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Can associative memory be modeled by quantum information?

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Associative memory is the ability to reveal similarities between unrelated items. Models of associative memory typically rely on significant assumptions about information encoding procedure, structure of underlying complex network, computational power of nodes, and communication capacity of links. Keeping assumptions plausible and at minimum, the search for association can be done on a network enhanced with quantum information processing exploiting non-locality and quantum state comparison.

KEYWORDS

association, memory, quantum information, entanglement, network

Introduction

The only definite thing we know about associative memory is that the brain does it much better than we can simulate it [1]. Many advanced models that incorporate different features of associative memory have been suggested to exploit classical [2] and quantum information processing [3]. Arguably, the most successful model so far—dense associative memory by Krotov and Hopfield [4]—powered by condensed matter physics methods and non-linear dynamics seems structurally and computationally excessive compared to neurons firing almost identical electrical signals, getting the job done quickly and at low energy cost [5].

Typically, associative memory models draw on the full arsenal of physics, computer science, and engineering to incorporate as much data from neuroscience as possible [see for example [6] and references therein]. In this Brief Report, I take a different approach. Rather than attempt to mimic actual brain functionality, I look for the minimum requirements to establish an abstract association.

At a most philosophical level, the search for similarity implies comparing two or more instances of information, which could be distantly located. When formulated this way, it seems natural to engage such quantum information processing features as quantum non-locality and direct quantum state comparison [7] to search for association. While non-locality makes physical location of the information units irrelevant, the direct state comparison gives a natural distance measure to conclude on similarity.

In the following, I consider a (classical) network enhanced with quantum information processing and show that the search for association can be done making the least assumptions about the structure of the network, the processing capabilities of the nodes, and the communication capacity of the links.

Results

Suppose we are given a connected network comprising processing and storage units (nodes) and communication channels (links). Information is stored on the nodes in some form, for example, as a bit string $x = \{0, 1\}^n$ of size n. Information may be stored on a single node or, in case of limited node's capacity, may be distributed over a cluster of nodes. In the latter case, it is reasonable to assume a uniform rule of how to store distributed information so that nodes in two clusters of similar content also carry similar pieces of information. For example, cluster A consists of five nodes x_i and $i = 1...5$ sharing a unit of information. Cluster B is similar to cluster A if contains x'_i so that x_i is similar to x'_i, i.e., $\Delta(x_i, x'_i) \ll \varepsilon$ for all i in a cense of some distance measure Δ. The clusters may have different size and connectivity, but the five strings i must be pairwise similar; otherwise, the problem to find association becomes ill-defined.

The nodes can communicate information over the links they share with their neighbors. Let me first suppose the nodes can encode all information they possess into an electromagnetic signal and communicate it. Then, the signals in the network are to be all different in their amplitudes and frequencies. Massive data exchange of all-different signals would be energy inefficient. Interestingly, this assumption contradicts evidence of brain operation [1]. Rather, the brain keeps data traffic low using almost identical signals. Therefore, let me assume the signals communicated over the links are to be (identical) quantum photonic states accompanied with at most few bits of classical information.

Let me also assume non-classical information processing in the nodes. Based on the classical information encoded into bit strings x_i, the nodes can generate strings of quantum states—qubits $|x\rangle_i$. There is no physical limitation on the number of quantum copies to generate from a piece of classical information [7]. In addition, each node must be capable to generate entangled states of photon to send one photon of the pair to its neighboring node through the link, keeping the other.

The above setup is, in fact, sufficient to search for association. Node Alice has information encoded in quantum state $|\psi\rangle_A$. Having shared an entangled pair with node Bob, Alice teleports her state $|\psi\rangle_A$ to Bob's location sending two classical bits of information per qubit with the next entangled photon as required by the teleportation protocol (see Methods). Roughly speaking, instead of communicating information itself Alice creates a quantum image of information she posses and teleports it to Bob for comparison.

Bob can directly compare his quantum state $|\psi\rangle_B$ with that received from Alice using natural distance measures of quantum theory. There are many slightly different ways for Bob to compare the two states he has: direct state comparison, projective measurement or positive operator valued measure (POVM) [8]. Ultimately, Bob gets single number, which represents the degree of similarity (distance) between $|\psi\rangle_A$ and $|\psi\rangle_B$, i.e., fidelity $F = |\langle\psi_A|\,\psi_B\rangle|^2$.

If fidelity is closer to unity, $|\psi\rangle_A$ and $|\psi\rangle_B$ are similar, meaning that Alice and Bob possess similar classical information. Imperfections in entangled pair generation and transmission may require repeating above procedure, which, however, does not affect the conclusion about similarity of the quantum states and corresponding classical information.

The search looks almost the same if Alice and Bob are not directly connected with a link because quantum networks permit creating non-local links with distant nodes [9, 10] by entanglement swapping [7]. Alice shares an entangled state with her neighbor Charlie, who is also neighbor for Bob, while Alice and Bob are not directly connected. Charlie separately checks similarity of his state $|\psi\rangle_C$ with Alice's state $|\psi\rangle_A$ and Bob's state $|\psi\rangle_B$ and if no similarity found, he performs swapping on entangled qubits received from Alice and Bob making them share an entangled pair, which may be understood as a virtual link [7]. Charlie tells Alice and Bob from which link he received the entangled pairs he swapped, so both Alice and Bob know the path they need to communicate in case their states are found to be similar.

In fact, any two nodes in the network can compare quantum copies having as many entanglement swapping on the way as the distance between them. Luckily, complex highly connected networks often exhibits small-world structure, i.e., the average distance between two nodes growth logarithmically with the network size [11], so it can be safely assumed in this model that the distance between any two nodes is relatively small, making multiple entanglement swapping practical.

Discussion

If Alice and Bob both belong to distant clusters and found similarity between their information, they may instruct other members of their clusters to check for similarity. Taking into account the arsenal of quantum information processing, comparing two clusters for similarity does not seem a problem, rather what is the optimal way, in terms of information encoding and the distance measure choice? Clusters of course may be of different size, but is it better to use just average fidelity for most similar information or have some sort of state mixing before comparing, e.g., quantum hashing?

The model as it is presented here relies on two fundamentally non-classical features: the possibility to compare two quantum states without their direct communication (teleportation), and fundamental non-locality of quantum networks that allows us to connect two distant nodes. Due to extreme simplicity of the suggested model, there are indeed many technical aspects to speculate about. An interesting option is to use POVM to establish similarity. Some sets of POVM are compatible, i.e., can be measured together with no effect on each other, while the others are not. This unique feature of quantum measurements can be of great use in models for associative memory. Consider two POVM measurements on a qubit $A_\pm(\mu) = \frac{1}{2}(I \pm \mu\sigma_x)$ and $B_\pm(\mu) = \frac{1}{2}(I \pm \mu\sigma_z)$, where $1 - \mu \in [0, 1]$ describes noisy spin measurements along x and z directions [8]. The measurements $A_\pm(\mu)$ and $B_\pm(\mu)$ are compatible, that is, jointly measurable for $\mu \leq \frac{1}{\sqrt{2}}$, while they are not compatible, that is, influence outcomes of each other for $\mu > \frac{1}{\sqrt{2}}$. Bob may vary the parameter μ depending on the number of entanglement swapping that separates him from Alice. The purpose is to target the distance to search for similarity. If, for example, the distance is less than three, Bob keeps POVM compatible; otherwise, he tunes μ to the regime, when POVM are not compatible.

Recent experimental advances in single-photon manipulations and detection [12–17] make the proof-of-principle experiment feasible, but understanding the collective dynamics of a complex quantum network [18, 19] with associative memory functionality requires the development of an accurate theoretical model that incorporates quantum information processing and machine learning [20, 21] with the latest neuroscientific findings.

Interestingly, synchronization in electromagnetic spikes in the brain [1] fits into the model because synchronization in entangled states exchange reduces the requirement to store entanglement before teleportation. The quantum state of a cluster may be repeatedly modified by a single node, which may be a reason to overwrite the classical memory [10]. Direct state comparison may be used not just for association search but for quantum machine learning [22]. Noise could make some paths more or less favorable for association [23]. It could even be that quantum information processing on network [24] may actually occur in the brain [25] and, exactly due to its spooky nature, may help demystify the origin of consciousness.

Methods

The four maximally entangled two-qubit states form Bell basis and are given by

$$|\psi_{\pm}\rangle = \frac{|00\rangle \pm |11\rangle}{\sqrt{2}}, \qquad |\phi_{\pm}\rangle = \frac{|01\rangle \pm |10\rangle}{\sqrt{2}}.$$

To teleport a qubit state $|\kappa\rangle$, Alice shares with Bob state $|\psi_{\pm}\rangle_{AB}$, so that each of then hold one qubit of the entangled pair. Then, Alice measures $|\kappa\rangle$ and her entangled qubit in the Bell basis and communicates result of her measurement to Bob via a classical channel.

Entanglement swapping is performed by Charlie, who shares entangled states both with Alice $|\psi_{\pm}\rangle_{AC}$ and Bob $|\psi_{\pm}\rangle_{CB}$. Charlie measures his qubits from the entangled pairs in the Bell basis and communicates the result of his measurement to the other parties. As a result, Alice and Bob share an entangled state, while Charlie is excluded from their communication.

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Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

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