Inverse design of few-mode fiber by Neural Network for weak-coupling optimization

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Abstract: We use a neural network to inversely design a four-ring few-mode fiber for weak-coupling optimization so as to support MIMO-less MDM optical communication. This method provides high-accuracy, high-efficiency and low-complexity for complexed fiber design.

1. Introduction

Inverse design has many advantages over traditional methods. For example, inverse design is helpful to break the fixed geometric structure of traditional devices and increase the parameter space of devices. This method can apply efficient optimization methods to achieve design automation, improve the device's performance to its limit, and even achieve some significant functions that traditional device structures can hardly achieve. Therefore, inverse design has a tendency to replace the traditional complex physical design process and propose a set of simple and fast design tools.

In recent years, inverse design has played a key role in the design of various photonic integrated devices. It can be used to form arbitrary structures, including particularly wavelength demultiplexer on silicon-on-insulator (SOI) [1], and ultra-compact power splitter with a QR code-like nanostructure [2]. This method brings a lot of convenience to device design with the aid of various algorithms, such as direct binary search (DBS) algorithm [2], genetic algorithm [3], and so on. Among them, neural network (NN) has lately received great attention for its high-efficiency and low-complexity, and this algorithm has been used to design the integrated photonic power splitters in Ref. [4].

Inverse design has been used early in optical fiber design, such as the optimization of chromaticity dispersion [5], and recently for nonlinear frequency conversion [6]. Nowadays, along with the advent of 5G era, the capacity of optical fiber system has been getting more tense, which makes few-mode fibers (FMFs) very attractive for next generation space-division-multiplexed (SDM) optical communication. Considering the mode coupling of FMFs, MIMO technology is usually used to compensate the crosstalk, while brings in high energy consumption and high cost. In MIMO-less MDM transmission, the minimum effective refractive index difference $\Delta n_{eff,min}$ among modes is the main factor causing crosstalk. Weakly coupled FMFs with low $\Delta n_{eff,min}$ and small crosstalk among different modes can ensure low bit error without MIMO at the receiver. An elliptical-core FMF realizes $\Delta n_{eff,min} > 10^{-3}$ to reduce the mode coupling between modes in Ref. [7]. And there are also many other special structures, like rod-assisted FMFs [8] to achieve this goal. However, all these results employ the traditional physical model to increase the $\Delta n_{eff,min}$. The structure is relatively simple with limited optimization capability, while the complex structure design will tremendously increase the difficulty.

In this paper, we propose an inverse design method based on NN to optimize the structural parameters of ring-assisted FMFs that can transmit four modes (groups), and ultimately realize $\Delta n_{eff,min}$ of 1.24×10^{-3}. The advantage of this method is that the trained NN can calculate the optical fiber structure parameters corresponding to $\Delta n_{eff,min}$ values simply and quickly. In theory it can realize optical fiber design with arbitrary $\Delta n_{eff,min}$ values, and can also be extended to a broad variety of fiber structures and parameters.

2. Inverse design process and neural network structure

Fig. 1 shows our main design process. Our objective is to optimize the weak-coupling performance of FMF. Obviously, the structure of the optical fiber determines its performance. So, we put the structural parameters into the simulation software to obtain the performance parameters. This forward design will produce a data set that can be used to train the neural network. In the inverse design process, we put our target performance into the trained NN to obtain the structural parameters. Finally, we can use these parameters to design FMFs that meet our initial requirements.

In our specific design process, we choose a ring-assisted optical fiber that can transmit the first four modes (the fundamental mode LP_{01}, and the higher-order modes LP_{11}, LP_{21} and LP_{02}). Its cladding is based on glass material, which has a refractive index of 1.445 at 1550 nm and a diameter of 125 um. The core of the optical fiber consists of four rings (shown in Fig. 2(c)), each of which has a core refractive index and a core radius. From the above analysis, we can see that we should make $\Delta n_{eff,min}$ as large as possible. We can obtain $\Delta n_{eff,min}$ from the effective refractive index of the four supported modes in the FMF (shown in Fig. 2(a)). We put $[r_1, r_2, r_3, r_4, \Delta n_1, \Delta n_2, \Delta n_3, \Delta n_4]$, into the simulation software (Lumerical) where r_i is the core radius, Δn_i is the refractive index difference between core and cladding, $i = 1, \dots, 4$, and then obtain $[n_{eff,01}, n_{eff,11}, n_{eff,21}, n_{eff,02}]$, where $n_{eff,mn}$ is the effective index of the LP_{mn} mode. We generate a data set, with $M = 6561$ elements, setting core radius and refractive index difference to uniform distribution: $r_1^i \sim U[7.2, 7.6]um$, $r_2^i \sim U[6.7, 7.1]um$, $r_3^i \sim U[6.2, 6.6]um$, $r_4^i \sim U[5.7, 6.1]um$, $\Delta n_1^i \sim U[0.008, 0.012]$, $\Delta n_2^i \sim U[0.0087, 0.0127]$, $\Delta n_3^i \sim U[0.0094, 0.0134]$, and $\Delta n_4^i \sim U[0.00995, 0.01395]$ for $i = 1, \dots, M$. This process took about 18 hours by our personal computer.

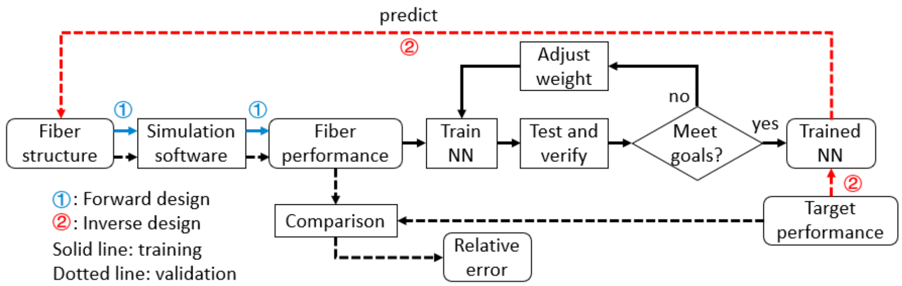

Fig. 1. Flow chart of the proposed NN assisted inverse design method.

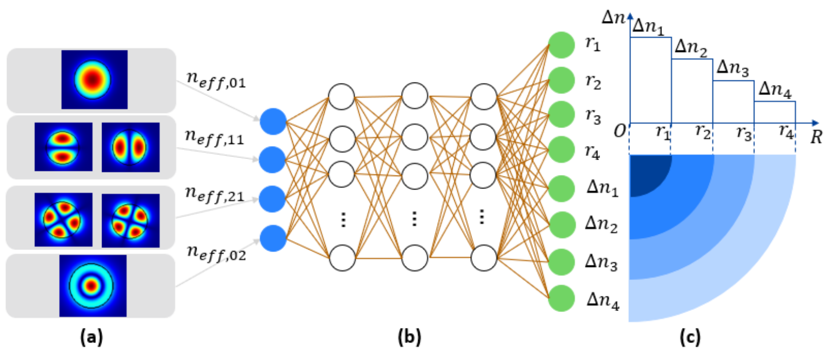

Fig. 2. The inverse design frame of NN. (a) The four modes (mode groups for LP11 and LP21); (b) NN structure; (c) 4-ring FMF structure

Then this data set is used to train the NN. As shown in Fig. 2, the effective refractive index of modes $[n_{eff,01}, n_{eff,11}, n_{eff,21}, n_{eff,02}]$ is NN's input, and the FMF structure $[r_1, r_2, r_3, r_4, \Delta n_1, \Delta n_2, \Delta n_3, \Delta n_4]$ is the output. We used Keras, an open source artificial NN library written in Python, to construct this NN. We used a sequential model with three hidden layers where each layer has 300 neurons. In this process, we tried to adjust different activation functions, so that the NN has better performance. The optimizer is Adam algorithm with good universal performance. Besides, we did a visual normalization to handle the original data for avoiding over-fitting. The training is terminated after a certain number of iterations. We can preliminarily determine whether the training effect of NN is perfect by checking the output relationship between the actual value and the predicted value. The number of iterations can also be adjusted within a certain range so that the error of training results can be within a relatively small range. The training took about 15 minutes. Then we formulated some data, $[n_{eff,01}, n_{eff,11}, n_{eff,21}, n_{eff,02}]$, based on the optimization objective $\Delta n_{eff,min}$ and put it into the trained NN to get the predicted values of FMF's structure. This process is almost instantaneous. The criterion for judging the perfection of the whole design is whether the difference between the pre-formulated $n_{eff,mn}$ values and the predict $n_{eff,mn}$ values obtained by putting the predicted structure parameters into the simulation software is small enough.

3. Results and analysis

Element $\Delta n_{eff,min}$ in the data set ranges approximately from 7.763×10^{-4} to 12.494×10^{-4}. In order to satisfy the requirement of weak coupling, we drawn up 100 $\Delta n_{eff,min}$ data in the range of $(8.8 \times 10^{-4}, 12.5 \times 10^{-4})$, and respectively formulated 100 sets of $[n_{eff,01}, n_{eff,11}, n_{eff,21}, n_{eff,02}]$ ($\Delta n_{eff,min}$ is a second-order parameter because there is no one-to-one mapping relationship between $\Delta n_{eff,min}$ and FMF's structure, while $n_{eff,mn}$, which is directly related to the NN, is a first-order parameter). These are actual data, and predicted data can be obtained by the above analysis. In order to evaluate the prediction accuracy of multiple sets of data, we use correlation graphs to compare actual data with predicted data. The correlation coefficient of the $n_{eff,mn}$ prediction is as high as 0.9997 for LP01, 0.9996 for LP11, 0.9992 for LP21, and 0.9993 for LP02, indicating good predictability. And the correlation of Δn_{eff} (index difference between different modes) is above 0.99 (shown in the Fig. 3(a)). It can be observed that the predicted performance coincides well with the original target performance. It allows us to make a judgement that the predicted structure can reproduce $n_{eff,mn}$ and $\Delta n_{eff,min}$ in good agreement with actual data. For a larger formulated $\Delta n_{eff,min}$, the predicted results are also good. For instance, when the actual $\Delta n_{eff,min} = 12.4943 \times 10^{-4}$, the relative errors of the predicted value of $n_{eff,mn}$ are respectively 0.0025%, 0.0011%, 0.0002% and 0.0005%, compared with the actual value. At the same time, the relative errors of the predicted value of Δn_{eff} are 1.16%, 0.73% and 0.85% (the predicted structural parameter and its corresponding mode curve are shown in the Fig. 3(b) and (c)). Therefore, NN provides a new method for inverse design of FMFs with robust reliability.

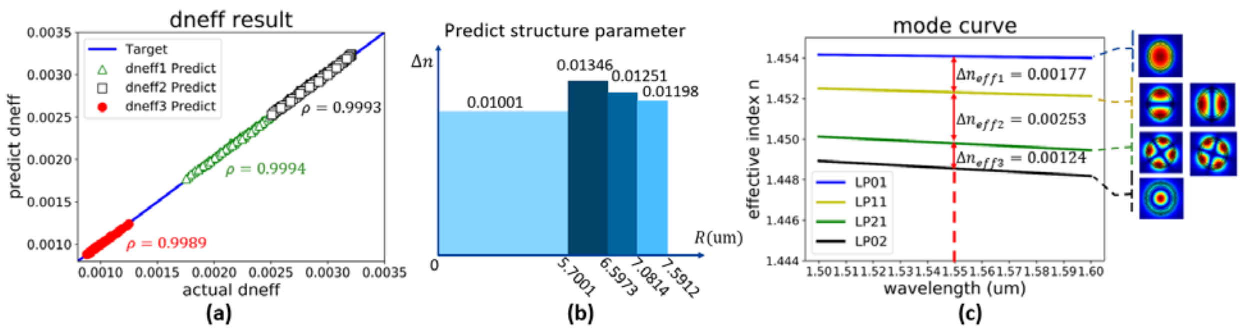

Fig. 3. (a) Correlation diagrams between actual and predict data to evaluate the design accuracy. (b) The predicted FMF structural parameter. (c) The predicted dispersion curve and field diagrams for the four modes.

By using NN in inverse design, we do not need to know the specific and complex mathematical or physical relationship between the structure and performance of FMFs. NN can automatically establish the mapping between input and output, which greatly facilitates our design. Besides, this method has a high universal applicability, because as long as there is a certain correlation between input and output, we can get an accurate prediction value by adjusting the weight of the NN. Once the NN is well trained, we can predict the structural parameters of the optical fiber instantaneously and this process is very fast. Compared with the traditional method based on physical principal [7, 8], the NN can get a relatively high accuracy result in a very short time. What's more, for any given specific value, such as $\Delta n_{eff,min}$ in this work, the optimized optical fiber structure can be inversely designed theoretically by this method.

4. Conclusion

We propose a novel method in this article to inversely design and optimize weakly coupled FMF. It has been demonstrated that neural network is an efficient tool to predict a ring-assisted FMF's structures of arbitrary effective index of modes. In this way, we have successfully designed an FMF's structure with a large $\Delta n_{eff,min}$ ($> 1.24 \times 10^{-3}$). Obviously, this proposed method can play an important role in the inverse design of FMFs with its good accuracy and low complexity.

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