Bending-Independent Imaging through Glass-Air Disordered Fiber Based on Deep Learning

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Abstract: We demonstrate a bending-independent imaging system for the first time by combining deep neural networks (DNNs) and a meter-long silica-air disordered optical fiber. High-quality artifact-free images can be reconstructed from the transported raw images.
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1. Introduction

The optical-fiber-based endoscope (OFBE) has important applications in biomedical imaging and clinical diagnostics, and different types of fibers were proposed for OFBE [1]. However, these solutions suffer from several limitations regarding system complexity, bending sensitivity, and image quality. For example, single mode fibers require complicated mechanical scanning heads; multimode-fiber-based imaging techniques are extremely sensitive to any movement or bending of the fiber; and images transported through multicore imaging fiber bundles will always be pixelated. Recent progress in light transmission through disordered optical fibers mediated by transverse Anderson localization provides a new solution [2-5]. With the disordered optical fiber, imaging can be performed without any extra lens or mechanical parts if the object is positioned adjacent to the input facet. Moreover, it has been proven that the image quality transported through polymer based disordered fiber can be better than that of images transported through the best multicore imaging fiber bundle [2]. In addition, the transversally localized states of the disordered fiber show bending-independent single mode properties [3]. Recently, a bending-independent imaging system based on glass-air Anderson localizing optical fibers (GALOFs) has been demonstrated [4,5], and GALOFs are expected to have even better performance than polymer based disordered fibers due to lower loss of glass materials and smaller beam point spread functions [2]. Even if the structural parameters of current GALOFs are still less than perfect which limits the quality of transported images, the progress of deep-learning based computational imaging can be utilized to eliminate artifacts from the transported images [6,7]. By combing deep learning and GALOF, it could be possible to design a simple, flexible and artifact-free OFBE.

In this work, we demonstrate experimentally that meter-scale GALOFs can transport bending-independent high-quality images of objects. This has been achieved without additional optical components by training of deep neural networks (DNNs). We show the recovery of objects when raw intensity image transported through a 90 cm-long GALOF are provided.

2. DNN training, experiment and results

A DNN attempts to generate a computational architecture that maps all input in a test set to their corresponding outputs based on a given training set. In our experiment, images of objects located at different working distances are transported through 90 cm of straight or bent GALOF and subsequently recorded by a CCD camera. The object reconstruction process can be described as:

$$X = HY_{measure} \quad , \tag{1}$$

where $Y_{measure}$ is the measured image matrix and X is the reconstructed image matrix. The pair, (X, $Y_{measure}$), corresponds to a test set, and H is an inverse operator that gives an estimation of the original object from the measurement. In past years, obtaining the inverse operator by solving the optimization problem has been studied in detail [8,9]. However, it requires accurate modeling and prior knowledge of the object. In contrast, DNNs can learn H from a provided training set and no prior knowledge of the object is required. The method applied here is an extension of a recent DNN study [7] which uses a convolutional residual neural network.

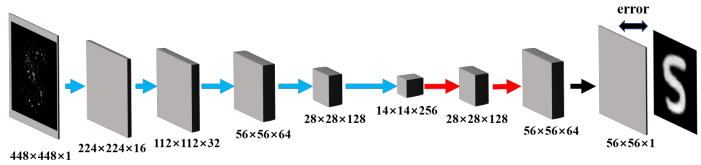

Fig. 1. Schematic of our DNN architecture.

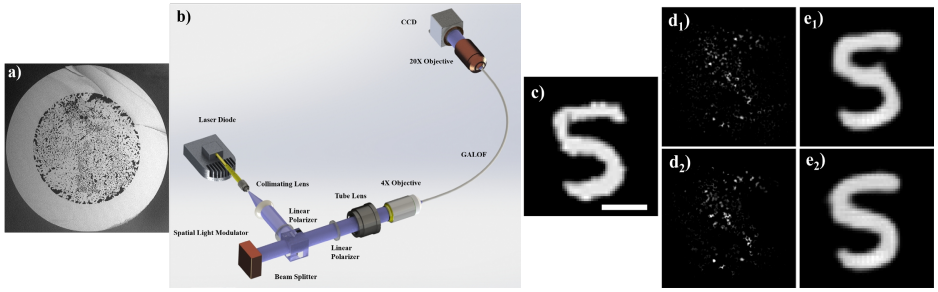

Fig. 2. a) SEM cross-section image of GALOF. The outer diameter is 414 μm and the diameter of the disordered core is 278 μm. The air-hole-fraction in the core is 28.5%. The air-hole feature sizes range from 0.8 μm to over 10 μm with a maximum in the size distribution around 1.6 μm. b) Imaging setup. c) A sample object from the MNIST database of handwritten digits. Image c) is projected directly into the GALOF input facet. d_1) Image of c) after transport through straight 90 cm of GALOF, and e_1) is the corresponding reconstructed image after DNN training. d_2) Image of c) after transport through the same GALOF which has been bent to form a 90 degree turn with a bend radius of 32 cm and e_2) is the corresponding reconstructed image using the same DNN training applied to the straight GALOF. The scale bar in c) is 45 μm.

The architecture of our DNN is shown in Fig.1. The input layer is a 448×448×1 pixel image cropped from the measured image. Then it is successively connected by five residual blocks of convolution+down-sampling (Fig. 1 blue arrows) followed by two residual blocks of deconvolution+up-sampling (Fig. 1 red arrows) and a single final standard residual block (Fig. 1 black arrow). At the very last layers of our DNN, the output represents an estimation of the object. The connection weights are trained by backpropagation on the mean absolute error between the network output images and the nominal appearance of the training images (Fig. 1 double-sided arrow) described as: $|X_{train} - G|/(wh)$, where w and h are the width and height of the output image, X_{train} is the output matrix of the last layer and G is the ground truth value matrix. We adopted an Adam optimizer in tensor flow with a batch size of 5, while the learning rate is set to 0.0001. The neural network was trained for 15 epochs with shuffling at each epoch.

The GALOF was fabricated at CREOL using fused-silica rods and tubes and the stack-and-draw method. A SEM image of the GALOF cross-section is shown in Fig. 2(a). The experimental arrangement is shown in Fig. 2(b). 405 nm laser light delivered by a single mode fiber is collimated by a lens (50 mm focal length). Then the light goes through the first polarizer oriented 45° with respect to the extraordinary axis of the spatial light modulator (SLM). The SLM (1920x1152 XY Spatial Light Modulator, Meadowlark Optics) is modulated by 8-bit grayscale input images (MNIST Digits). After reflection from the SLM, the beam goes through a second polarizer with the same polarization orientation as the first one. Then the imaging area of the SLM is projected onto the GALOF input facet directly by the combination of a tube lens and a 4x objective. At the output end of the GALOF the fiber facet is projected onto a CCD by a 20x objective. 2000 images from the MNIST dataset are fed into the system when the GALOF is straight to generate corresponding raw intensity images. These 2000 image pairs are used to train our DNN. The training time is 50 minutes on GPU (GTX 1070 Ti). Another different 200 raw intensity images are collected as the test set for both straight GALOF and bent GALOF. The values of mean absolute error on test sets are 0.038 and 0.043 for straight and bent GALOF, respectively. Results are shown in Fig 2. Fig. 2 c), d) and e) show the original object, raw intensity images and the corresponding reconstructed images. Comparing raw intensity images and the corresponding reconstructed images, it is apparent that our trained DNNs are able to recover the true images remarkably well and the reconstruction is independent of bending effect. Importantly, no retraining is required to reconstruct images transported through the bent GALOF.

3. Conclusion

In conclusion, we demonstrate the first bending-independent disordered optical fiber based imaging system where a trained DNN is utilized to reconstruct objects from raw intensity images transported through 90 cm of fiber.

4. References

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