A dynamic neural field mechanism for self-organization

Lucian Alecu[1,2], Hervé Frezza-Buet[2]

[1] CORTEX, INRIA Nancy Grand-Est, 615 rue du Jardin Botanique, Villers-lès-Nancy, 54600, France

[2] IMS, SUPELEC Metz, 2 rue Edouard Belin, Metz, 57070, France

E-mail: Lucian.Alecu@Supelec.fr, Herve.Frezza-Buet@Supelec.fr.

Introduction

Dynamic neural fields (DNF) are a mathematical formalism aiming to describe the spatio-temporal evolution of the electrical potential of a population of neurons. The paradigm, first introduced by Wilson and Cowan [1] and then extended by Amari [2], is intended to model the activity of a cortical population of neurons.

The neuronal activity of the population (or field) is implicitly described by the expression of one or more non-linear differential equations. Each neuronal unit of the field is influenced by two main factors: the input stimuli and the lateral connections of each unit with the other units of the field. Generally, the field responds to the external stimuli by emerging high activity bumps in places where the input is locally strong. This response develops a local competition mechanism, enabling the usage of such paradigm as a biologically inspired computational paradigm in various applications. Based on this feature, and therefore benefiting from local, distributed, robust computation, DNF have successfully been used in a number of applications: for modeling visual attention [3], for moving a robot arm [4], for developing sensori-motor maps [5].

Motivation

Aiming to extend the applicative area of DNF, we are hereby interested in using this computational model to implement self-organizing mechanisms. Generally, solving a self-organizing task comes to reorganize a set of prototypes to map the best an input distribution of periodically randomly tossed samples. In order to solve this task with neural fields, we adapt the Kohonen's classical self-organizing maps (SOM) algorithm [7] and propose the following 3-layers architecture. The first layer is represented by the 1D or 2D map of initially randomly distributed prototypes . The second one is formed by the matching responses of each prototypes to a currently tossed sample. Finally, the third layer is the response of a dynamic neural field to the distribution of matching responses given by the second layer. The profile of the neural field activity will thus take place of the learning kernel from the SOM algorithm, modulating learning and readjusting the connections weights between the prototypes from the first layer. As the algorithm converges, the prototypes from the first layer will reorganize as to finally represent a topological projection of the input distribution of the tossed samples.

The advantage of this architecture is definitely the fully distributed bio-inspired computation performed by each of its entities, unlike the centralized computation of the Kohonen's classical algorithm needed to find the global maximum of the matching responses for applying the learning kernel. In order for the 3-layers mechanism to behave equivalently as the classical Kohonen algorithm, it is required for the neural field to comply two conditions: it should emerge only one high amplitude bump at a time, and the bump should change accordingly when the matching responses of the prototypes change.

Once built this mechanism, we investigate the abilities of classical DNF models, i.e. fields governed by Amari [2] or Folias [6] equations, to perform some basic self-organizing tasks. As seen in fig.1.b. and c., the two fields fail to reach satisfactory result. The aspects that impede them to behave well are related to the inability of the fields to emerge high amplitude bumps, or if they eventually succeed in doing so, the bump remains locked and can no longer follow the changes from the matching responses distribution of the prototypes. As a consequence, either every prototype will learn slowly the same input sample, or only the same very few prototypes will learn, while all the others will be ignored and thus, will not readjust their connection weights at all.

Given these deficiencies, we proceeded in proposing an original system of equations that may successfully achieve self-organizing tasks with the help of the described architecture.

A new DNF system of equations

We propose an enhancement of the classical DNF models, extended from the Folias model, implementing therefore a mechanism that provokes a delayed reinhibition of neural activity (bumps) that is no more sustained by pertinent input stimuli.

Let us first define the excitation and inhibition influence, computed by each unit *x* of the field at any given time *t*:

$$\mathcal{E}(x,t) = \sigma_1 \left(\int_{x'} w^+(|x-x'|) f(u(x',t)) \mathrm{d}x' \right)$$
$$\mathcal{I}(x,t) = \sigma_2 \left(\int_{x'} w^-(|x-x'|) f(u(x',t)) \mathrm{d}x' \right)$$

where *u* is the activity of the field, w^+ and w^- are weighting functions, and σ_1, σ_2 and *f* are sigmoid functions.

The following two equations describe the mathematical formalism underlining the above described behaviour:

$$\tau \cdot \mathrm{d}u(x,t)/\mathrm{d}t = i(x,t) + \alpha \cdot \mathcal{E}(x,t) - \beta \cdot \sigma(\mathcal{E}(x,t)) \cdot \mathcal{I}(x,t) - \gamma \cdot g(i,v) \quad (1)$$
$$\mathrm{d}v(x,t)/\mathrm{d}t = h(\mathcal{E}(x,t)) \quad (2)$$

where $i(x, t)$ represents the input stimulus perceived by the unit *x*, σ is a positive sigmoid function, and α, β, γ and τ are constants. The novelty of this equations, in respect to other DNF formalisms, is the introduction of the *g* function. This is a function of the values of the input stimulus *i* and the variable *v*, in particular chosen as a product of two sigmoids, as it may be seen in figure 2.(left). As observed, *g* remains small (almost zero) whenever *v* is also small. In such conditions, the field performs like a classical Amari one. In fact, the contribution of *g* is significant only when both *i* is small and *v* is high. As *v* can be seen as a ▪ gdelayed ▪ h reaction of the field's excitation (as imposed by the *h* function that describes the evolution of *v*, as seen in figure 2.(right)). If the input stimulating the field is low, even if a bump has been emerged, given the fact that the local excitation of the field increases, the values of *v* increase accordingly, but with a small delay. This will finally trigger the increase of the values of *g*, an effect that will force the emerged bump to be re-inhibited and thus, decrease until zero. The proposed equations develop thus a local adaptive behaviour, allowing the field to readjust the local excitation/inhibition balance in the field if no input is reecived at the bump site, re-enabling the field the ability to re-emerge a bump elsewhere, namely in the place of the new pertinent matching response of the input.

Results

When implementing the same self-organizing task with the support of the presented 3-layer architecture, where the third layer is defined by a dynamic neural field evolving according to the newly proposed system of equations, the developed mechanism achieved good results, as seen in figure 1.d. The success of the new approaches introduced here give us the motivation to continue our researches towards using them in implementing multimodal information processing mechanisms that requires self-organizing features and that may solve more complex cognitive tasks.

Figures

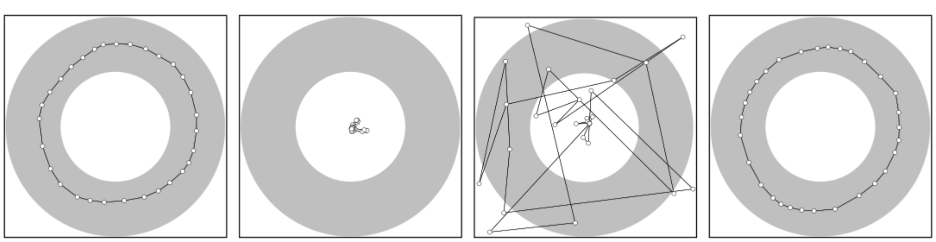

Figure 1. Solving a one dimensional self-organizing task, aiming to learn the herein shown coronal shape (inner radius 0.5, outer radius 1.0), with the support provided by the 3-layer architecture described in the document. From left to right: a. Kohonen classical SOM; b. Amari DNF; c. Folias DNF; d. the new DNF system of equations.

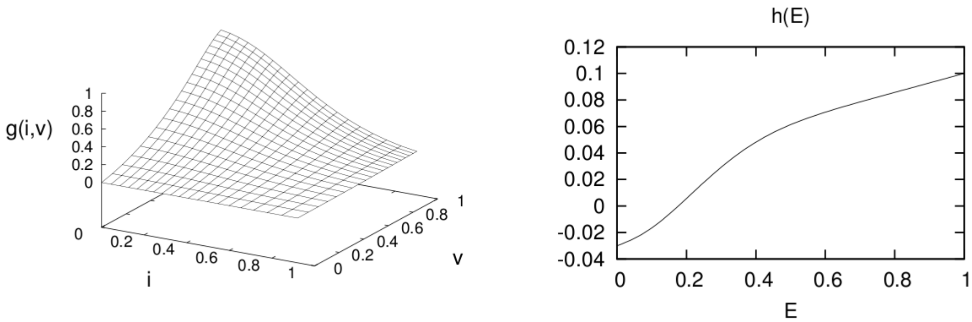

Figure 2. The g (left) and h (right) functions used in equations 1 and 2.

References

1. Wilson HR and Cowan JD: **A mathematical theory of the functional dynamics of cortical and thalamic nervous tissue.** *Kybernetik*, **13:**55–80, 1973.
2. Amari S: **Dynamics of pattern formation in lateral inhibition type neural fields.** *Biological Cybernetics*, **27**:77–87, 1977.
3. Rougier NP and Vitay J: **Emergence of attention within a neural population.** *Neural Networks*, **5(19):**573–581, 2006.
4. Iossifidis I and Steinhage A: **Controlling an 8 dof manipulator by means of neural fields.** In A. Halme, R. Chatila, and E. Prassler, editors, *Int. Conf. on Field and Service Robotics*, Helsinki, 2001.
5. Toussaint M: **A sensorimotor map: modulating lateral interactions for anticipation and planning.** *Neural Computation*, **18(5):**1132–1155, 2006.
6. Folias S. E. and Bressloff P. C.: **Breathers in two-dimensional neural media.** Physical Review Letters, 95, 2005.
7. Kohonen T.: **Self-Organization and Associative Memory**, volume 8 of Springer Series in Information Sciences. Springer-Verlag, 1989.