Bioinspired Associative Memories

Roberto A. Vazquez
Center for Computing Research, IPN, Mexico

Humberto Sossa
Center for Computing Research, IPN, Mexico

INTRODUCTION

An **associative memory** AM is a special kind of neural network that allows recalling one output pattern given an input pattern as a key that might be altered by some kind of noise (additive, subtractive or mixed). Most of these models have several constraints that limit their applicability in complex problems such as **face recognition** (FR) and **3D object recognition** (3DOR).

Despite of the power of these approaches, they cannot reach their full power without applying new mechanisms based on current and future study of biological neural networks. In this direction, we would like to present a brief summary concerning a new associative model based on some neurobiological aspects of human brain. In addition, we would like to describe how this **dynamic associative memory** (DAM), combined with some aspects of **infant vision system**, could be applied to solve some of the most important problems of pattern recognition: FR and 3DOR.

BACKGROUND

Humans possess several capabilities such as learning, recognition and memorization. In the last 60 years, scientists of different communities have been trying to implement these capabilities into a computer. Along these years, several approaches have emerged, one common example are neural networks (McCulloch & Pitts, 1943) (Hebb, 1949) (Rosenblatt, 1958). Since the rebirth of neural networks, several models inspired in the neurobiological process have emerged. Among these models, perhaps the most popular is the feed-forward multilayer perceptron trained with the back-propagation algorithm (Rumelhart & McClelland, 1986). Other neural models are associative memories, for example (Anderson, 1972) (Hopfield, 1982) (Sussner, 2003) (Sossa, Barron & Vazquez, 2004). On the other hand, the brain is not a huge fixed neural network as had been previously thought, but a dynamic, changing neural network. In this direction, several models have emerged for example (Grossberg, 1967) (Hopfield, 1982).

In most of these classical neural networks approaches, synapses are only adjusted during the training phase. After this phase, synapses are no longer adjusted. Modern brain theory uses continuous-time model based on current study of biological neural networks (Hecht-Nielse, 2003). In this direction, the next section described a new dynamic model based on some aspects of biological neural networks.

Dynamic Associative Memories (DAMs)

The dynamic associative model is not an iterative model as Hopfield's model. It emerges as an improvement of the model and results presented in (Sossa, Barron & Vazquez, 2007).

Let $\mathbf{x} \in \mathbf{R}^n$ and $\mathbf{y} \in \mathbf{R}^m$ an input and output pattern, respectively. An association between input pattern $\mathbf{x}$ and output pattern $\mathbf{y}$ is denoted as $(\mathbf{x}^k, \mathbf{y}^k)$, where k is the corresponding association. Associative memory: $\mathbf{W}$ is represented by a matrix whose components w_{ij} can be seen as the synapses of the neural network. If $\mathbf{x}^k = \mathbf{y}^k \forall k = 1,\ldots,p$ then $\mathbf{W}$ is auto-associative, otherwise it is hetero-associative. A distorted version of a pattern $\mathbf{x}$ to be recalled will be denoted as $\tilde{\mathbf{x}}$. If an associative memory $\mathbf{W}$ is fed with a distorted version of $\mathbf{x}^k$ and the output obtained is exactly $\mathbf{y}^k$, we say that recalling is robust.

Because of several regions of the brain interact together in the process of learning and recognition (Laughlin & Sejnowski, 2003), in the dynamic model there are defined several interacting areas; also it integrated the capability to adjust synapses in response to an input stimulus. Before the brain processes an input pattern, it is hypothesized that pattern is transformed and codified by the brain. This process is simulated using the procedure introduced in (Sossa, Barron & Vazquez, 2004).

This procedure allows computing *coded patterns* and *de-coding patterns* from input and output patterns allocated in different interacting areas of the model. In addition a simplified version of $\mathbf{x}^k$ denoted by s_k is obtained as:

$$s_k = s\left(\mathbf{x}^k\right) = \mathbf{mid}\ \mathbf{x}^k \qquad (1)$$

where **mid** operator is defined as $\mathbf{mid}\ \mathbf{x} = x_{(n+1)/2}$.

When the brain is stimulated by an input pattern, some regions of the brain (interacting areas) are stimulated and synapses belonging to these regions are modified. In this model, the most excited interacting area is call *active region* (AR) and could be estimated as follows:

$$ar = r\left(\mathbf{x}\right) = \arg\left(\min_{i=1}^{p}\left|s\left(\mathbf{x}\right) - s_i\right|\right) \qquad (2)$$

Once computed the *coded patterns*, the *de-coding patterns* and s_k we can build the associative memory.

Let $\left\{\left(\overline{\mathbf{x}}^k, \overline{\mathbf{y}}^k\right) \middle| k = 1,\ldots,p\right\}$, $\overline{\mathbf{x}}^k \in \mathbf{R}^n$, $\overline{\mathbf{y}}^k \in \mathbf{R}^m$ a fundamental set of associations (coded patterns). Synapses of associative memory **W** are defined as:

$$w_{ij} = \overline{y}_i - \overline{x}_j \qquad (3)$$

In short, building of the associative memory can be performed in three stages as:

1. Transform the fundamental set of association into coded and de-coding patterns.
2. Compute simplified versions of input patterns by using equation 1.
3. Build **W** in terms of coded patterns by using equation 3.

There are synapses that can be drastically modified and they do not alter the behavior of the associative memory. On the contrary, there are synapses that can only be slightly modified to do not alter the behavior of the associative memory; we call this set of synapses *the kernel* of the associative memory and it is denoted by $\mathbf{K_W}$.

Let $\mathbf{K_W} \in \mathbf{R}^n$ the kernel of an associative memory **W**. A component of vector $\mathbf{K_W}$ is defined as:

$$kw_i = \mathbf{mid}\left(w_{ij}\right), j = 1,\ldots,m \qquad (4)$$

Synapses that belong to $\mathbf{K_W}$ are modified as a response to an input stimulus. Input patterns stimulate some ARs, interact with these regions and then, according to those interactions, the corresponding synapses are modified. An adjusting factor denoted by Δw can be computed as:

$$\Delta w = \Delta\left(\mathbf{x}\right) = s\left(\overline{\mathbf{x}}^{ar}\right) - s\left(\mathbf{x}\right) \qquad (5)$$

where *ar* is the index of the AR.

Finally, synapses belonging to $\mathbf{K_W}$ are modified as:

$$\mathbf{K_W} = \mathbf{K_W} \oplus \left(\Delta w - \Delta w_{old}\right) \qquad (6)$$

where operator $\oplus$ is defined as $\mathbf{x} \oplus e = x_i + e\ \forall i = 1,\ldots,m$.

Once synapses of the associative memory have been modified in response to an input pattern, every component of vector $\overline{\mathbf{y}}$ can be recalled by using its corresponding input vector $\overline{\mathbf{x}}$ as:

$$\overline{y}_i = \mathbf{mid}\left(w_{ij} + \overline{x}_j\right), j = 1,\ldots,n \qquad (7)$$

In short, pattern $\overline{\mathbf{y}}$ can be recalled by using its corresponding key vector $\overline{\mathbf{x}}$ or $\tilde{\mathbf{x}}$ in six stages:

1. Obtain index of the active region *ar* by using equation 2.
2. Transform $\mathbf{x}^k$ using de-coding pattern $\hat{\mathbf{x}}^{ar}$ by applying the following transformation: $\widehat{\mathbf{x}}^k = \mathbf{x}^k + \hat{\mathbf{x}}^{ar}$.
3. Compute adjust factor $\Delta w = \Delta\left(\widehat{\mathbf{x}}\right)$ by using equation 5.
4. Modify synapses of associative memory **W** that belong to $\mathbf{K_W}$ by using equation 6.
5. Recall pattern $\widehat{\mathbf{y}}^k$ by using equation 7.
6. Obtain $\mathbf{y}^k$ by transforming $\widehat{\mathbf{y}}^k$ using de-coding pattern $\hat{\mathbf{y}}^{ar}$ by applying transformation: $\mathbf{y}^k = \widehat{\mathbf{y}}^k - \hat{\mathbf{y}}^{ar}$.