MAX-PLANCK-INSTITUT FÜR PLASMAPHYSIK

Wendelstein 7-X

Auto-encoding quadrature components of modulated dispersion interferometers

paper rehearsal for PPCF (ECPD 2025 proceedings)

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EUROfusion

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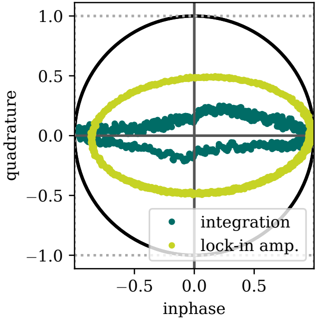
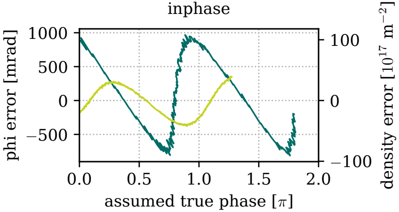
Motivation

- Dispersion interferometry is a key control diagnostic in an increasing number of fusion experiments
- At W7-X the interferometer suffers from distortions of the quadrature constellation in all phase evaluation methods (Brunner et al. [2022])
  - quadrature components in short: $s(t) \propto e^{i\Phi(t)} = inphase(t) + i \cdot quadrature(t)$
- Cause systematic errors in phase space that change over time and can only be partially corrected
- correction is static, which is a problem for steady-state operation





Previous work and placement within

- We want to use artificial neural networks (ANN) to address the errors
- Quadrature component extraction is a common problem and has been attempted with neural networks, e.g. in radio communication
- in interferometry the first application was Li et al. [2003] followed by other correcting nonlinearities in the constellation of homodyne interferometers
- only Olyaee et al. [2014] attempted this with a heterodyne interferometer and again only to correct errors after the measurement

Our approach :

- this is the first attempt at extracting quadrature components directly using an auto-encoder without training on *known results*
- nobody has attempted this, esp. not with a modulated dispersion interferometer
- The general training methodology can be applied to other quadrature detection schemes outside of interferometry even

Background

- The temporal interferogram of a modulated dispersion interferometer in the time domain can be described by a sum of integrals (Brunner et al. [2018])

$$\textit{inphase}: \quad \int_0^{T_m/2} \tilde{s}(t)\mathrm{d}t + \int_{T_m/2}^{T_m} \tilde{s}(t)\mathrm{d}t \propto C_i(\rho)\cos\phi_p \tag{1}$$

$$\textit{quadrature}: \quad \int_0^{T_m/2} \tilde{s}(t)\mathrm{d}t - \int_{T_m/2}^{T_m} \tilde{s}(t)\mathrm{d}t \propto C_q(\rho)\sin\phi_p \tag{2}$$

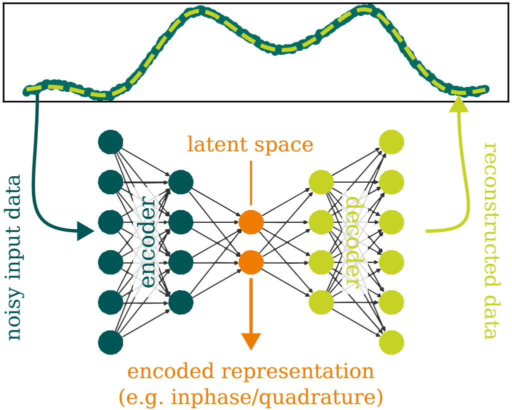
- Hornik et al. [1989] have shown, that artificial neural networks (ANN) are universal approximators
- Lloyd et al. [2020] have shown that an ANN can act as a universal integrator on $\mathbb{R}^n \to \mathbb{R}$
- Hence, an ANN should be able to learn quadrature components directly

The catch

- A normal ANN learns on a *ground truth*, e.g. in our case a "known integral"
- In our case the known data would have to come from the experiment and would inherit the error we are trying to remove
- We need to train the ANN to extract the phase from the signal without a known value $\Rightarrow$ Autoassociative self-supervised learning
- Most common class of ANN used for this purpose is an auto-encoder (AE)

Auto-Encoders

- Are a type of reproductive ANN used for dimensionality reduction, feature extraction and noise removal (Rumelhart et al. [1986], Hinton and Salakhutdinov [2006])
- The network attempts to reproduce an input by compressing it to some encoded representation and then decoding that representation again
- The decoded data is a (usually noise reduced) reproduction of the input
- often the latent space is ignored



Training an intelligible latent space

- An AE will find an arbitrary solution in the latent space that allows it to reproduce the output $\rightarrow$ latent space is normally unintelligible
- We reduce the latent space solutions to only the ones with certain mathematical properties using regularization on the latent space directly:

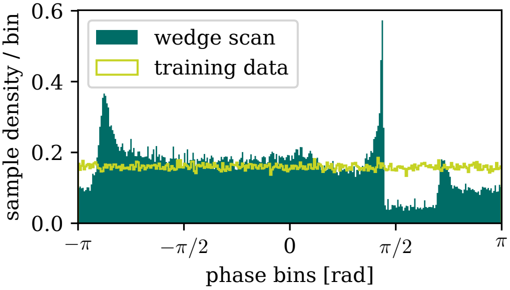
$$MSE_{\perp} = \sum_{N} \left(x_{i,1}^2 + x_{i,2}^2 - 1 \right)^2 \tag{3}$$

$$MSE_{\text{origin}} = N \cdot \left(\left| \text{mean}(x_{i,1}) \right| + \left| \text{mean}(x_{i,2}) \right| \right) \tag{4}$$

- $MSE_{\perp}$ enforces the first two latent space variables to reside on the unit circle
- MSE_{origin} enforces the first two latent space variables to be centered on the origin. This is only true for large randomly sampled batch sizes (i-index)

Sampling for training without a sampling gap

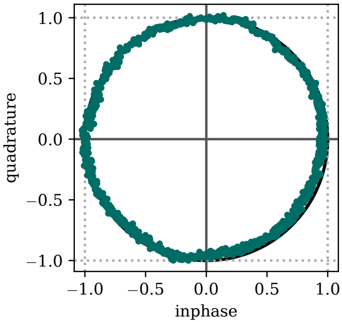
- In a quadrature scheme the entire range of possible ANN inputs can be sampled, since phase is contained within $(-\pi, \pi)$
- We scan the unit circle using a wedge scan, which is always acquired at W7-X for quadrature correction (Brunner et al. [2018, 2022])

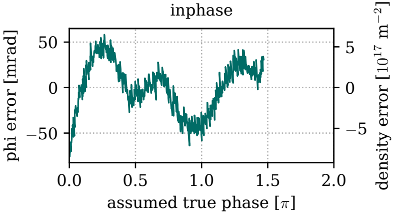


- from the wedge we randomly sample such that the resulting distribution is uniform in $(-\pi, \pi)$
- The batch size is arbitrarily chosen with 3 times the number of bins
- This scheme also allows training on plasma data, but no difference in performance was seen, so we use the wedge (not shown in the paper)

ANN constellation error

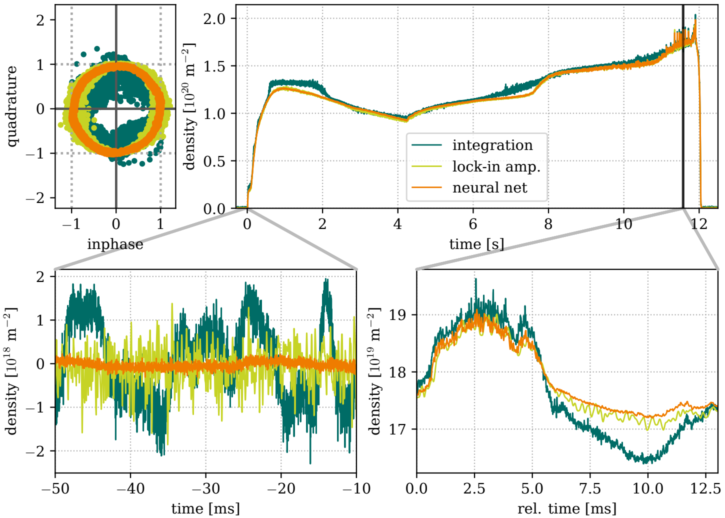
- network architecture tuned using *keras_tuner*:
  - asymmetric auto-encoder
  - single hidden layer (least computational effort)
  - roughly 150 neurons (different for en- and decoder)
  - 3 latent space variables
- ANN derived constellation is incredibly clean with minor residual distortions (need to be investigated in the future)
- The systematic error is on par or lower than the *corrected* lock-in amplification method's (currently the best achievable)





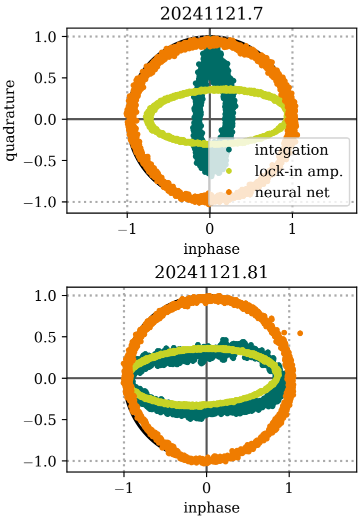
Program performance

- plasma data from program #20241112.62
- noise is significantly lower in the no-plasma case
- resolution of highly dynamic plasma situations with incredible fidelity



Discussion

- method can be used to train a network on multiple programs
- allows us to effectively mitigate constellation drifts over the course of the day (omnipresent at W7-X and currently ignored in the real-time system)
- highly interesting for real-time applications, which currently cannot correct these drifts
- The neural network is small enough to fit on an FPGA, i.e. real-time capable



Summary

- We have developed a method to extract quadrature components from the temporal interferogram of a modulated dispersion interferometer directly
- We show that the fidelity of the W7-X IEDDI system can be enhanced by almost an order of magnitude at full bandwidth and by a factor of 2 in both precision and accuracy when compared to the lower bandwidth lock-in amplification method
- The scheme can be expanded to mitigate constellation drifts at W7-X, which occur over the course of an experiment day and is compatible with the W7-X real-time FPGA evaluation
- The training scheme presented here is not confined to the dispersion interferometer field and prob. applicable to most quadrature detection schemes
- One could envisage a continuous incremental training to constantly calibrate the system during a density steady-state flat-top phase

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