Seeing Through Multimode Fibers

Tsarantanis Dimitrios, AM 4479
Ximerakis Ioannis, AM 4450

ABSTRACT

When images are propagated through multimode fibers (MMFs), the resulting output on the distal side is a speckle pattern. Using neural networks, the input images are reconstructed and classified from the intensity of these speckle patterns. Two methods were implemented for the classification, classifying the speckle patterns directly and classifying reconstructed images from the speckle patterns. This was performed for two different fiber lengths, 10cm and 1km respectively, using a dataset of 20000 speckle patterns of written digits.

INTRODUCTION

Multi-mode fiber (MMF) is a type of optical fiber that can transmit information through parallel channels. This makes it appropriate for use in telecommunications and endoscopy for medical diagnosis. However, when a pattern is projected on the proximal side of a MMF, the image received on the distal side is a speckle pattern since the input couples into multiple fiber modes, which travel with different propagation constants along the fiber length. Additionally, local defects along the fiber length induce mode coupling, which further randomizes the propagation of the input field. Therefore, the phase between local image features decorrelates fast after a few millimeters of a MMF, resulting in the formation of a speckle pattern.

Neural networks can be used on the speckle patterns and interpret the fibers' input. In this project a database of a large number of intensity speckle patterns is used. The database contains 20000 handwritten digits split randomly into a 16000 training set, a 2000 validation set and a 2000 testing set.

In the following section a rundown of the experimental setup is presented along with a figure of the optical system used to collect the data.

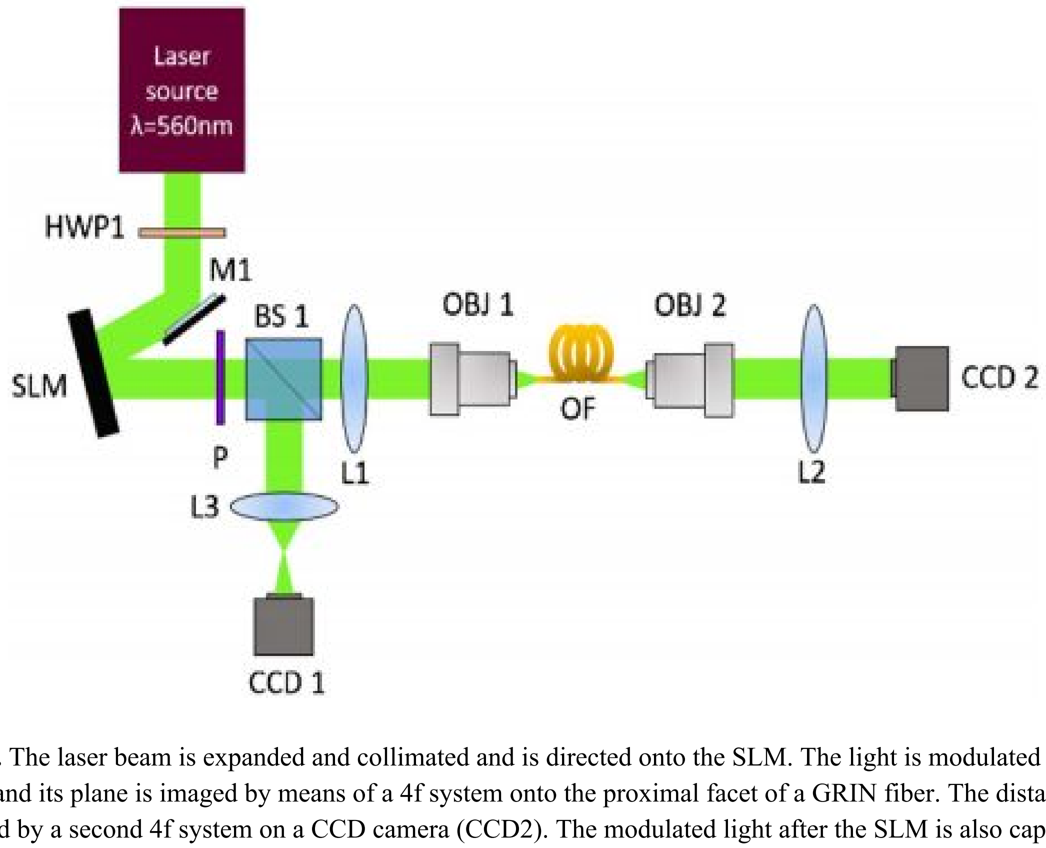


Fig. 1. The laser beam is expanded and collimated and is directed onto the SLM. The light is modulated by the SLM and its plane is imaged by means of a 4f system onto the proximal facet of a GRIN fiber. The distal facet is imaged by a second 4f system on a CCD camera (CCD2). The modulated light after the SLM is also captured by an imaging system in 2f configuration on the CCD1. HWP, half-wave plate; M, mirror; SLM, spatial light modulator; P, linear polarizer; L, lens; BS, beam splitter; OBJ, microscope objective lens; OF, optical fiber; CCD, camera.

The laser beam is used to illuminate a graded-index (GRIN) multimode fiber. The input patterns are displayed on a spatial light modulator (SLM), and the SLM plane is imaged onto the proximal facet of the MMF by means of a 4f imaging system. Another 4f system is placed at the distal end of the fiber to image the speckle pattern emerging from the distal facet on a camera. An additional camera is used on the proximal side to monitor the images reflected by the SLM. A half-wave plate and a linear polarizer are placed before and after the SLM (see Fig. 1), respectively, in order to test both phase and amplitude patterns as inputs to the GRIN fiber. The patterns generated by the SLM were handwritten digits from the MNIST database. Before being processed by the DNN, each image recorded by CCD1 or CCD2 is cropped to a 1024 × 1024 pixel window centered on the digit and the speckle, respectively. The cropped images of the speckle patterns recorded by CCD2 were then downsampled to 32 × 32 pixels and used as input for the DNNs.

An example of the projected digits at the proximal fiber facet is shown below, where the digit three is shown, along with the corresponding amplitude and phase modulation speckle patterns captured at the distal fiber end for 1km fiber length.

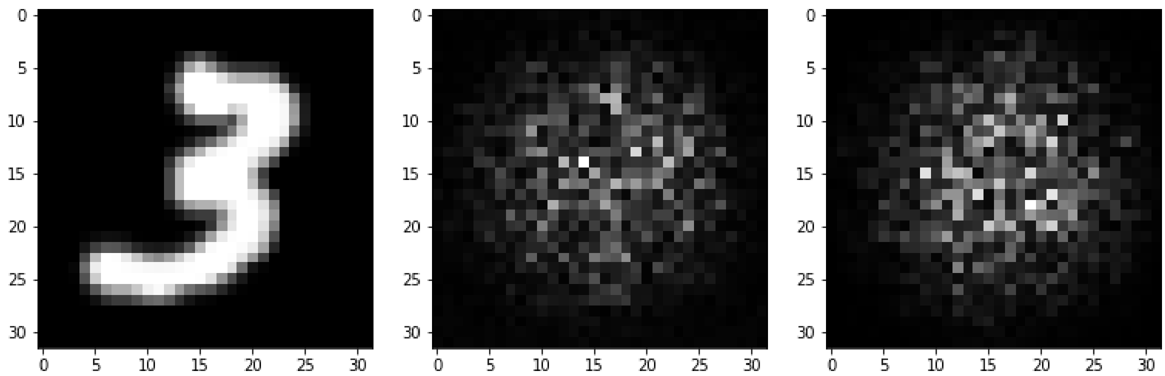


Fig. 2. a) Mnist digit, b) Amplitude modulated speckle pattern, c) Phase modulated speckle pattern.

The results presented are obtained by adjusting the SLM so that the patterns entering the fiber are phase-only or amplitude-modulated images of the digits. The goal is to classify both the amplitude and phase patterns and show that the classification performance is enhanced if the reconstructed images are used as input images.

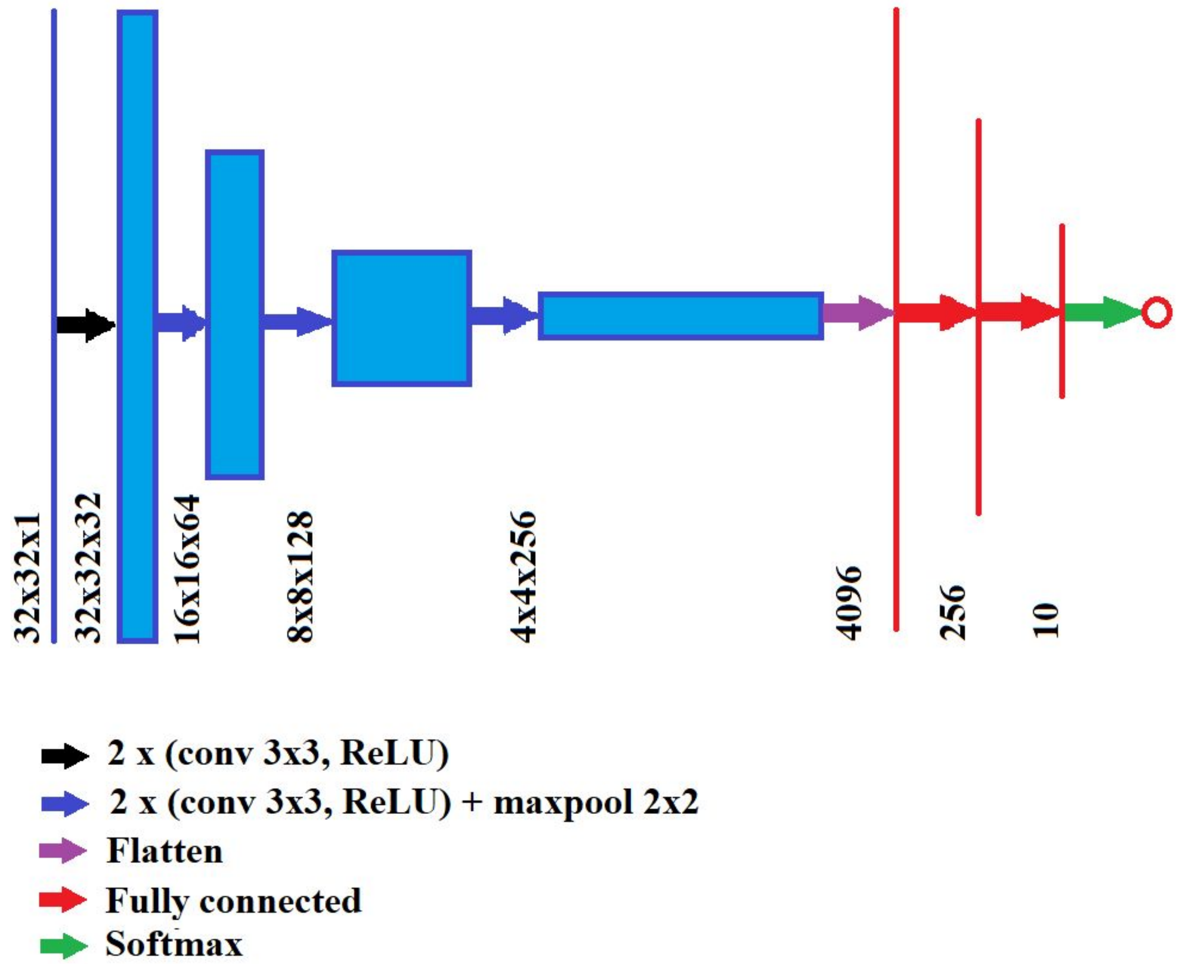
METHODOLOGY

Two methods were implemented to classify the speckle patterns to their corresponding digits. The first one uses a CNN classifier to classify the speckle patterns directly. The second method uses the same CNN classifier but the input images are reconstructed from the speckle patterns through the use of a U-net type network. Both methods are presented below in more detail.

A. Speckle Image Classification

A VGG type CNN was used to classify the distal speckle images. These networks consist of a convolutional front end with downsampling for encoding and a fully connected back end for classification. The obtained 20000 distal speckle pattern images were randomly split into 16000 training, 2000 validation, and 2000 testing sets. The training sets were processed in 500 image batches. An adam optimizer with a learning rate of 1 x 10^{-4} was used to minimize a mean square error cost function. The network was trained for a maximum of 50 epochs, using early stopping and dropout to avoid overfitting.

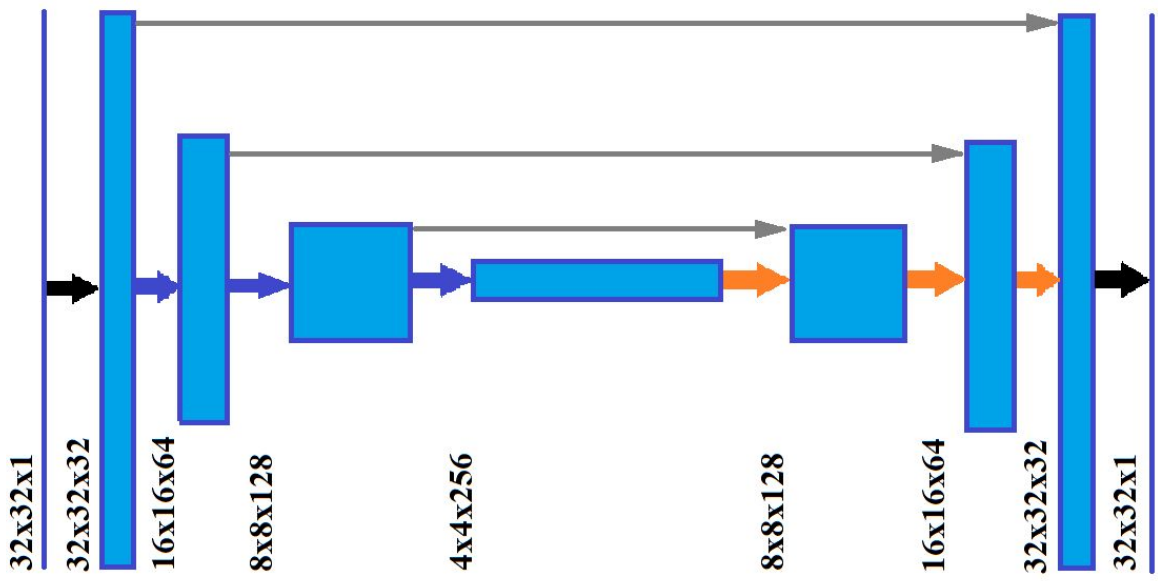
The basic architecture of the VGG type classifier is shown in the figure below.



B. Reconstructed Image Classification

A U-net type CNN with 14 hidden layers was used to reconstruct the SLM input image from the recorded distal speckle intensity pattern. This nearly symmetric network architecture comprises a convolutional encoding front end with downsampling to capture context and a deconvolutional decoding back end with upsampling for localization. Skip connections copy feature layers produced in the contracting path with features layers in the expanding path of the same size, thus improving localization. The same training and validation sets mentioned above were combined into one 18000 images training set. The training set was processed in 50 image batches with an adam optimizer with a learning rate of 1×10^{-4}. This network was trained for 35 epochs. After training, all 20000 images were reconstructed and split in the same way as before into a 16000 training, 2000 validation, and 2000 testing set. Then, the VGG type CNN network was trained with the reconstructed images.

The basic architecture of the U-net is shown in the figure below.



2 x (conv 3x3, ReLU)
2 x (conv 3x3, ReLU) + maxpool 2x2
2 x (conv 3x3, ReLU) + up sample 2x2
Skip connections

RESULTS AND CONCLUSION

Using the previously mentioned U-net, the speckle pattern images are reconstructed into new images. An example of a reconstructed image for phase modulated and amplitude modulated speckle patterns respectively, is shown in Fig. 3.

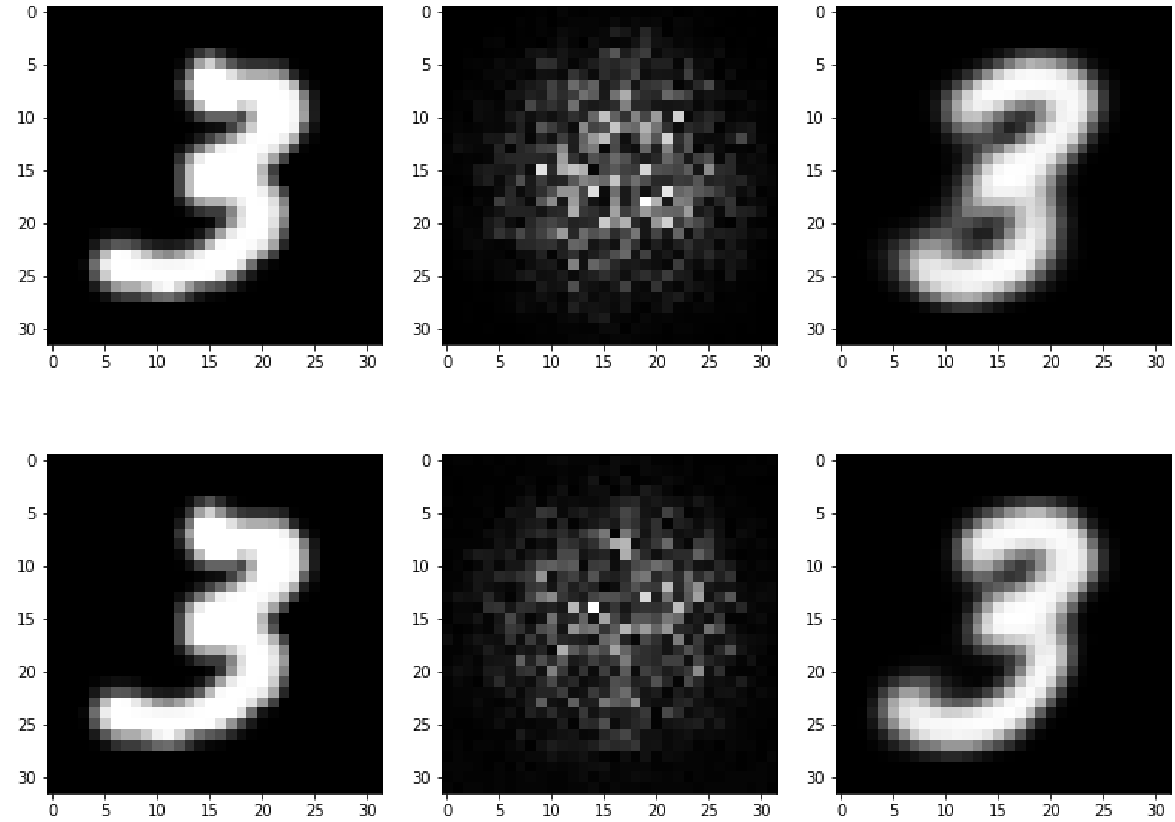


Fig. 3. 1. a) Mnist digit, b) Phase modulated speckle pattern, c) Reconstructed Image
2. a) Mnist digit, b) Amplitude modulated speckle pattern, c) Reconstructed Image

Results for the classification of the distal speckle intensity patterns and the reconstructed images are presented in Table 1. Although appearing random, the speckle patterns contain information about the propagation of the input field through the fiber. In fact, the results confirm the above statement, showing that the recovery of the input is possible with an intensity-only image of the distal speckle pattern using the U-net CNN.

Table 1

Fiber Length [m]	Proximal Input	Distal Speckle Intensity Accuracy	Reconstructed Input Accuracy
0.1	Amplitude	92.35%	97.80%
	Phase	90.60%	97.30%
1000	Amplitude	50.20%	78.95%
	Phase	30.10%	67.20%

The results show that the classification accuracy, defined as the percentage of correctly recognized digits, decreases with increasing fiber length for both amplitude and phase-modulated proximal facet input modes. This decrease can be attributed to increased scattering losses, mode coupling, and drifting of the distal speckle pattern with increasing fiber lengths.

The main result of this project is that neural networks can efficiently reconstruct and recognize the inputs to a MMF from intensity-only measurements of its corresponding output. The measured classification accuracy was excellent for the 10 cm fiber (97.8%) and reduced to 78.95% for the 1 km fiber. In all cases, the classification performance improved when we first used the U-net DNN to reconstruct the input image followed by a second DNN (VGG) that was trained to classify the reconstructed images.

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