Chapter 5
Computer Simulations and Applications of Quantum Associative Network

5.1 CENTRAL QUANTUM HOLOGRAPHIC MODEL

Quantum holography (Peruš M. et al,2004-2005), is a new paradigm of quantum information processing that constructs the Hopfield-like associative neural networks in an extremely natural way by exploiting quantum physical system. Instead of utilizing complicated and complex quantum-based devices abiding to quantum mechanics, Quantum Holography harnesses the fact that an open system can be manipulated in a specific measurement-like way by triggering non-linear, non-unitary and irreversible collapse like phenomena instead of the Schrodinger evolution of the quantum state. It is a parallel-distributed process at quantum level which operates similarly to (oscillatory) associative neural nets. Since the natural fundamental quantum-wave dynamics is harnessed, it allows much easier and cheaper physical realization with

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bigger sizes and resolutions of images than the mainstream quantum-computing approaches like Turing-machine based quantum computing using quantum logic gates. The birth of the approach is due to big experimental success on holography followed by fast development of quantum optics. With quantum realm resolution, it promises to implement the Hopfield model and its generalizations in an original way into a new framework where its former obstacles such as memory capacity limitations and crosstalk due to non-orthogonal patterns are substantially weakened.

The implementation is based on translation on encoding of intensity of pixels to their encoding by wave-phases, that is, a parallel-distributed encoding of a N-pixel image into a front of waves ($A_1e^{i\phi 1}, A_2e^{i\phi 2}, A3e^{i\phi 3}......$). The encoding has 2 special cases, which is, encoding in amplitudes A only, and encoding in oscillatory φ phases only. The two cases enable effectively the same image processing as far as the following variable exchange can be made in the mathematics of the model/algorithm: $A \leftrightarrow e^{i\varphi}$. It will be shown that wave-based model is equivalent to intensity-based model.

The simplest Hopfield neural network incorporates Hebbian storage of patterns $\overset{\to k}{v}$ into correlation matrix J, that is, $J = \sum_{k=1}^{p} \overset{\to k}{v} \otimes \overset{\to k}{v}$, and memory-influenced transformation of patterns $\vec{v}$: $\overset{\to output}{v} = J \overset{\to input}{v}$, with each pattern stored denoted by superscript *k*. Preferably orthonormal patterns, which become Hopfield net Eigen states (attractors), can be complex-valued and can be quantum-encoded into the net-state $\vec{q}(= \sum_k c^k \vec{v}^k)$. For the quantum implementation, we will henceforth use the quantum notation, i.e. Ψ corresponds to $\vec{q}$, and Ψ^k corresponds to $\vec{v}^k$ ($= A^k$ if non-oscillatory). Wave function Ψ describes the whole state of the quantum system/net; k describes the kth of its Eigen states. Thus, images are assumed to be encoded into quantum Eigen-wave-functions k. It is: $\Psi = \sum_k c^k \psi^k$. The images (if huge and random) and quantum Eigen states share the orthonormality property.

For quantum-physical realization, like neural nets and holography, there is a storage and preparation phase governed by (5.1), and a "collapse"-like retrieval or measurement phase governed by (5.2). Associative memory matrix J consists of interaction-weights J_{hj} which are correlations (from quantum perspective, junctions in wave-interference array) of unit-states Ψ_j (j,h=1,…,N, for N units; N is huge):

$$J_{hj} = \sum_{k=1}^{p} \psi_h^k (\psi_j^k)^*, \tag{5.1}$$

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