Polarization-Based Data Reuploading

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Abstract

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***Abstract*— We propose imperfection-tolerant optical machine learning of data reuploading by polarization rotation. While the conventional optical unitary transformation method is impractical due to prohibitively high requirement in its optical coupler accuracy, the proposed method eliminates the couplers at comparable performance in a classification task.**

Keywords—optical computing, data reuploading, polarization

I. Introduction

Advancements of artificial intelligence is supported by classical computing, which causes significant increase in power consumption. This situation leads to the demands of alternative computing schemes such as quantum computing and optical computing [1, 2]. As a quantum machine learning, data re-uploading was proposed for solving classification tasks [3], which repeatedly applies parameterized unitary operations to input data. This is a quantum algorithm, but is implementable with classical optical components, e.g., 2×2 unitary transformation on photonic integrated circuits [4].

The optical data reuploading is implementable with 50:50 directional couplers and phase shifters without optical nonlinearity operations [5]. On the other hand, this method is vulnerable to the imperfection of the coupling ratios and easily degrades the performance in the classification tasks. Thus, in this work, we propose a novel method of polarization-based data reuploading. It newly introduces the use of polarization controllers and can exclude the couplers required in the previous work. Based on the straightforward implementation method of the polarization-based data reuploading, we further examine several modifications in data embedding for reducing the number of the optical components at almost the same performance in a classification task.

II. Principle

We summarize the schematics of the conventional and the proposed methods in Fig. 1, where Figs. 1(a) and (b) show the ones with quantum hardware [4] and optical unitary transformation [5], respectively. In the original quantum algorithm, data-dependent and trainable parameter operations are alternately performed on a single qubit [4]. Trainable parameters are optimized through classical machine learning to map inputs to correct class assignments. A single qubit state is plotted on the Bloch sphere (initially |0>), and each operation $U(\ )$ changes the location. The classification is based on the final location (northern or southern hemisphere). This can solve complex classification problems with sufficient layers [6]. The

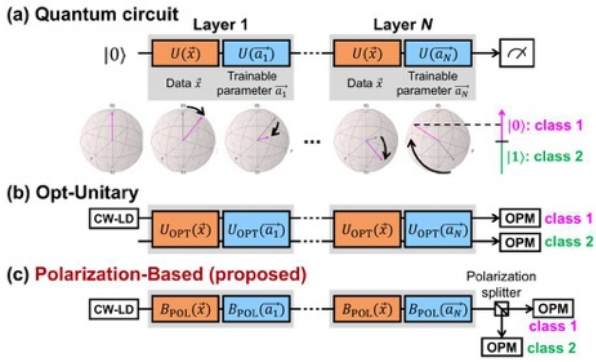

Fig. 1 Schematics of data reuploading by (a) quantum circuit, (b) optical unitary transformation, and (c) proposed polarization-based methods. The orange and blue boxes represent operations determined by data and trainable parameters, respectively. CW-LD: continuous wave laser diode; OPM: optical power monitor.

optical unitary transformation method holds the mathematical equivalence between qubits and optical wave representations, with classification determined by comparing output port intensities. This method requires a directional coupler and three phase shifters for a single arbitrary rotation gate denoted by $U_{OPT}(\ )$.

Fig. 1(c) shows the schematic of the proposed method. With the orthogonal decomposition, a polarization state form a two-dimensional complex vector analogous to a single qubit. We manipulate these states by polarization controllers [7] having two parameters of the tilt angle $\alpha/2$ and the phase shift δ. Such a polarization state is plotted on the Poincaré sphere for a given parameters, e.g., $\alpha/2 = \pi/4$ rotates around the X-axis by δ, while $\alpha/2 = 0$ rotates around the Z-axis by δ.

Fig. 2 shows the details in the single layer of the proposed method. Fig. 2(a) is a three-polarization-rotator (Z-X-Z) configuration for arbitrary polarization rotation $B_{POL}(\ )$ requiring for a complete data reuploading. Classification results are obtained by comparing intensities in orthogonal polarization components. While the ZXZ configuration offers complete rotational freedom, the three-polarization-rotator configuration is complex and errors will increase due to the high complexity. We expect that most classification tasks would have some redundancy and would not require such complete universality in machine learning circuit. We therefore introduce a full degree of freedom (full-DoF) method that utilizes all available parameters for both data encoding and training to compress the hardware scale. Fig. 2(b) shows the full-DoF configuration. The full-DoF configuration can reduce the polarization controller by 3 times

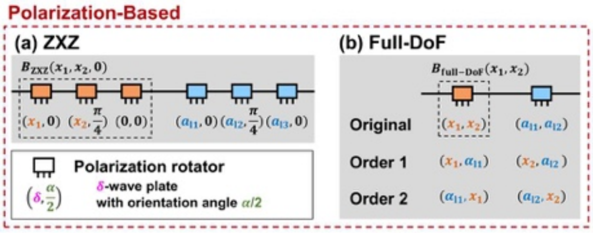

Fig. 2 Single layer schematics for the proposed (a) ZXZ and (b) full-DoF methods. Each black dotted rectangle is the minimum building block.

in this case (just one component per minimum building block), at hopefully comparable performance with the ZXZ configuration. Furthermore, we introduce additional options to full-DoF method in terms of the embedding allocation of data and trainable parameters, as shown in Fig. 2. The order 1 embeds the data to only the phase shift δ, while the order 2 to only the tilt angle α/2.

III. Results

Here, we compare the proposed methods with the conventional ones through numerical simulations with a binary classification task of points (x_1, x_2) as inside or outside a circle.

We firstly evaluates only the proposed methods to find better options. Fig. 3 shows the test accuracies as a function of the number of (a) layers and (b) polarization rotators. In Fig. 3(a), full-DoF performance meaningfully depends on the embedding order. While the best performance is given by the order 2 for 1 to 6 polarization rotators and by the order 1 for 7 polarization rotators or more, respectively. In Fig. 3(b), every full-DoF methods shows better performance than ZXZ at a small number of polarization rotators. In both Figs. 3(a) and (b), full-DoF (original) and full-DoF (order 2) show the limited performance compared with the others. An example of the classification results for full-DoF (original) is shown in Fig. 4(a), where the vertical (x_2) classification performance is low. The possible reason would be that the tilt angle α/2 has smaller influence on the classification than the phase shift δ. Note that the limited performance of full-DoF (order 2) at the large numbers of layers and polarization rotators might be caused by a similar mechanism.

According to the results for the proposed methods above, we choose ZXZ and full-DoF (order 1) as the representatives for the proposed methods. Fig. 4(b) shows the classification performance as a function of the number of layers for the conventional and the proposed methods. The proposed polarization-based ZXZ and full-DoF (order 1) achieved equivalent performance compared with the conventional methods by quantum circuit and optical unitary transformation. From the whole examinations in this work, the polarization-based data reuploading works well and thus we can avoid the use of the directional couplers required in the optical unitary transformation method. Moreover, the full-DoF (order 1) is expected to be the best choice for balancing the classification performance and hardware complexity.

IV. Conclusion

We proposed and numerically evaluated polarization-based data reuploading. With this method, the compression of the

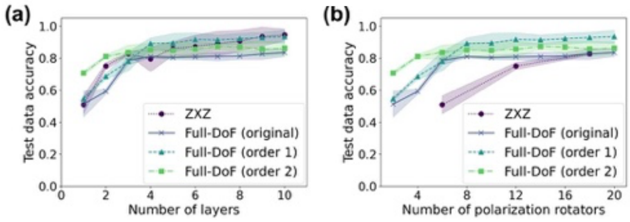

Fig. 3 Classification performance of the proposed methods with several options obtained by numerical simulation; dependence on the numbers of (a) layers and (b) polarization rotators.

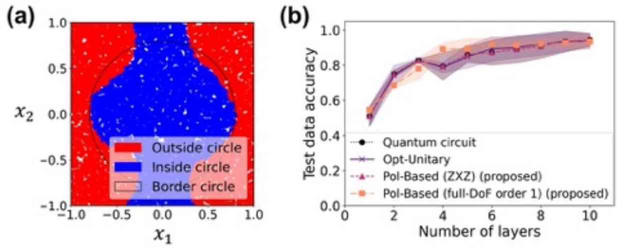

Fig. 4 Classification performance obtained by numerical simulation: (a) Classification results of original full-DoF (original) with 10 layers; (b) comparison of the conventional and the proposed methods.

hardware scale by full-DoF, utilizing all available parameters for both data encoding and training, having a proper allocation of the data and training parameter embedding to the phase shift and tilt angle in the polarization rotation. With the best setting of the embedding allocation, the proposed method with full-DoF shows comparable performance with the conventional methods by quantum circuit and optical unitary transformation (under the use of ideal directional coupler) at 3 times fewer optical components than the complete configuration of ZXZ. Future work includes the analysis on the influence of the hardware imperfection for the polarization-based data reuploading to further examine the feasibility.

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