How can natural brains help us compute?

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Abstract. A model of biologically inspired natural computing is reviewed. Recurrent neural networks are set up so as to take advantage of emergent spatiotemporal chaotic regimes. Seminal work explaining the emergence of complexity in initially homogeneous physical and biological systems can be attributed to Alan Turing himself. Dynamical complexity provides a variety of computational modes and rich input-output relations in a dynamical perturbation scheme. Our model is initially proposed as an 'operational' device most suitable for the processing of spatially distributed input patterns varying in continuous time. Formalizations leading to hypercomputation can be envisaged.

Key words: natural computing; Alan Turing; emergence; neurodynamics; spatiotemporal dynamics; chaos; subsymbolic computation.

1 Introduction

There is an obvious similarity between our title and that of Barry Cooper's recent article [1] concerning computing with natural paradigms as well as the related subject of computing by Nature itself. But we specifically intend to pay homage to Alan Turing's efforts in understanding computation taking place in that special natural system which is the brain. Thus our focus here is on that particular system which we take as inspiration for a computing paradigm.

We would also like to bring out a *third* way by which Turing —albeit probably unintentionally— may have contributed to the field of computing in the whole. The *first* 'Turing way' needs little discussion: it is embodied in the Turing machine and is practically synonymous with classical computation. The *second* Turing way has been appreciated only recently and can be viewed as an early proposal of connectionist methods, in the form of so-called 'unorganized machines' [2] (see also the review of Turing's anticipation of neural networks in [3]). It must be said that this incursion of Turing into connectionism went largely unnoticed. In these first two ways, Turing sought analogues with human reasoning. In doing so, he actually tried to capture some aspects of the brain's workings.

The aforementioned third way can only now begin to be appreciated in view of the growing interest in natural computing paradigms and methods. The scientific community, from both the natural and the computational sciences, regards an increasing number of 'naturally' occurring phenomena as qualifying as computation. These may provide additions to the collection of computational paradigms where e.g. the neural networks referred above have a more established status. The apparent lack of a formal definition of computation that might encompass all the alternative forms of 'unconventional' computing, as compared to the solid definitions of classical computability, has been a matter of criticism. The formal difficulties can sometimes be compensated by the promise, or actual demonstration, of practical applications where some operational advantage is obtained as compared to the operation of classical digital machines.

Our approach in this paper will be of the latter, 'operational', kind. This does not mean we cannot briefly point e.g. to the hypercomputational possibilities of the model(s) under discussion. 'Hypercomputation' is used here in the sense of computing non-Turing-computable functions, which is something we regard as theoretically possible with the models we propose. Our work is within the context of dynamical systems, which does allow a number of possible reasonable formal definitions of continuous-time analog dynamical computation, be it exact computation or otherwise. Generalization of classical concepts such as input data, memory, program, and output, may be less than obvious, but are nonetheless possible. Notwithstanding, such formalization will not be attempted in the present publication.

At this point we return to Turing's third contribution to computation, which at the time appeared to have no direct implication for computation itself. Turing's last ground breaking contribution to science, shortly before his premature death, was his attempt of explaining morphogenesis in living systems. To be technically more precise, it was actually an attempt of explaining the presence of spatial patterns in living tissue, and the slow time-variation thereof. One seminal paper, "The chemical basis of morphogenesis"[4], was published during his lifetime. That article seems to have had a more profound influence among theoretical biologists —at least among those who could understand the math— and, lately, among chemists and physicists, than it has had for computer science. As it comes, it is not even considered relevant for computer science, apart from the need for computer-aided numerical simulations that it brought about.

In a broad sense, computation might have been served by, say, Turing having achieved a proper explanation of morphogenesis in neural tissue. This would have, at least partially, contributed to the understanding of the physical substrate of 'computation' in living beings. However, that was not quite the case. A proper explanation of morphogenesis could indeed only be achieved with the advent of molecular biology and the discovery of DNA. Yet, Turing did provide a powerful explanation of the *emergence* of patterns in an initially homogeneous spatially extended system, as he proposed the so-called reaction-diffusion mechanism. The latter was presented as an explanation of naturally occurring patterns based solely on the laws of physics, but could also serve as a recipe for the technological creation of such type of patterns if desired. Experimental verification of Turing's principles can be found e.g. in [5].

Reaction-diffusion may be briefly described as the reaction between an activator substance and an inhibitor, accompanied by the spatial diffusion of both substances at different rates. For appropriate values of the reaction and diffusion rates, the interplay between both mechanisms can give rise to spatial patterns, denoting an inhomogeneity in, say, the activator's concentration. Here there is no explicit term in the original equations that describe the system, and which might point to the spatial structures that do arise. For instance, emergent correlations and observed wavelengths are not explicit beforehand. Such quantities tend to be intrinsic, i.e., dependent upon the substances and associated intensive parameters, and not (at least in a first approximation) upon imposed geometrical or boundary conditions constraints.

What Turing provided was one of the first rigorous explanations of emergence itself, in terms acceptable to the natural science community. The fact that emergent observable quantities are mostly intrinsic in reaction-diffusion systems provides a most elegant example of self-organization. In other systems, such as in hydrodynamics, emergent structures may be dependent upon externally imposed geometry and boundary conditions [6].

Turing was primarily interested in explaining essentially static patterns. However, he did consider concepts such as the state of the system —which is implicit in the mathematical description itself— and the evolution thereof, hence dynamics. This use of dynamics would concern mainly the slow evolution from a homogeneous state to some 'final' pattern. Regularity was sought, be it along the spatial or the temporal dimension. For another example of this regularity, simple traveling waves were acknowledged as a possible solution of the dynamical equations. More modernly, non-convergent solutions are also considered, including the extreme case of spatiotemporal chaos, where the system may present different degrees of (ir)regularity along both the spatial and the temporal dimensions.

The real world is nonlinear, and Turing gave an important and seminal contribution for the description of emergence in this world. Originally, the reaction-diffusion system's dynamical evolution does not seem to have been proposed as a computational model or computational paradigm per se. However, in our research on computation, we acknowledge the influence of the explanatory trend initiated by Turing concerning the emergence of complex dynamics in the natural world.

We are particularly interested in evaluating the relevance of complex spatiotemporal dynamics for the computations that living organisms might perform. On the other hand, we seek to propose actual computation paradigms inspired by those observations, and which might therefore be classified as 'natural computing'.

Our approach, chiefly operational at start, falls most naturally into the category of *practical* computation with natural paradigms. However, as noted above, the road is open for a formalization of the proposed type of analog computation. Namely, *exact* analog computation can be contemplated at the formal level.

For now, let us call our starting point a *Baconian* one [1], that is, observing Nature itself as a first step.

2 The chaotic brain — what use could it have?

Around twenty years ago, the discovery of putative chaotic electrical signals in the brain [7, 8] elicited a discussion on the possible functional role of chaos in cognition. Advantages such as *flexibility*, or the possibility of performing *non-linear search* for some data or concept, were highlighted based on very general arguments. In our own work, chaos is taken for a fact, and the question is then what actual use it may have, if any, for living brains. Furthermore, we ask how 'natural computing' paradigms might be proposed as inspired by this observation of biology.

2.1 A model

The computational model presented in [9] (see also references therein) has the double aim of explaining biological cognitive phenomena and proposing a possible computing device or paradigm. Models such as this one are indeed continuous-time recurrent neural networks where a range of complex spatiotemporal phenomena can be observed. Such complex behavior occurs due to nonlinear properties of the nodes and, especially, due the system being spatially extended. The degree of complexity is dependent upon parameters such as the system's size and details of the connectivity. Spatiotemporal chaos is one of the possible regimes.

Most interesting in view of computing are the parameter regions for which a certain temporal and spatial coherence is kept among nodes (or 'neurons'), that is, a form of low-dimensional spatiotemporal chaos. These have been called by some authors the 'edge of chaos' regions.

The equations describing the essential aspects of the neurons' dynamics in [9] happen to be a discretization of the Ginzburg-Landau equation for oscillating reaction-diffusion systems. This normal-form approach abstracts away most of the details of chemical systems and becomes convenient in describing generic populations of (diffusively) coupled oscillating units. In our case, it was a first approach in trying to capture the essential dynamical features of neural populations. Assessment of the model's computational capabilities initially includes analytical investigation of its dynamical structure. This is complemented by numerical simulations (on a digital computer. . .) which are instrumental in the obtainment of practical results.

2.2 Computing with the model

The idea which is reviewed and expanded in [9] consists in exploring the Unstable Periodic Orbits (UPO) structure of chaos. In dynamical terms, chaos is a 'reservoir' containing a countably infinite number of UPOs. Such UPOs cannot be spontaneously observed. However, by using suitable control methods, they can be stabilized from within chaos in a flexible way and via perturbations of very small magnitude. One fruitful approach consists in viewing each of these UPOs as a computational mode (or 'program') which could be selectively stabilized according to the requirements of computational tasks.

A dynamical systems viewpoint is adopted, in which the input data, the so-called program and the output data are all real functions of continuous time. This does not exclude the particular case of discrete or symbolic data, as well as the particular case of static input.

An essential feature of the computing model is that a transient response — or eventually a permanent response, in the case of static input— is measured and is interpreted as the result of applying some function to the input data. In dynamical terms, the input data constitutes a time-dependent perturbation of the main system. Given this setting, the computed function is actually an operator. Through further processing stages, the device can also be made to compute a (scalar-valued) functional of the input data, or simply a discrete-valued functional of the same data.

The computational task chosen for illustration in [9] is the processing of spatiotemporal visual input patterns. The intrinsic dynamics of the original system, either viewed as each of the UPOs or the collection thereof, is itself spatiotemporal and has therefore certain spatiotemporal symmetries. The exploration of the interplay between these symmetries and the ones of the input patterns is a key aspect of the practical application of this computing paradigm. The reader is referred to [9] for more details.

Let us also note that such type of computation could be viewed as an instance of what is modernly called "reservoir computing", for which we may cite Echo State Networks [10] and Liquid State Machines [11] as application-oriented examples. The latter are probably philosophically closer to a 'black-box' model of computation.

2.3 A more 'neural' model

The diffusive nature of the connectivity in [9], along with a general lack of biological detail, albeit theoretically justifiable, faces difficulties among purist neurobiologists. To test our ideas in a more biologically realistic setting, and also with the purpose of exploring novel spatiotemporal chaotic regimes, we turned to the model in [12]. The latter closer incorporates neurophysiological features.

Although it is not central to our discussion, we note that this model could have a physical implementation e.g. in the form of an electronic analog machine. When comparing the computational power of any such physical embodiment with that of the theoretical model which abstracts it, one would suggest that such issues as measurement and parameter precision would imply a lowering of the computational power of the physical version.

The essential 'UPO reservoir' property is once again established in [12] for the chaotic attractor. Preliminary examples of rather simple computation with this model are presented in [13], along with the proposal of different versions of 'chaotic' computing via a dynamical perturbation scheme. The processing of more complex patterns is a possibility for subsequent exploration.

Although more realistically neural, the present model can be compared in dynamical terms with the markedly 'reaction-diffusion' model of Section 2.1. In the present neurons, the role of activation is assumed by neural excitation, whereas the role of inhibition is assumed by neural inhibition. The existence of an interplay between neural excitation and inhibition is well known in biology. Here it turns out essential in the generation of complex spatiotemporal patterns, which are indeed a mixture of regular and irregular behavior at different time-scales. The careful balancing of excitation and inhibition, as well as an appropriate setup of network connections and delays in signal transmission, provide a range of possible behaviors to be explored in view of computation.

2.4 A digression: chemical computers

Over the years, practical applications of reaction-diffusion principles have been proposed as 'chemical computers', namely featuring variants of the Belousov-Zhabotinskii reaction [14, 15]. In [14], elementary image processing is performed by perturbing chemical waves with light. In [15], logic gates are built out of chemical waves. These approaches differ from ours in that they feature a *local* type of processing, whereas we seek *global* dynamical responses for given input data. Also, information flow and the actual dynamical regimes that may be present in neural networks tend to be richer than with the simpler reaction-diffusion systems. Moreover, the 'gate design' approach of [15], for instance, is a re-implementation of standard digital circuitry, although in a novel substrate. Regarding the essence of computation, no new paradigm is actually proposed.

A clarifying distinction can also be made between our use of a global dynamics and the local processing in certain models which can be related to chemical computers, such as the Excitable Lattice model [16]. In the latter, particle-like waves represent quanta of information. Binary collisions between particle-like waves are used as implementations of logical gates, thus in close agreement with the basic idea illustrated e.g. in [15]. Our model in [13] is not originally intended to directly implement logical gates. However, an actual implementation of the XOR function is provided as an arbitrary illustration of yet another possible usage of the device. Let us recall that the primary purpose of our model is the processing of more complex spatiotemporal patterns, where some obvious advantage might be obtained over classical digital processing. In our case, whichever function is computed (including the XOR and other Boolean functions), the processing is globally done by the neural population.

3 Discussion

We propose a computational model which tries to capture the essentially dynamical, nonlinear way by which Nature itself 'computes' whatever it may be that it computes most of the time. Our model supports a basic digital processing mode if required —as is certainly the case with Nature for certain tasks. However, it preserves a fully analog computation power, to be subsequently explored.

Dynamical regimes as complex as spatiotemporal chaos are not avoided as if they were a nuisance. Rather, they are explicitly taken advantage of. A setting within neural networks is adopted, although markedly deviating from standard presentations of such networks.

It is a valid endeavor to try to generalize concepts from classical computation into this new analog dynamical context. Even if a direct translation of concepts is not possible, questions such as the assessment of computational power remain very relevant, both in practical usage and in an exact analog computation setting.

In retrospect, we also appreciate the seminal contribution of Alan Turing himself to the rigorous description of complexity in the natural world, eventually leading to our own work.

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