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Feedback associative memory based on a new hybrid model of generalized regression and self-feedback neural networks

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ABSTRACT

The focus of this paper is to propose a hybrid neural network model for associative recall of analog and digital patterns. This hybrid model consists of self-feedback neural network structures (SFNN) in parallel with generalized regression neural networks (GRNN). Using a new one-shot learning algorithm developed in the paper, pattern representations are first stored as the asymptotically stable fixed points of the SFNN. Then in the retrieving process, each pattern is applied to the GRNN to make the corresponding initial condition and to initiate the dynamical equations of the SFNN that should in turn output the corresponding representation. In this way, the corresponding stored patterns are retrieved even under high noise degradation. Moreover, contrary to many associative memories, the proposed hybrid model is without any spurious attractors and can store both binary and real-value patterns without any preprocessing. Several simulations confirm the theoretical analyses of the model. Results indicate that the performance of the hybrid model is better than that of recurrent associative memory and competitive with other classes of networks.

1. Introduction

Associative neural networks (AsNN) have been extensively studied for their ability to store and properly recall patterns and images. In general, memory patterns are represented by binary (digital) or real-valued (analog) vectors (Amiri, Davandeh, Sadeghian, & Seyyedsalehi, 2007; Davande, Amiri, Sadeghian, & Chartier, 2008). Those networks have the property of being robust to noisy patterns or partial information. AsNNs are dynamical nonlinear systems capable of processing information through the evolution of its state in a high-dimensional state space (Amiri, Saeb, Yazdanpanah, & Seyyedsalehi, 2008). The main requirement associated with AsNNs is that every given memory should be an asymptotically stable equilibrium (*attractor*) of the system (Amiri, Menhaj, & Yazdanpanah, 2008; Atiya & Abu-Mostafa, 1993). If the learning is performed adequately, such networks are able to generalize to new stimuli. In other words, they can retrieve a previously learned pattern from an example that is similar to one of the previously presented patterns (Chartier, Boukadoum, & Amiri, 2009). This property of associative neural networks makes them suitable for a variety of applications such as image segmentation (Cheng, Lin, & Mao, 1996) and recognition of chemical substances (Reznik, Galinskaya, Dekhtyarenko, & Nowicki, 2005).

Since the seminal paper of Hopfield (1982), many networks have been proposed to store binary (or bipolar) patterns. However, few networks can store analog patterns. An example of a model with analog pattern storage capabilities is the nonlinear dynamic recurrent associative memory (NDRAM) (Chartier & Proulx, 2005), which is based on an unsupervised time-difference covariance matrix. This model is able to develop both analog and bipolar attractors. Moreover, the model is able to develop less spurious attractors and has a better recall performance under random noise than many Hopfield-type neural networks (Chartier & Proulx, 2005).

A self-feedback neural network (SFNN) is a simple recurrent, two-layer network, where the output layer contains self-feedback units (Fig. 1). In this model, there are no interlinks among units in the feedback layer. The self-feedback connection of units only ensures that the output of the SFNN contains the complete past information of the system. Since there are no interlinks among units in the feedback layer, the SFNN has considerably fewer weights than the fully recurrent neural network and the network is noticeably simplified (Ku & Lee, 1995).

The generalized regression neural network (GRNN) was introduced by Nadaraya (1964) and Watson (1964) and rediscovered

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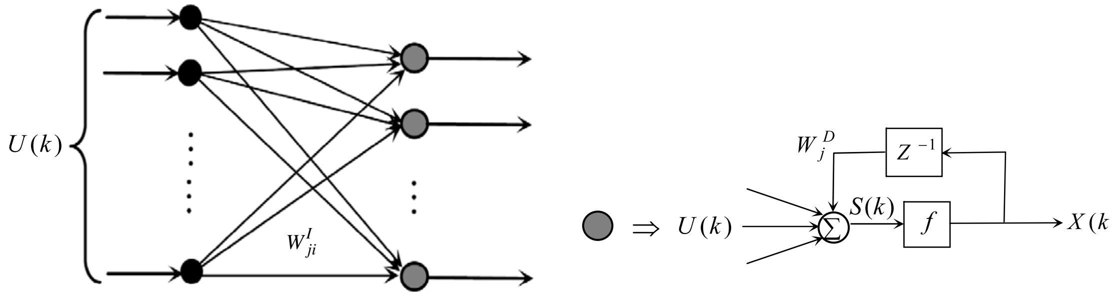

Fig. 1. The structure of the SFNN model.

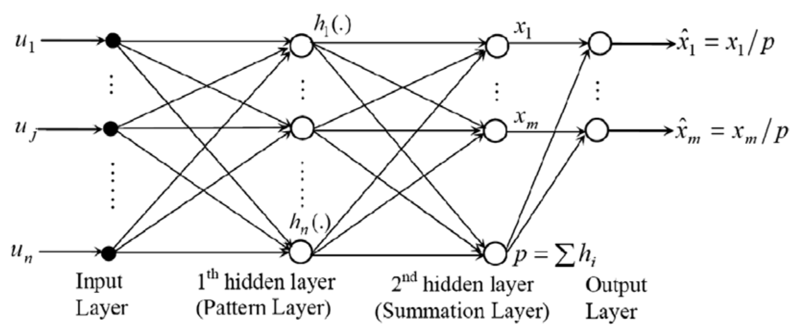

Fig. 2. The GRNN architecture.

by Specht (1991) (Fig. 2). This model is a generalization of both radial basis function networks (RBFN) and probabilistic neural networks (PNN) that can perform linear and nonlinear regression (Wachowiak, Elmaghraby, Smolikova, & Zurada, 2001). These feedforward networks use basis function architectures that can approximate any arbitrary function between input and output vectors directly from training samples, and they can be used for multidimensional interpolation (Specht, 1991; Wachowiak et al., 2001; Watson, 1964). Although GRNNs are not as commonly used as RBFNs or back-propagation-trained networks, they have been applied to solve a variety of problems including prediction, control, plant process modeling or general mapping problems (Patterson, 1995; Rutkowski, 2004). GRNNs have the advantage of being easily trained and required only one free parameter.

SFNNs are simple recurrent neural networks that have difficulties learning and storing analog and digital patterns as associative memories (Amiri, Saeb et al., 2008). On the other hand, GRNNs can find a solution for any given problem, but lack a recurrent structure to filter noise. Therefore, in this paper we propose a hybrid model of SFNN and GRNN for associative recall of analog and digital patterns (Fig. 9). First, lower dimension representations of the patterns are stored as the asymptotically stable fixed points of the SFNN by a new one-shot training algorithm. Next, we utilize the input patterns and corresponding desired initial conditions, i.e., lower dimension representations, of the SFNN as the input and desired output vectors of the GRNN, respectively. These desired initial conditions are obtained by selecting an arbitrary point in the attraction domain of each asymptotically stable equilibrium point. In the recognition stage, each pattern is first applied to the GRNN in order to obtain the corresponding initial condition of that pattern that will be used to initiate the dynamical equations of the SFNN. Then, according to the input and the initial condition, the SFNN will output the corresponding representation. It will be shown that this new hybrid model is able to perform essential properties found in associative memories such as generalization, completion and recognition of corrupted patterns.

The remainder of the paper is organized as follows. In Section 2, some relevant definitions and theorems will be introduced, and then SFNN and GRNN models will be described. In Section 3, based on the stability analysis of SFNN, a new training algorithm is developed to store the desired number of stable equilibrium points in the SFNN. Estimation of the boundaries of attraction domains for each stored attractor in terms of the network parameter values are also carried out in this section. In Section 4, the hybrid model and its working mechanism are described. The simulation results and comparisons with different classes of neural networks, auto-associative NDRAM (Chartier & Proulx, 2005; Storkey & Valabregue, 1999) and competitive (ART2 Carpenter & Grossberg, 1987, 2003) will be presented in Sections 5 and 6, respectively. Finally, Section 7 concludes the paper.

2. Methods

2.1. Preliminaries

In general, dynamical systems may be discrete or continuous, depending on whether they are described by difference or differential equations. The difference equation for a general time-invariant discrete dynamical system can be written as:

$$X_{k+1} = f(X_k) \quad k = 0, 1, \ldots \qquad (1)$$

where $f : \Re^n \to \Re^n, X \in R^n$ can be a linear or nonlinear function of X_k. Using (1), the following definitions and theorems are of interest (Kulenovic & Merino, 2002):

Definition 1. A point $\bar{x} \in \Re$ is an *equilibrium point* for the dynamical system (1), or a *fixed point* for map f, if $f(\bar{x}) = \bar{x}$.

Definition 2.a. A fixed point $\bar{x}$ of (1) is said to be *stable* if for any $\varepsilon > 0$ there exists $\delta > 0$ such that whenever $|x_0 - \bar{x}| < \delta$, the point $\bar{x}$ satisfies $|x_k - \bar{x}| < \varepsilon$ for all k.

Definition 2.b. A fixed point $\bar{x}$ of (1) is said to be *unstable* if it is not stable.

Definition 2.c. A fixed point $\bar{x}$ of (1) is said to be *asymptotically stable* or an *attracting* fixed point of the function f if it is stable and, in addition, there exists $r > 0$ such that for all x_0 satisfying $|x_0 - \bar{x}| < r$, then the sequence x_k satisfies $\lim_{k\to\infty} x_k = \bar{x}$.