Artificial Neural Network Decoding for the Surface Code

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Surface codes are one of the leading quantum error correction schemes to implement fault-tolerant quantum computing. With remarkable recent progress in quantum hardware development, quantum devices are approaching sizes and error rates required to already demonstrate small-scale surface code implementations [1]. One of the challenging aspects in the working of surface codes is to construct an accurate and efficient classical decoder which can process syndrome measurements over large qubit arrays and suggest appropriate corrections. Leading classical algorithms for the processing of syndrome measurements, such as minimum weight perfect matching (MWPM) [2], can achieve satisfactory decoding accuracy. However, demonstrating acceptable performance in real-time remains an open problem. More recently, artificial neural networks (ANNs) have been investigated for this task and have shown promising results on small systems and/or when implementing single logical qubit memory operations [3,4,5,6]. We have developed an ANN decoding technique readily applicable to large-scale systems (consisting of up to four million physical qubits) and demonstrated its working with microsecond latency [7]. The ANN decoder is benchmarked for surface codes subject to a variety of noise models and containing multiple logical qubits in configurations facilitating multi-qubit logical operations. We discuss possible generalizations using techniques applicable in a fault tolerant setting where errors can occur during syndrome measurement circuits and logical operations.

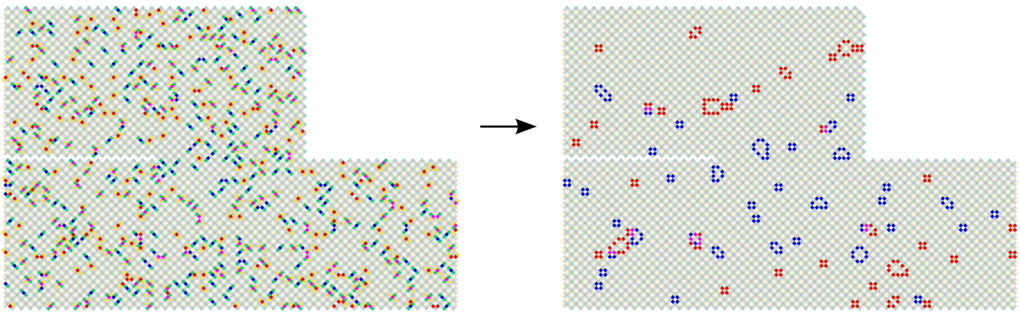

Figure 1: A system of merged surface code patches experiencing depolarizing noise and subsequent correction with ANN decoding.

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