Machine Learning for Modal Analysis

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Abstract

We train autoencoder artificial neural networks on simulated multimodal images and their corresponding modal power coefficients to reconstruct the component modal profiles and obtain a network capable of modal decomposition.

Index Terms

Laser modes, Machine learning, Statistical learning

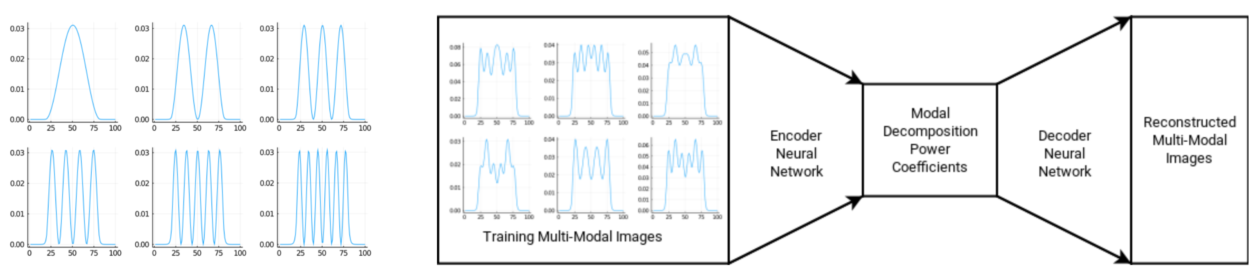
I. Introduction

The ability to analyze transverse modes is vital to evaluating mode engineered lasers, such as those that we have proposed and are fabricating [1]. While laser mode fields form an orthogonal basis, the laser mode intensities which we can image are not orthogonal. As such, the problem of analyzing the modal composition of multi-modal beam images (often referred to as modal decomposition) is non-trivial. Furthermore, most methods of modal decomposition require knowledge of the individual modal intensity profiles. These may be either obtained from simulation (which requires sufficient knowledge of the laser system to accurately model the modes) or by a spectrally resolved beam imaging experimental setup [2]. We propose the use of autoencoder networks to simultaneously extract the modal profiles and learn to decompose beams into component transverse modes using a set of beam images labeled with modal power coefficients (coefficients that convey how much power is in each of the transverse modes). Once trained, one can use the encoder and decoder components of the autoencoder to perform modal decomposition and obtain the individual modal intensity profiles, respectively.

As multi-modal beam images are linear summations of modal intensity profiles (with some noise), one could use least squares fit on a per pixel basis to determine the modal intensity profiles, provided that the modal power coefficients are known (perhaps obtained by analyzing the optical spectrum to determine the relative intensity of the modal peaks). Once the modal intensity profiles are known, modal decomposition can then be performed on a beam profile image to obtain the unknown modal power coefficients. By virtue of the problem, most methods for modal decomposition involve an optimization over the modal power coefficients as to minimize the error between the measure beam image and reconstructed beam image [3].

II. Proposed Machine Learning Method

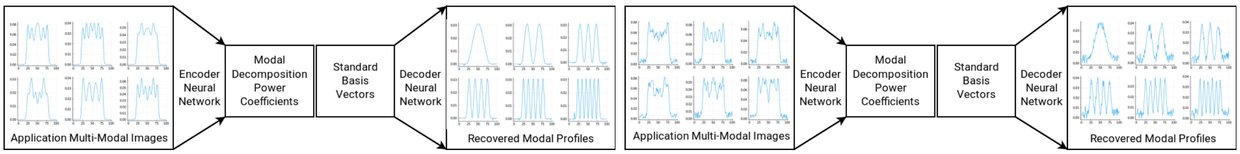
Machine learning has been proposed as a method for modal decomposition (given a known set of modal intensity profiles) that effectively shifts much of the computational cost of optimization from the experimental modal decomposition step to the network training step, enabling real-time modal decomposition. Past work used a set of known modal intensity profiles obtained from simulation to obtain a training dataset [4]. In this work we propose the use of measured multi-modal beam images with the corresponding modal power coefficients as a training set to an autoencoder.



(a) (b)

Fig. 1: (1a) Simulated modal intensity profiles used to created training data, and (1b) diagram of autoencoder.

The autoencoder is comprised of an "encoder" network that encodes the higher dimensional multi-modal images into the modal power coefficients in a lower dimensional "latent space" and a "decoder" network that decodes the modal power coefficients back into intensity profiles [5]. Using a set of 6 simulated modal intensities (for the modes of a dielectric slab waveguide), shown in Figure 1a, we constructed a set of 40 random multi-mode images along with the modal power coefficients describing the relative power in each mode. This set of intensity profiles was used in conjunction with the corresponding modal power coefficients to train an autoencoder, as shown in Figure 1b, to minimize the difference between the training images and reconstructed images, as well as between the modal decomposition coefficients and the training coefficients.



(a) (b)

Fig. 2: Diagram of the encoder and decoder applied to modal decomposition and modal recovery, as trained on "clean" data (2a) and noisy data (2b)

After training the set of standard basis vectors in the latent space was decoded to obtain the reconstructed modal intensity profiles shown in Figure 2a. We also similarly trained an autoencoder on simulated multimodal images with noise added, with the resulting reconstructed modal profiles shown in Figure 2b. The addition of noise decreased the quality of the reconstructed mode profiles but they are still distinctly recognizable as the modes of a dielectric slab waveguide.

The proposed autoencoder requires a training dataset of measured multi-modal beam images that contain as a whole all of the modes that are expected to be encountered in the application of the trained model. Furthermore, it also requires that the training dataset is labeled with the modal power coefficients for those modes (whose modal intensity profile is not known). It is expected that these could be estimated from experimental optical spectrum measurements as the relative powers of the spectral peaks for the modes. We will apply these methods to analyze the modes of few mode semiconductor lasers.

III. Conclusion

We used simulated multi-modal (intensity profile and relative modal power coefficient) data to train an autoencoder to encode multi-modal intensity profiles into modal power coefficients and decode them back to the intensity profiles. The trained autoencoder could them be used to obtain the intensity profiles of the individual modes, as well as perform modal decomposition. This method has the advantage over conventional modal analysis and decomposition of not requiring knowledge of the intensity profiles of the component modes, nor complicated experimental setups. This material is based on work supported by Joint Transition Office Multidisciplinary Research Initiative, Award No. 17-MRI-0619.

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