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Logistic Neural Networks: Their chaotic and pattern recognition properties ☆

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ABSTRACT

The goal of this paper is to catalog the *chaotic* and Pattern Recognition (PR) properties of a network of Logistic Neurons (LNs). Over the last few years, the field of Chaotic Neural Networks (CNNs) has been extensively studied because of their potential applications in PR, Associative Memory (AM), optimization, multi-value content addressing and image processing. The research in chaos theory has thus expanded to report numerous neural models that, by virtue of their inter-connections, yield chaotic behavior. Recently, the Adachi Neural Network (AdNN) and its variants have been shown to yield an entire spectrum of properties including chaotic, quasi-chaotic, PR and AM as its/their parameters change. To *simplify* the AdNN model and to also investigate the design philosophy of the CNN model, in this paper, we consider the consequences of networking a set of LNs, each of which is founded on principles of the Logistic map. By appropriately defining the input/output characteristics of a fully connected network of LNs, and by defining their set of weights and output functions, we have succeeded in designing a Logistic Neural Network (LNN). Although the LNN is much simpler than other CNNs such as the AdNN, it possesses some of those properties mentioned above. The chaotic properties of a single-neuron have been formally proven using the theory of Lyapunov analysis and by examining its Jacobian matrix. As far as we know, the results presented here, that the LNN can also demonstrate both AM and PR properties, are unreported, and we submit that it can, hopefully, lead to a new method of PR and AM.

1. Introduction

At a very fundamental and philosophical level, the field of Neural Networks (NNs) deals with understanding the brain as an information processing machine. Conversely, from a computational perspective, it concerns utilizing the knowledge of the (human) brain to build more intelligent computational *models* and computer systems. Thus, in the latest decade, NNs have been widely and successfully applied to an ensemble of information processing problems, and the areas of Pattern Recognition (PR) and forecasting are rather primary application domains. Quite briefly, for example, the author of [12] applied the classical BP neural network for the segmentation of Meteosat images. The literature [8] reported an alternative approach to protein structural class prediction by means of NNs. These authors announced that their proposed scheme maintains the same level of classification accuracy, although it is achieved with minimum computation time. Oliver and his co-authors [17] verified the effectiveness of an adaptation of the neural network through the design and development of some urban network problems.

As a backdrop to this paper, we mention the phenomenon that the brain is capable of displaying both chaotic and periodic behavior. The premise of the paper is that it is expedient to devise artificial neural systems that can display these properties too. Indeed, Freeman's clinical work has clearly demonstrated that the brain, at the individual neural level and at the global level, possesses chaotic properties. He showed that the quiescent state of the brain is chaos. However, during perception, when attention is focused on any sensory stimulus, the brain activity becomes more periodic [11]. Thus, as applied scientists, if we are able to

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develop a system which mimics the brain to achieve chaos and PR, it could leads to a new model of NNs, which is the primary goal of Chaotic Neural Networks (CNNs), and *chaotic* PR.

CNNs which also possessed PR were first proposed by Adachi and his co-authors [1–5]. It would be fair to state (and give them the honor) that they pioneered this "new" field of CNNs. In their papers, by modifying the discrete-time neuron model of Caianiello, Nagumo and Sato, they designed a new simple neuron model possessing chaotic dynamics, and an Artificial Neural Network (ANN) composed of such chaotic neurons. Their experimental results demonstrated that such a CNN (referred to the AdNN in this paper) possesses both Associative Memory (AM) and PR properties, as will be illustrated in Section 2.1.

Historically, the initial and pioneering results concerning these CNNs were presented in [1–5]. In the next year, the author of [18] proposed two methods of controlling chaos with a small perturbation in continuous time, i.e., by invoking a combined feedback with the use of a specially designed external oscillator or by a delayed self-controlling feedback without the use of any external force to stabilize the unstable periodic orbit of the chaotic system. Subsequently, motivated by the work of Adachi, Aihara and Pyragas, various types of CNNs have been proposed to solve a number of optimization problems (such as the Traveling Salesman Problem, (TSP)), or to obtain Associative Memory (AM) and/or PR properties. An interesting step in this regard was the work reported in [23], where the authors utilized the delayed feedback and Ikeda map to design a CNN to mimic the biological phenomena observed by Freeman [11]. Later, in [13,21,22] Hiura and Tanaka investigated several CNNs based on a piecewise sine map or the Duffing's equation to solve the TSP. Their simulations showed that the latter model yielded a better performance than the former.

More recently, based on the AdNN, Calitoiu and his co-authors made some interesting modifications to the basic network connections so as to obtain PR properties and "blurring". In [6], they showed that by binding the state variables to those associated with *certain*[1] states, one could obtain PR phenomena. However, by modifying the manner in which the state variables were bound, they designed a newly created machine, the so-called Mb-AdNN, which was also capable of justifying "blurring" from an NN perspective. Another valuable work related to chaos and NNs was reported in [10]. The authors of [10] applied chaotic NNs to the original Bidirectional Associative Memory (BAM) family and designed the Chaotic Bidirectional Associative Memory models (C-BAM). Their work demonstrated that the C-BAM family can access patterns that members of the original BAM family were incapable of accessing.

While all of the above are both novel and interesting, since most of these CNNs are *completely* connected graphs, the computational burden is rather intensive. Aiming to reduce the computational cost, in our previous paper [15], we proposed a mechanism (the Linearized AdNN (L-AdNN)) to reduce the computational load of the AdNN. This was achieved by using a spanning tree of the complete graph, and invoking a gradient search algorithm to compute the edge weights, thus minimizing the computation time to be linear.

Although it was initially claimed that the AdNN and M-AdNN possessed "pure" (i.e., periodic) PR properties, in actuality, this claim is not as precise as the authors claimed. We shall now clarify this. Indeed, as we mentioned in our previous papers [15,16], if the AdNN weights the external inputs with the weights $a_i = 2 + 6x_i$, the properties of the system become closer to mimicking a PR phenomenon. Adachi et al. claimed that such a NN yields the stored pattern at the output periodically, with a short transient phase and a small periodicity. However, it turns out that if *untrained* patterns are presented to the system, they also appear periodically, although with a longer periodicity. Besides, the untrained input patterns can lead to having the system occasionally output *trained* patterns. Although the former can be considered to be a PR phenomenon, the latter is a handicap because we would rather prefer the system to be chaotic for all untrained patterns—which the AdNN cannot achieve for these settings. This phenomenon is also pertinent for the M-AdNN, i.e., the output can be periodic for both trained and untrained input patterns.

To complete this historical overview, we mention that in [15], we showed that the AdNN goes through a spectrum of characteristics (i.e., AM, *quasi*-chaotic, and PR) as one of its crucial parameters, α, changes. In particular, it is even capable of recognizing masked or occluded patterns.

The primary aim of this paper is to use a completely different neuron as a primitive element in the network, and to see if we can obtain chaotic, PR and AM properties. Aiming to develop a completely new chaotic PR system, in this paper, we present a CNN which is founded on the *Logistic* Map.

Our new model has the same topological structure (completely connected) as the CNNs listed above. It is, indeed, also characterized by the definition of a recurrent NN described in terms of a Present-State/Next-State and a State/Output function. The sigmoid function is still used as the transfer function. The main difference between our new model and other CNNs mentioned above lies in the Present-State/Next-State equation, as will be explained in Section 3. But more importantly, the work presented in this paper is a prelude to a novel strategy for the design of CNNs. Essentially, the chaotic feedback module of this newly proposed model can be easily modified and then substituted for by *other* chaotic systems. Simultaneously, the network, in and of itself, can be seen to possess analogous properties as long as the respective parameters are appropriately tuned. Based on numerous simulation results, we demonstrate that this new NN possesses the desirable properties of AM and PR for different settings.

Although the Logistic NN presented here is much simpler than the models reported in [2,13,14,21,22], it possesses equivalent or even more fascinating properties. It is one of the best examples of an effective application of chaos to technology.

As far as we know, the results presented here, that the LNN can also demonstrate both AM and PR properties, are unreported and novel to the field of CNNs, and we submit that it can, hopefully, lead to a new method of PR and AM.

1.1. Contributions of the paper

The primary contributions of this paper are:

1. We introduce a new PR system which is founded on the theory of chaotic NNs, and in particular, where the primitive neural unit is a Logistic Neuron.
2. We analyze the dynamics of this new model of CNNs, the Logistic NN, which is simple in structure but powerful in functionality.
3. We show that the LNN possesses both PR and AM properties. Compared to the AdNN, the LNN is able to recall/recognize stored patterns more often, which is helpful in dynamic information retrieval.
4. We especially focus on the stability of the network and its transient and dynamic retrieval characteristics. This analysis is achieved using eigenvalue considerations, and the Lyapunov Exponents.
5. We provide explicit experimental results justifying the claims that have been made.

[1] In the interest of brevity, the details of these bindings are omitted here.