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Comparison between Ising Hamiltonian and Neuro-inspired Hamiltonian for Quantum Associative Memory

In order to enlarge the applicable fields of quantum computing, it has been investigated the fusion of neural and quantum computing because neural computing has succeeded to provide conventional computers with an effective way to obtain new algorithms by learning [1]. Thus, some pioneers have investigated the quantum analog of neural networks, for example, Ventura et al. proposed a quantum associative memory (QuAM) by introducing quantum dynamics into neural associative memory [2]. They used quantum logic gates to memorize patterns and modified Grover’s database search algorithm [3] to recall memorized patterns. Contrary to the previous study, we studied another approach to realize a QuAM in consideration of its hardware implementability. In this research, we propose a novel QuAM achieved with a qubit network by employing adiabatic Hamiltonian evolution [4]. To study the details of its dynamics in memorizing and retrieving procedure, we examine two types of Hamiltonians to memorize patterns; Ising Hamiltonian [5] which has diagonal elements and is similar to cost function of Hopfield network, and neuro-inspired Hamiltonian [6, 7] which has non-diagonal elements and is based on interactions of arbitrary two qubits. Numerical simulation results indicate that the proposed methods for memorizing and retrieving patterns work well with both types of Hamiltonians. The difference of the two Hamiltonians appears when we evaluate the probability of retrieving a target pattern with a one-bit flipped key input. When the number of memorized patterns M is small, the retrieving probability of the QuAM with an Ising Hamiltonian is larger than that with a neuro-inspired Hamiltonian. When M is getting larger, the difference of the retrieving probabilities is getting smaller. This dissimilarity is probably caused by the size difference of search space. On the other hand, the difference of the Hamiltonians doesn’t influence the memory capacity M_{cap} of the QuAM which reaches 2^{N-1}, where N is a number of qubits. In fact, the average retrieving probability of the QuAM exceeds 70% for 4-qubit patterns no matter which Hamiltonian you choose. Therefore, we can conclude that the choice of which Hamiltonian to adopt depends on the hardware implementation feasibility.

Because M_{cap} of a conventional neural network is limited to at most 0.14N [8], the large memory capacity of the QuAM would be a big advantage.

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