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Controlling deterministic output variability in a feature extracting chaotic BAM

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ABSTRACT

In this work, a chaotic feature extracting BAM that is capable of generating various behaviors is introduced. These behaviors arise from different attractors, ranging from a stored fixed point to a wandering chaotic region, including variations of all stored fixed points. Variations of stored patterns are generated by the network via the setting of the variability exhibited by every extracted feature. A control method is applied in order to move the network's trajectory into the desired regions and generate chaotic itinerancy, which is reported as a salient property of the brain system. This control is achieved by adjusting the free parameters of the feature extracting units' activation functions. Moreover, it is shown that the higher the number of units applied as feature extractors, the more local features are obtained, control of which leads to greater output uncertainty. However, the structure of this model is very simple and its complex behavior is a result of the interaction among feature units. These observations imply that the proposed model can be feasibly applied in information processing, such as searching in memory, pattern recognition in the presence of noise and variability, modeling episodic memory and decision making in a changing environment.

1. Introduction

The main goal of artificial intelligence is to develop systems capable of mimicking the behavioral functions observed in the human/animal brain. Since the seventies, a class of Artificial Neural Networks (ANNs), known as recurrent autoassociative memory (RAM) models and their direct generalization of bidirectional associative memory (BAM) models [40], constituted biologically inspired attempts to generate attractor-like (or categorical) dynamic representation behavior. RAM models use a feedback loop to achieve new pattern generalization, noise filtering, and pattern completion. This structure enables the model to shift progressively from an initial pattern towards an invariable state (attractor). Since the information is distributed among the units, the network's attractors are global. If the model is properly trained, the attractors should then correspond to the learned patterns [33]. However, in such associative memories, patterns are stored as immutable objects, which contrast with those stored in the human brain where patterns change over time.

In the last decade, an innovative concept was proposed illustrating that memories in the human brain are a dynamic representation of the interactions between modules at different levels of the nervous system [31]. Freeman [21] established the existence of chaotic behavior (deterministic aperiodic fluctuations) in the rabbit olfactory system, thus the static view of information represented by stable attractors (e.g., Hopfield-type networks) was challenged by the dynamics of neural activities [7,17,39] and behaviors, where spatial patterns could be stored in dynamic orbits [58]. Those phenomena suggest that, in real neural systems, information is stored and retrieved via both stable and dynamic orbit (possibly chaotic) attractors. Evoked activities in the cerebral cortex representing perceptual features show a large variability, even under the identical presentation of a given stimulus. These variable activities may be translated into different observable behaviors [4].

On the other hand, recent mathematical findings allow us to differentiate highly erratic yet deterministic behavior of nonlinear chaotic systems from true randomness or stochastic behavior [47]. Therefore, in order to model nonlinear (and especially chaotic) dynamics in the activity of natural neurons, chaos theory was introduced to the ANNs field [7,18,62]. Numerous models of chaotic ANNs have been studied in recent years [1–3,14,16,29,44,55], some of the works investigating ways to incorporate chaotic dynamics at the macroscopic level [18,55] with others working at the microscopic level [15,32,43,45,51]. In these models, memories are not represented by states but rather by a process. This process includes transient activities among low-dimensional attractors through high-dimensional chaos wandering. Therefore, these networks have the potential to generate a solution by exploring the possible states

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at a high level and then exploiting them at the lower level. Furthermore, when they exploit a solution leading to unsatisfactory results, they are capable of generating a new solution by exploring other states. In other words, if chaos could be controlled properly in such networks, it would be possible to design models that can satisfy the requirements for stability and flexibility found in the brain.

One of these is the Chaotic BAM model, which was introduced using a semi-logistic function as its units' activation function [10] with the objective of incorporating chaotic dynamics into the attractor-type behavior of BAMs. This model and other similar ones [8–12,23,24] are applied in many tasks and have shown high efficiency. In recent works [8,11], it was shown that this BAM model can generate chaotic associative memory dynamics for binary and gray-level patterns through the modification of the output parameter. The network was able to show various types of attractors such as fixed point, periodic, constrained chaotic and unconstrained chaotic behaviors. Freeman's studies showed that the dynamics of the neural system are essentially chaotic and that, with presence of a stimulus, the system rapidly simplifies itself and shifts towards more ordered and nearly periodic attractors [21]. Therefore, the associative memory dynamics demonstrated by Chaotic BAM make it a promising technique for designing an interesting model of recognition and learning process within biological neural systems. It can help in the understanding of the mechanisms of information processing, such as searching procedure during memory recall [13], pattern completion or recognition, one-to-many association, etc.

However, chaotic RAM and BAM models, similar to the standard ones, have difficulties when dealing with noise. Contrarily to what is found in real-world situations, this is due to the fact that they store information using noise free versions of the input patterns. Moreover, humans must regroup the unique noisy inputs from multiple perceptual events into a finite number of stimuli or categories in order to overcome the possibly infinite number of stimuli processing, but this type of learning in the presence of noise has not been taken into account by BAM models, which does not make them very economical.

In everyday life, human beings use perceptual features in their cognitive system [22], which are stored within an implicit dimension reduction procedure during the learning process [26]. In order to overcome the aforementioned shortages, another modification of the Chaotic BAM was introduced and is referred to as Feature Extracting BAM (FEBAM) [9]. In this method, one set of external connections was removed from the BAM to take into account the unsupervised extraction of features. This Feature-Extracting BAM still has two layers, but it is now trained in an unsupervised fashion. The network learns to extract a set of perceptual features from inputs only. It can then associate a given noisy pattern to its extracted features and reconstruct the original pattern through recurrent connections. It is interesting to note that if the number of units in the second layer is lower than the number of units in the input layer, the model will perform a dimension reduction. In previous works, this model was used in its fixed point manner and it was shown that it can exhibit many properties, such as feature extraction [9], category development [23], and creation of perceptual features [24], as would be expected from a brain-inspired memory model.

In this work, our aim is to propose a model that can mimic the dynamic feature extraction and feature binding processes in the brain in order to generate various attractors and behaviors, which is the key to simultaneous flexibility and stability. To have such a model, we take advantage of the FEBAM structure mentioned before, which is able to create a set of perceptual features of data through an unsupervised learning algorithm and has the potential to generate various attractors within its feature extracting units. The only issue that is needed to achieve such modeling is to find a method that enables us to control chaos in FEBAM by acting upon its features. This control method is introduced in this work in order for the chaotic FEBAM to be able to generate the desired attractor (behavior) varying from a fixed point output corresponding to a stored pattern, to a chaotic one including varieties of all stored patterns. Further, once a set of patterns have been stored, the system will be able to exploit its knowledge in a novel fashion by combining different variations of its features. Chaos control is accomplished by adjusting the transmission parameters of the feature units' activation functions to move the network's trajectory to a desired region. This way, the model can show chaotic itinerancy, which is reported as a salient property of the brain and plays a crucial role in dynamic information representation [35]. Contrary to standard FEBAM [9], chaotic FEBAM can operate heterogeneously and the free parameters of feature units do not need to be the same. In other words, it can adjust the importance of some features over others to enable the network to impact variously on its stored memory. In other words, it can increase the importance of some features and attenuate that of others to generate new versions of stored patterns, or it is capable of fixing some features and alternating some others to generate clusters of stored features. The designed system is able to address the various behaviors and generate different sequences of stored patterns' exemplars [28–30,42,60,61] in order to adapt to new environments or situations.

This paper is organized as follows: Section 2 describes the nonlinear dynamics of the output function that will be used in the model; Section 3 presents the structure of the model, the multi-dimensional output function and the learning algorithm; Section 4 introduces the control method applied to the identification of free parameters of the feature extracting units; Section 5 shows the results of the various simulations. Finally, the discussion and conclusion are presented in Section 6.

2. Nonlinear dynamics of the FEBAM output function

The output function used in Chaotic BAM and FEBAM is based on the classic Verhulst equation [9,10]. Because this quadratic function has only one stable fixed point (at 1), it is extended to a cubic form, where both −1 and +1 are stable fixed points, while zero remains unstable. The nonlinear dynamics of this function without saturating limits have been studied and implemented in [8]. The most interesting characteristic observed in this model is its capacity to exhibit various attractors during recall, ranging from periodic to different volume chaotic ones. These attractors can be obtained through the modification of the free parameter values of the output function. In FEBAM, the model could be used to replicate the same dynamic behaviors. Moreover, through feature extraction, it could have the possibility to affect specific memory patterns without disturbing the others. For example, if the network learns 26 letters, we could ask it to output only the vowels by finding the output parameters that would create a chaotic wandering for those letters only. In other words, we could model the search process within a general memory. We could also make the network generate some stable outputs in specific attractor regions that have various degrees of uncertainty in representing exemplars of trained (prototypes) patterns.

In FEBAM, the output is bound at −1 and 1 by the inclusion of saturating limits. The presence of saturating limits completely changes the dynamics of the output function, and the range of parameter values that allows the presence of chaos is entirely different from the unsaturated one discussed in [8]. In the following we will investigate the nonlinear dynamics exhibited by this function.