Critical Analysis on Bi-directional Associative Memory

In the proposed paper of BAM, the author put focus on the study of BAM for short term learning. In which, how associative pattern problems are solved and how correctly associative patterns are converged. This task can be done using Artificial Intelligence but with some limitations of memory.

Authors also emphasis on history of BAM, where how basic model of BAM with iterative high learning rate convergence, now enhanced with a model (introduced by (Chartier & Boukadoum, 2006b; 2011)) which has rapid learning in various situation but with limited storing capacity.

The **BHM (Bidirectional Heteroassociative Memory,** (Introduced by (Chartier & Boukadoum, 2006b; 2011) model is able to learn rapidly with limited iterations which enhances the convergence performance for correlated patterns for bipolar patterns and real valued patterns.
The BHM architecture is based on two interconnected Hop-field neural networks which process the information in head to tail fashion, with the bidirectionally flow. The architecture is basically based on 3 process which are Transmission Function, Learning Rule and Learning Rule modification.
The **Transmission function** is based on the classic Verhulst equation extended to a cubic form with a saturating limit at ±1 (Chartier & Boukadoum, 2006b) with no asymptotic behaviours in the transmission and has an advantage over other BAM models(based on Bipolar attractors), of exhibiting grey-level attractor behaviour.
Learning Rule of weights is based on Hebbian/anti-Hebbian approach (Storkey & Valabreque, 1999; Bégin & Proulx, 1996), which says if learning rate is based on :- $\eta < \frac{1}{2(1-2\delta)Max[M,N]}, \delta \neq \frac{1}{2}$ network convergence is guaranteed.
To reduce the time of convergence of pattern association, **Learning Rule Modification** stated to decrease the memory capacity using a recency parameter during learning time.

BHM Advantages :-

One of the major advantage of BHM is Memory traces between past and current associations which doesn't in Kosko or hop field models. Because of this memory traces, the learning performance is increase thus faster learning for long term memory.

In BHM there is no Memory overload, thus there is no need of reset of connection weights between every learning of a group while it is required in Kosko or hop field models, otherwise there is Memory overload will occur in these models.
This model is able to learn all associations whether they are present in any number of group for auto and hesteroassociations, but Kosko and hop field all only able to learn associations perfectly when they are in groups of two.

So with the help of modification in learning rule of BHM, conclude to a better model for rapid learning with great performance for pattern associations convergence.