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MA3.4: Machine Learning for Modal Analysis

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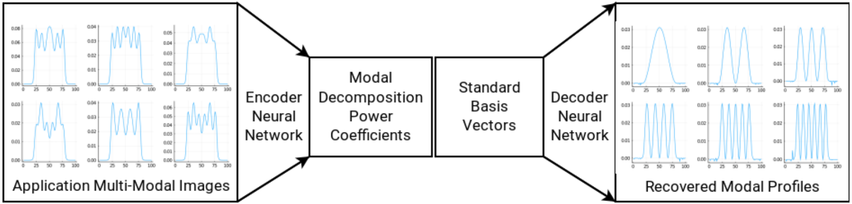
The Basic Problem

- We want to analyze the lasing (transverse) modes of a laser, but we don't know beforehand the mode profiles
- Modal decomposition methods could determine the relative modal powers, *if we knew the mode profiles*
- If we have some near-field images and corresponding modal power coefficients, then pixel-wise linear least squares can estimate the modal intensity profiles needed for modal decomposition on other near-field images

Can machine learning provide a better way of analyzing the transverse modes?

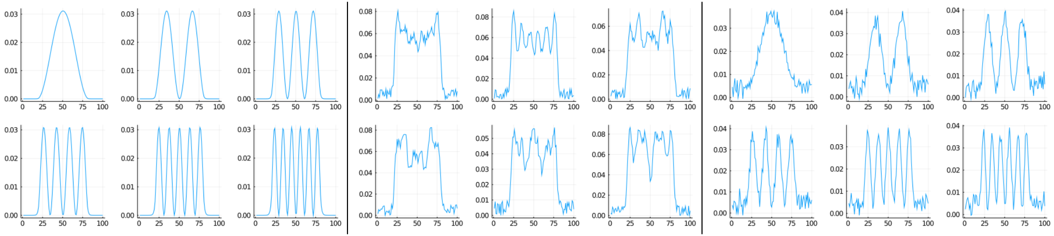
The Basic Approach

- Autoencoder (AE) artificial neural network (ANN): A combination of a high-to-low dimension encoder ANN and low-to-high dimension decoder ANN
- Encoder: predict modal power coefficients from near-field images
- Decoder: predict near-field images from modal power coefficients
- Train both networks simultaneously with a set of near-field images labeled with modal power coefficients



Proof of Concept: 1D Simulated Mode Profile Recovery

We create a set of simulated noisy near-fields, and use an AE to recover the original modal intensity profiles:



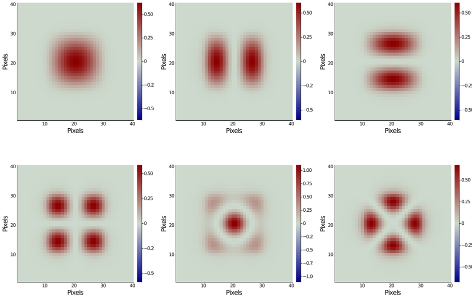
Original intensity profiles Noisy near-fields Recovered intensity profiles

Moving to 2D Images

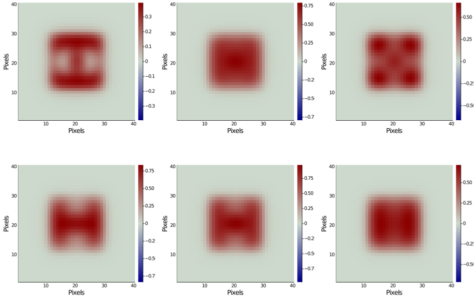
- 2D images have a lot more pixel's than our 1D simulated profiles, so we will need to use lower resolution images for performance reasons
- We also explore a convolutional neural network (CNN) based encoder, as CNNs may be better suited for image recognition tasks
- Let's start with a set of simulated modes and multi-moded images...

2D Simulated Mode Profiles

We create a set of simulated 2D near-fields from a set of 6 mode intensity profiles, obtained from waveguide simulation:



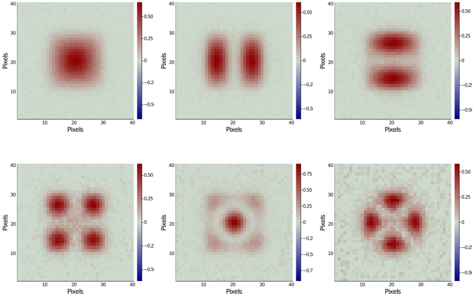
Simulated modal intensity profiles

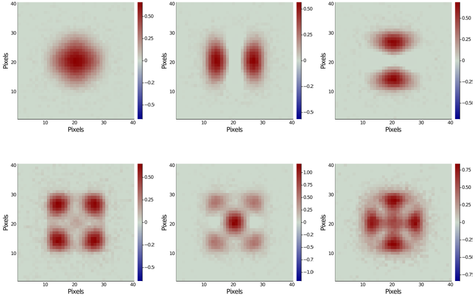


Random multi-modal near-fields (biased towards lower orders)

2D Simulated Mode Profile Recovery

Estimated mode intensity profiles obtained from the decoder trained on simulated data:



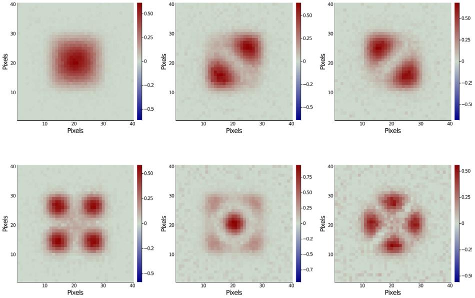


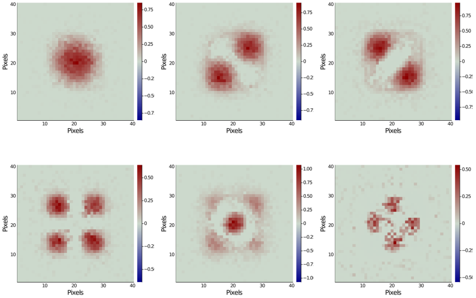
Conventional AE

CNN AE

2D Simulated (Noisy) Mode Profile Recovery

Estimated mode intensity profiles obtained from the decoder trained on noisy simulated data. Modes 2 and 3 are now distinctly distorted:





Conventional AE

CNN AE

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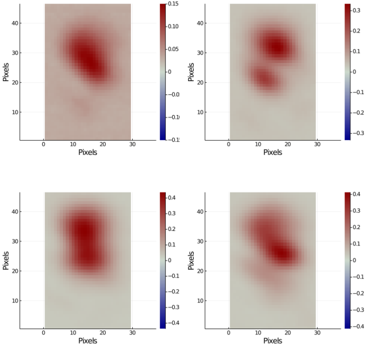
Moving to Experimental Application

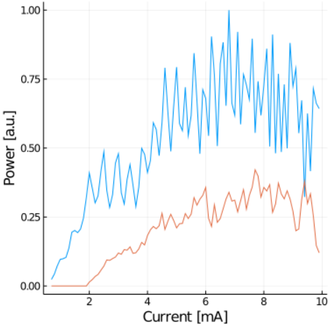
- Case study: Transverse modes of oxide-confined VCSELs
- We want to analyze the 2D modal intensity profiles given a set of near-field microscope images
- We determine the modal power coefficients from the modal peak power in optical spectra
- 2D images have a lot more pixel's than our 1D simulated profiles, so we down-sample and trim the images
- Consider a 2 μm aperture oxide-confined 850 nm VCSEL...

2 μm VCSEL: Near-Field Images and Modal Power Coefficients

A relatively simple system with only two modes:



A few near-field images used for training



Modal power for the two modes as a function of current, for the training near-field images

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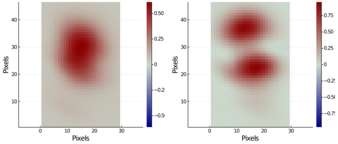
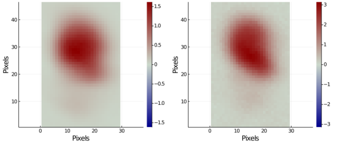
2 μm VCSEL: Recovered Mode Intensity Profiles

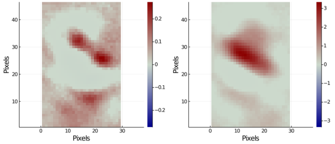
With lots of training data and few modes least squares appears intuitively correct while ML methods perform worse.



Least squares



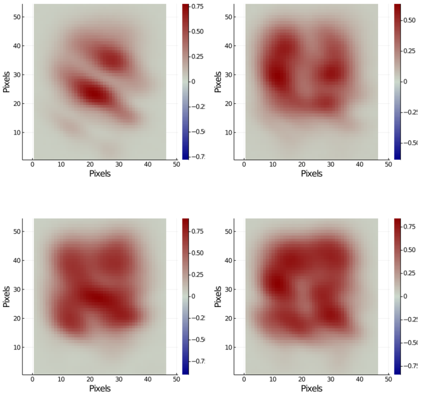
Conventional AE

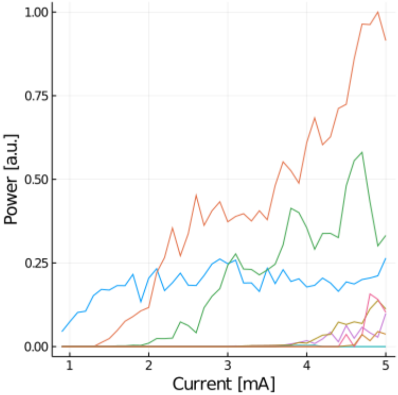


CNN AE

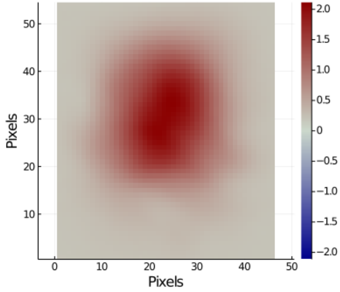
4 μm VCSEL: Near-Field Images and Modal Power Coefficients

Eight modes, but the first three are dominant:

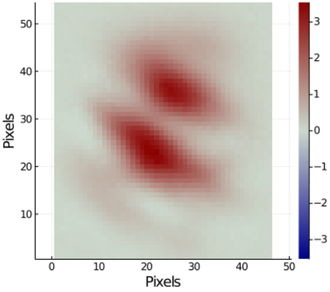




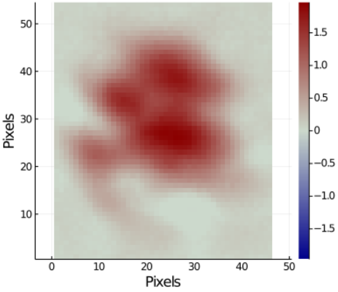
4 μm VCSEL: Recovered Mode #1 Intensity Profiles



Least squares



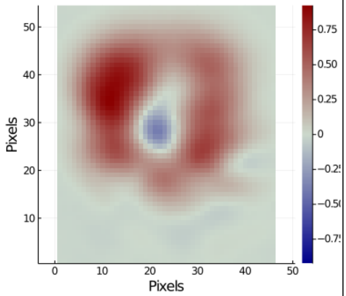
Conventional AE



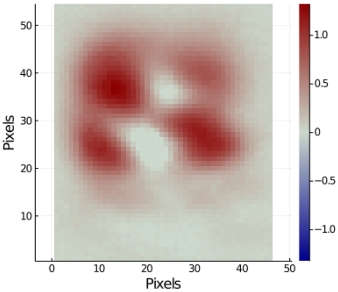
CNN AE

4 μm VCSEL: Recovered Mode #2 Intensity Profiles

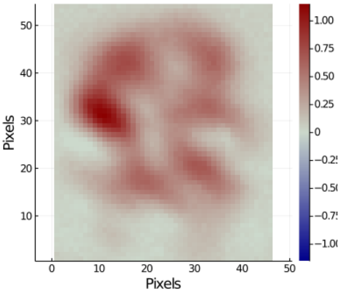
Least squares finds *negative* intensity values. Machine learning methods are non-negative:



Least squares



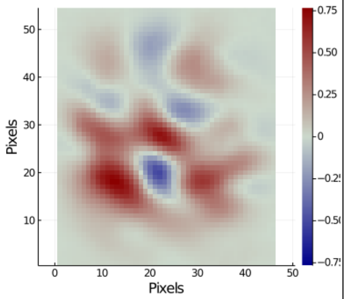
Conventional AE

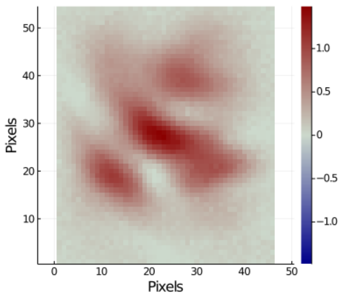


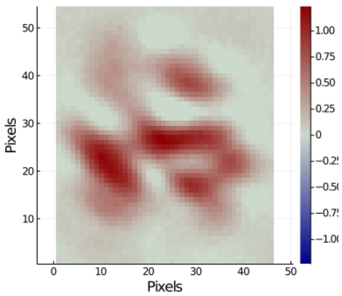
CNN AE

4 μm VCSEL: Recovered Mode #3 Intensity Profiles

Least squares finds *negative* intensity values. Machine learning methods are non-negative:







Least squares

Conventional AE

CNN AE

Applications and Conclusions

- Autoencoder neural networks can be used for modal profile recovery and modal decomposition
- This enables analyzing the transverse modes with lower experimental and equipment complexity
- While machine learning approach is computationally expensive, it makes no assumptions with regard to the underlying theory, allowing it to provide better results in situations where simple least squares breaks down
- Results with experimental dataset are rather lackluster, possibly due to noise in measurements and/or insufficient dataset to overcome noise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