Determinating Full Parameters of U-Matrix for Reconfigurable Boson Sampling Circuits using Machine Learning

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Abstract: A method of tuning a reconfigurable silicon photonic circuit into an arbitrary unitary operator with machine learning was proposed to bypass the traditional phase-voltage calibration process and make the prediction of applied heating voltage directly.

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1. Introduction

Silicon photonic chip based optical circuit has advantages to be in large size fabrication and phase reconfigurable, comparing with free space and laser writing technologies. Thus such large reconfigurable silicon photonic optical circuits can be tuned to realize arbitrary unitary operator with sufficient modes and phase shifters [1]. However, the beam splitter ratio error, phase-voltage calibration process, heater cross talks and many other conditions are hard to control, which make the real phase-voltage tuning process of realizing a specific operator quite difficult and complicate. Here, we proposed a new phase voltage adjustment method with machine learning to bypass these errors without doing calibration for each component.

2. Design and Working Principle

An *N*-mode optical circuit consists of *N(N-1)/2* Mach-Zehnder Interferometers (MZIs), that is *N(N-1)* beam splitters and phase shifters. It can represent an arbitrary $N \times N$ matrix *U(N)* [2] by tuning each phase shifter.

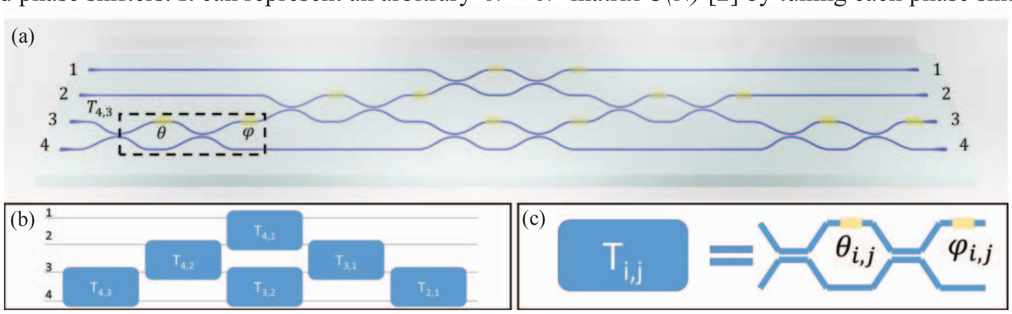

Figure. 1. (a) Demonstration of the proposed 4 mode chip based on silicon nanophotonic technologies; (b) Schematic of a 4 mode reconfigurable circuit consist of 6 MZIs; (c) Structure of a MZI unit controlled by beam splitters and phase shifters θ and φ.

In Figure 1. (a) we proposed a 4 mode reconfigurable circuit. The operator can be expressed as

$$U(4) = T_{4,3} \cdot T_{4,2} \cdot T_{4,1} \cdot T_{3,2} \cdot T_{3,1} \cdot T_{21} \cdot D \tag{1}$$

Where $T_{i,j}$ is the unitary operator of a MZI in Figure 1.(b), *D* is the diagonal matrix. The footnotes index *i, j* refer to the waveguide indexes and $T_{i,j}$ is expressed as

$$T_{i,j} = \begin{bmatrix} e^{i\varphi_{i,j}} sin\theta_{i,j} & e^{i\varphi_{i,j}} cos\theta_{i,j} \\ cos\theta_{i,j} & -sin\theta_{i,j} \end{bmatrix} \tag{2}$$

In real condition, however, the beam splitter is not exactly 1:1 and the optical length is not exactly identical. So the actual expression will be more complicated. Also, the phase-voltage relationship varies with each other and the coefficient should be carefully measured, then the cross talks between heaters have to be corrected [1]. These are complicated and costly processes so we want to introduce the machine learning method to tune the operator U into arbitrary form. We randomly set 12 phase shifter heating voltages $\{Vi\}$ and get the corresponding 16 matrix elements in absolute value square $\{|a_{i,j}|^2\}$. Such two sets of data could be the original input for machine learning. The algorithm in machine learning program was BP-AdaBoost and Figure 2 its flowchart and implementation steps.

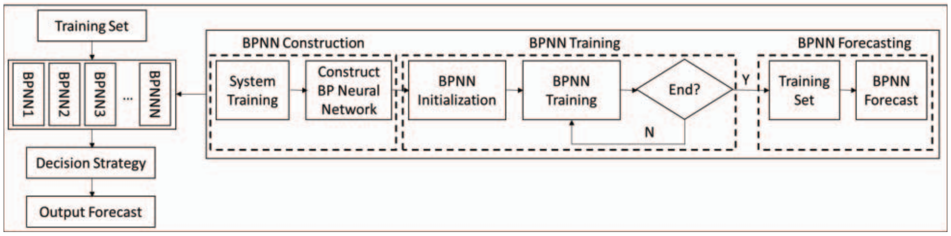

Figure.2. Flowchart of BP-AdaBoost algorithm and implementation steps.

3. Results and Discussions

Our current works were based on simulation. We generate the mathematical function of final matrix *U(4)* elements $\{|a_{i,j}|^2\}$ with variables of phase voltages $\{\varphi_i\}$. Then set the phase-voltage equation to be $\varphi(V) = \alpha + \beta V^2 + \gamma V^3$ [1]. We assigned the three parameters $\{\alpha, \beta, \gamma\}$ with random real numbers for 12 phase shifters. The heating cross talks between heaters were also considered. Finally we added some errors for 12 beam splitter ratios.

After the system initialization above, we randomly generated 10000 sets of voltages $\{Vi\}$ and calculated the corresponding matrix elements $\{|a_{i,j}|^2\}$, among which 9900 sets were for program training and the rest 100 sets were for prediction testing. The general results are shown in Figure 3. (a) that average absolute error for voltages range from 0.2 V to 1 V. The Figure 3. (b) shows the prediction results (red line) of voltage on $\theta_{3,1}$ for the 100 test sets. Most errors (blue line) are close to zero and the average error is 0.22 V. From Figure 1. (a) we can see the $\varphi_{4,1}$, $\varphi_{3,1}, \varphi_{2,1}$ (corresponding to voltage 9, 11, 12) mainly change the phases of final distributions and only have weak effects on the amplitude through heat cross talks. So the prediction error for them are relatively high. The Figure 3. (c) shows at the iteration time of 5, the program reaches the best performance.

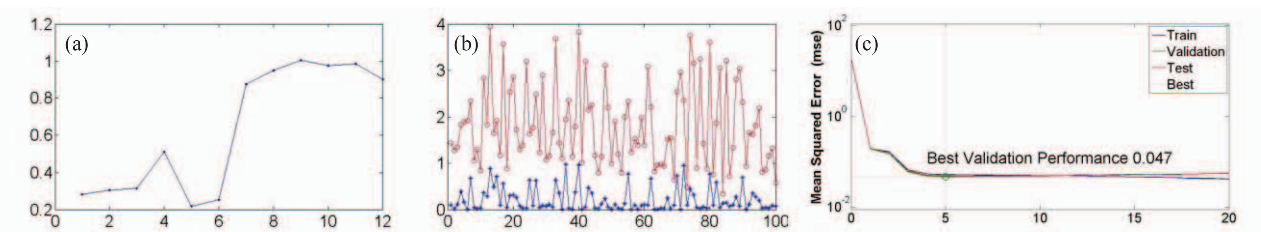

Figure.3. (a) The absolute average error of 12 voltage predictions after 10000 training sets. (b) The 100 predictions of Voltage on $\theta_{3,1}$ after 10000 training sets. The blue line represents the predicted results, red line represents the absolute error with real results. (c) The program reaches the best performance when iteration reaches 5 times.

4. Summary

We proposed a new method of tuning the reconfigurable optical circuit into a specific unitary operator by machine learning program. It simplified the traditional method of calibrating each single phase-voltage relation by building connections between distributions and voltages through the whole system and bypass the problems like heater cross talks, beam splitter ratios errors with machine learning. The simulation results were promising that the minimum error could be 0.22 V with large training sets and this new method would become a power tool for the study of quantum circuits.

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5. References

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