

Introduction

In this work we present a computational model of primary somatosensory cortex using neural fields. In a previous work [1] we presented a particular ability of neural fields, a **match** property, to relax their activity at the level of input. By using this property a neural field is able to drive a plasticity process and therefore topographic maps can emerge. Moreover, we keep the lateral weights steady by learning only the feed-forward weights of the model. This means that lateral weights contribute to a competition between neurons instead of feed-forward weights, which contribute with more effort to self-organization. In order to examine also some neurophysiological aspects we subjected the model to cortical lesions (e.g. strokes, hematomata) and sensory deprivations (periphery nerve deprivation) [2]. The model was able to reorganize itself in the face of such lesions. However, the model is not able to promote the receptive fields refinement after a cortical lesion or sensory deprivation. A possible reason for this phenomenon is the lack of a learning rule concerning lateral weights.

Materials & Methods

Neural Fields

A neural field equation, which was introduced firstly in [1], was used also throughout this work and it is given below:

$$\frac{1}{\tau} \frac{\partial u(\mathbf{x}, t)}{\partial t} = -u(\mathbf{x}, t) + \alpha i(\mathbf{x}, t) + \alpha \int_{\Omega} w_l(|\mathbf{x} - \mathbf{y}|) f(u(\mathbf{y}, t)) d\mathbf{y} \quad (1)$$

where, $u(\mathbf{x}, t)$ is the local activity of a population of neurons, located at position \mathbf{x} at time t , τ is the temporal decay constant of the synapse, α is a scaling constant, $i(\mathbf{x}, t)$ is the input to the network and is given by $i(\mathbf{x}, t) = \left(1 - \frac{|s(t) - w_f(\mathbf{x})|}{n}\right) G(\mathbf{x}; \mu_c, \sigma_c)$. Here $G(\mathbf{x}; \mu_c, \sigma_c)$ is a corrective Gaussian function, and $s(t)$ is the stimulus to the skin patch, n is the size of the field, and $w_f(\mathbf{x})$ is the feed-forward weights which modulate the input, $i(\mathbf{x})$ for each position \mathbf{x} , $w_l(\mathbf{x})$ is the strength of connections between neurons, according to $w_l(x) = w_e(x) - w_i(x)$ where, $w_e(x)$ and $w_i(x)$ are the excitatory and inhibitory kernels, respectively,

$$w_e(x) = K_e \exp\left(-\frac{x^2}{2\sigma_e^2}\right) \text{ and } w_i(x) = K_i \exp\left(-\frac{x^2}{2\sigma_i^2}\right) \quad (2)$$

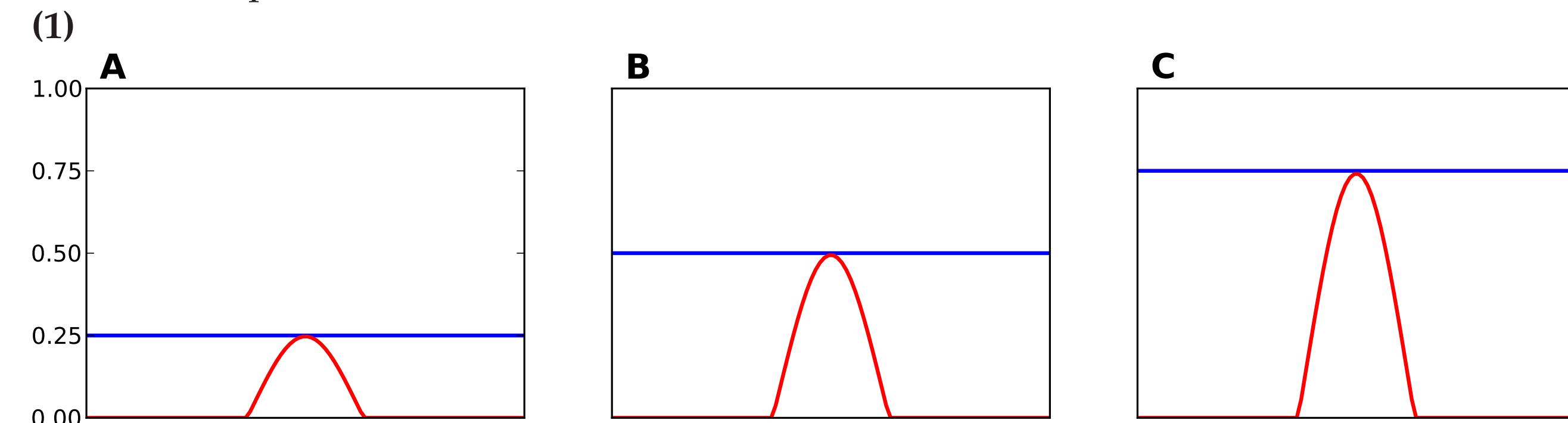
and $f(x)$ is the firing rate function of a single neuron,

$$f(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases} \quad (3)$$

Ω is a compact subset of \mathbb{R}^m , $m = 1, 2$. Additionally, the field is generally considered to be homogeneous using an isotropic kernel of the form $w_l(|\mathbf{x} - \mathbf{y}|)$.

Match Property

We are interested in spatially localized solutions (a.k.a. bumps) that may drive the cortical plasticity and we would like the activity of the field to reflect to some extent a measure of the input, e.g. a measure of the distance between the feed-forward weights of the most activated units (i.e. units from the bump) and the current stimulation. Using a specific set of parameters $\mathcal{P} = \{K_e, K_i, \sigma_e, \sigma_i, \alpha\}$, the field can achieve the following property: *for any uniform input $i(\mathbf{x}, t) = v$, $v \in [0, 1]$, the maximum activity of the field is v .* The one-dimensional case is illustrated in figure 1. Furthermore the same property holds true in the two dimensional case using the same set of parameters, \mathcal{P} .



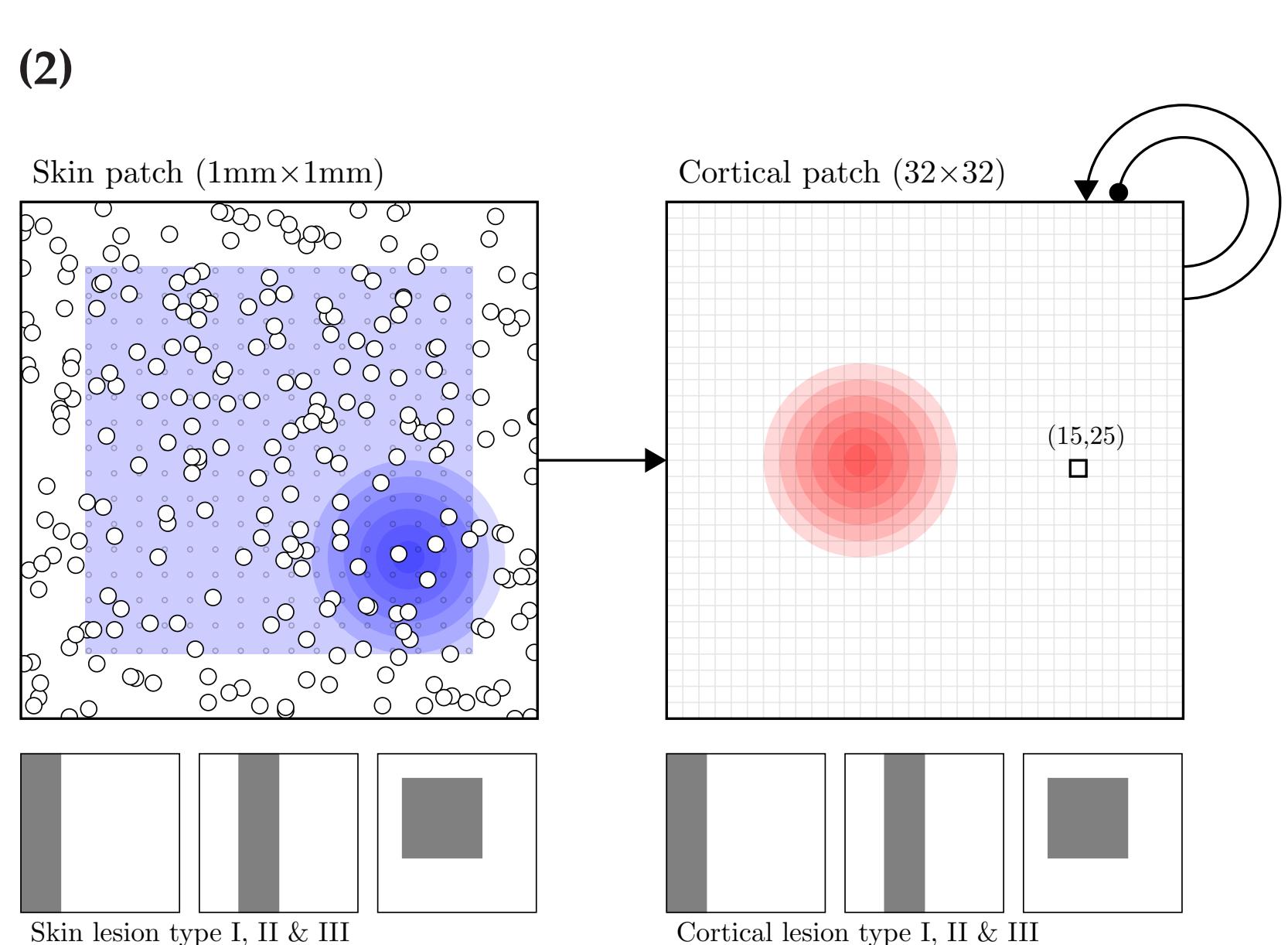
Plasticity Rule

As learning rule we used a Hebbian-like which adapts only the feed-forward connections. The learning rule is given by the following equation:

$$\frac{\partial w_f(\mathbf{x}, t)}{\partial t} = \gamma L_e(\mathbf{x}, t) (s(\mathbf{x}, t) - w_f(\mathbf{x}, t)) \quad (4)$$

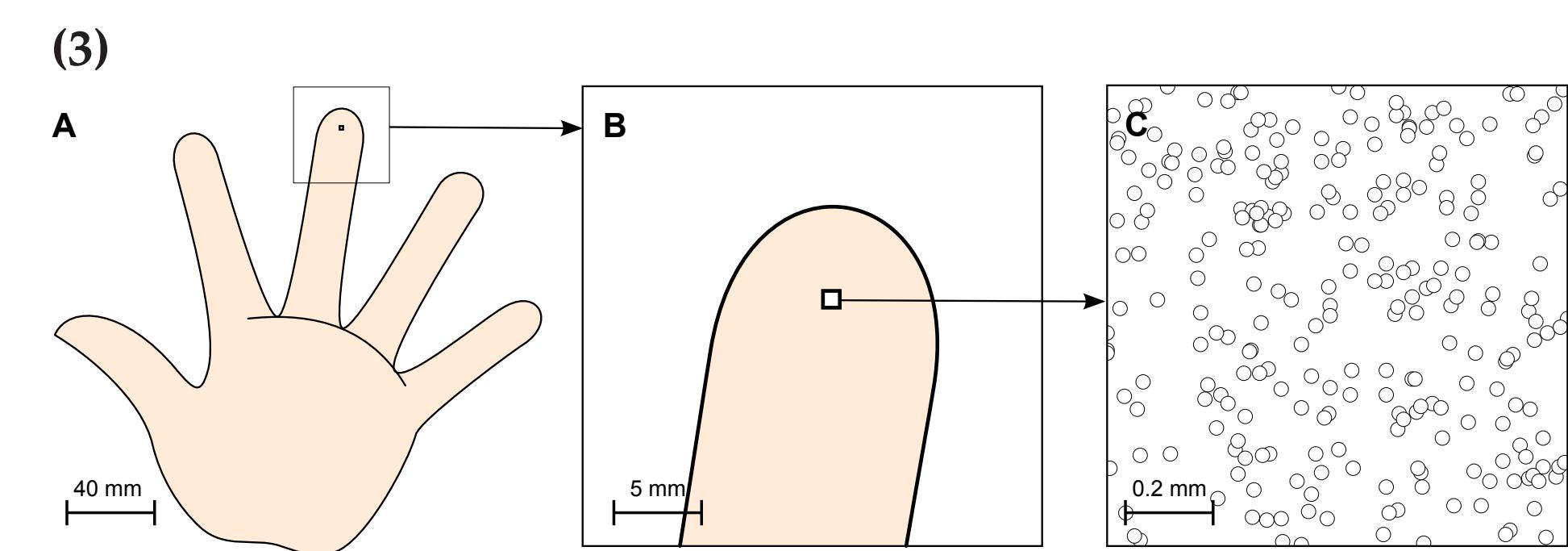
where γ is the learning rate and $L_e(\mathbf{x}, t)$ is the total excitation received at the point \mathbf{x} which is given by the two dimensional spatial convolution between the excitatory part of the kernel function and the field activity. Therefore, we have:

$$L_e(\mathbf{x}, t) = \int_{\Omega} f(u(\mathbf{y}, t)) w_e(|\mathbf{x} - \mathbf{y}|) d\mathbf{y} \quad (5)$$



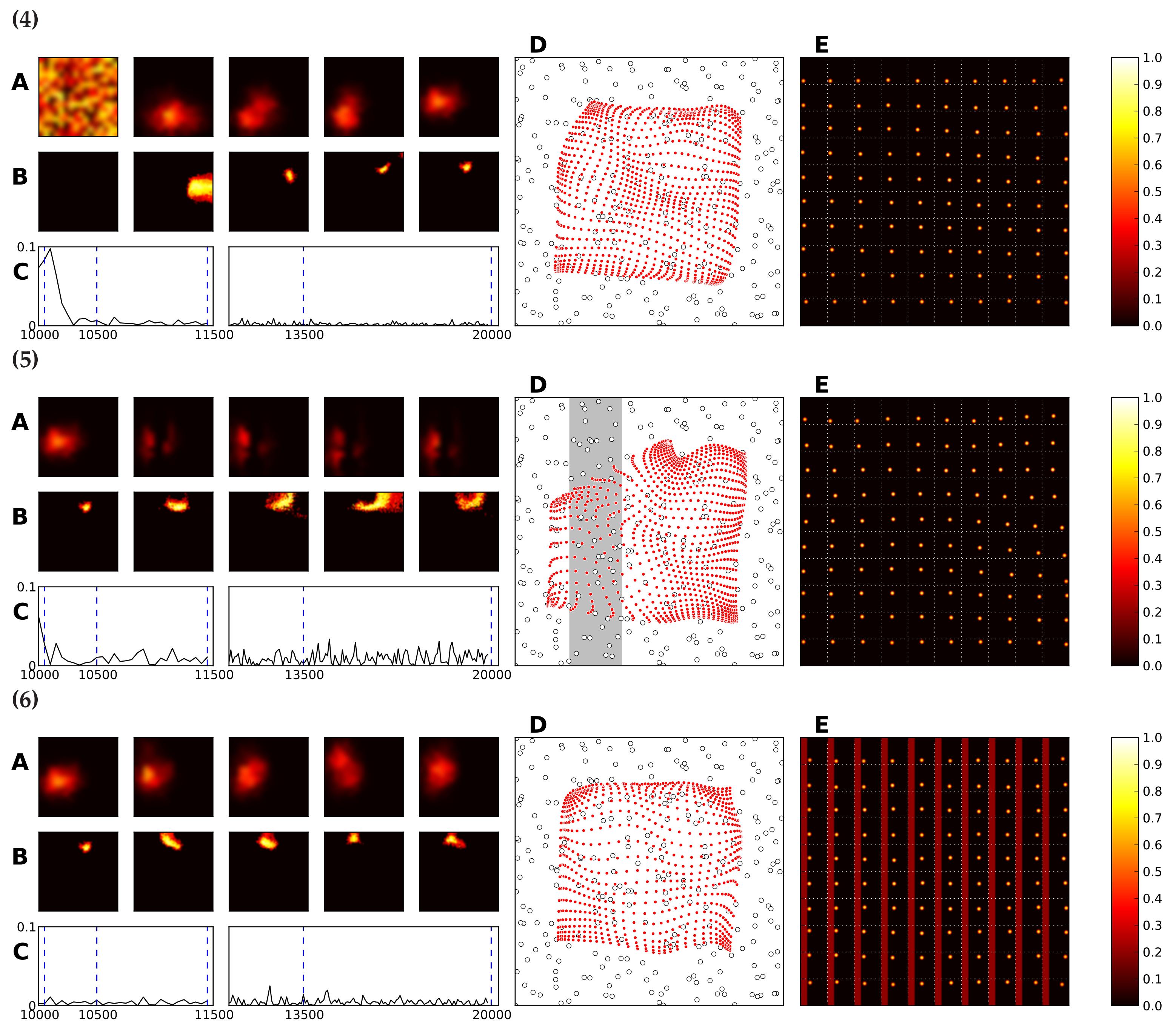
Experimental Setup

A skin patch ($[-1, 1]^2$) of the index digit has been modelized by a regular 16×16 grid of receptors. Receptors grid is slightly disturbed by adding a 5% jitter in order to make the receptors model more realistic. The skin patch as well as the receptors grid are represented in figure 3. A schematic of the model is given in figure 2, where the receptors grid is connected to the dynamic neural field. Moreover, the types of receptors and cortical lesions are illustrated in the same figure. The model is composed by 32×32 spatial elements. Each of these elements are composed by 256 elements. Stimuli is two-dimensional Gaussian functions covering the grid $[-0.75, 0.75]^2$ as it is depicted in figure 2.



Results

In order to simulate the network we used as input two-dimensional Gaussian functions by applying them on the skin patch. Receptors work as samplers and thus the actual input to the neural field is the resulting samples of receptors. We used as input set 256 different stimuli covering the square $[-0.75, 0.75]^2$ and stimulated the field over 10000 epochs in so as to ensure convergence. After the convergence a topographic map has emerged as it is depicted in figure 4. Then we examined the behavior of the model in the presence of a sensory deprivation (e.g. skin lesion) and in a cortical lesion (for lesions see figure 3). The model was retrained over 10000 epochs and a reorganization was achieved. The results about receptors and cortical lesions are depicted in figures 5 and 6, respectively.



Results of emergence, maintenance and reorganization. (A) The evolution of the 256 elements of neuron $(15, 25)$, (B) the evolution of the receptive field of the same neuron, (C) the evolution of the neuron according to, $\bar{\epsilon}_i = |\mathbb{E}[w_{f_{new}}^i] - \mathbb{E}[w_{f_{old}}^i]|$, (D) the mapping between receptors and weights of the whole field (i.e. a way to illustrate the preferred place of each neuron in the field), (E) the response of the neural field to 100 different stimuli in order to confirm the emergence or the reorganization of a topographic map.

Conclusions

In the end, well-shaped topographic maps have emerged indicating that the present model is adequate to obtain self-organization and it can be used in the investigation of self-organization of cortical areas. In addition, the model is able to simulate conditions such as cortical lesions and/or sensory deprivations. In these cases new topographic maps can emerge but the receptive fields of the neurons in this case lack of a refinement. One reason for this deficient reorganization is the steady lateral weights. Therefore, the model is able to adapt only its feed-forward connections. As future work we would like to investigate further the role of lateral connections, homeostatic mechanisms and the phases of reorganization as it has been cited by [3, 4].

References

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