RNN-based Model for Self-adaptive Systems
The Emergence of Epilepsy in the Human Brain

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Abstract: The human brain is the self-adaptive system *par excellence*. We claim that a hierarchical model for self-adaptive system can be built on two levels, the upper structural level *S* and the lower behavioral level *B*. The higher order structure naturally emerges from interactions of the system with its environment and it acts as coordinator of local interactions among simple reactive elements. The lower level regards the topology of the network whose elements self-organize to perform the behavior of the system. The adaptivity feature follows the self-organizing principle that supports the entanglement of lower level elements and the higher order structure. The challenging idea in this position paper is to represent the two-level model as a second order Long Short-Term Memory Recurrent Neural Network, a bio-inspired class of artificial neural networks, very powerful for dealing with the dynamics of complex systems and for studying the emergence of brain activities. It is our aim to experiment the model over real Electrocorticographical data (EcoG) for detecting the emergence of long-term neurological disorders such as epileptic seizures.

1 INTRODUCTION

A self-adaptive system is "a closed-loop system with a feedback loop aiming to adjust itself to changes during its operation" (Salehie and Tahvildari, 2009) and also "a system capable to adjust its behavior in response to its perception of the environment and of the system itself" (Cheng et al., 2009). Furthernore a complex system is, roughly speaking, a system made by a huge, finite, number of components interacting each other in a nonlinear way, with some peculiar abilities to self-organize and to exhibit an emerging behavior[1]. According to these two definitions, most of biological systems are complex systems, whose behavior is self-adaptive because it evolves to adapt to new environmental conditions. Two important examples are the human brain, described as complex networks (Sporns et al., 2004), and the human immune system, as a metaphor of a self-adaptive system (Merelli et al., 2014). The human brain is made up by about 10^{11} (one hundred billion) excitable cells: the neurons. They are linked each other in a complex network by about 10^{15} (one million of billion) synapses, that in turn can produce an enormous number, about ${10^{11}}^{15}$, of different patterns of connectivity: the possible emerging behaviors of the brain. Moreover, the brain can be seen working at two levels, the higher one coordinates the interactions among neurons and the lower one performs the functional activities by regulating the strengths of their synapses or physically rewires their connections (see Figure 4 in Section 3). This feature, known as plasticity, allows the brain to properly adapt to new environmental conditions (Ashby and Isaac, 2011). Thus, studying the human brain requires a dramatic change in paradigms that sees reductionism challenged by holism where brain activities and its pathologies, such as epilepsy, can be discovered as "emerging behaviors" of the system-brain. Nowadays formal modeling of self-adaptive systems has been advocated as a way to deal with complex systems (Merelli et al., 2012; Khakpour et al., 2012; Bruni et al., 2012). Therefore, we consider complex systems as systems that "live" in an environment with which interact, by perceiving and reacting to environmental events, and by learning and adapting to new conditions by exposing new behaviors. Moreover, they are in a sort of dynamic equilibrium: the systems remain in the state of equilibrium until external conditions do not change. When new conditions arise, it must adapt by evolving to reach a new state of equilibrium. Consequently, the human brain might be modelled as a self-adaptive system.

[1] http://www.dym-cs.eu/

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We claim that a self-adaptive system can be modeled with a hierarchical model built on two basic levels: an upper structural level S, describing the adaptation dynamics of the system, and a lower behavioral level B, accounting for the behaviour of the system. The upper level acts as coordinator of local interactions among elements, that fill up the lower behavioral level. As a consequence, the higher order structure emerges from the interaction of the system with its environment, and the adaptivity feature follows the self-organizing principle that supports the entanglement of lower level elements and the higher order structure.
In this proposal, we aim to exploit our recent experience in collecting real-time electrocorticographical data (EcoG) of epilepsy (Piangerelli et al., 2014), a neurological disorder traditionally viewed as a "hypersynchronous" activity (Kramer et al., 2010) of the neurons in the brain, for modeling this process as an emerging pathology of the brain activity. We want to study a reason why the adaptation phase failed, to this end we start to pose some key-questions: "how the brain process can be modeled as a self-adaptive system? How can a model freely evolve to allow the system to adapt?' What does it mean that the system cannot adapt or it adapts in a wrong way?".
By taking into account our previous work, inspired by the immune system (Merelli et al., 2014), where the adaptation phase is represented as a topological application of the $S[B]$ paradigm suitable to identify, classify and learn new relationships among antibodies, in this position paper we address the above questions by building a hierarchical model as a Recurrent Neural Networks (RNN) application of the $S[B]$ paradigm.
RNNs are a bio-inspired class of artificial neural networks very powerful for dealing with the dynamics of complex systems and for studying the emergence of brain activities, to develop a self-adaptive model able to discriminate between the physiological and pathological human brain processes; in particular, between the physiological and epileptic conditions. The challenging idea is to describe the $S[B]$ two-level model as a second order Long Short-Term Memory (LSTM) Recurrent Neural Network. The LSTM-RNN architecture was introduced in 1997 (Hochreiter and Schmidhuber, 1997). Like most RNNs, a LSTM network is universal in the sense that, given the proper weight matrix, it can compute anything a conventional computer can compute as program.

2 RECURRENT NEURAL NETWORKS: A POWERFUL METHOD

Artificial Neural Networks (ANN) are computational (non-linear) models biologically inspired by human central nervous system (brain). They consist in a set of nodes, also called neurons or processes, connected each other like the real neurons, and able to process input signals. The ability of learning is exactly the most important feature of an ANN: learning means evolving and adapting to the changing context for reacting to different situations. A kind of self-adaptive system with an hidden adaptivity phase. The simplest example of an ANN is the McCulloch-Pitts neuron (McCulloch and Pitts, 1943), followed by perceptron, whose limit was overcome by the introduction of multilayered perceptrons with back-propagation, known as FeedForward Neural Networks (FFNN). Details about this subject can be funded in (Minsky and Papert, 1988).

Nowadays a great interest is rising upon artificial Recurrent Neural Networks that differ with respect to FFNNs in modeling the neurons with the ability to sending feedback signals to each others neurons (see Figure 1).

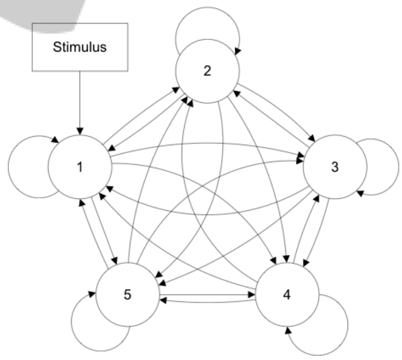

Figure 1: An example of RNN. This network presents feedback connection but it is fully connected too. Not all the RNNs are required to be this way.

2.1 The RNN Strong Points and Limitations

The main features of RNNs, due to the presence of loops, are basically three:

- RNNs develop a system dynamics even without input signals;
- RNNs are able to store, in their hidden layers, a non-linear transformation of the input. They have memory of past inputs;

- the rate of change of internal states con be finely modulated by the recurrent weights to give robustness in detecting distortions of input data.

RNNs are universal approximations of any dynamical system (Funahashi and Nakamura, 1993); the brain itself can be seen having an RNNs-architecture (Ashby and Isaac, 2011) (see Figure 2). Cortical networks present an incredible ability to learn and adapt via a number of plasticity mechanisms which affect both their synaptic and neuronal properties. The self-adaptive mechanism might allow the recurrent networks in the cortex to learn representations of complex spatio-temporal stimuli. Neuronal responses are highly dynamic in time (even with static stimuli) and contain a rich amount of information about past events, i.e. memory. This can be the reason why they

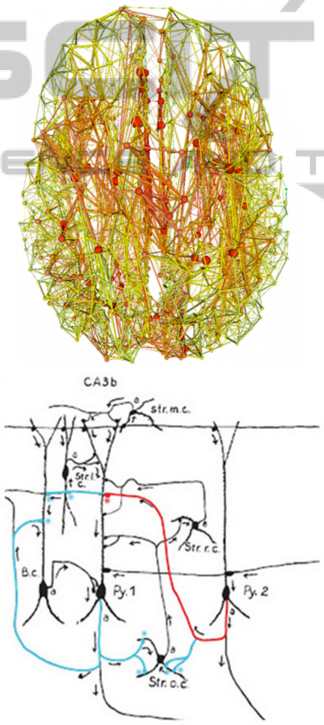

Figure 2: (Left) The brain as a functional recurrent network (van den Heuvel and Sporns, 2011). (Right) A drowning of a recurrent anatomical network in the brain.

are biologically more plausible and computationally more powerful than other adaptive approaches such as Hidden Markov Models, they have no memory at all, FFNNs and Support Vector Machines (SVM). One of the main problem is the relative low storage capacity meaning that the influence of a given input either decays or exponentially blows up since it cycles around the net's loops. This problem is well know as *vanishing gradient problem*, it does not allow past events to influence present events.

2.2 Long Short-term Memory Recurrent Neural Networks

Long Short-Term Memory Recurrent Neural Networks are a particular architecture of RNNs. The basic unit of an LSTM network is the memory block, such as the one shown in Figure 3, containing one or more memory cells and three adaptive, multiplicative gating units shared by all cells in the block. Each memory cell has at its core a recurrent self-connected linear unit (orange) called the "Constant Error Carousel" (CEC). The CEC rules constant error flow, and overcomes a fundamental problem plaguing previous RNNs preventing error signals from decaying quickly as they "get propagated back in time". The adaptive gates (green) control inputs and outputs of the cells (input and output gate) and learn how to reset the state of the cell once its contents are obsolete (forget gate). All errors are cut off once they leak out of a memory cell or gate. Although they are useful to change the incoming weights. The result is that the CECs are the only part of the system through which errors can flow back forever, whereas the gates learn the nonlinear aspects of sequence processing. LSTM learning algorithm is local in space and time and O(1) is its computational complexity per time step and weight. Suffice it to say here that the simple linear unit is the reason why LSTM nets can learn to discover the importance of events that happened 1000 discrete time steps ago, while previous RNNs already fail in case of time lags exceeding as few as 10 steps.

LSTM networks overcome the vanishing gradient problem connected with RNNs allowing to store and access information over a long period of time time. This makes an LSTM network well-suited to learn from experience, to classify, process and predict time series when there are very long time lags of unknown size between important events. Recent applications of RNNs are handwriting recognition, speech recognition, image classification, stock market (time series) prediction and motor control and rhythm detection. LSTM RNN are second-order neural networks (NNs): the gate units serve as the additional sending units for the second-order connections (Monner and Reggia, 2012). By second-order NNs, we mean a network that not only it allows normal weighted connections from one sending unit to one receiving unit, but also it allows second-order connections: weighted links from two sending units to one receiving unit. In this case the signal received is dependent upon the product of the activities of the sending units with each other and the connection weight (Miller and Giles, 1993).

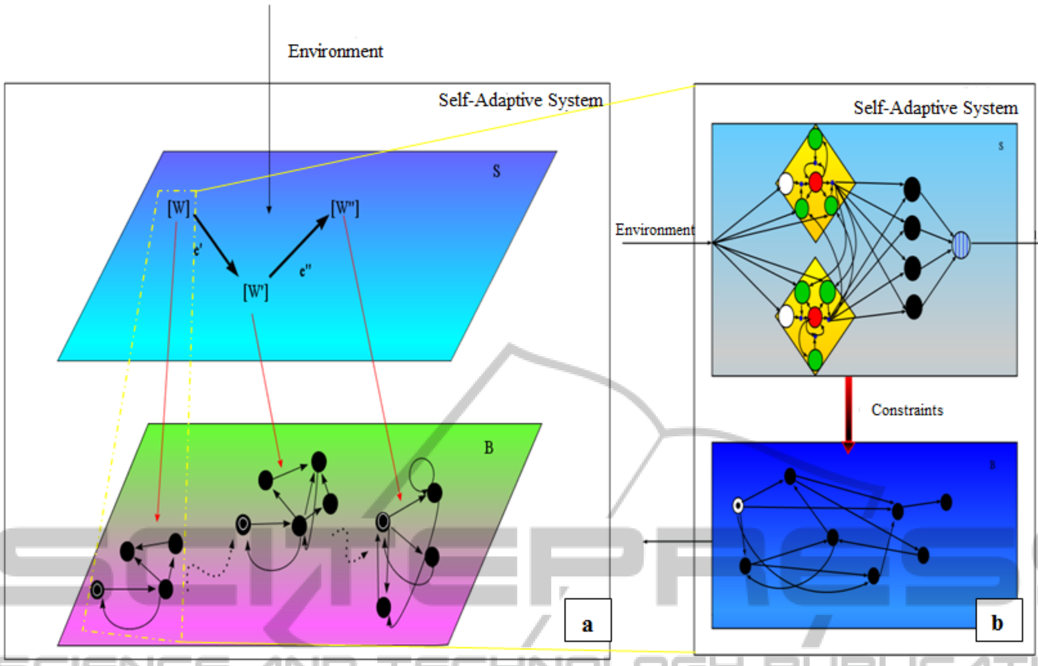

Figure 4: A schematic view of a self-adaptive system. On the left, the panel (a) shows the evolution of the system: LSTM RNNs are indicated by their *weight matrix [W]* and some events *e* could make the system adapt and evolve changing the weight matrix. For each weight matrix is possible to obtain a DFA describing the behavior of the system. On the right, the panel (b) describes in a more detailed way an instant of the evolution: it is possible to see a LSTM-RNN and the related DFA.

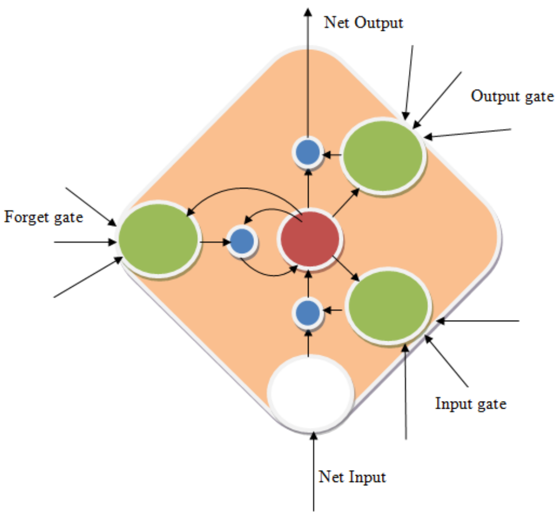

Figure 3: A LSTM cell. The linear unit lives in a cloud of nonlinear adaptive units needed for learning nonlinear behavior. Here we see an input unit (white) and three (green) gate units; small blue dots are products. The gates learn to protect the linear unit from irrelevant input events and error signals.

3 EMBEDDING RNNS IN A HIERARCHICAL MODEL FOR SELF-ADAPTIVE SYSTEM: THE IDEA

As explained in the previous section, RNNs have been shown to be a powerful tool to deal with different issues regarding adaptivity. That is the reason why we believe that they might be used with proficiency in the development of a model for self-adaptive systems based on the architecture shown in Figure 4. The model should consist in two levels: the reactive Behavioral B level and the intelligent Structural S level. S is the "brain" of our model, it is able to sense all the external stimuli and represent them as a set constraints (the weigh matrices $[W]$ in the Figure 4) those that will guide the B level to react with a correct behavior. Whenever the B level can not anymore satisfy the set of constraints imposed by S, must evolve its network topology to adapt its behavior to the new set of constraints, by using the real RNN weight matrix. The general framework presented in Figure 3 of the paper (Merelli et al., 2014) remains valid if we consider as invariants of the model a measure of the network topology for example the RNN weight matrix.

The evolution of the model relies on how the coding of the set of perceptions (data space in the figure) that the brain will be store within the S level and on how the corresponding B level will be modeled. Thus the general approach based on the use of RNNs can be view as an application of the $S[B]$ paradigm.

To facilitate the concrete application of the $S[B]$ paradigm we are going to use, as a collection of data, the set of electrical signals of the brain (time series), that are the proofs of the brain activity. They contain all the information regarding the (topological network, such as the) internal states of the brain and its connectivity. They are the input data for training a LSTM RNN whose topology will be measured to characterized the adaptation phase of the proposed model. According to the work of Giles and others (Giles et al., 1992) a second-order recurrent neural network can be mapped into a Final State Automaton (DFA), likewise the LSTM RNNs will be likely mapped into the classes of DFAs whose corresponding set of accepted regular terms will be used to describe the cerebral activities and discriminate the physiological from the pathological one.

The real data over which we will experiment the proposed approach are the electrocorticographical signals: they are recorded using a new device, the ECOGIW-16E (Piangerelli et al., 2014; Cristiani et al., 2012), developed by two Italian companies: AB-MEDICA s.p.a. and Aethra Telecommunications s.r.l.. the device, completely wireless will provide a huge amount of data, continuously recording electrical brain activity.

4 FINAL REMARKS

Starting from the description of the human brain as a self-adaptive system and exploiting the features of the second-order LSTM-RNNs, we proposed to develop a hierarchical model made up by two levels, S the structural one and B the behavioral one, entangled via a unique adaptation phase. The study of the evolution of the model, rested on the adaptation phase, is characterized by the way in which the space of data is analyzed. In our scenario, the space of data represents the environment, the set of perceptions through which the behavior of a system evolves and its knowledge updates. We proposed to analyze the set of data by an RNN for deriving the so called *weight matrix* that allows us to build the corresponding complex network that represents the emerging model at the current time. In the study of the evolution of the complex network, we aim to consider the recent important results reached by some researchers of the TOPDRIM project [1] (Franzosi et al., 2014): a geometric entropy measuring networks complexity for detecting the emergence of the "giant component" as the emergence of a neurological disorders such as epileptic seizures.

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