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Application of deep learning to instability tracking using high-speed video cameras in magnetic confinement fusion device

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with the HBT-EP Group:

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Motivation and key results

- External, optical-based **magneto-hydrodynamic (MHD) instabilities** diagnostics can be beneficial for future fusion reactors.

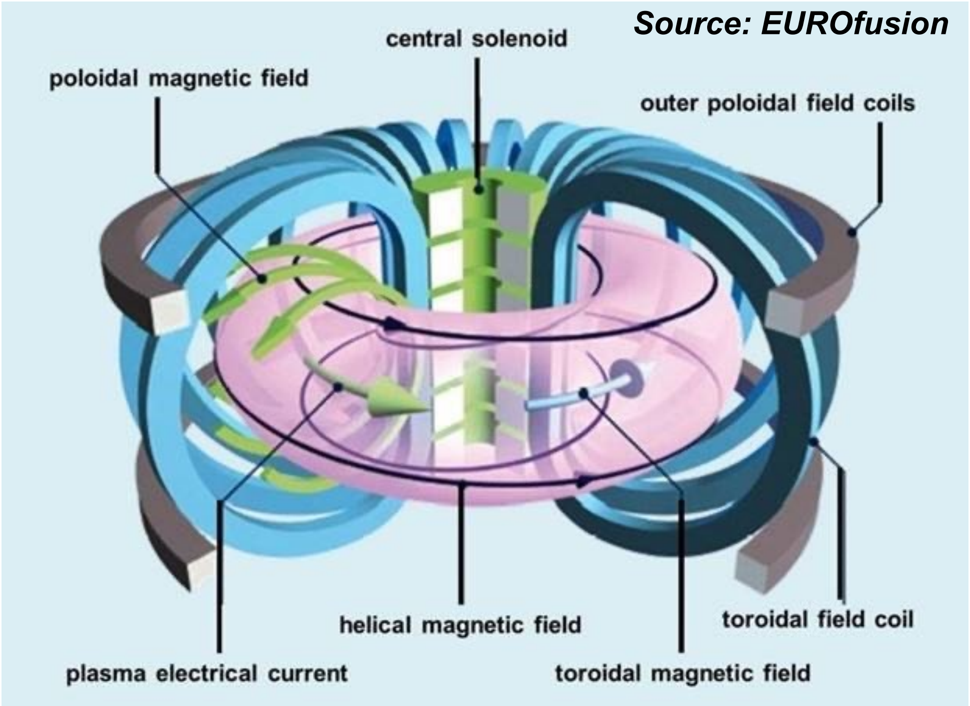
- We developed a MHD instability mode tracking algorithm using image data from high speed cameras and deep learning algorithm (convolutional neural network).
  - Implemented using a dataset of 86,275 images from 45 plasma discharges on the HBT-EP tokamak
  - Better amplitude and phase accuracy than other tested methods.

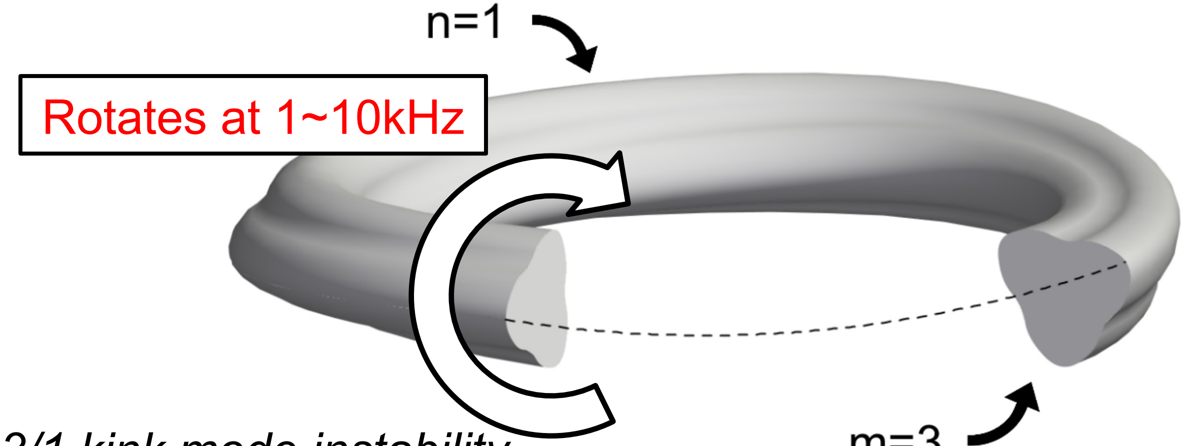
- We are currently exploring the feasibility for deploying this algorithm for microsecond-level real-time feedback control on HBT-EP.

PART 1 – Plasma instability diagnostics and feedback control in tokamak

- Plasma instability diagnostics and feedback control in tokamak
  - Fusion, tokamak, and MHD instabilities
  - Instability mode tracking using high speed cameras on the HBT-EP tokamak
- Implementing and testing the deep learning model
- (IN PROGRESS) Plans for deploying the model in real-time

Fusion, tokamak, & MHD instabilities





3/1 kink mode instability

- **Tokamak**: leading candidate for a future fusion reactor
- A tokamak uses magnetic fields to confine high temperature plasma:
  - Fusion plasma: ~10 times temperature of solar core.
- Tokamak plasma develops instabilities (”modes”) which could lead to disruption, causing damage to reactor.
- Active control of plasma instabilities is crucial for tokamak operation.
  - Requires knowing the amplitude & phase of the instabilities in real-time *(Mode tracking)*

Introduction to the High Beta Tokamak – Extended Pulse (HBT-EP) device

HBT·EP

- HBT-EP research program studies diagnostics and control of plasma instabilities

- Extensive MHD diagnostics and control actuators including:
  - Over 200 magnetic sensors
  - 64 poloidal EUV detectors
  - 120 in-vessel saddle control coils
  - Quadrature biased probe array

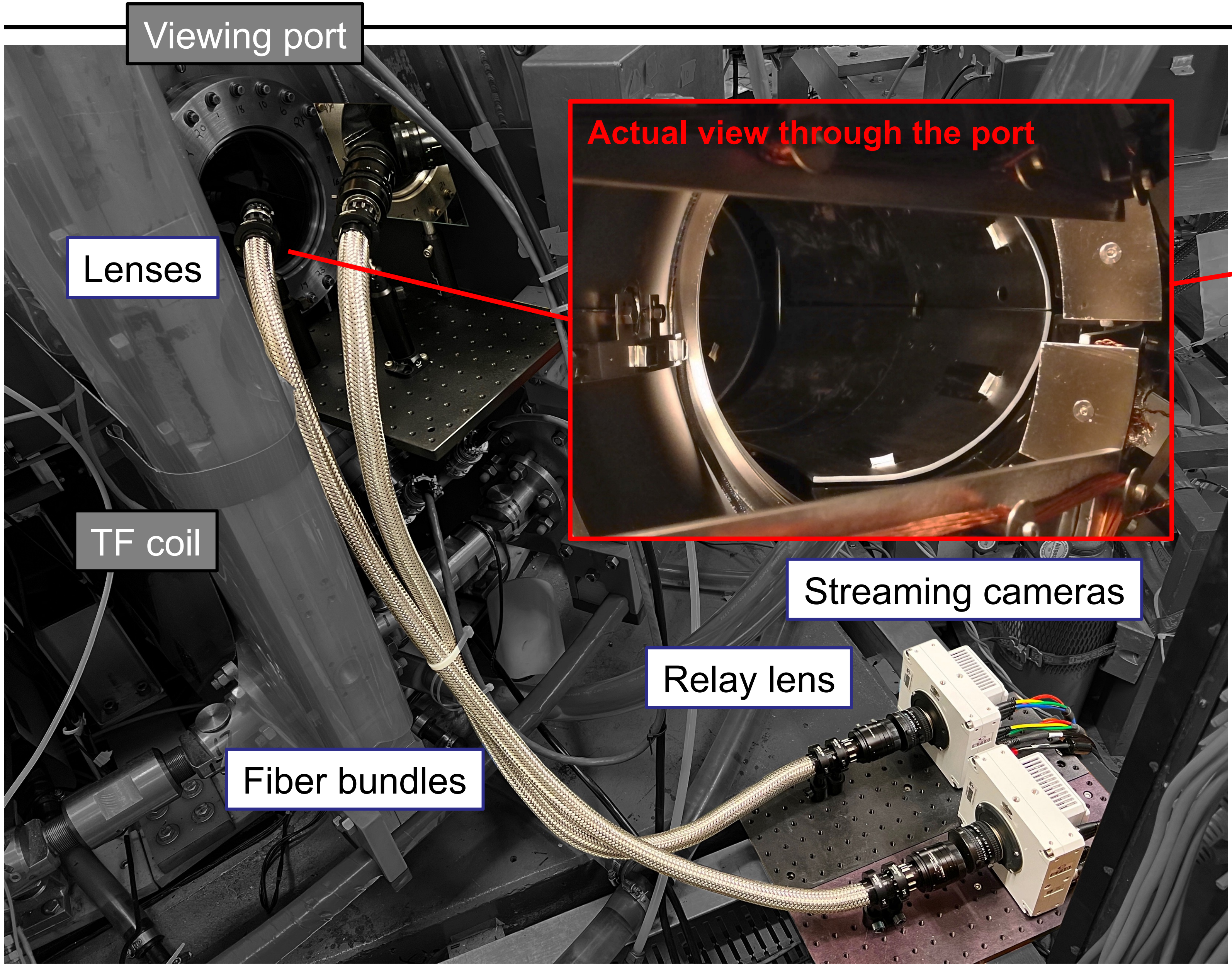
- Demonstrated mode tracking & suppression with latency < 20 μs

Typical HBT-EP discharge parameters

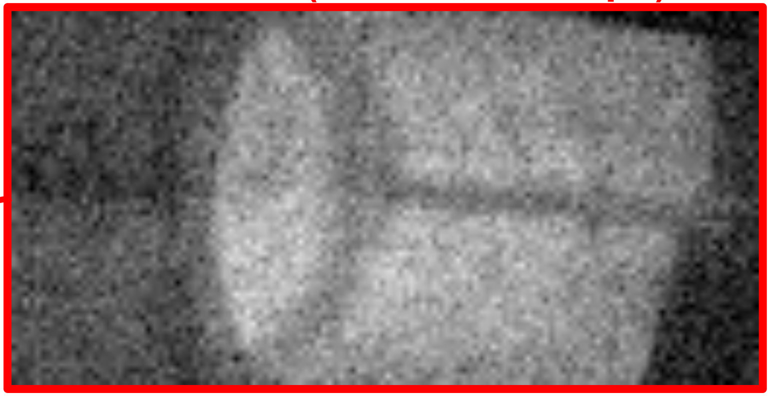
Major Radius:	92 cm
Minor Radius:	15 cm
Plasma Current:	~15 kA
Plasma Temperature	~100 eV (10^6 K)
Plasma Density:	~10^{19} /m^3
Mode Frequency:	~10 kHz
Pulse Length:	5 – 10 ms

D A Maurer et al 2011 *PPCF* **53** 074016

MHD diagnostics using fast cameras



111461 2-4 ms (128x64, 250 kfps)



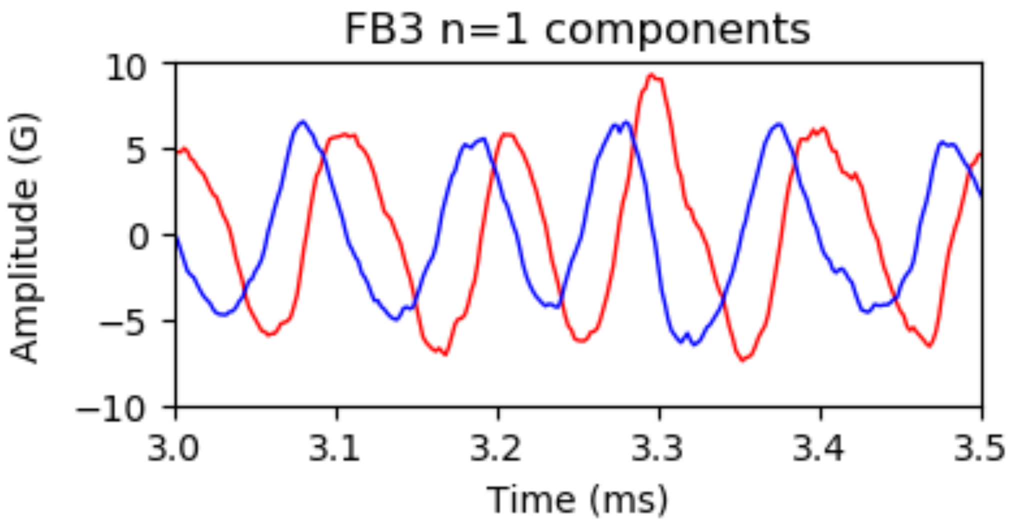
- 2 Phantom S710 streaming cameras
  - Framerate: 100 - 400 kfps
  - Exposure: 9 - 1.5 μs
  - Resolution: 256x96 - 128x32 pixels
  - Flexible view setup, including cross-sectional and zoomed-in views

Mode tracking: from linear transformations to deep learning

$$\vec{b} = F(\vec{x}) = A\vec{x}$$

- $\vec{x}$: measurements from some sensor array at time t
- $\vec{b}$: predicted sine & cosine components of the tracked mode at time t
- A: some time-independent matrix – *linear control system*
- *Works with diagnostics with simple & well-defined geometry (e.g. magnetics)*

sine & cosine mode components measured by magnetics

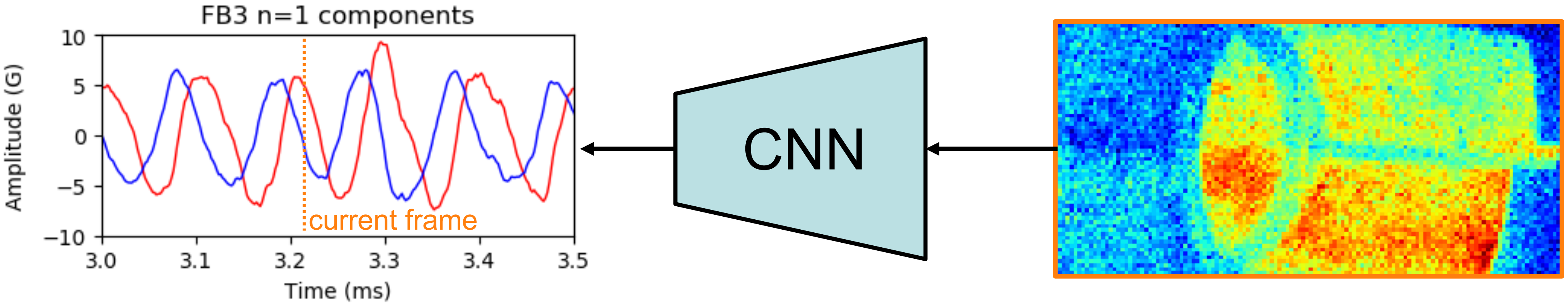


Mode tracking: from linear transformations to deep learning

- For fast cameras, it's difficult to determine A from first principles, because:
  - 3D geometry with hollow emission profile
  - Highly non-linear system due to emission mechanism
  - Dependence on plasma parameters unavailable in real-time

$$\vec{b}_{MHD} = F(\vec{x}_{camera})$$

- $\vec{x}$: fast camera frame images
- $\vec{b}$: sine & cosine components of the MHD instability measured using another method
- Model function F using a convolutional neural network (CNN)



Mode comp. (output)

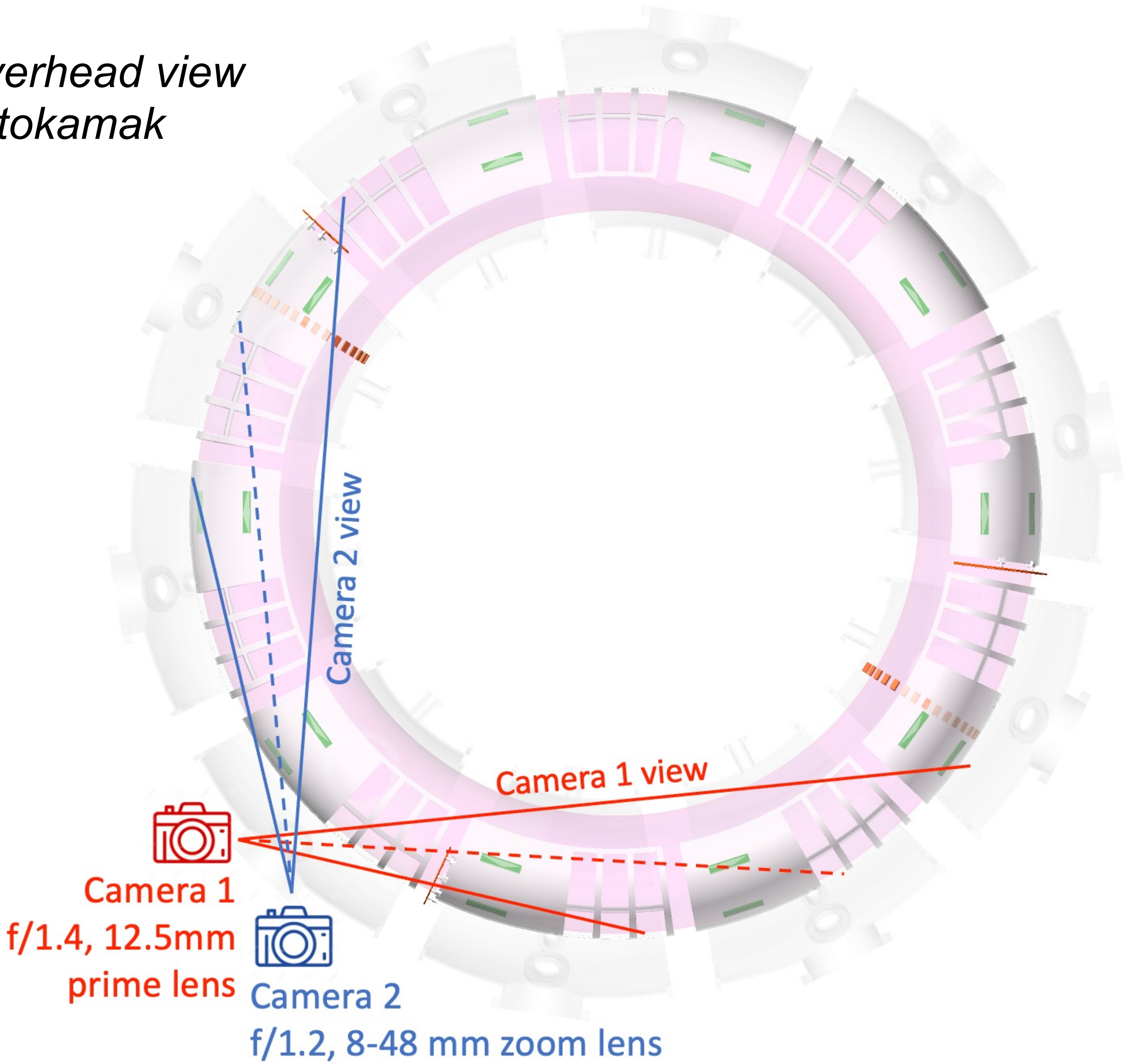
Camera frame (input)

PART 2 – Implementing and testing the deep learning model

- Plasma instability diagnostics and feedback control in tokamak
- Implementing and testing the deep learning model
  - Assembling the fast camera dataset
  - Mode tracking results
- (IN PROGRESS) Plans for deploying the model in real-time

Assembling the fast camera dataset

Overhead view of tokamak



- Dataset consists of 45 discharges taken in 3 consecutive run days
  - 86,275 frames per camera
  - Last 5 shots (9,300 frames per camera) were selected as testing set
- Camera setup:
  - Resolution: 128x64 pixels
  - Framerate: 250 kfps (4 μs interval)
  - Pixel intensity: 12 bits (0-4095)
  - Cross-sectional view toward opposite directions
- Sine & cosine components of the instability mode from magnetic sensors were used as target.

Implementing the CNN model

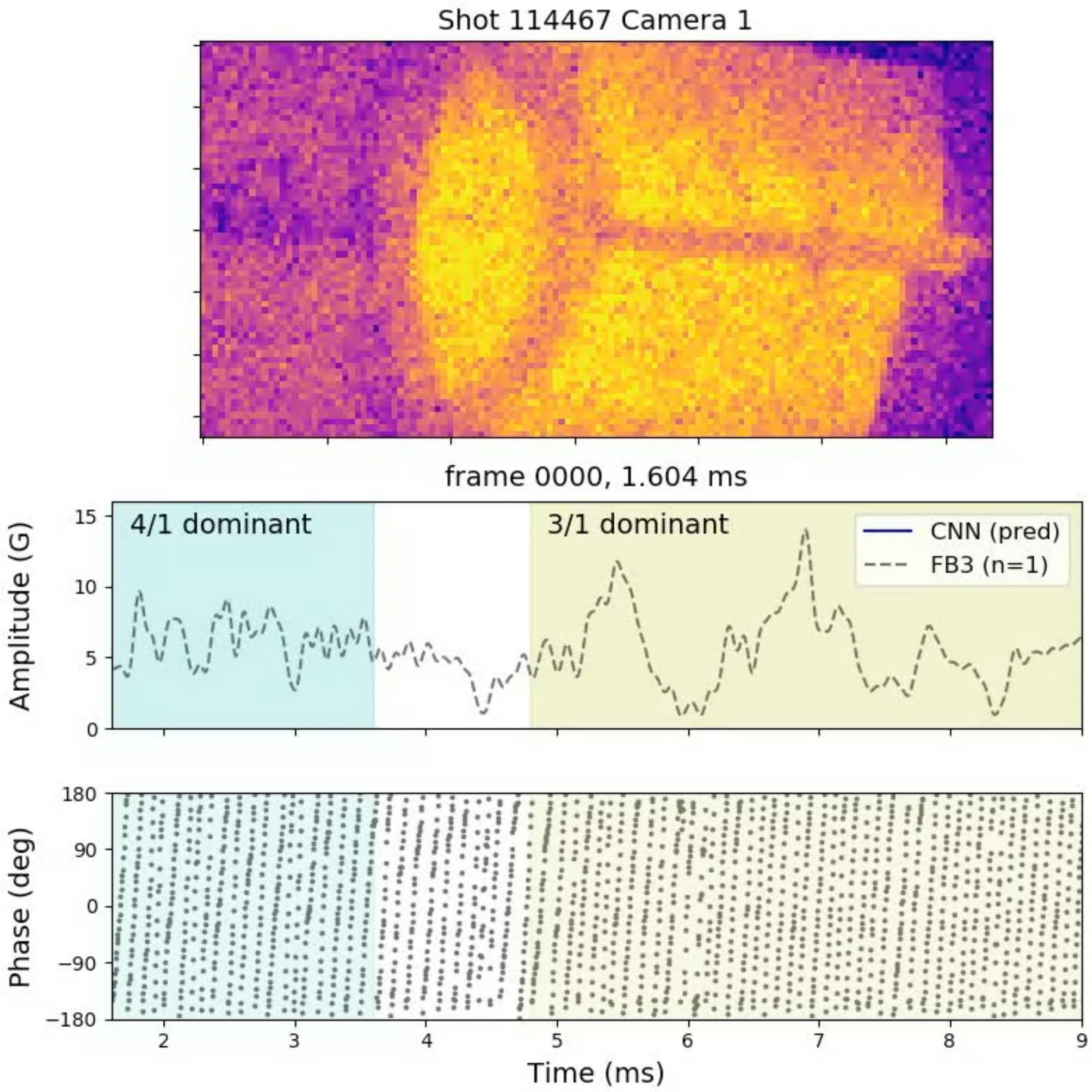
https://xkcd.com/1838/

Network Architecture (Single Camera)

Input layer	shape=(64, 128, n_frames)
Conv. block	Conv2D-MaxPooling2D filters=[8, 8, 16], padding='valid', kernel=(3, 3)
Dense block	units=[256, 64]
Output layer	units=2, 'linear'
Loss function	mean squared error
Optimizer	Adam with step decay schedule
Epochs	50

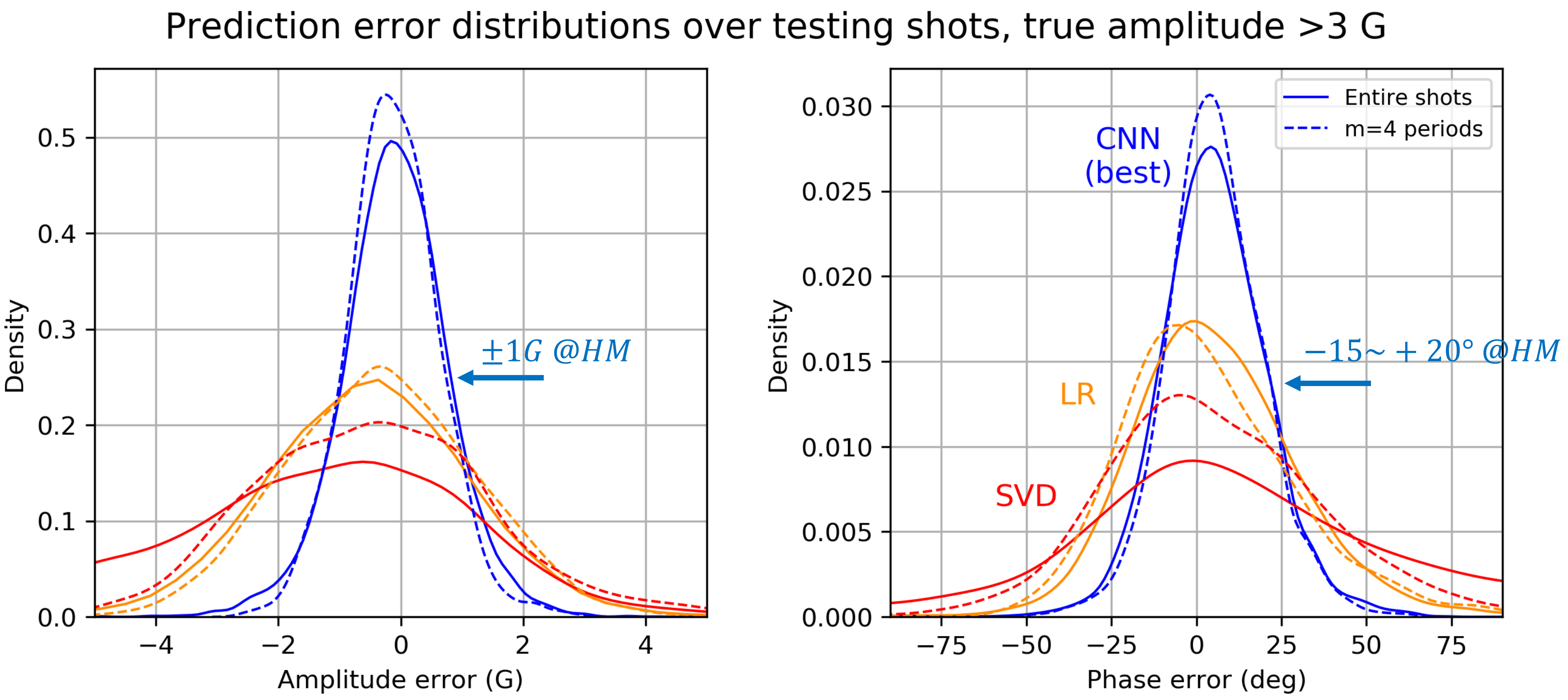
- Implemented using `Tensorflow`
- Used `KerasTuner` & hand tuning to optimize hyperparameters
  - Training & validation set: 9:1 random split
- Final models were trained using all training & validation data

Single shot tracking using the trained CNN model

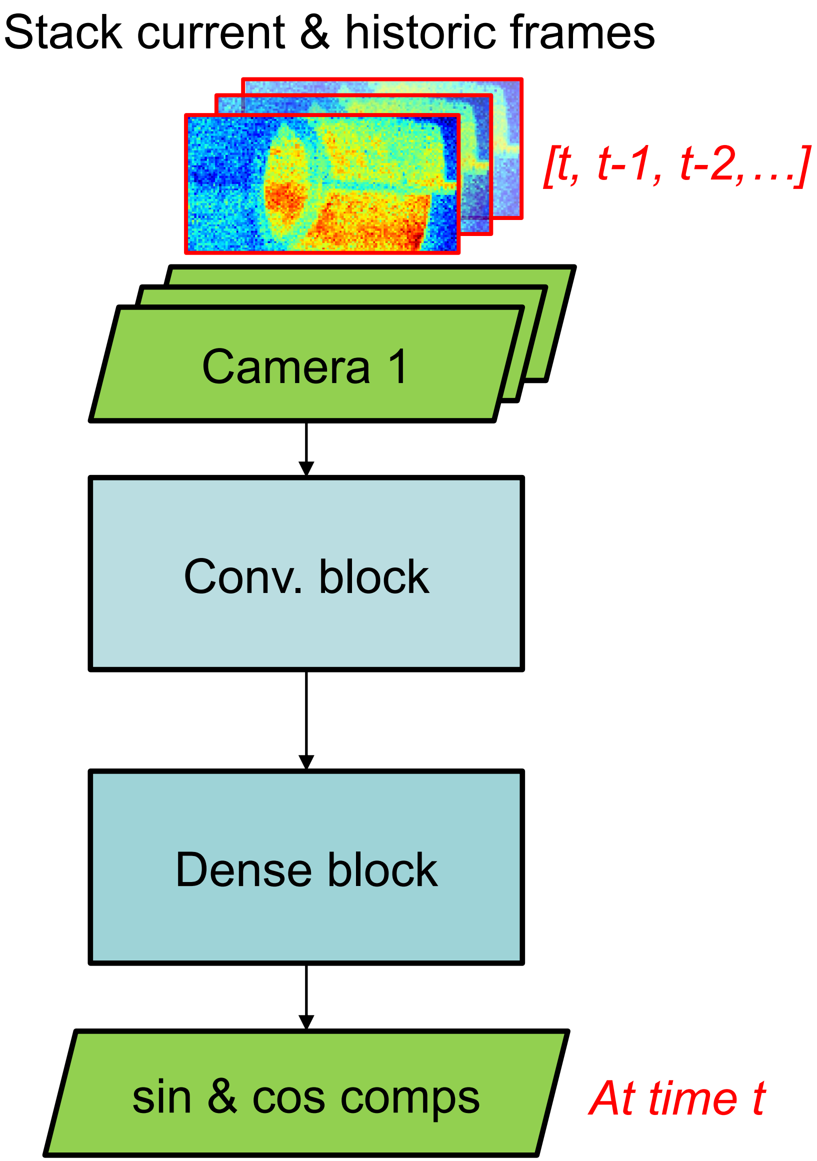


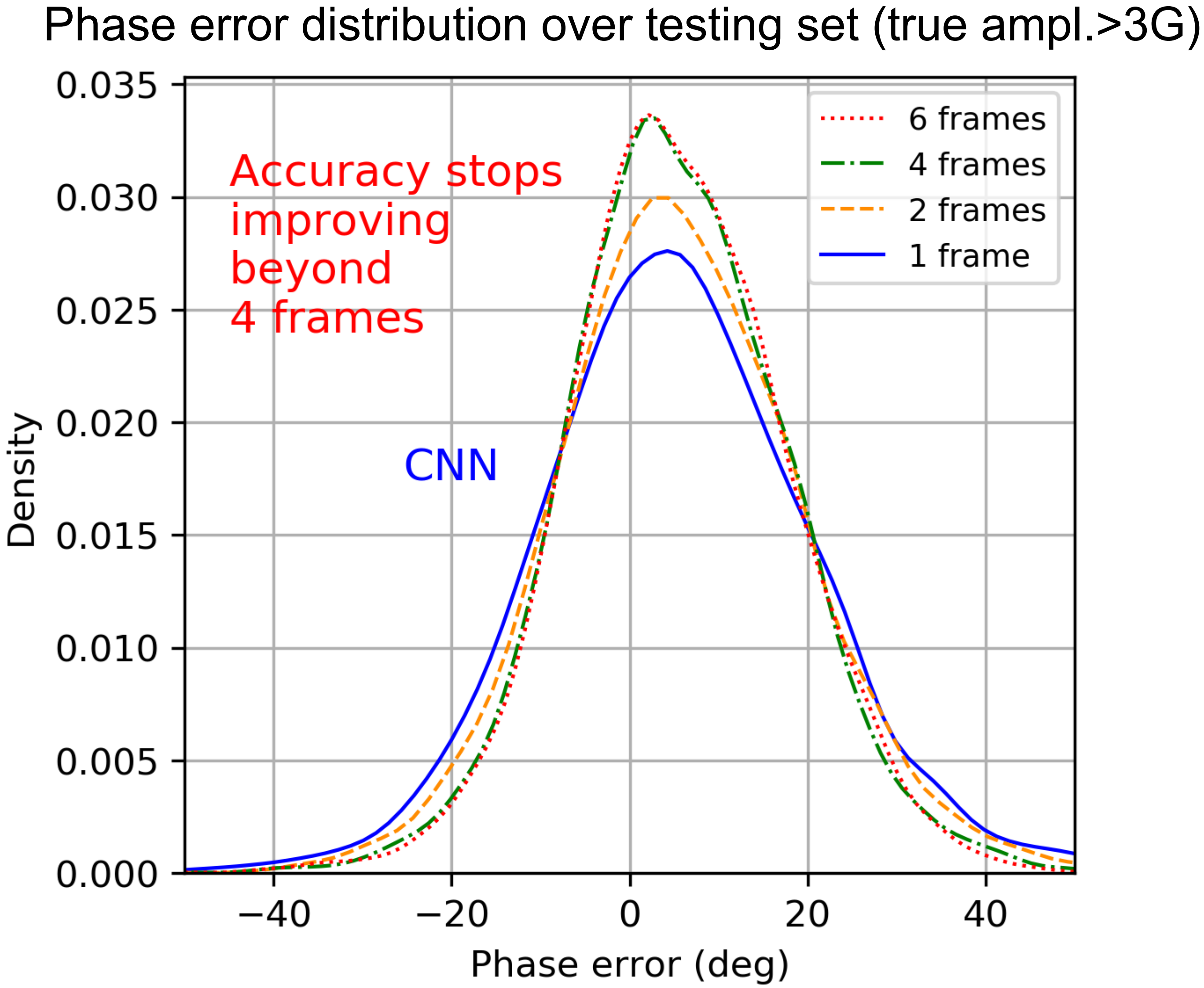
- Shot 114467 (testing set)
- Inputs: Camera 1
- Outputs: sine & cosine components of n=1 instability mode
  - Predicted amplitude and phase are calculated afterward to compare with magnetic measurements.

CNN model gives the most accurate predictions among tested methods over testing set data



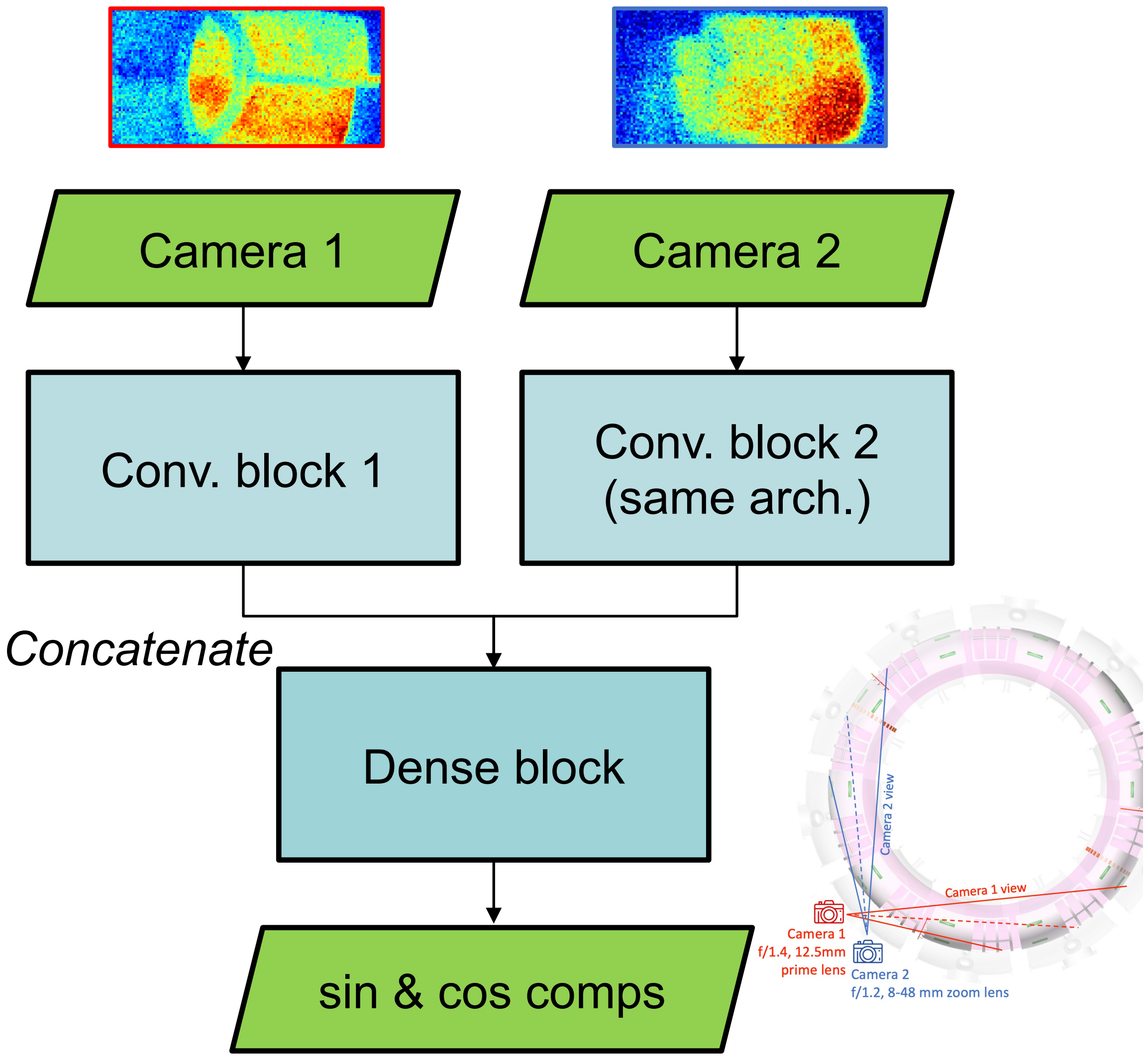
Adding temporal information by stacking frames improves predictions up to 4 frames



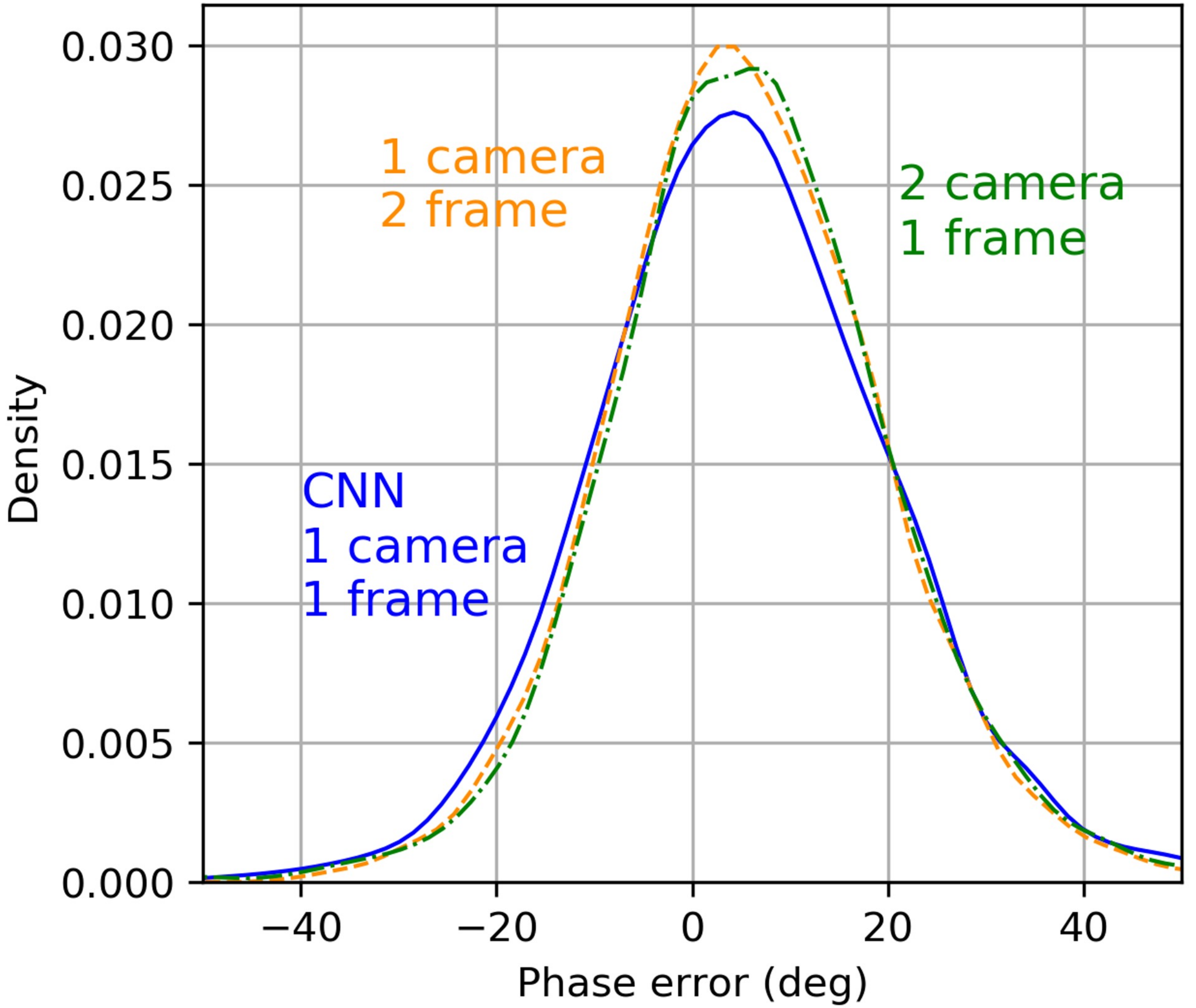


Adding a second camera gives marginal improvement similar to adding a second frame

Add a second camera



Phase error distribution over testing set (true ampl>3G)



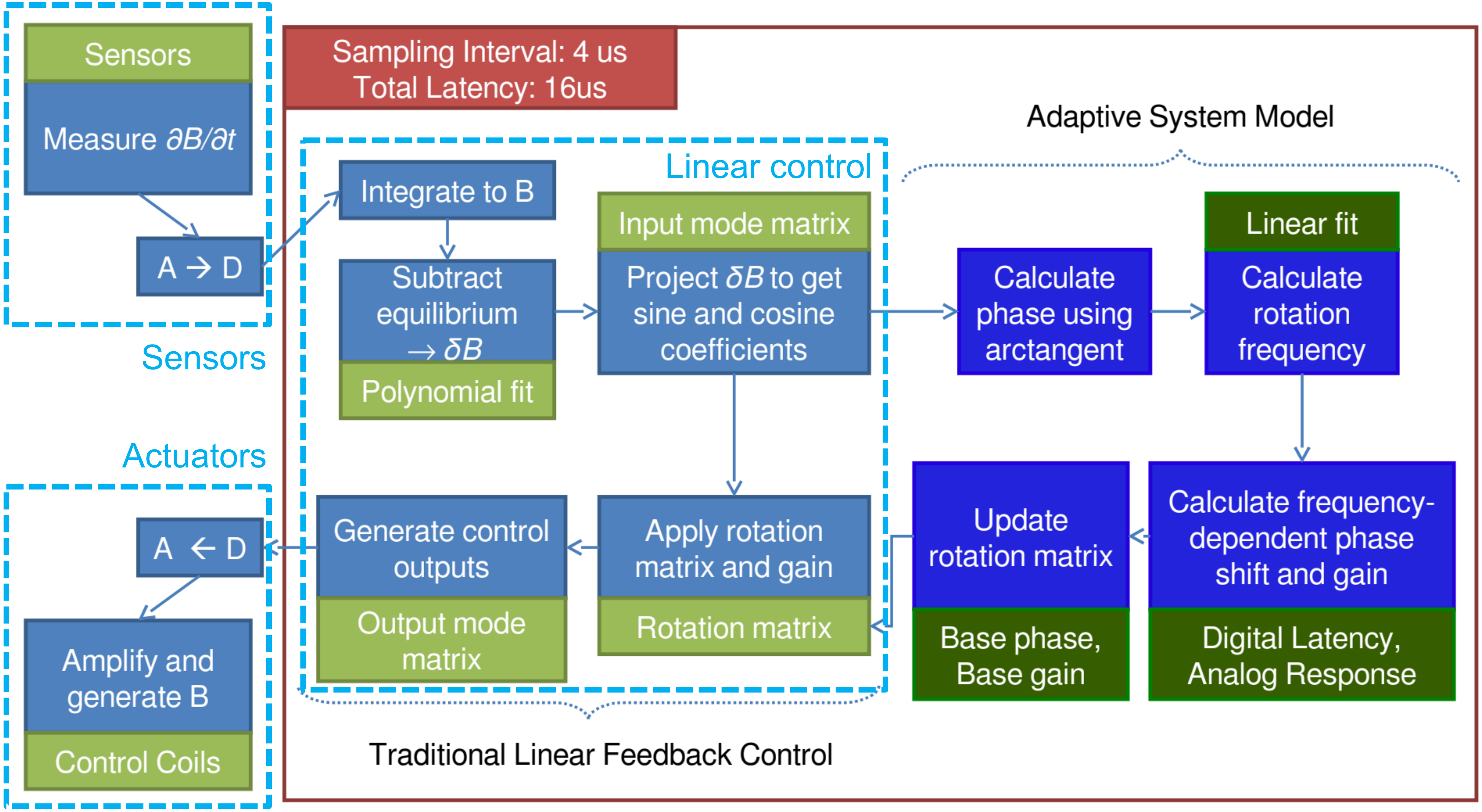
PART 3 – Plans for deploying the model in real-time

- Plasma instability diagnostics and feedback control in tokamak

- Implementing and testing the deep learning model
  - Assembling the fast camera dataset
  - Mode tracking results

- (IN PROGRESS) Plans for deploying the model in real-time

Fastcam & ML model fits in existing HBT-EP feedback control framework



N Rath et al 2013 *PPCF* **55** 084003

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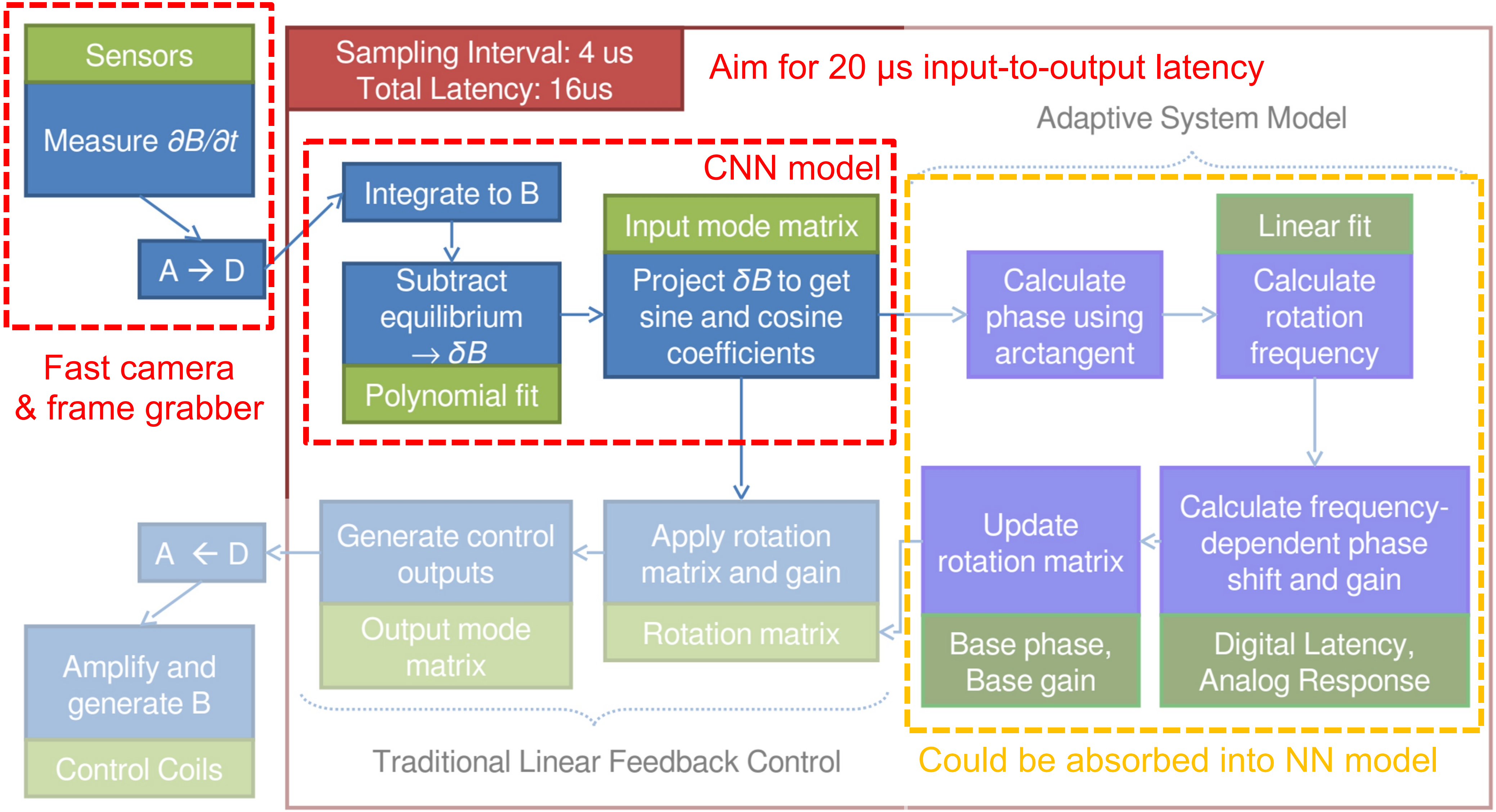


N Rath et al 2013 *PPCF* **55** 084003

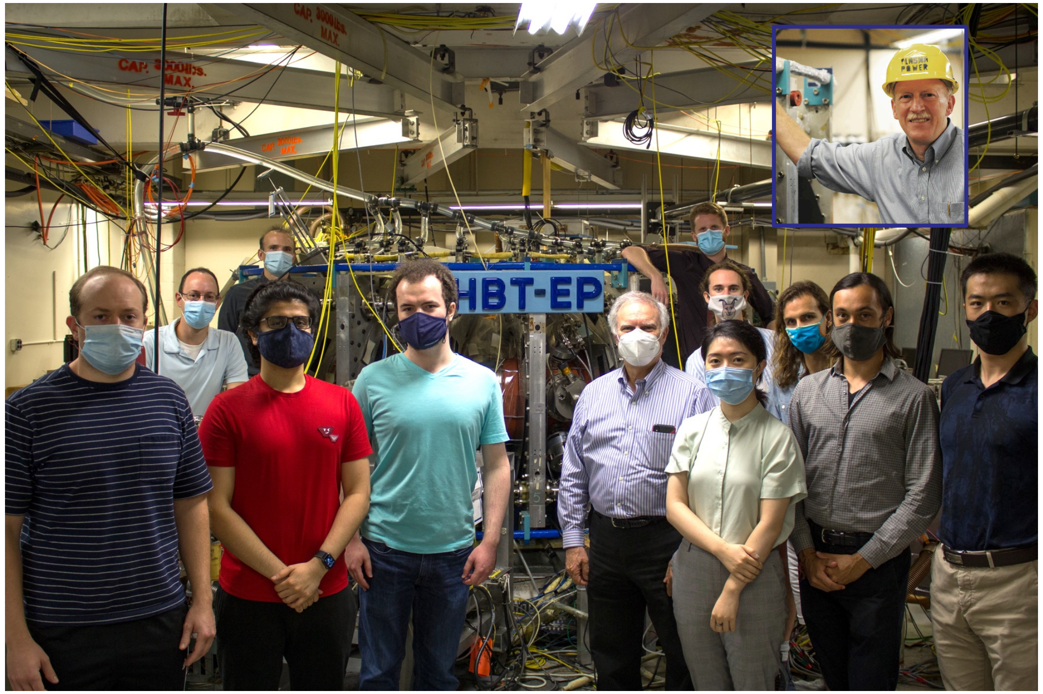
Potential implementations using GPU or FPGA

- **GPU implementation**
  - NVIDIA TensorRT + CUDA
  - Can use existing feedback control hardware & framework
  - Requires data forwarding from frame grabber to GPU (add additional latency)

- **FPGA implementation**
  - Xilinx Vivado + HLS4ML package
  - Run inference directly on the FPGA component on the frame grabber
  - Existing studies using similar networks able to lower inference latency down to 5~20 μs
  - Require extensive compression & optimization to fit model within available resource limits
  - Need to build new control framework

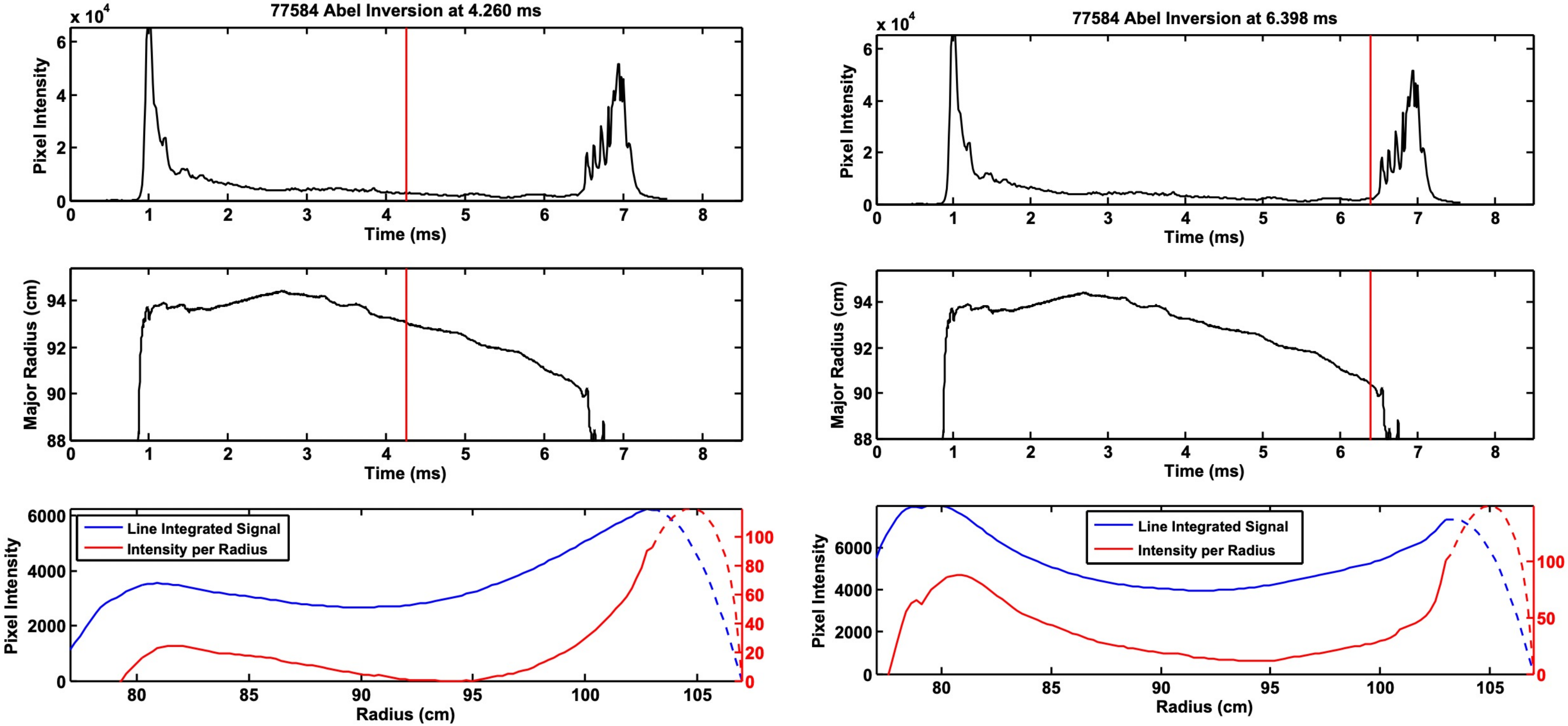
Summary

- A MHD instability mode tracking algorithm was implemented using high speed camera images and deep learning algorithm.
  - This algorithm performs better than SVD-based dominant mode pair method and linear regression over the testing set.
- Potential approaches for implementing this algorithm for real-time feedback control on HBT-EP are currently being studied.



BACKUP SLIDES

Abel inversion of camera profile



Sarah M Angelini *et al* 2015 *Plasma Phys. Control. Fusion* **57** 045008

Singular Value Decomposition/Biorthogonal Decomposition

- Biorthogonal decomposition is based on Singular Value Decomposition

$$A = U\Sigma V^\dagger$$

$$\begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \mathbf{s}_1 & \mathbf{s}_2 & \cdots & \mathbf{s}_n \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} = \begin{pmatrix} \uparrow & \uparrow & & \uparrow \\ \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_n \\ \downarrow & \downarrow & & \downarrow \end{pmatrix} \begin{pmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_n \end{pmatrix} \begin{pmatrix} \longleftarrow & \mathbf{v}_1 & \longrightarrow \\ \longleftarrow & \mathbf{v}_2 & \longrightarrow \\ & \vdots & \\ \longleftarrow & \mathbf{v}_n & \longrightarrow \end{pmatrix}$$

where $\quad \mathbf{u}_i \cdot \mathbf{u}_j = \delta^i_j, \quad \mathbf{v}_i \cdot \mathbf{v}_j = \delta^i_j$

Temporal modes that track m/n MHD mode amplitude evolution

OR $\quad A = \sum \sigma_i \mathbf{u}_i \otimes \mathbf{v}_i$

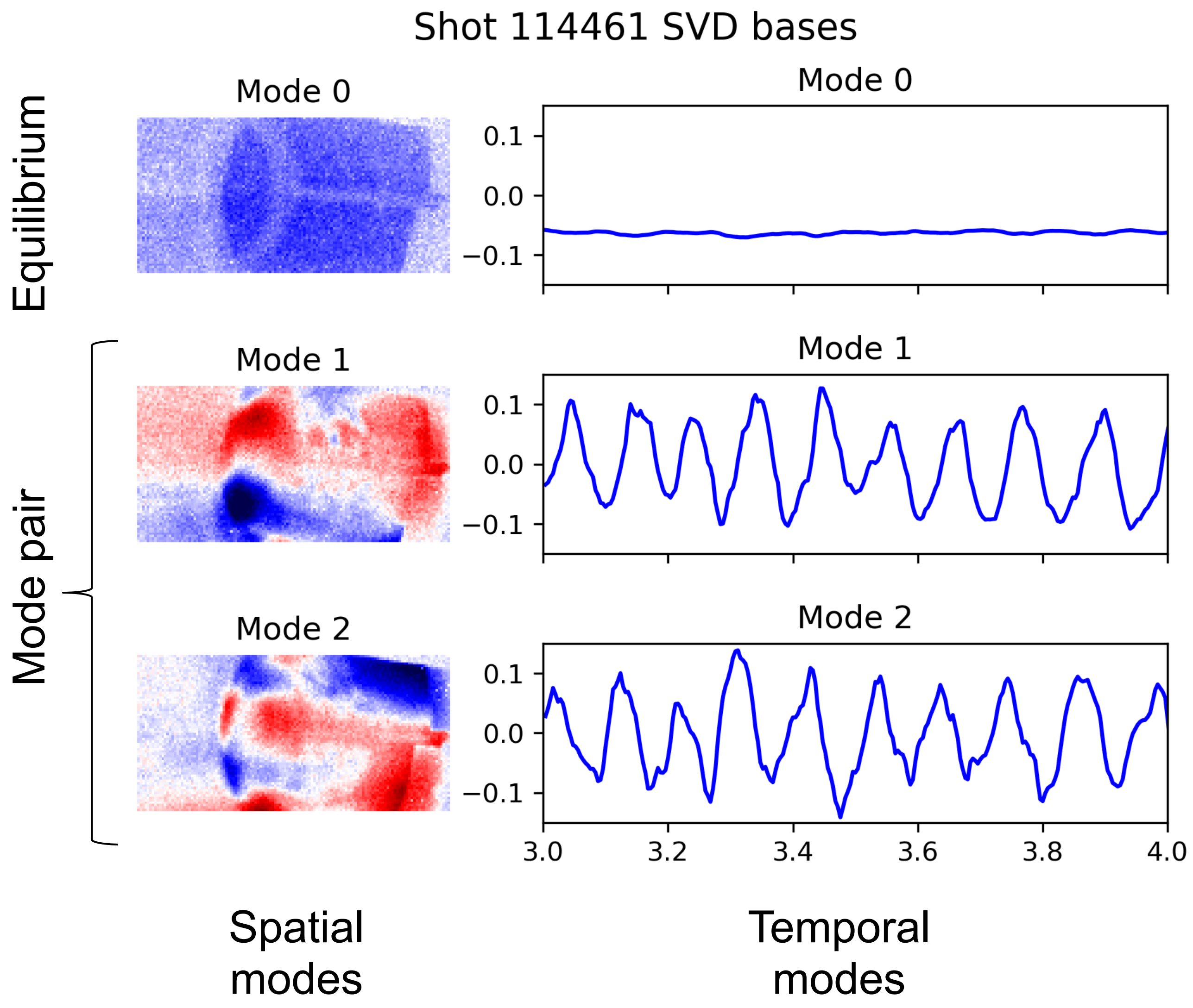
Time independent spatial modes that capture the m/n structure of an MHD mode

- Robust against sensor calibration/alignment errors

- Eigenmodes based on at sensor measured fluctuation structure

- Measured biorthogonal modes will be used to quantify plasma response to magnetic perturbations

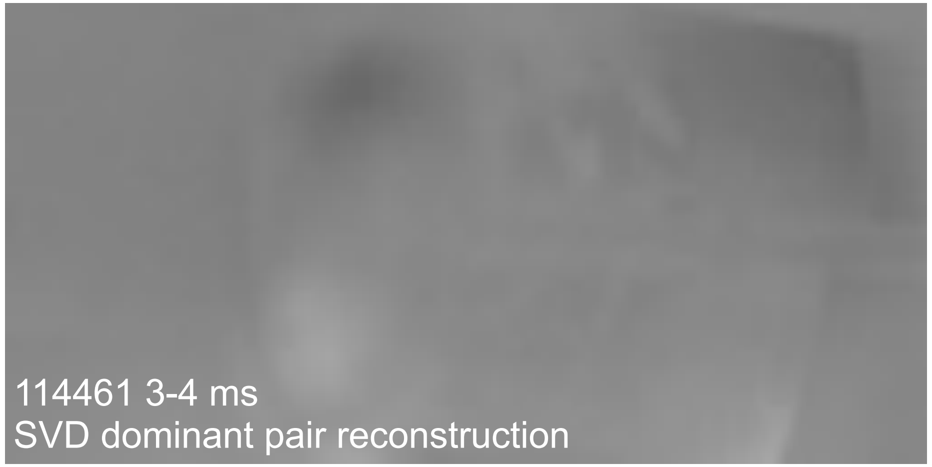
SVD analysis captures dominant mode information from camera video

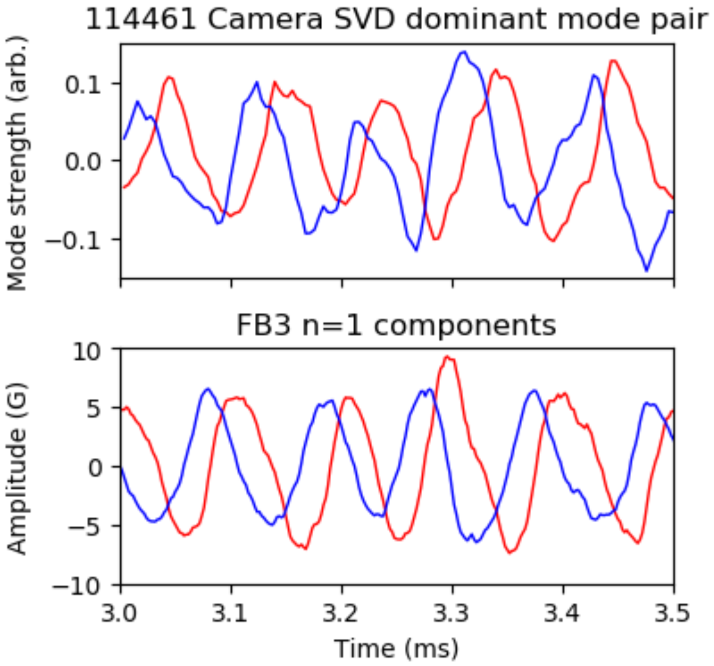


- **Singular Value Decomposition (SVD)** splits spatiotemporal data into coherent, orthogonal modes of fluctuation structures ("spatial" and "temporal modes")
- By decomposing camera data from a specific time interval, we found the first mode pair correlates with the sine & cosine components of the dominant MHD mode.
  - SVD requires selecting the proper time interval to produce valid results
- Can we apply this technique for mode tracking?

Method from Sarah M Angelini *et al* 2015 *PPCF* **57** 045008

SVD analysis captures dominant mode information from camera video





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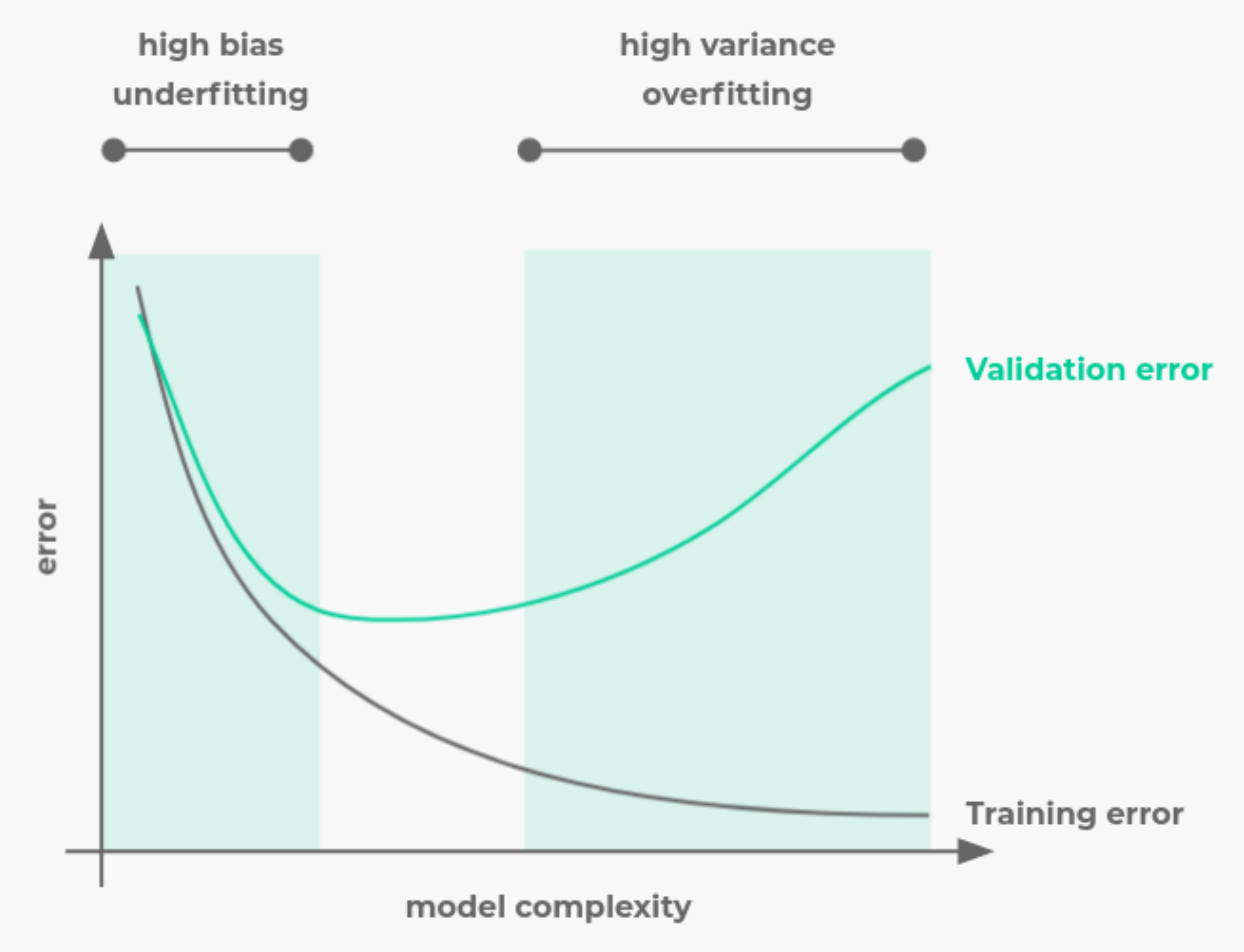
Method from Sarah M Angelini *et al* 2015 *PPCF* **57** 045008

Underfitting & overfitting



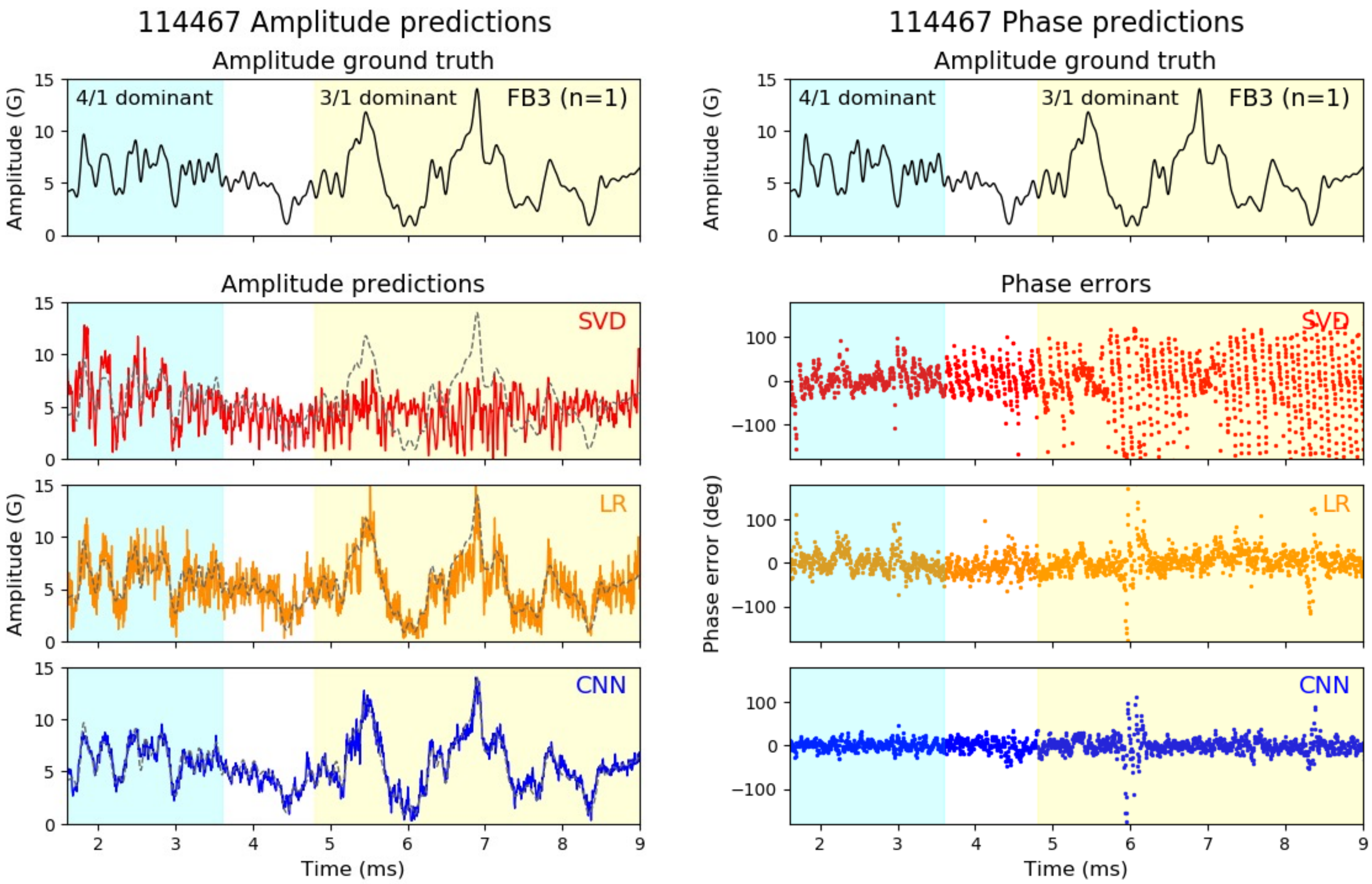
CNN gives more accurate predictions compare to existing tracking methods

Magnetic (ground truth)

SVD mode pair (bases: 114461 m=4)

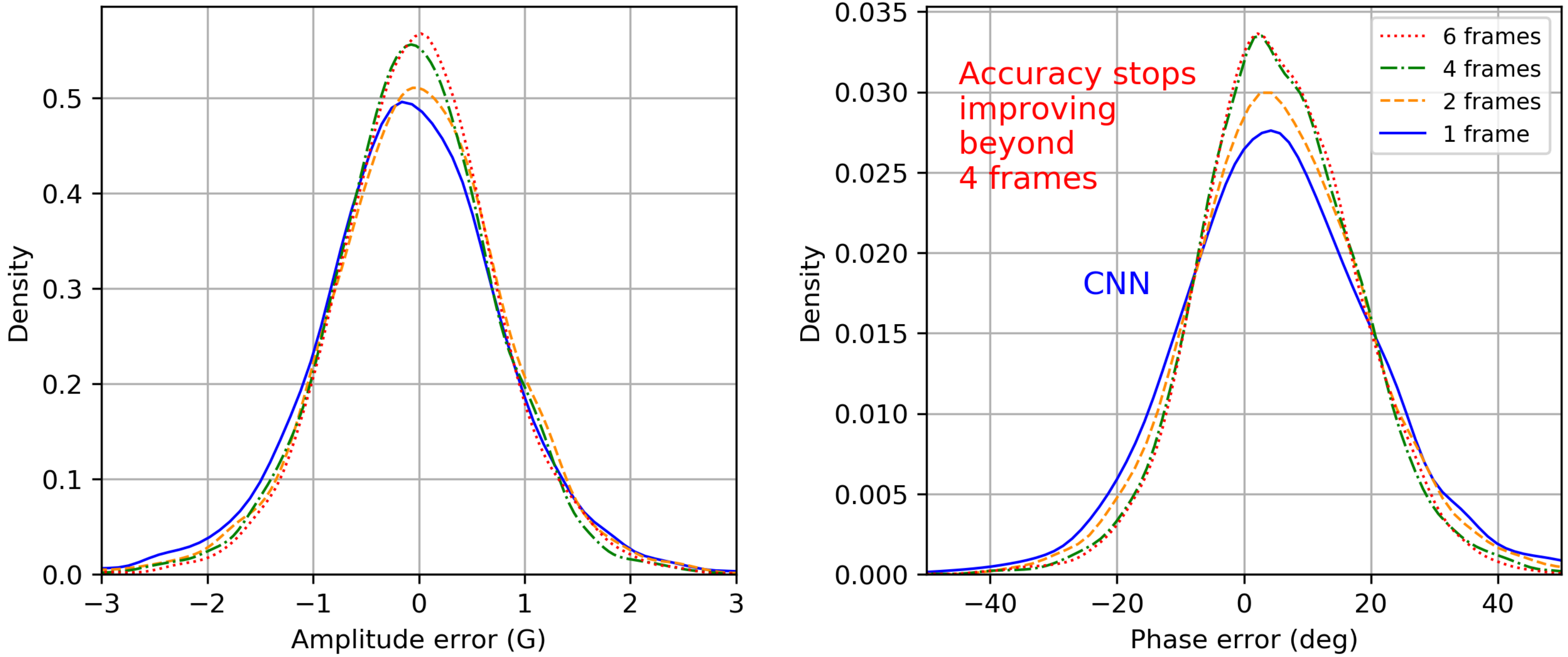
Linear Regression

Convolutional Neural Network



Stacking historic frames

Prediction error distributions over testing shots, true amplitude >3 G



Adding the 2nd camera

Prediction error distributions over testing shots, true amplitude >3 G