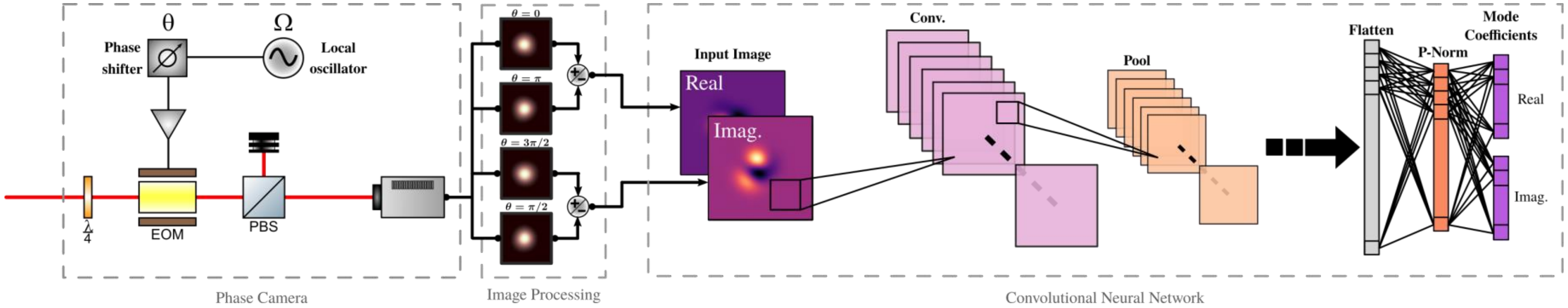
Mode decomposition of phase camera images with convolutional neural networks



Mitchell G. Schiworski, Daniel D. Brown, and David J. Ottaway

OzGrav, Australian Research Council Centre of Excellence for Gravitational Wave Discovery
Department of Physics and The Institue of Photonics and Advanced Sensing (IPAS), University of Adelaide, SA, 5005, Australia

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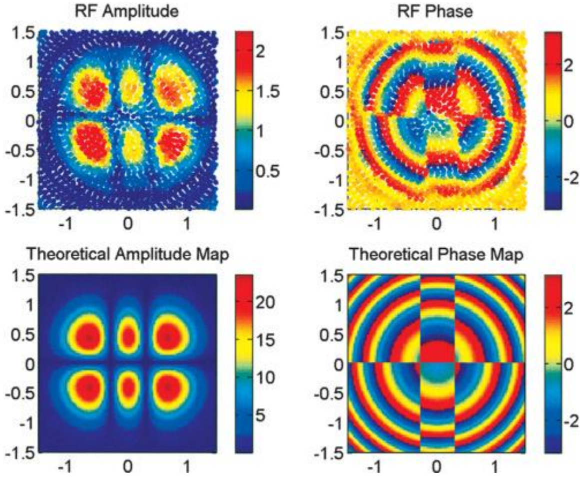
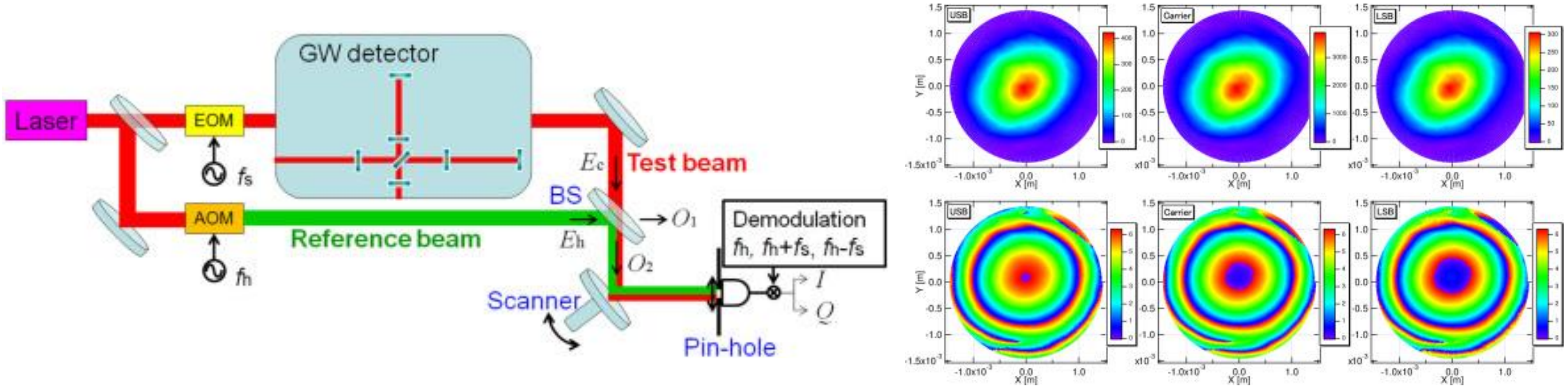
Phase cameras

- Frequency selective wavefront sensors

- Demodulate at multiple transverse positions to recreate amplitude & phase profile of beat field



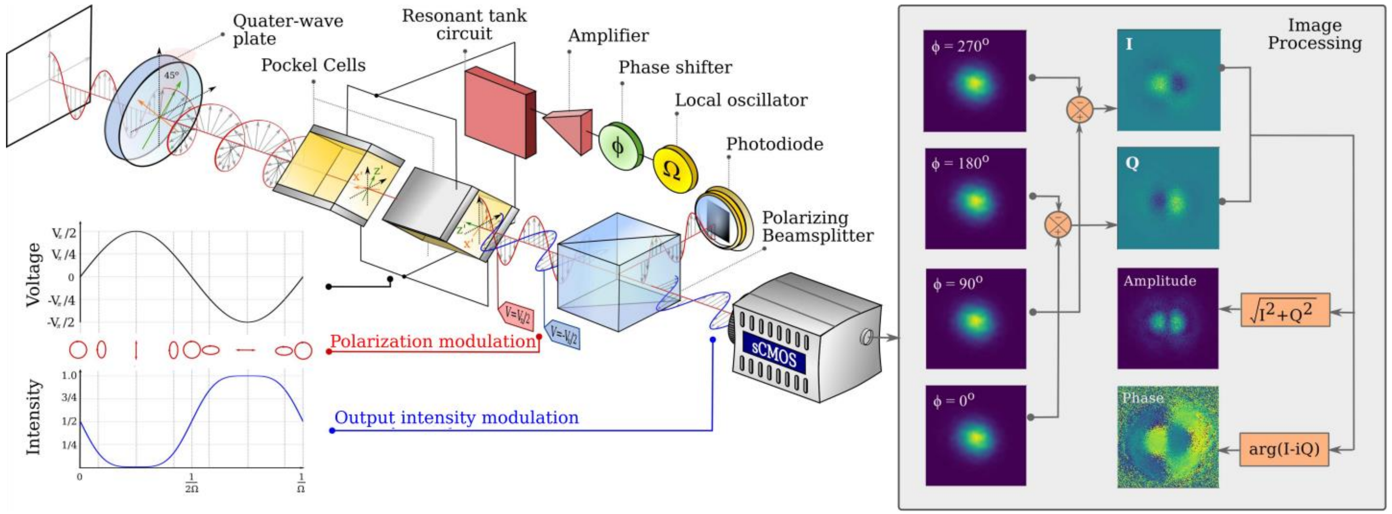
Keisuke Goda *et al.* , "Frequency-resolving spatiotemporal wave-front sensor," (2004)



Kazuhiro Agatsuma *et al.*, "High-performance phase camera as a frequency selective laser wavefront sensor for gravitational wave detectors," (2019)

Optical lock-in phase camera

- Optical demodulation achieved using QWP, EOM & PBS
- Each camera pixel acts like demodulated photodiode



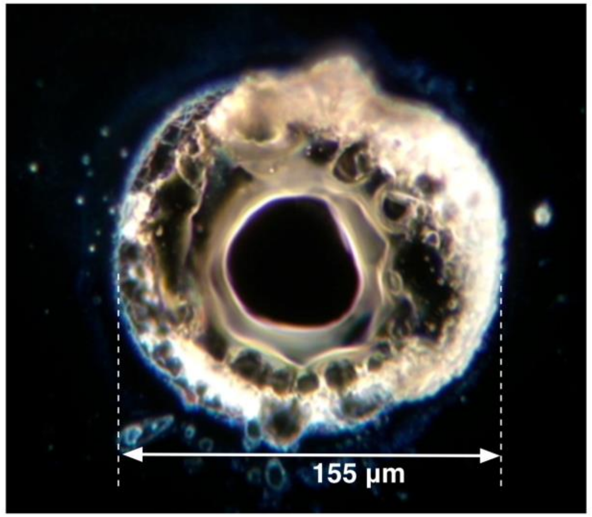
Huy Tuong Cao, Daniel D. Brown, Peter J. Veitch, and David J. Ottaway. *"Optical lock-in camera for gravitational wave detectors."* Opt. Express 28, 14405-14413 (2020)

Phase camera use cases

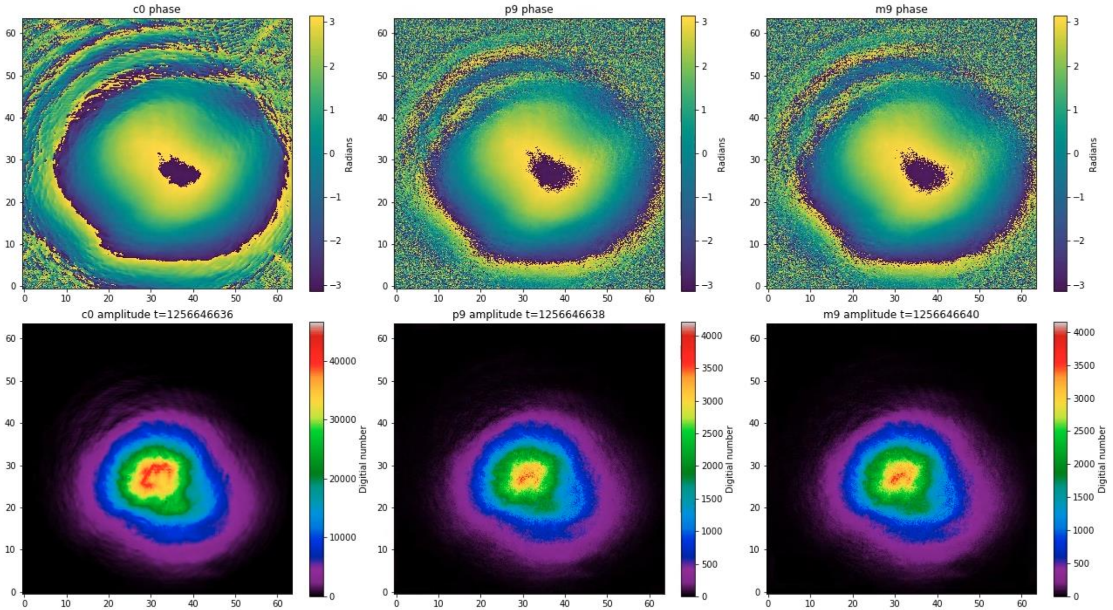
Sense higher order effects:

- Point absorbers
- Thermal deformations
- HOMs in control signals

- Assisting with comissioning
- Feed back into models to infer details about interferometer state



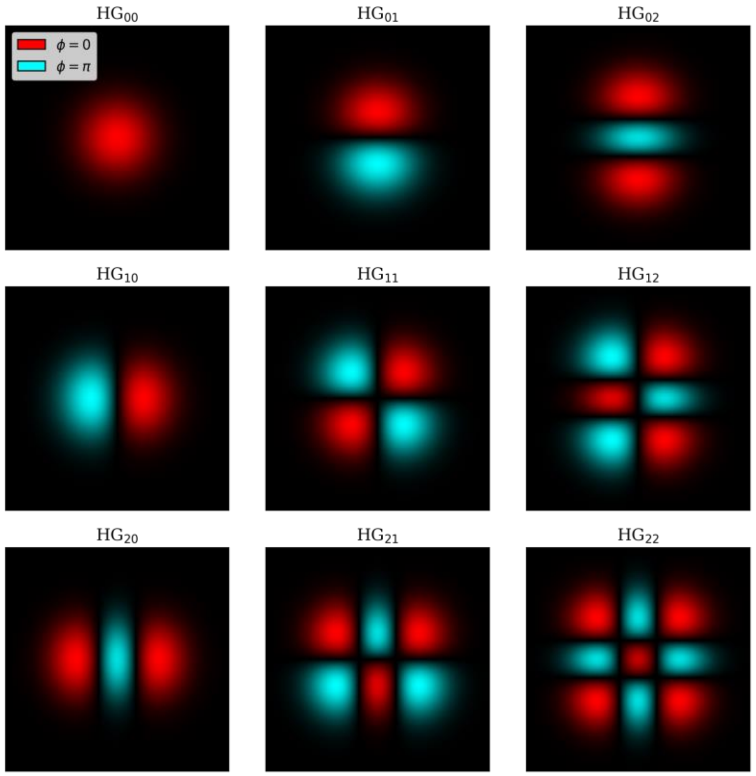
Brooks, Aidan F., et al. "Point absorbers in Advanced LIGO." (2021)



https://alog.ligo-wa.caltech.edu/aLOG/index.php?callRep=52927

Mode decomposition

- Represent field as a sum of orthogonal modes
- Mode content useful for error signals, feeding information to models
- Compression algorithm for high resolution images, for effecient transfering & storing data



$$\tilde{U}(x, y, z_0) = \sum_{n,m} c_{nm} \mathrm{HG}_{nm}(x, y, \tilde{q})$$

Overlap integral decomposition

Slow and cumbersome for real time processing:

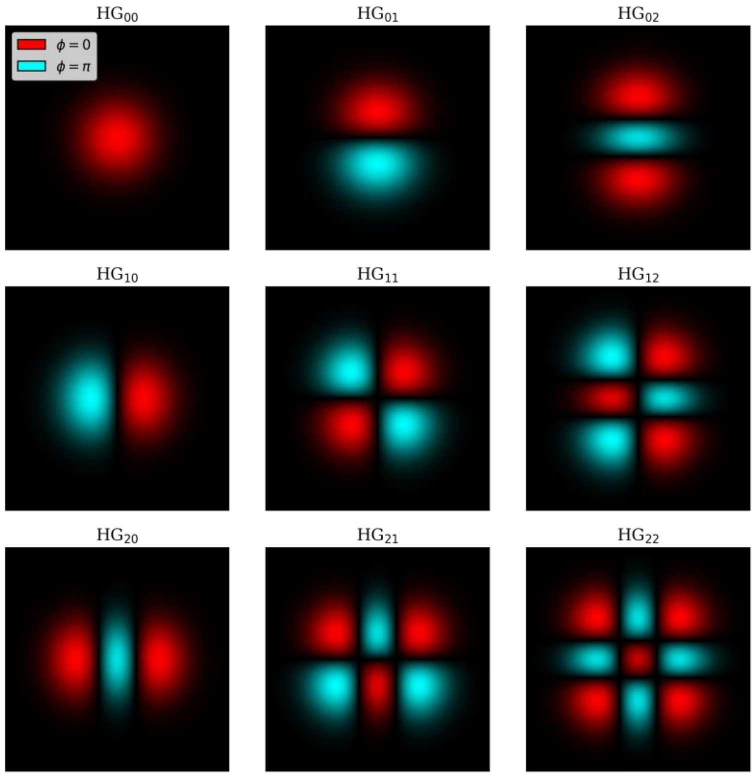
- Compute overlap integral with each HG mode:

$$c_{nm} = \int\int \tilde{U}(x, y, z_0)\mathrm{HG}^*_{nm}(x, y, \tilde{q})\, dx\, dy$$

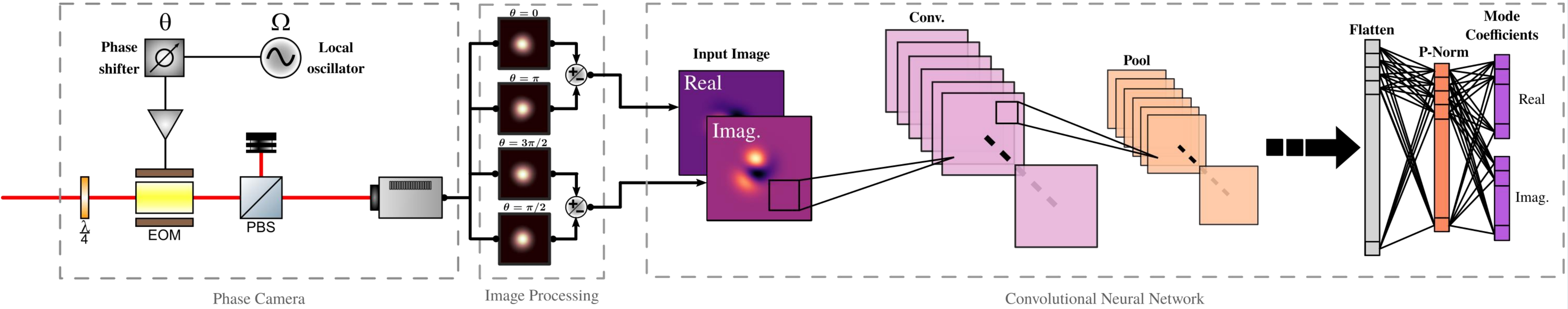
- Need to calculate beam centre to avoid translation errors in mode coefficients

- Calculating coefficients of sideband field only requires even more processing steps

$$\tilde{U}_{meas}(x, y, z_0) \propto \tilde{E}^*_{carrier}(x, y, z_0)\tilde{E}_{sideband}(x, y, z_0)$$



CNN decomposition

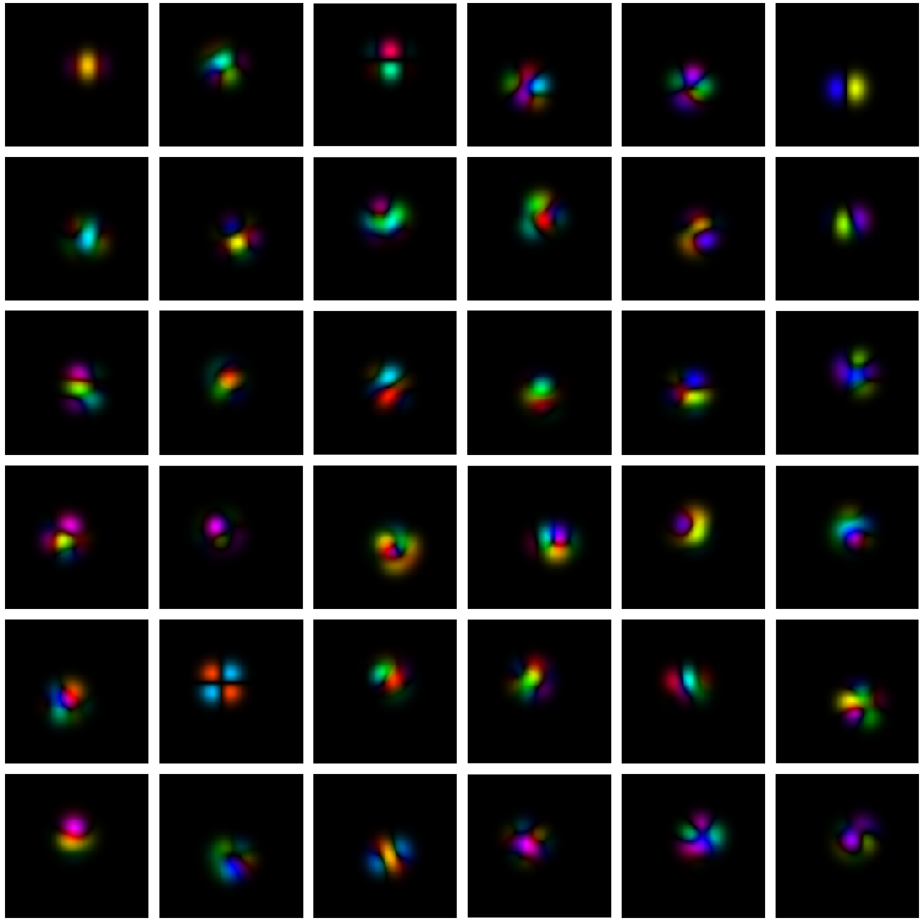


- Very fast when delployed on GPUs/FPGAs
- Calculate beam centre, unwrap carrier field & evaluate mode coefficients in a single step
- Network learns sets of filters to decompose the image into a set of features, which are then translated into mode coefficients

Schiworski, Mitchell G., Daniel D. Brown, and David J. Ottaway.
"Modal decomposition of complex optical fields using convolutional neural networks." arXiv preprint arXiv:2104.08458 (2021).

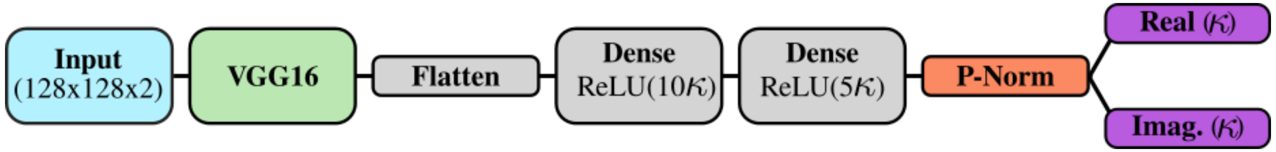
CNN decomposition - training data

- Need a large dataset of phase camera images and mode coefficients to train network
- Generate simulated phase camera images of beams with randomised mode content
- Random offset in beam position
- Fixed Gaussian reference and q



***Colour hue represents beam phase**

CNN decomposition - network architecture

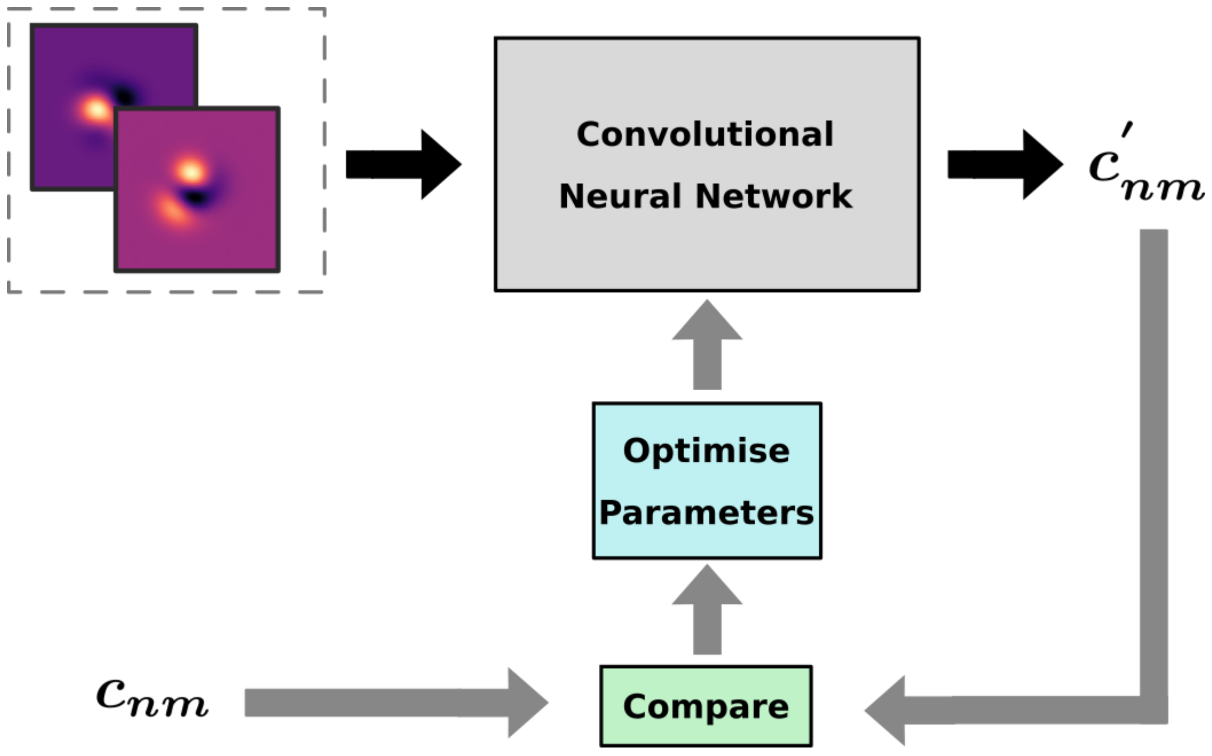


- I & Q phase camera images as input
- Pre-trained VGG16 network
- Dense layers scale with order of decomposition
- Normalise mode coefficients before output

CNN decomposition - training

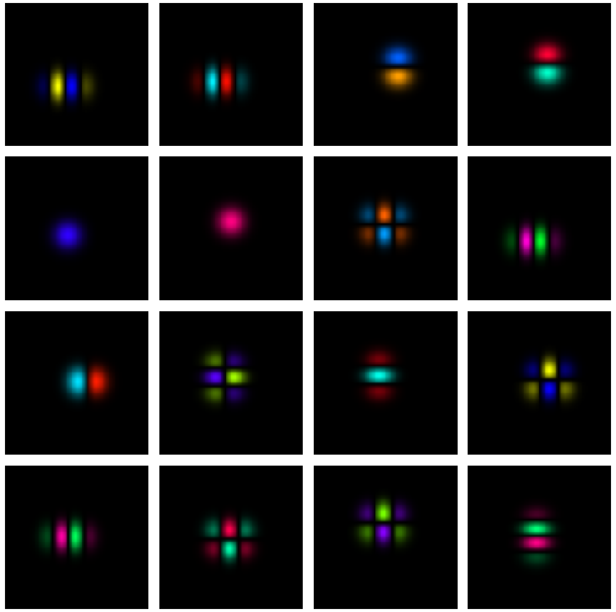
- Network trained through iterative process

- Training images are passed to the network & parameters are optimised so the predicted mode coefficients match

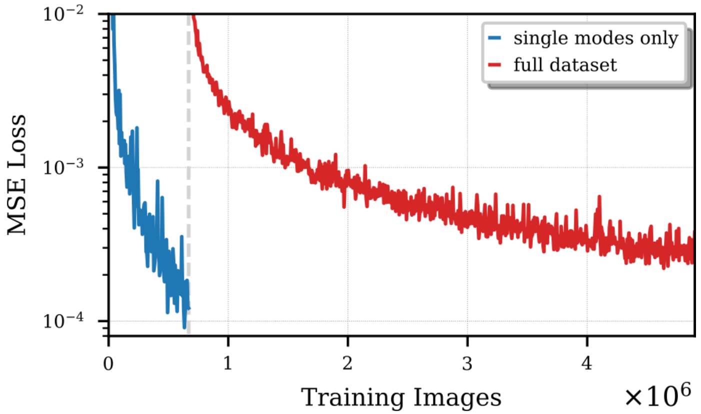


CNN decomposition - curriculum learning

- Traditional learning approach ineffective at higher decomposition orders
- Train network on individual modes first
- Creates better initial conditions for optimization landscape



Images of single modes



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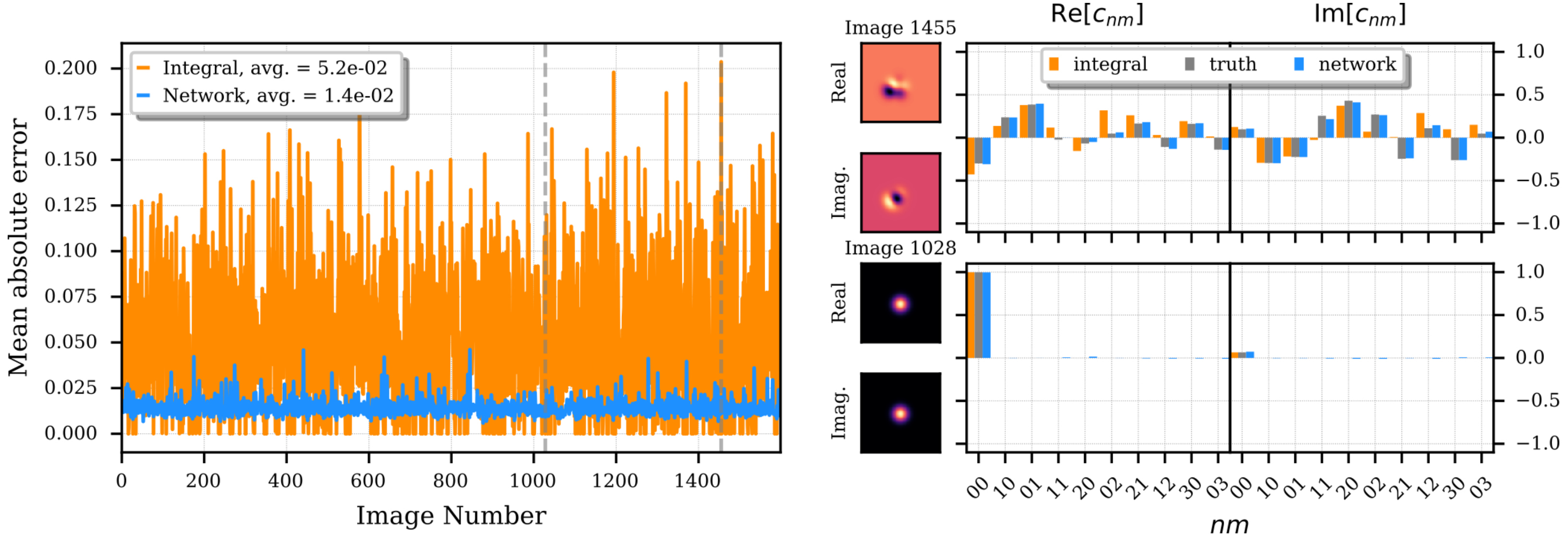
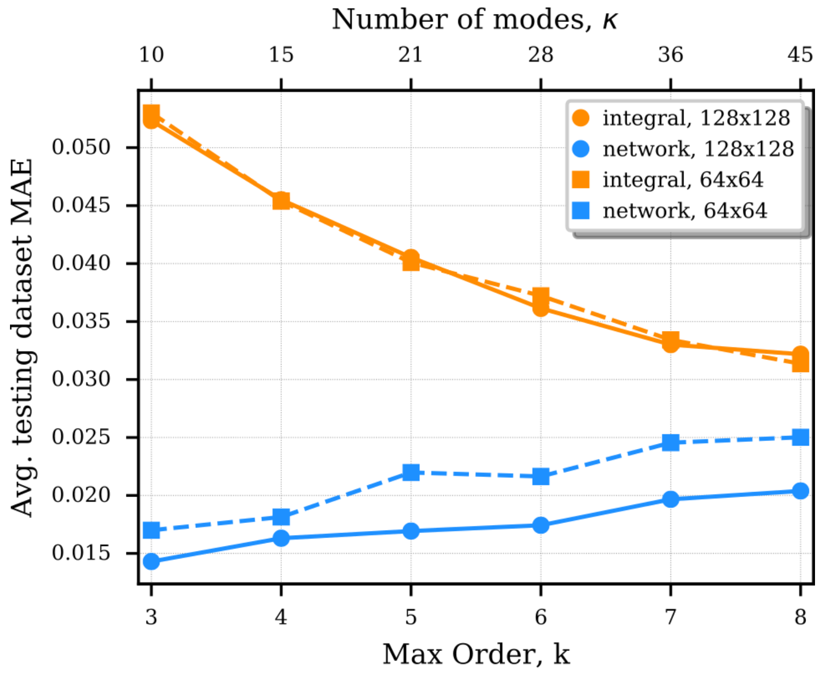
CNN decomposition - results



- Network less susceptible to beam centering and mode content
- Integral method more accurate when beam has spherically symmetric intensity distribution

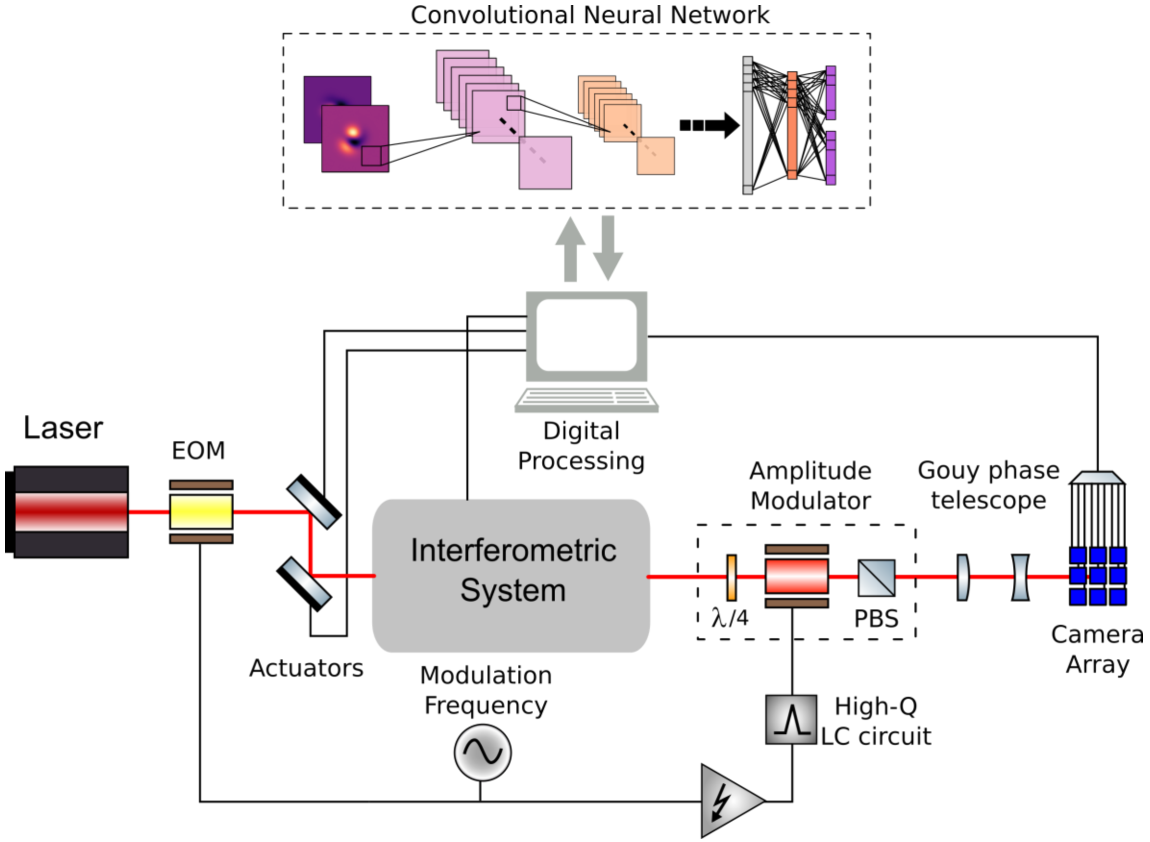
CNN decomposition - results

- Network benefits from higher resolution images
- Average network error per mode increases with the decomposition order
- Network evalutation time approx. independant of decomposition order, number of overlap integrals required increases quadratically
- May be able to improve accuracy by exploring more network architectures

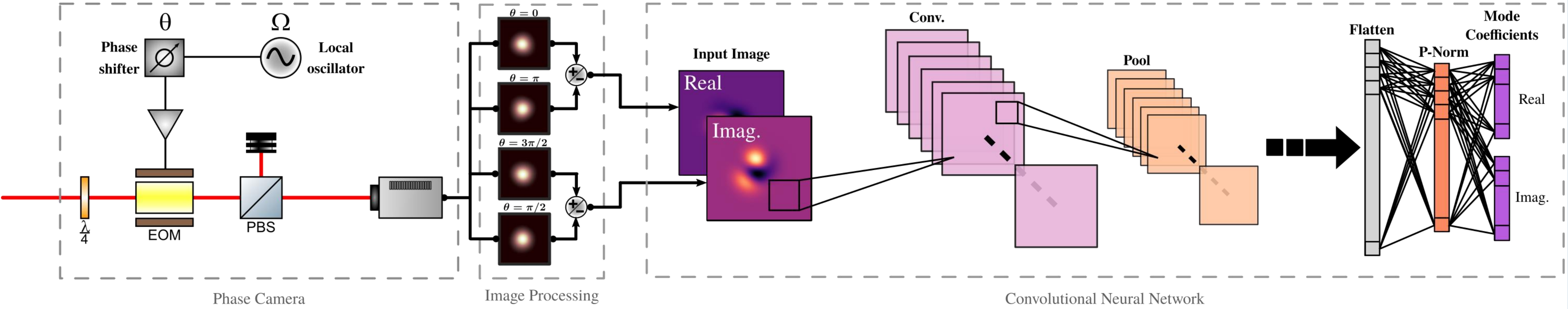


Future work

- Experiment at Adelaide digitally processed phase camera images for alignment & mode-matching error signals
- Instead use CNN to analyse real-time phase camera images
- Convert high resolution images into useable error signals



Summary



- Phase cameras are useful tools for diagnosing & controling gravitational wave interferometers, but it can be slow/difficult to interpret their images
- CNNs can provide processing of phase camera images into Hermite-Gaussian modes at real-time speeds
- Hope to process CNN calculated mode coefficients into error signals & use as inputs to feed into models