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Reconciling Neural Fields to Self-Organization

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Abstract. Despite being successfully used in the design of various biologically-inspired applications, the paradigm of dynamic neural fields (DNF) does not seem to have been exploited at its full potential yet. Partly because of the difficulties concerning a comprehensive theoretical study of them, essential aspects as learning mechanisms have rarely been addressed in the literature. In the current paper, we first show that classical DNF equations fail to offer reliable support for self-organization, unveiling some behavioural issues that prevent the fields to achieve this goal. Then, as an alternative to these, we propose a new DNF equation capable of deploying indeed a self-organizing mechanism based on neural fields.

1 Cognitive tasks need smart competition

Different from "purely cloning biological data into silicon", the goal of our research is that of proposing computational models inspired from biology, that can provide a new insight for solving cognitive tasks, as they may benefit from the efficient solutions that nature has developed throughout the process of evolution. Embracing this functional approach, the present paper highlights the applicative power of the *dynamic neural fields* (DNF), and in particular their ability to support the implementation of self-organizing mechanisms (SOM). A classical expression of this paradigm was proposed by Amari [2] and intensively studied by the research community since then.

In DNF, the responses of the units in a population are characterized by the formation of sparse *bumps* of neural activity, distributed along the field at places corresponding to locally-strong input activity. This process may be regarded as a locally-driven competition mechanism, aiming to select the "relevant" information from the input.

Taking also advantage from features like local and parallel processing, neural fields have been successfully used in different applications, as for controlling a robotic arm [5, 11], for integration of multimodal sensory-motor control [7] or for modelling visual attention [10]. However, despite these significant results, studies regarding the ability of this paradigm to deploy learning techniques have rarely been addressed. We consider that this aspect is a sine qua non condition to support viable implementations of self adaptive cognitive mechanisms and, as a consequence, we claim that the DNF paradigm is not yet used at its full applicative potential.

Notable studies in this direction started with the Kohonen's proposal of a biologically plausible mechanism, similar to that of neural fields, implementing his well-known self-organizing map algorithm [6, chap.4]. However, his approach

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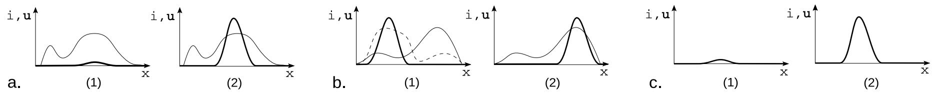

Fig. 1: Some expected effects of a quality one-dimensional neural field activity (thick plot) reacting to various inputs (thin plot). For each case, two states of the field are shown: (1) when a new input is submitted to the field and (2) when the field stabilizes its response after some steps. The field is assumed to generate a single bump of activity. a. competition, b. adaptation, c. exploration.

requires some periodic clearing of the map, in order to restart learning "from scratch" before drawing each new data sample. Aiming to model information processing mechanisms from the primary visual cortex, Miikkulainen and colleagues [8] proposed a suite of biologically-inspired architectural models that extend the SOM at columns level, considering afferent and horizontal (excitatory and inhibitory) connections separated. We have previously proposed [4] a competition mechanism based on the evaluation of local maxima, instead of local sum (as in classical DNF), as well as a computational architecture based on multimodal associative maps, where neuronal competition is driven by DNF equations [7]. All these works reflect the necessities but also the difficulties to control the dynamics of a field when the competition result is used for learning.

In the light of these perspectives, we attempt in the current paper to examine in more detail these aspects. Further on, a DNF mechanism able to respond affirmatively to our requests is proposed as alternative to the current models.

2 Are neural fields suitable for implementing SOM?

In this section we propose a possible answer to the question of *how smart neural fields should behave*, in order to be capable of supporting the deployment of learning mechanisms. As a consequence, a list of desirable properties regarding the dynamics of the fields is first identified and then it is shown that while classical DNF models fail to support the implementation of SOM, fields satisfying these properties can successfully fulfil this demand.

2.1 Some desirable properties regarding the dynamics of the field

As already mentioned, general remarks on the fields dynamics may be summarized by the following statement: *neural fields tend to increase their activity by the raise of activity bumps in places where the input is locally strong.* Actually, such behavior proves rather difficult to achieve in practice, for mainly two reasons. First, the emerged bumps are too small when the local stimuli level is low, i.e. the field "clones" the input, instead of choosing some place (through high bumps) where learning should occur. Second, the bumps lock forever in the places where they first emerged, being incapable of following changes of external stimuli, i.e. the field ignores the input.

Previous studies [9] have already investigated the dynamics of the fields in

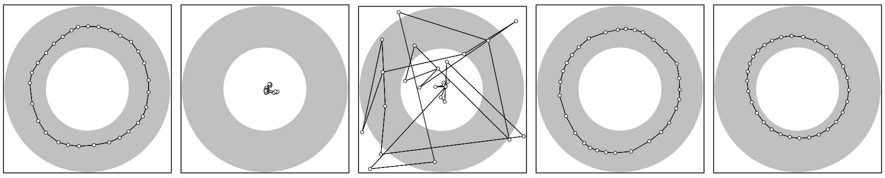

Fig. 2: Results of the SOM algorithm after several steps, with different WTM policies. The task aims to learn the herein shown coronal shape (inner radius 0.5, outer radius 1.0). From left to right: a. Kohonen classical SOM; b. Amari DNF; c. Folias DNF; d. a potentially optimal DNF; e. our proposed DNF.

specific situations, and in every case the authors advocated for a certain evolution, considered optimal or at least convenient. Based on their suggestions, we propose here an extended list of this kind of desirable behaviours, that the fields should exhibit in some key scenarios (see figure 1).

Not intuitively, even in the absence of input, the field should generate one or more high neural bumps in order to start focusing its activity somewhere in the field. This is an essential condition when using the DNF paradigm for implementing a SOM, since in such circumstance the field should raise high bumps from scratch in order to start learning. This may be regarded as an exploration of the field, when all the external stimuli seem equally weak. This request is thus critical in scenarios pertaining to unsupervised learning tasks.

2.2 Attempts to use neural fields in cognitive tasks

In order to prove the relevance of the desired properties suggested before, we propose here to examine the ability of such assumed quality fields to perform a basic self-organizing task. In comparison, we present the results of the same experiment, produced by neural fields driven by some classical DNF equations.

The experiment used to test our approaches consists in developing a simple mechanism able to self-organize a one-dimensional network of units, in order to represent the topological projection of the coronal surface seen in figure 2. At each epoch, to every unit x is submitted the same input ξ tossed from the coronal-shaped distribution. The units compute permanently their matching, $i(x)$, to the ξ sample, as a decreasing function of the distance between ξ and their prototype (prototypes are the white circles in figure 2, randomly initialized). The field response $u(x)$, usually a bump-shaped distribution, is permanently updated according to the experimented DNF equation. Prototypes are continuously updated with a SOM rule, modulated by $u(x)$ (Winner Take Most (WTM)). After some evolution steps a new epoch starts. A new ξ is then tossed without any artificial reset in the field.

In comparison with the classic SOM algorithm, that does not involve neural fields (figure 2.a.), either Amari [2] (figure 2.b.), or Folias [3] (figure 2.c.) models fail to perform the task. The problems that prevent the two models (b. and c.) from achieving the self-organizing objective are mainly twofold. The first one is related to their inability to emerge full-grown bumps from quasi-null input

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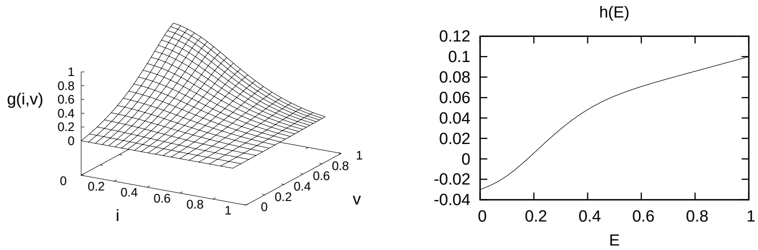

Fig. 3: The g (left) and h (right) functions used in equations 1 and 2.

(at the beginning of the learning process, when units match poorly the data samples). The second one reveals a "locking" effect of the bumps once they are formed, an effect that impedes the adaptation of the field to the input changes. Besides, the two effects are inter-related, as perceived in the general behaviour of these classical models. Indeed, trials aimed to diminish one of the effects lead unluckily to the occurrence of the other. *It seems therefore impossible with classical DNF to enable both exploration (raising bumps even in low input conditions) and exploitation (tracking higher inputs with bumps).*

In contrast, fields that would satisfy our assumed quality criteria could deliver effective results to the considered task, as seen in figure 2.d. Nevertheless, such fields are obtained in our experiments from a non-neural exhaustive and combinatorial optimisation procedure, that serves as a benchmark, but cannot be used effectively (see [1] for details). Based on these remarks, we propose in the next section a DNF mechanism that can indeed reliably perform this task and behave as expected.

3 Neural fields supporting self-organization

3.1 The neural field equation

Let us define as below the lateral excitation and lateral inhibition respectively, as the separated positive and negative influence of the horizontal connectivity of each unit in the field, as in [8].

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

where σ_1, σ_2 and f are sigmoid functions. Inspired from the previously examined models, we propose a new DNF formalism described by the following equations:

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

$$\mathrm{d}v(x,t)/\mathrm{d}t = h(\mathcal{E}(x,t)) \quad (2)$$

keeping $u(x)$ and $v(x)$ between 0 and 1. Used values for g and h can be seen in figure 3. The other parameters values used in our simulations are: $\tau = 0.1, \alpha = 0.45, \beta = 0.5, \gamma = 5$. The novelty of these equations is the introduction of g, that allows to switch, according to i, between exploration and exploitation mode, solving thus the dilemma mentioned in the previous paragraph.

3.2 Dynamical behavior of the field

As the density of bumps that can simultaneously emerge within a field depends exclusively on the exhibition-inhibition ratio, we limit our following discussions to the context of fields yielding a unique neural bump. We summarize below some observed dynamics of the field in the most common scenarios.

1. *Stationary input with only low stimuli.* In these conditions, the emergence of a bump in the field is strictly determined by the second and third terms of the equation 1. Once the bump is formed, the excitation in its neighbourhood becomes high, a fact that induces a delayed increase of the v variable. At its turn, v triggers the increase of g values, that counterbalances the excitation influence, and forces thus the bump to descend. After some time, the bump reemerges in some other place in the field. The evolution continues similarly, unless some high-amplitude stimuli appear in the field. This mechanism allows therefore to suppress periodically all the bumps that are not sustained by strong stimuli. We assert that the field is hereby "exploration-driven" (as in figure 1.c).

2. *Stationary input with some strong stimuli.* In this case, the bump will first raise where the strongest stimuli patch is found, as it is the input term of the equation 1 that provides now the main contribution. Once the bump formed, this stays on until the input changes. g remains low, both in the bump (since i is strong), and in the rest of the field (as this is not excited). We state therefore that the field is actually "input-selective" (as in figure 1.a) in such scenario.

3. *Dynamical changes of input.* Whenever the current bump is no more fed by strong stimuli, the units in the bump have still strong v. The influence of these v on u was null when i was strong, but inhibition of u through g suddenly grows as i is removed in that bump. Therefore, bumps no more supported by strong input will descend quickly, disinhibiting other units in the field to become selective. Finally, if all the input stimuli fall to low values, the current bump in the field will be suppressed due to the g term, and the evolution described in scenario 1 will be recorded. These remarks entitle us to consider the field behaviour as adaptive (as seen in figure 1.b).

As a conclusion, we may state that the proposed DNF mechanism exploits the benefits of classical DNF equations, handling their both advantages and deficiencies. The exploration-exploitation dilemma pointed out in paragraph 2.2, is successfully solved through g, that switches the field's behaviour between the two modes, whenever required. The global dynamics relies also on the intensive use of non-linearities, an aspect that makes the dynamics of the field difficult to analyze mathematically.

3.3 Solving self-organization tasks

Based on the behaviour of the new neural fields equations, the self-organization algorithm was re-implemented. The only difference from the other two presented implementations of this task through DNF (see 2.2) is that in this case we use the values of $\mathcal{E}(x)$ instead of $u(x)$ to modulate learning. Driven by the new equations, the experimented task was finally solved successfully, as confirmed by the wellorganized prototypes in figure 2.e. The outcomes of this behaviour is explained as follows. At the beginning of the self-organizing task, as the prototypes are random, the units of the network respond very low, hardly matching the input samples. However, due to the capacity of the field to generate high activity bumps, even in the absence of input, the learning proceeds well. Units start then little by little to organize and, as a consequence, to enhance their matching responses to new input. As the profile of these matching reactions changes, the neural field behaviour changes accordingly, through g, thanks to its ability to perceive and follow the dynamics of external stimuli.

4 Conclusion

In the current paper we investigate first the advantages and the deficiencies of current DNF models, asserting thereafter some expected properties of this paradigm needed to support the deployment of learning mechanisms. Following this analysis, a new DNF mechanism is proposed and its ability to attain the requested objectives is examined. Our model succeeded in fulfilling self-organizing tasks, making a step forward to reconcile functional needs and theoretical approaches aimed to solve essential cognitive tasks. Future works regard a detailed qualitative analysis of the behaviour of such fields in benchmark scenarios, as well as the usages of this mechanism in the development of multimodal architectures, implementing reliable coherent learning, as started in [7].

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