Modes classification in multimode optical fibers with a deep learning network

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Introduction

Currently, multimode optical fibers are gaining popularity in both application and fundamental research [1]. In this kind of medium nonlinear interactions between different spatial modes drive to complex dynamics and enable new alluring phenomena. Studies of light propagation in multimode fibers could bring deeper understanding of nonlinear optics. They also address the great expectations concerning application in new telecommunication systems [2] and in high-energy fiber lasers [3]. Multimode optical fibers can support multiple guided modes for a given wavelength. Their number is determined by the optical frequency and the refractive index profile of investigated fiber. Each guided mode propagates in specific manner, which could be shown as its electromagnetic field distribution. Identification of linearly polarized (LP) modes is based on determining the number of extremes along two field cross-sections: radial and transversal. The field distribution of the same mode could be slightly different depending on wavelength and reflective index profile. To exhibit a dispersion characteristic for multimode fibers over a wide spectral range, a verification of refractive index value for a particular mode at a specific wavelength is needed. Manual verification of mode based on its field distribution is a time-consuming and error-prone process. To avoid these issues, we've used convolution neural networks (CNN) to accomplish the task [4].

Multimode optical fiber



To ensure compatibility between different data simulation programs we implemented the CNNs using MATLAB deep learning framework. We trained the convolutional neural network based on models that has been pretrained on the ImageNet data set [5]. In the end ResNet50 [6] model was chosen, as it achieves more accurate results on the simulated electromagnetic field patterns. First the image resolution of 224 \times 224 pixel was chosen to match the input layer of the pretrained ResNet CNNs, and then the network is fine-tuned on our training data.



Figure 2. Comparison of index profiles of graded- and step-index multimode fibers together with normalized electric of exemplary modes for step-index fiber: $LP_{0,1}$, $LP_{0,5}$, and $LP_{0,10}$.

In nonlinear fiber optics, studies consider fibers

Figure 3. Normalized electric field component E_x of LP₃₂ mode. m and I numbers indicate the number of extrema along two field cross-sections: radial and transversal.



Research objectives

We divided our research into two stages:

- 1) Attempt to distinguish modes from $LP_{0,n}$ family for 4 fibers with different index profiles and size of core diameter, but the same wavelength:
 - **1** step-index: $\Phi = 50, 105, 200 \,\mu m$,
 - **2** graded-index: $\Phi = 200 \,\mu m$.
- Classify modes in few fibers with refractive index profile changing smoothly from step to graded with core diameter $\Phi = 10 \,\mu$ m in wide spectral range from 400 nm to 2500 nm.

that support up to hundreds of modes. The number of modes tells us how many ways light can propagate throughout the fiber. The electric field of linear-polarized (LP) mode p is equal $\mathbf{F}_{p}(x, y) = e^{c}F_{p}(x, y)$, where $c \in \{x, y\}$ for each linear polarization. The field distribution of the same mode could be slightly different for refractive index profile and different wavelength. Gradedand step-index refractive index profile n(r) was presented in Fig. 2, while dependence of chromatic dispersion, defined as $D = \frac{-\lambda}{c} \frac{d^2 n(\lambda)}{d\lambda}$, on wavelength for some modes was shown in Fig. 4.

> **Figure 4.** Normalized E_x field component of mode solutions in multimode fiber.

Bibliography

Conducted experiments

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Confusion Matrix for Test Data													
LP01	109	18										85.8%	14.2%
LP02		93	34									73.2%	26.8%
LP03			78	49								61.4%	38.6%
LP04				71	56							55.9%	44.1%
LP05				2	69	56						54.3%	45.7%
LP06					1	63	62	1				49.6%	50.4%
I P07						3	71	48	2	1		56.8%	43.2%



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Acknowledgments

Project "Nonlinear phenomena in multimode fibers - multimode solitons and frequency conversion" is co-financed by the National Science Centre, Poland (2018/30/E/ST7/00862).

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and row summaries in conducted studies for first formulated

problem - distinguished modes from $LP_{0,n}$ family. Model act

better with smaller number of extinguished extrema rings (for

Predicted Class

Figure 5. A picture of how machine learning improved mod Table 1. The precision and recall for each class by using column verification of modes for classical graded-index fiber. Problem with mode recognition remains in cases where the solver returns a distorted electric field. ML-asisted verification was based on the determination of coupling coefficients for normalized electric fields.

Conclusions

lower modes).

Our results demonstrate that the automation of mode recognition by using machine learning tools could improve achieved results. This study appears as a good starting point to prepare tool to make the recognition of the guided modes from recorded output spectrum from real live experiment.