/or low inhibition. These reflect the presence of circular waves which propagate from the central focus to the periphery, in a condition when excitation is not counterbalanced by inhibition; (iii) irregular patterns with very small amplitude and a wide frequency content can be observed when several circular waves coexist within the network, or several circular waves coalesce to assume a spiral pattern; (iv) isolated spikes are sometimes observed, when a large travelling wave disappears, or a new wave abruptly appears, resulting in a sudden change in the average potential. This behaviour is generally associated with an increase in inhibition; (v) regular low-frequency patterns with large amplitude occur in the presence of large inhibition, as in termination phase of Fig. 9. These patterns reflect the occurrence of only rare waves which propagate slowly.

A third important point concerns the way the previous patterns alternate after a change in a single parameter. Although the variability of the results (consequence of randomness) and the number of possible parameters involved do not permit to reach definite conclusions, nor to make predictions, we can draw some general rules. Increasing excitation causes a progressive increase in the EEG frequency content (for instance, this is evident looking at the temporal evolution in Fig. 6). An initial phase with low-frequency large-amplitude patterns (pattern v) is followed by a phase of irregular patterns with wider frequency (pattern i) and then by a signal with very high frequency but small amplitude (pattern ii). The latter represents the status of maximal uncontrolled excitation in the network, which propagates rapidly. Another interesting example is shown in the middle phase of Fig. 7, when the extension of excitation (i.e. the fan-in and fan-out of neural units) is progressively increased. Here, we can observe various patterns which alternate rapidly, without apparent regularity. A strong increase in the extension of inhibition starting from a high-frequency phase (as in Fig. 9), causes
the appearance of irregular large-amplitude patterns, and then leads to a condition of low-frequency quasi-sinusoidal patterns (see the last phase in Fig. 9), which may represent a terminal phase when seizure finishes and inhibition predominates again.

Some of these examples are corroborated by results in clinical neurophysiology. Seizures often show a significant increase in the spectral power above 35 Hz, with a five-fold increase in the 80–120 Hz (Fisher et al., 1992) during the initial phase. This high-frequency increase is especially localized in the region of the focus (Fisher et al., 1992) and appears to characterize small epileptogenic zones (Gotman et al., 1995). Interictal EEGs are characterized by an increased power at low frequencies (Drake et al., 1998), suggesting a reduction of excitation or an increase in inhibition.

A few previous theoretical results also agree with the present findings, although obtained with different input or using different models. Examples of spatio-temporal patterns of activity in LIF neurons are reported in Milton et al. (Chu et al., 1994; Milton et al., 1993), as a function of the strength of the excitatory input. Their results share some aspects with those presented here, showing the presence of circular travelling waves, spiral waves and more complex patterns by increasing excitation. Using phase oscillators, Ermentrout and Kleinfeld (2001) showed that a multiplicity of patterns may occur in a two-dimensional network, depending on the nature of the synaptic connections, boundary conditions, initial state and cellular mechanisms for the oscillations. These patterns include rotating waves and synchronization.

Finally, it is important to point out some restrictions or limitations of the present study, which may be removed in future works and may be the target of additional studies. First, the number of neurons simulated (2500) is too small to be representative of a real epileptogenic zone. This limitation, of course, has been imposed by computation limits. We expect that similar behaviour may also occur in larger networks of neurons, in which each neuron receives a greater number of synapses (i.e. it exhibits great fan-in and fan-out) and excitation may propagate more rapidly with distance. Actually, we expect that a single LIF unit in the present model may be representative not necessarily of

Fig. 11. Sensitivity analysis on the role of the membrane time constant (i.e. parameter $\tau_m$ = in Eq. (1), modified by changing the capacitance $C_m$). The disposition and the meaning of the panels are the same as in Fig. 3. The parameter values used for the simulations shown in each row are: (a) $\tau_m = 20\,\text{ms}$; (b) $\tau_m = 30\,\text{ms}$; (c) $\tau_m = 50\,\text{ms}$; (d) $\tau_m = 60\,\text{ms}$. The average strengths of excitatory synapses have been given the value $W_{ex0} = 0.6$, while the average strength of inhibitory synapses has been given the value $W_{in0} = 0.7$ in all simulations (these are the same values as in panel b of Fig. 2). The other parameters have the same value as in Table 1.
a single neuron, but of a group of neurons which fire almost in synchronism.

Another important point is that, in the present work, we simulated just conditions in which waves originate from a central focus, i.e. a group of central units (3 \( \times \) 3) are continuously simulated by a strong depolarizing current. The effect of a smaller or a greater focus (as in Chu et al., 1994; Milton et al., 1993), or the response of the network to a single impulse of current with brief duration (after which the network evolves freely), have not been investigated here, but may be the target of future simulations with the same model.

Another important aspect, which deserves discussion, concerns the disposition of synapses. In the present study, we assumed that inhibition has a wider extension than excitation (in the average), and that the synaptic strength (both excitatory and inhibitory) decreases with distance. Nonetheless, synapses in our model may differ from one neuron to another, according to a random distribution around the average values, reflecting individual variability and/or the effect of previous learning. Although this disposition of synapses is consistent with some models of the cortex (for instance, topological networks, in which proximal neurons are connected with a Mexican-hat topology (Hertz et al., 1991; Rolls and Treves, 1998), it may be inadequate to reproduce other brain regions. For instance, a sparse matrix of synapses may be more appropriate to mimic associative networks (Rolls and Treves, 1998) (for instance the hippocampus). Small-world networks, in which proximal neurons are strongly connected, but a few long-range connections link some distal neurons, have also received much attention recently (Watts and Strogatz, 1998). The use of synapses according to a small-world disposition might allow excitation to be transmitted rapidly from one cluster of neurons (like that used here) to other distal ones, thus allowing a quick propagation of activity in larger cortical regions. It is credible that a different disposition of synapses may induce a different spatio-temporal behaviour (for instance, synchronization among neural clusters, avalanches, oscillations) which deserve ad hoc simulations.

Furthermore, we must consider the possibility that travelling waves may occur not only in pathological conditions (like epilepsy) (Chervin et al., 1988; Chu et al., 1994; Milton et al., 1993) but also in a more physiological state. Ermentrout and Kleinfeld (2001) discussed the emergent properties of networks of coupled oscillators, and reached the conclusion that, in a network dominated by short-range connections, the electrical activity is characterized by travelling waves. They also discussed some potential benefits and possible computational roles of travelling electrical waves. Some examples of these waves have been actually observed in the olfactory and visual cortex of animals (Delaney et al., 1994; Precht et al., 1997; Roelfsema et al., 1997). Hence, it is possible that this behaviour is not only pathological (like in epilepsy) but might also occur in more physiological conditions, and may play a computational role (Ermentrout and Kleinfeld, 2001). The crucial point, in these networks is the compelling trade off between the need for stability, on one hand, and the necessity to transmit information quickly. The present model may help in the analysis of these conditions, including the shift from wave to synchronism. Another possible application of the model lies in the analysis of electrical propagation in culture of neurons, where various models of spontaneous or evoked activity have been reported (Beggs and Plenz, 2003; Plenz and Aertsen, 1996) and can be described with great accuracy.

Of course, an important limitation of our study is that we neglected many biophysical and biochemical aspects of real networks, in favour of a simplified approximation. Among the main drastic simplifications adopted, we neglected the real biochemistry of the synapses by using a first-order kinetic function, we did not consider glial cells, which are now known to be important in epileptic processes, and we adopted a very simple anatomy (consisting of a rectangular square of neurons). Of course, these simplifications have been adopted since the objective of this work was to investigate the stability of a network of neurons, and the patterns of travelling waves which can be produced in it as a consequence of an unbalance between excitatory/inhibitory mechanisms. For this purpose, we deem that also a simplified network can be able to grasp the fundamental relationships between instability, travelling waves, and synaptic alterations. Development of a more realistic model of a real neural tissue (including glial cells, biochemical aspects of synapses and a rigorous anatomy) may provide additional important results, which may enrich and expand the present ones. These aspects may be the subject of future more ambitious and more detailed models.

Another important aspect, which deserves attention, is that our model aspires to simulate propagation of epileptic activity in a portion of the cortex (i.e. EEG measured with intraoperative cortical electrodes, often named ECoG), nor activity in different brain structures, such as the hippocampus, nor EEG measured in the skull. Although the hippocampus is the most important site for the genesis of epilepsy, it is well known that epileptic seizures can generate in the cortex too, and can propagate from the central focus to adjacent regions. It has been demonstrated that a small group of neurons in the cortex is sufficient to initiate, generate and propagate epileptiform activity (Connors, 1984; Connors and Gutnick, 1990). This choice justifies the pattern of connectivity adopted in this work (i.e. synapses which decrease with distance): this kind of connectivity, in fact, has been observed in several cortical regions (Braitenberg and Schuz, 1991). This choice also justifies why ECoG has been computed as a simple linear summation of potential in different points, assuming that the output signal is measured by a local intracortical electrode, and that attenuation is negligible with small distance. Of course, a different anatomy, and a different
pattern of connectivity should be adopted to simulate epileptic seizures in the hippocampus (where connectivity is stronger, and anatomy plays a fundamental role). Simulation of seizure in the hyppocampus would require, for instance, a model with a higher degree of excitatory recurrent connections among CA3 neurons, including distant connections, and fewer recurrent connections among CA1 neurons (Netoff et al., 2004). Similarly, simulations of EEG in the scalp would require a more complex computation of the output signal, to account for the effect of interposed tissues.

In conclusion, we are aware that the present results are just qualitative in nature, since our network is much simpler than any real cortical slice: however, these results are indicative of the possible patterns which might occur when a group of neurons is strongly activated, neural units communicate via local reciprocal excitation and inhibition, and inhibition is insufficient to prevent the occurrence of travelling waves. Moreover, our simulations suggest some possible relationships between the temporal patterns of average potential, observed on EEG, and the spatio-temporal organization of travelling waves in the cortical surface. The study of spatio-temporal distribution is of great interest in present neurophysiology, since recent studies suggest that both spatial and temporal distribution of neural activity may be essential features in the process of neural integration and in information processing by the brain (Beggs and Plenz, 2003; Ermentrout and Kleinfeld, 2001). Spatio-temporal patterns may include oscillations, synchronization (Engel et al., 2001), wave-like behaviour (Chervin et al., 1988; Ermentrout and Kleinfeld, 2001) or avalanches (Beggs and Plenz, 2003). Each of these activities may be associated with a different computational status of the network, with a distinct physiological or pathological condition, different synaptic rules, and with different computational capabilities.

References


