Generative model approach on TFM data based on variational inference for muti-fidelity data generation

Gerardo Granados, Giorgia Colombera, Filippo Gatti, Roberto Miorelli, Didier Clouteau, Sébastien Robert

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Generative model approach on TFM

1. **Introduction**
   - Industrial context, motivation et applications
   - Challenges for UT inspection
   - Case of study: TFM data-set

2. **Method**
   - Conditional U-Net as generator architecture

3. **Results**
   - Metrics on test set
   - Latent space (looking inside the network)

4. **Conclusions and perspectives**

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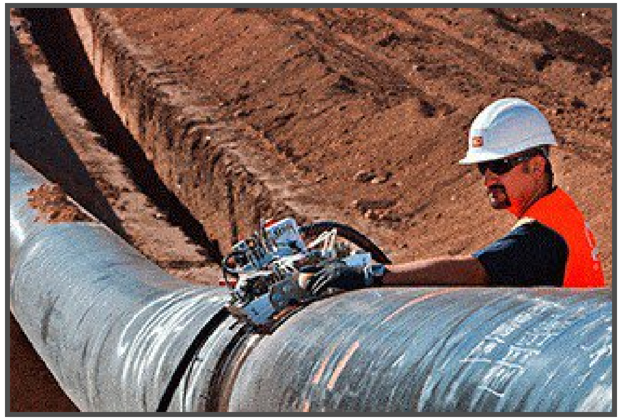
Examples of applications in industrial fields

- Nuclear
  - Inspection of welds
  - Characterization of materials
- Metallurgy
  - Inspection of parts during manufacturing process
  - Characterization of materials
- Aeronautics and aerospace
  - Multi-layer structure
  - Composite materials



NDT&E and SHM modelling

- Data generation for diagnostic, life time prediction
- Materials characterization (Advanced Manufacturing)
- Performance demonstration
- Probe optimization
- Defect detection, classification and characterization

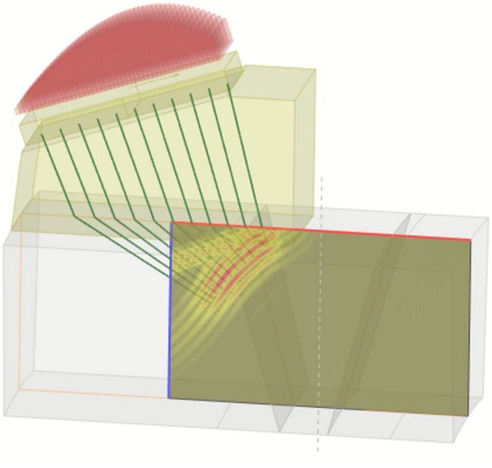
Exploitation of fast and reliable models

- Dimensioning and defect characterization (form/type/criticality)
- Confidence intervals on estimation (e.g., uncertainties).
- Assessment of the “well-posed” nature of the inverse problem
- Rapid Inversion (Online diagnostic)

On the application of ML to nondestructive testing and evaluation (NDT&E) and in particular in ultrasound testing (UT)

Peculiarity, challenges, and issues of UT inspection problems:

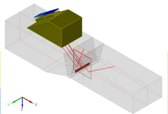
- **Access to reliable simulations** (semi-analytical approaches finite elements models, etc.)
  - model driven ML approaches are feasible
- **Lack of public realistic datasets** (security and secrecy constraint issues)
  - data driven ML approaches are very often not feasible
- Operational conditions **may impact** the measurements (from the ML perspective)
  - non-negligible impact on the acquisitions
- **Lack of knowledge** associated to the inspection scenarios
  - non-negligible aleatoric uncertainty in the data



Objective: Coupling of reliable simulations and experimental data for enhancing ML performance in view of developing UT inspection and diagnostic tools

Investigated solution: Multi-fidelity deep generative model aiming at combining low fidelity (LF) simulated data and high fidelity (HF) experimental acquisitions for enhancing the performance of automatic diagnosis tools in NDT&E

Forward Problem



LF (simulations) → ML → HF (measures)

+ faster | + accurate

Diagnostic tools for NDT&E

- Regression
- Classification
- Statistical analisys
- Performance study

Industrial context: inspection of complex welded structures via ultrasonic testing (Total Focusing Method -TFM-) imaging

LF

CIVA NDE

Simulation data

1. Wave emission and propagation (inspected area)
2. Interaction (diffusion) with acoustic discontinuities.
3. Simplified approach for attenuation and structural noise.

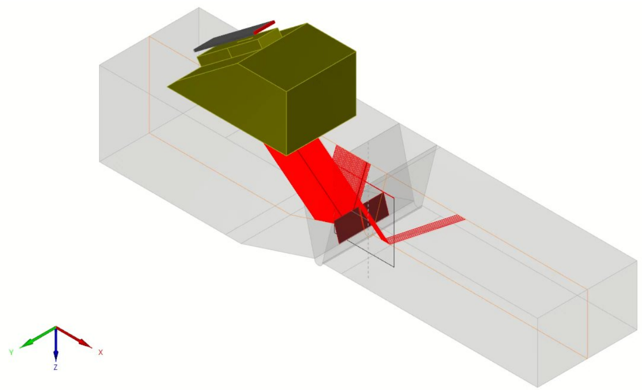


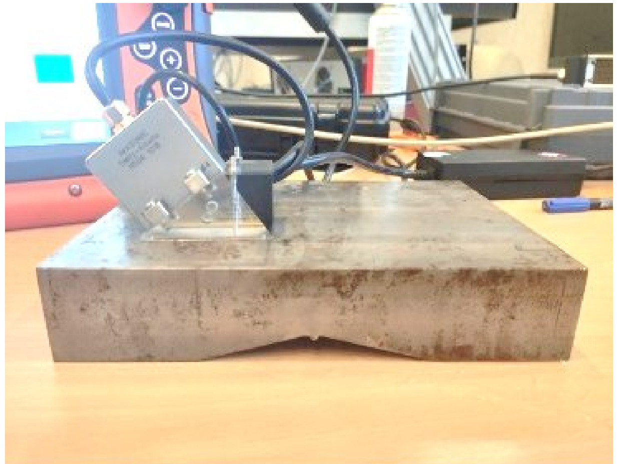
Fig 1 - CIVA configuration for simulated welded structure NDT inspection.

HF

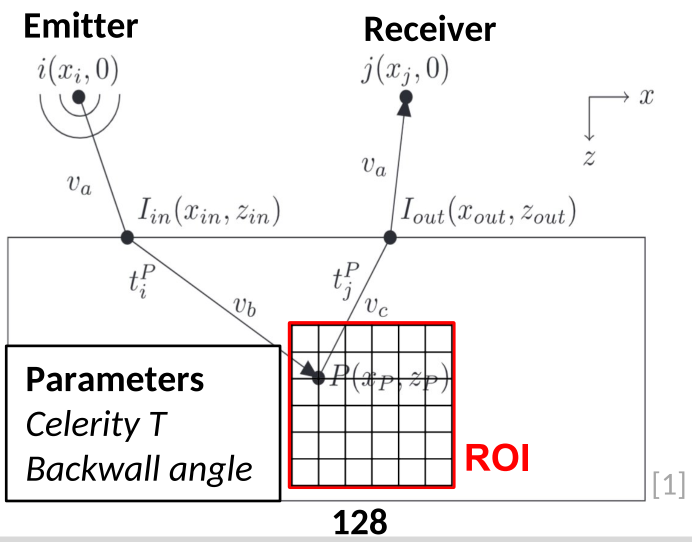
ADVISE Euratom

Advanced Inspection of Complex StructurEs

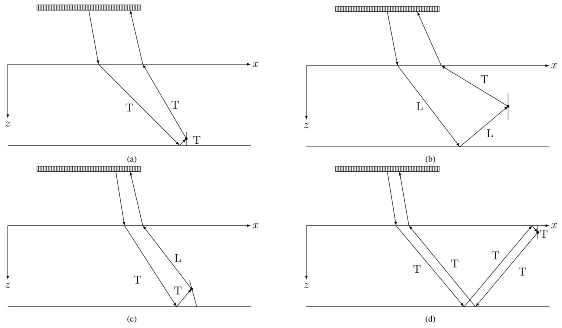
Experimental acquisitions



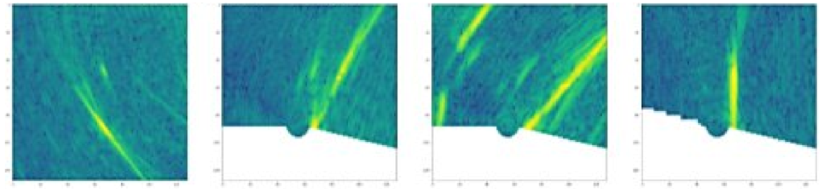
Some background on the generation of TFM dataset images



[1]



[2]



Pixel amplitude

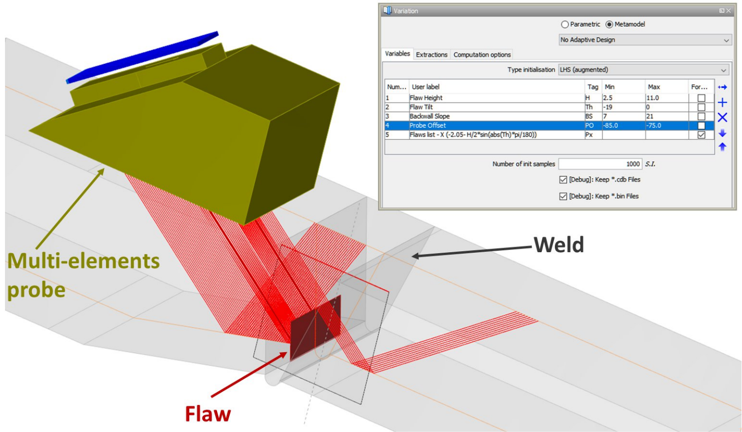
$$s_{ij} = k_{ij}(t) + jH(k_{ij}(t))$$

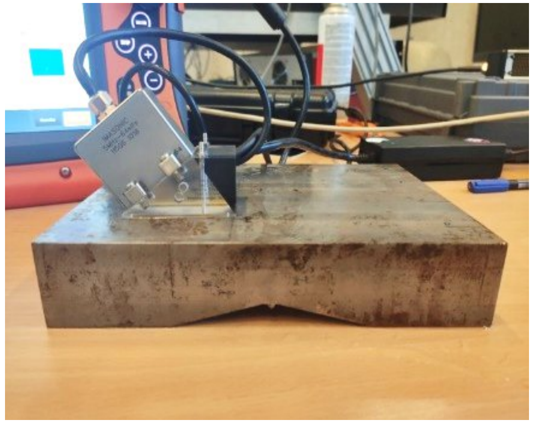
$$A(P) = \left| \sum_{i=1}^{N} \sum_{j=1}^{N} s_{ij}(t_i^P + t_j^P) \right|$$

[1] L. Le Jeune, S. Robert, E.L. Lopez Villaverde, C. Prada, (2016)
[2] L. Merabet, S. Robert, C. Prada (2020)

Simulation on CIVA and TFM imaging

Multi-fidelity deep generative model: mixing mode- & data- driven approaches



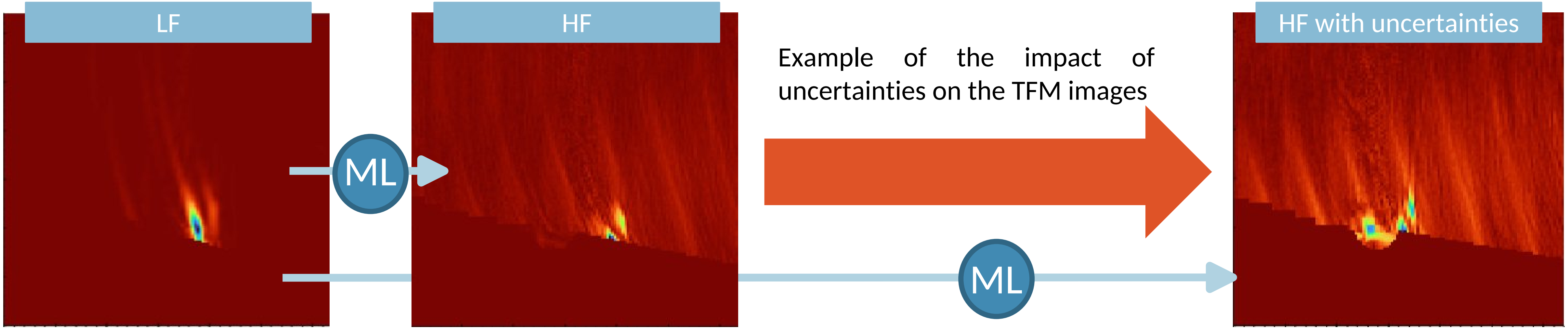


Parameters (labels)	Valeurs
Flaw orientation	Vertical ; Tilted
Flaw high	3mm ; 10mm
Wave speed T (reconstruction image)	[3080; 3380]
Alpha (angle) (reconstruction image)	[10;18]

Uncertain parameters

Example of same realisation: simulation and experience TFM reconstruction parameters without uncertainties

Same experimental realisation with uncertainties on wave speed of the piece (same flaw geometry, etc.)



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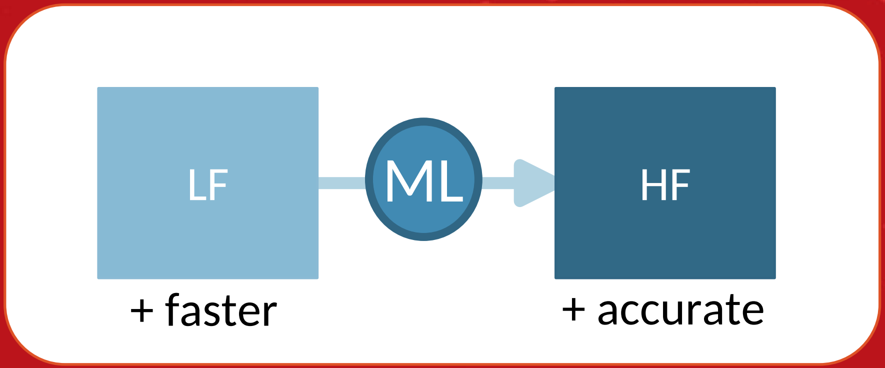
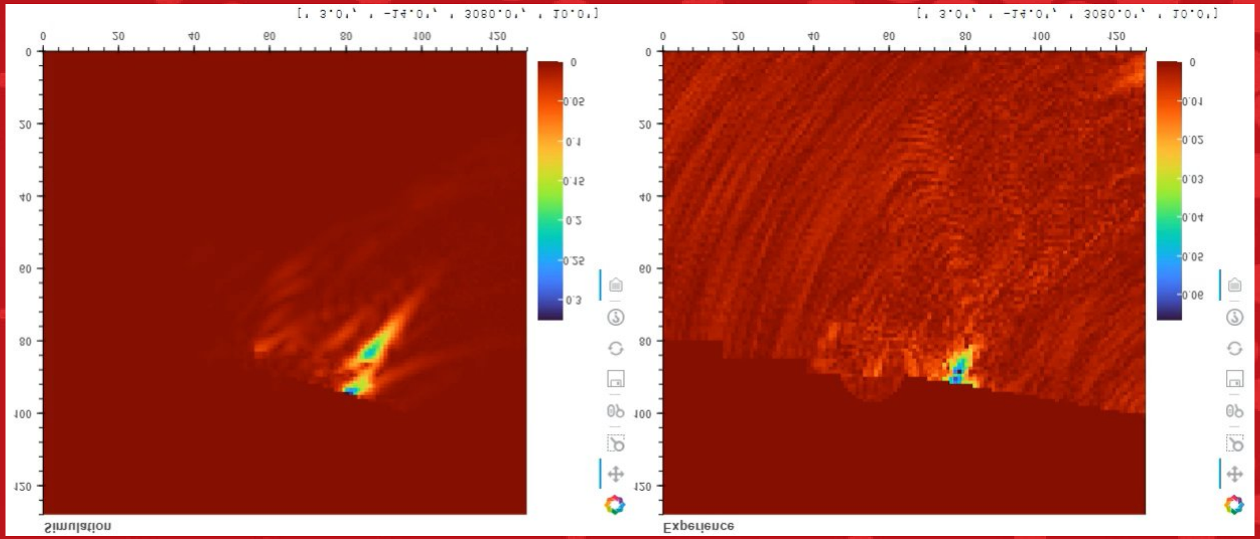
Meta Model (ML)



Sim. (LF) vs Exp. (HF)



TFM samples: ~3k per class (2 classes)

Approch:

Conditional U-net on ultrasonic testing (UT) TFM images

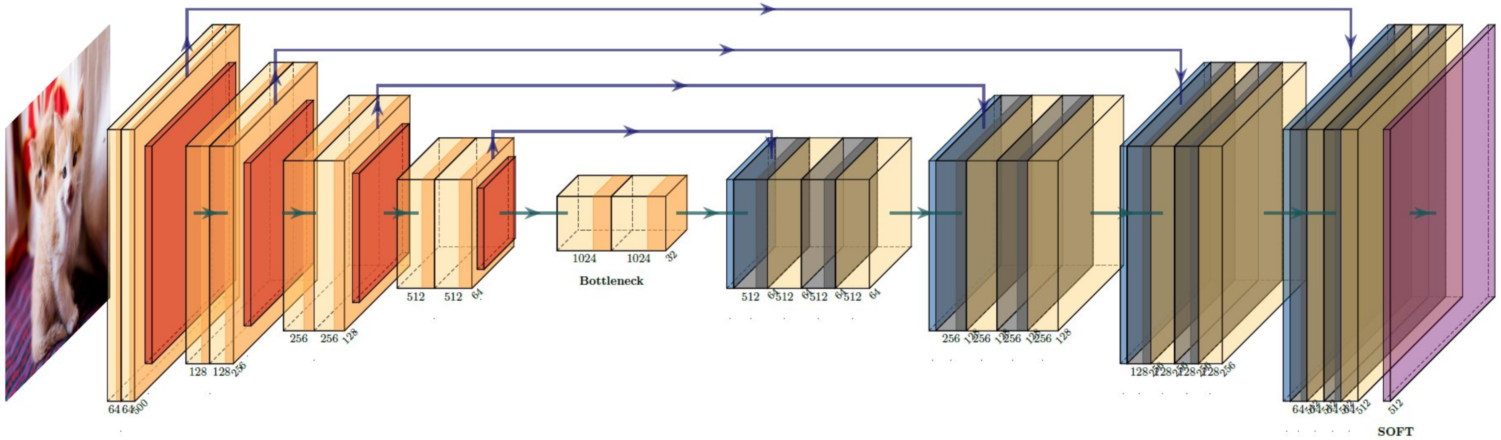
Conditional U-Net as generator on TFM data

Architecture

U-Net common applications

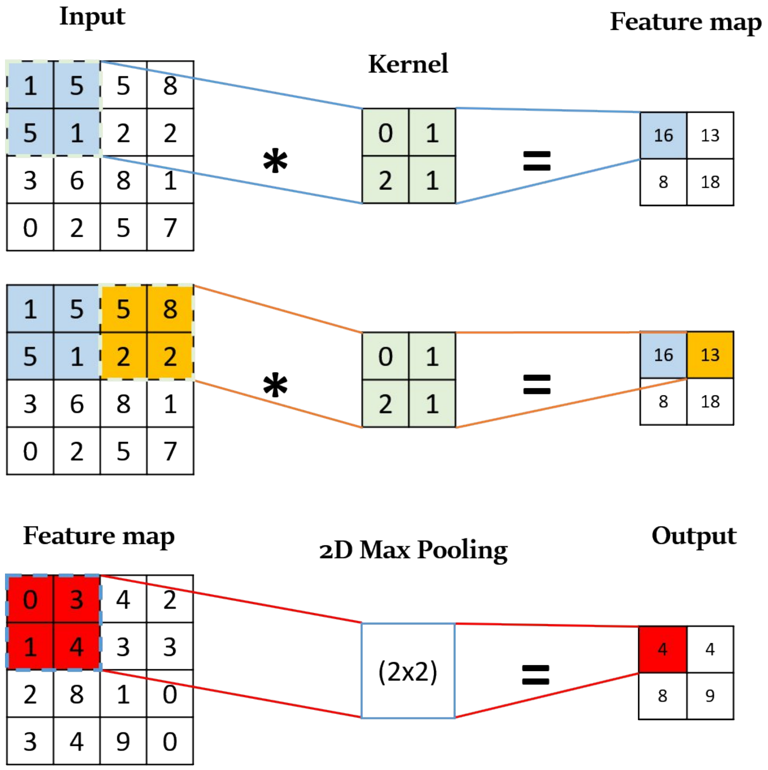
- Image classification (class distinction)
- Objects detection (label and localization)
- Semantic segmentation (label for each pixel)
- Style transfer
- Image super-resolution
- Conditional U-Net for multitask (multi-label and multi-class)

U-Net base architecture [3]



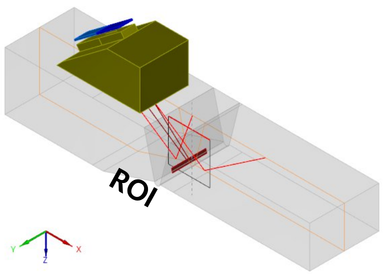
[3] Ronneberger, O., Fischer, P., Brox, T. (2015).

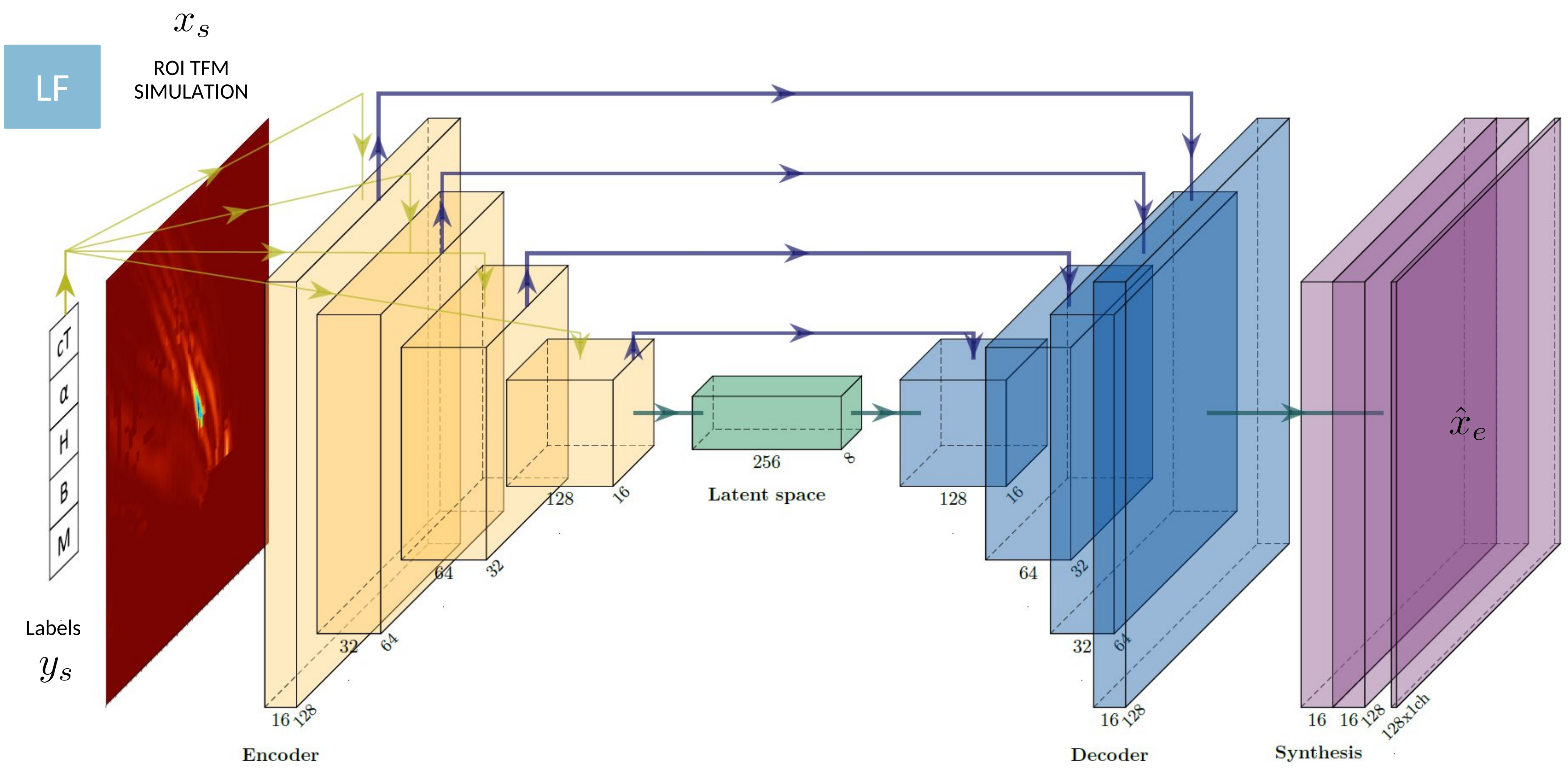
Convolution and 2D Max Pooling

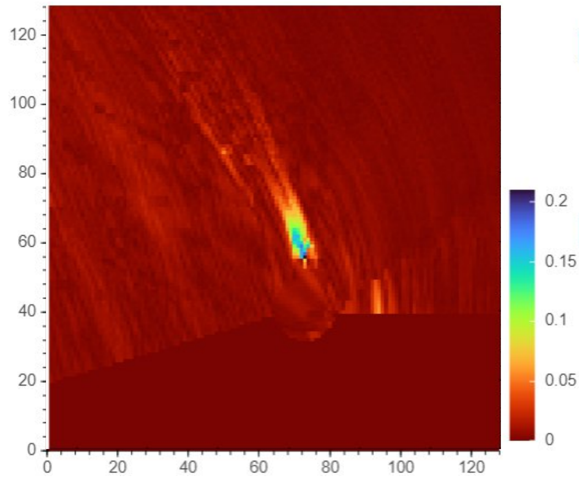


- **Spatial features extraction**
- **Learns hierarchy on images**
- **Less parameters than FC layers**

Conditional U-Net as generator on TFM data (supervised)
Architecture: encoder – latent space – decoder – synthesis







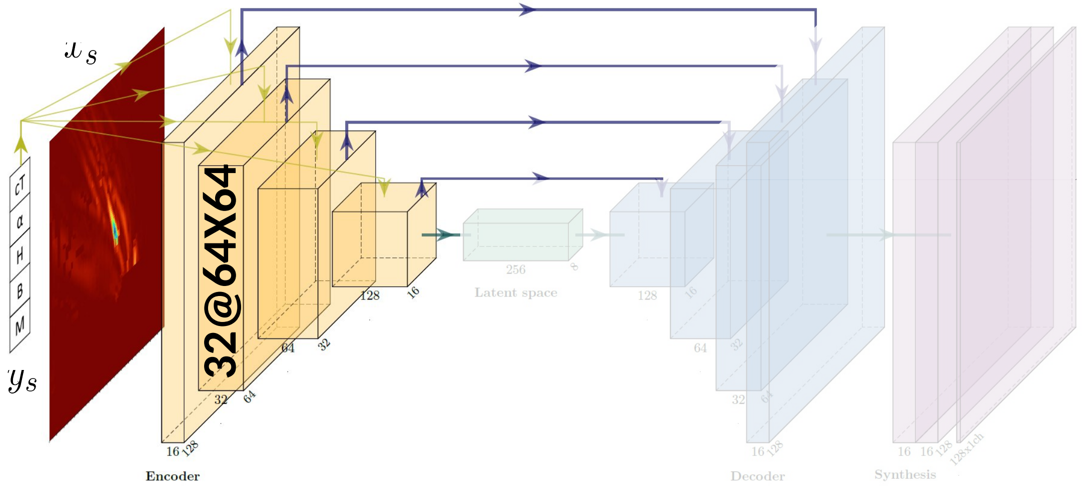
Losses: Mean Square Error
Focal Frecuency Loss

Metrics: Echo **amplitude**
Echo **location**

Fig 6 – Conditional CNN U-net architecture for realistic image generation.

Conditional U-Net as generator on TFM data (supervised)
Encoder: FiLM [4] + ST [5] + Convolution

Encoder (conditioned)



conditioning   conditioning

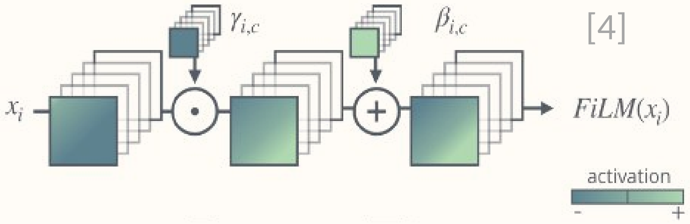
$$FiLM(x_k) = \gamma_k(y_s) \cdot \frac{x_k - E[x_k]}{\sqrt{Var[x_k] + \epsilon}} + \beta_k(y_s)$$

$\beta_k \in \mathbb{R}^{n_{ch_k}}$

$\gamma_k \in \mathbb{R}^{n_{ch_k}}$

[4]

FiLM complex layer (Co):
independent affine transformations are applied to each feature map c.



The new per-channel statistics modify the relative importance of features for the subsequent convolution operation.

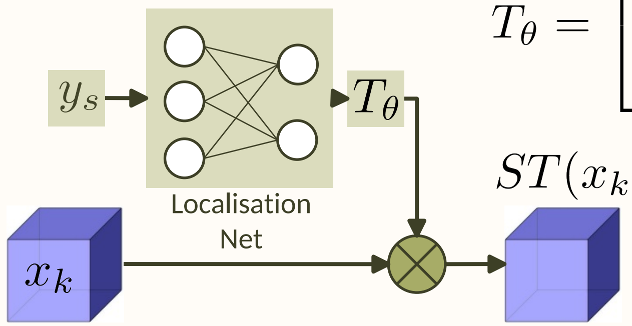
conditioning

$$ST(x_k) = T_\theta(y_s) \cdot x_k$$

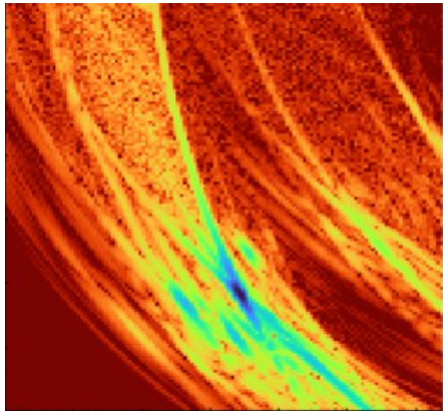
$T_\theta \in \mathbb{R}^{3\times 3}$

$\theta \in \mathbb{R}^6$

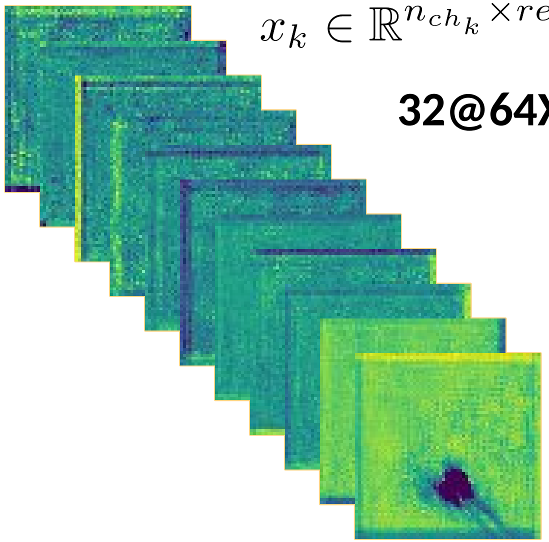
$$T_\theta = \begin{bmatrix} s & 0 & t_x \\ 0 & s & t_y \\ 1 & 1 & 1 \end{bmatrix}$$



[5]



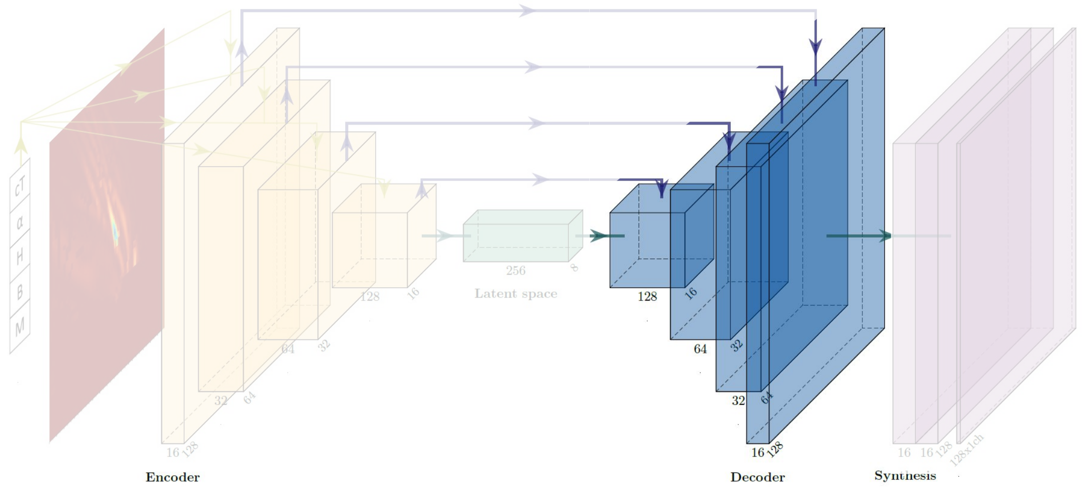
$x_k \in \mathbb{R}^{n_{ch_k} \times res_k \times res_k}$



[5] M. Jaderberg, K. Simonyan, A. Zisserman, and K. Kavukcuoglu (2015).
[4] E. Perez, F. Strub, H. De Vries, V. Dumoulin, and A. Courville (2022)

Encoder: Instance Normalisation for fast stylization [6]

Decoder



Principal layers:

- Convolutive Neural Network
- Fast stylization through Instance Normalisation

Task:

- Learns the difference between classes (mse+ffl loss)
- Take into account uncertainties from experience
- Generate new experience data (new instances) in a supervised way

Instance Normalisation

$$IN(x_k) = \frac{x_k - E[x_k]}{\sqrt{Var[x_k] + \epsilon}} \times \gamma_k + \beta_k$$

$\beta_k \in \mathbb{R}^{n_{ch_k}}$

$\gamma_k \in \mathbb{R}^{n_{ch_k}}$

Learned bias and scale

[6] D. Ulyanov, A. Vedaldi, and V. Lempitsky, “Instance Normalization: The Missing Ingredient for Fast Stylization,” Jul. 2016, doi: 10.48550/arxiv.1607.08022.

Conditional U-Net as generator on TFM data

Results on

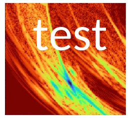
Realistic data-set generation

Surrogate model

Testing realistic data generation and TFM parametric modelling

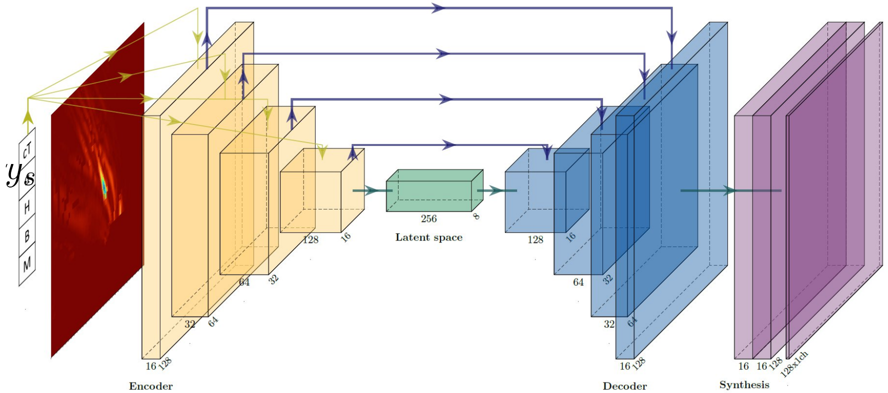
Realistic data-set generation

$XS_{test}+YS_{test}$ → cU-NET → XE_{test}



cT
α
H
B
M

Simulations from CIVA

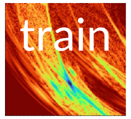


- ❑ Generate experience images
- ❑ Need new simulations

Surrogate model

$XS_{train}+YS_{test}$ → cU-NET → XE_{test}

fixed



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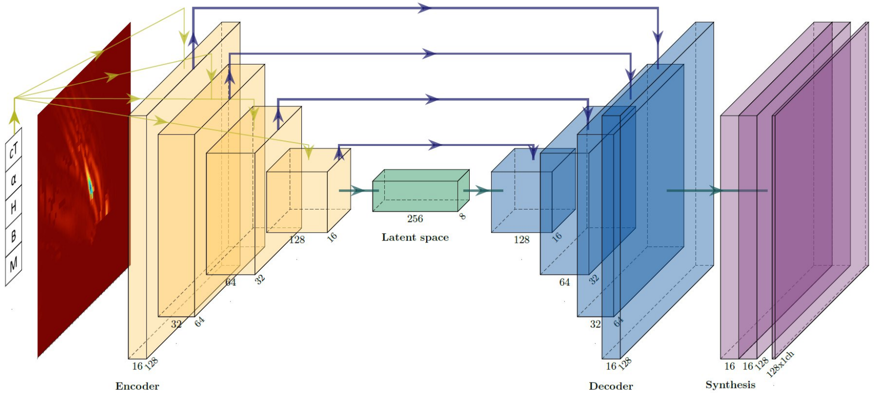
regression



- ❑ Metamodelling just changing parameters
- ❑ No new simulation needed

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Conditional U-Net as generator on TFM data (supervised)
Results on Test: Realistic data-set generation

U-Net Generation

- Generative frame on imaging
- Transfer experience to simulation
- Account uncertainties from experience
- Generate new data to train diagnostic tools

$Xs_{test}+Ys_{test}$ → cU-NET → Xe_{test}

SIMULATION → EXPERIENCE

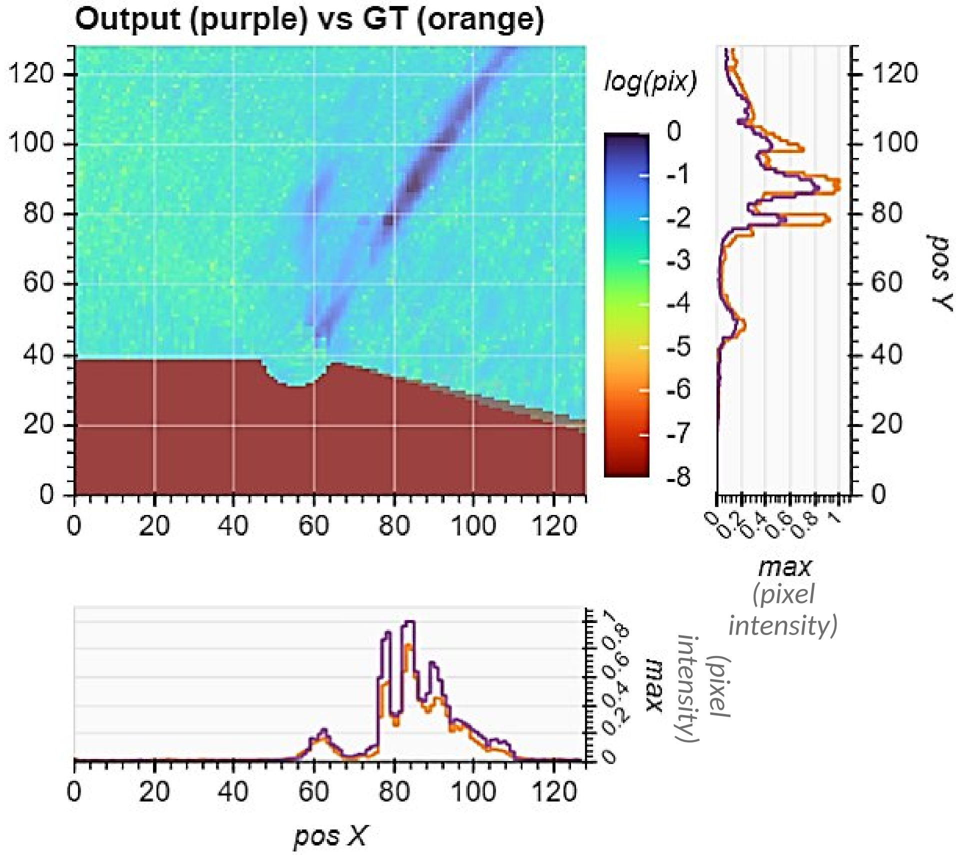


Fig 7 - Example for image generation vs ground truth. Comparison of maximum pixel value and (x,y) position.

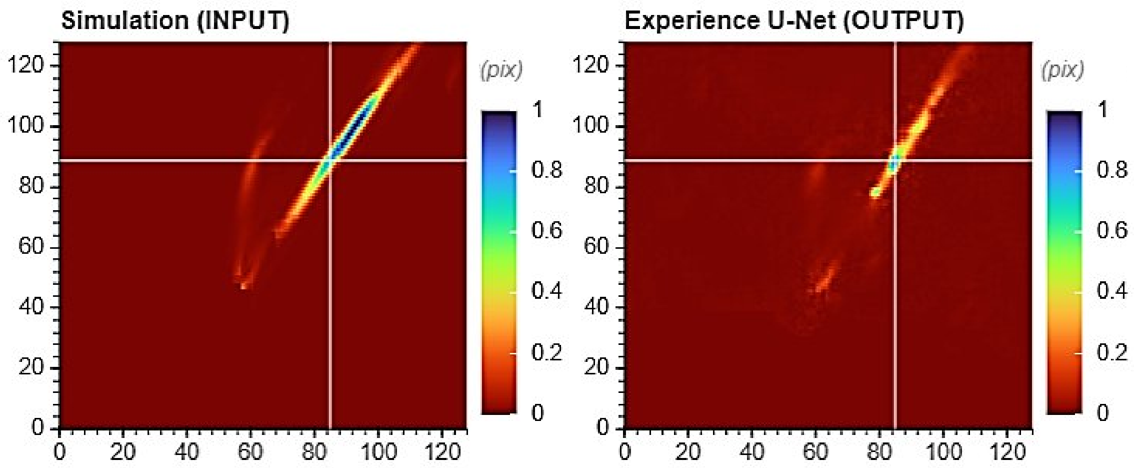
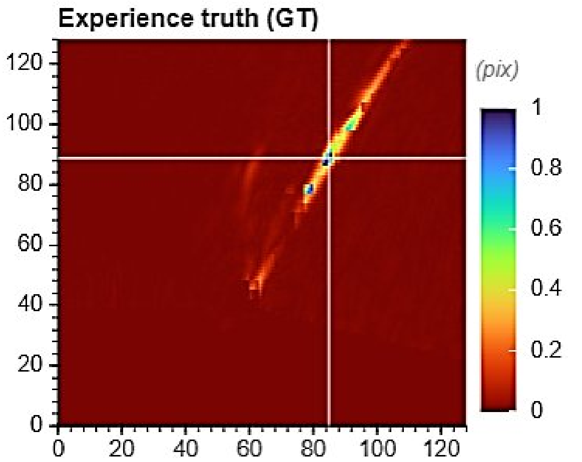


Fig 8 - Example for input image vs image generation.

mse = 0.008 (Test set)

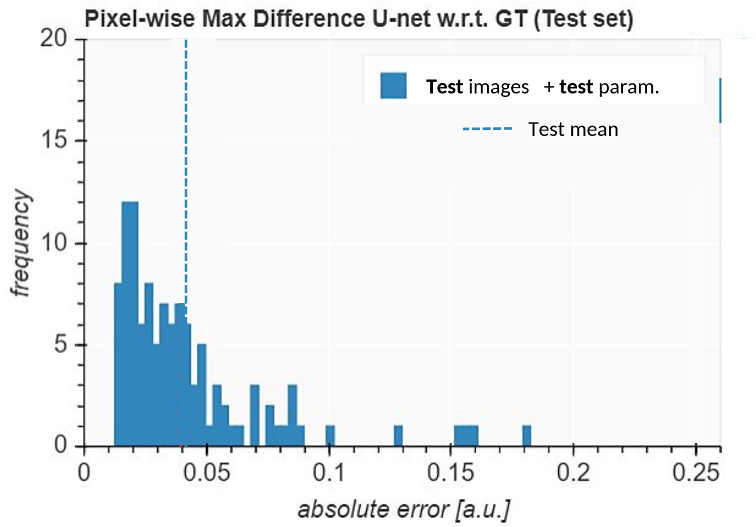


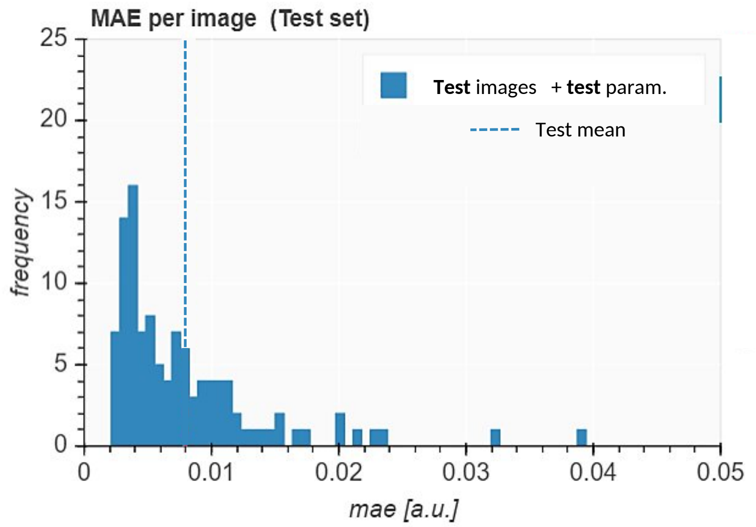
Conditional U-Net as generator on TFM data (supervised)
Results on Test: Realistic data-set generation

cU-Net as multifidelity generator

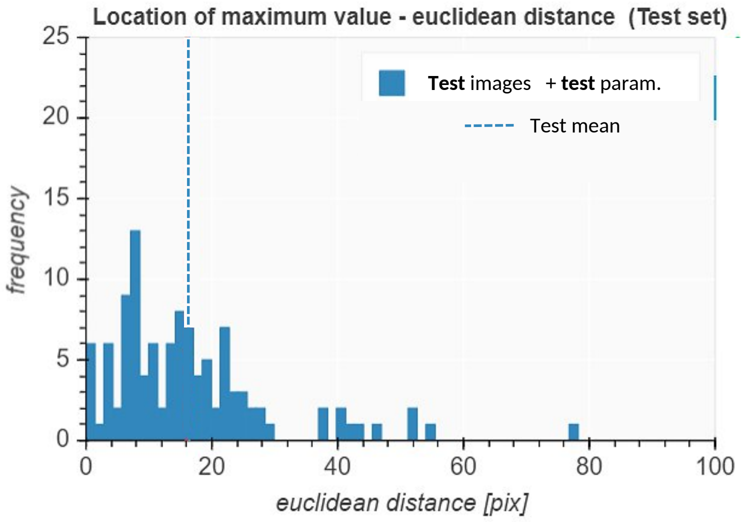
SIMULATION → EXPERIENCE

Echo amplitude

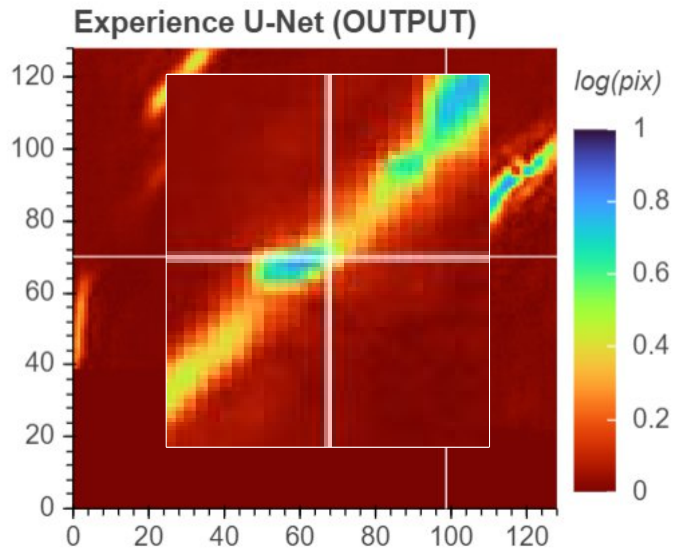


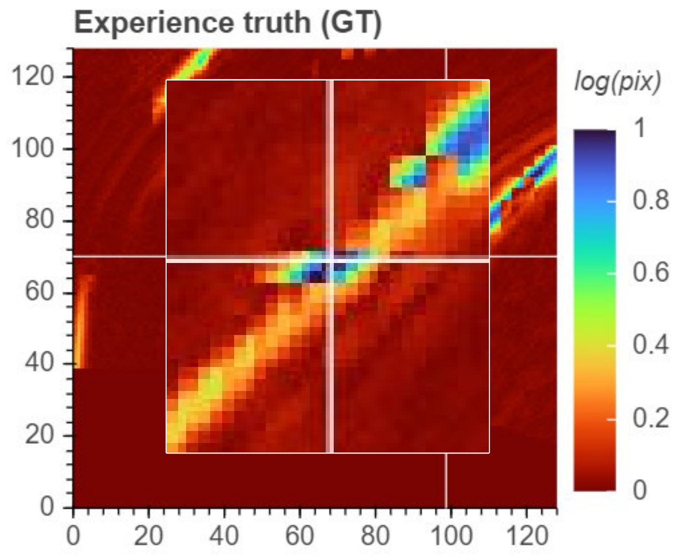


Echo localisation



$Xs_{test}+Ys_{test}$ → cU-NET → Xe_{test}

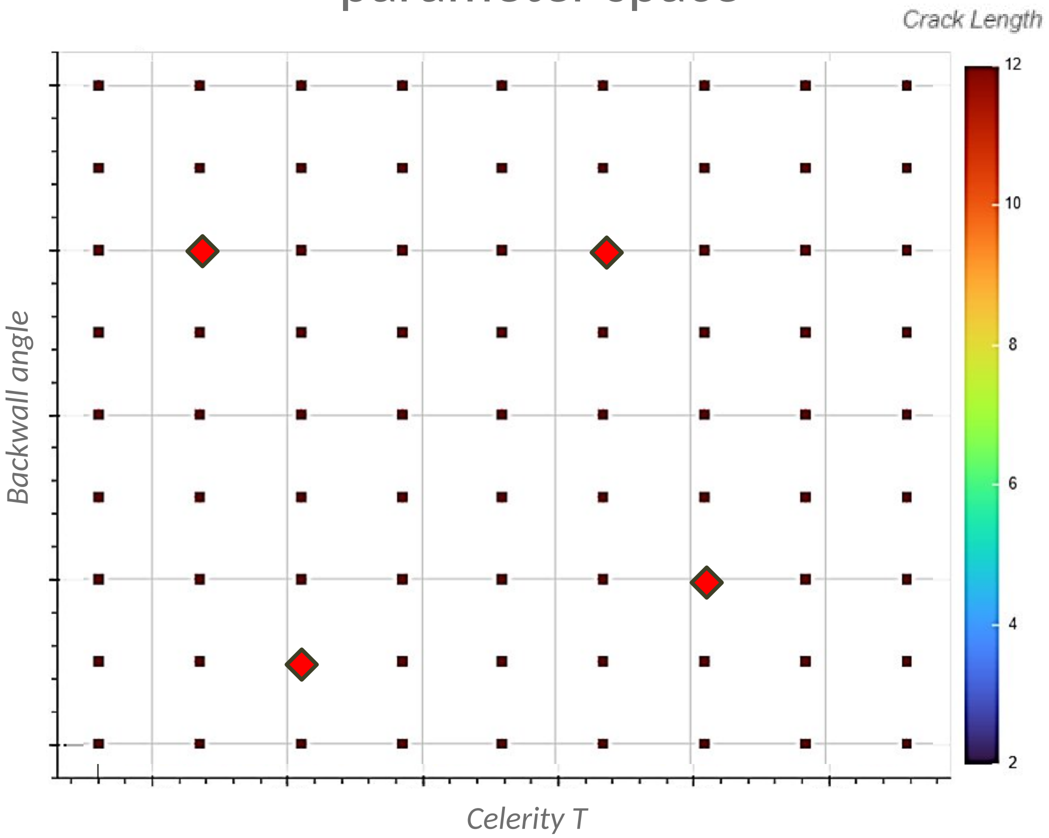




Results on Test: Realistic data-set generation

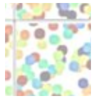
cU-Net as multifidelity generator

Sampling from simulation parameter space



Examples of points is **test set**

Examples of points is **training set**

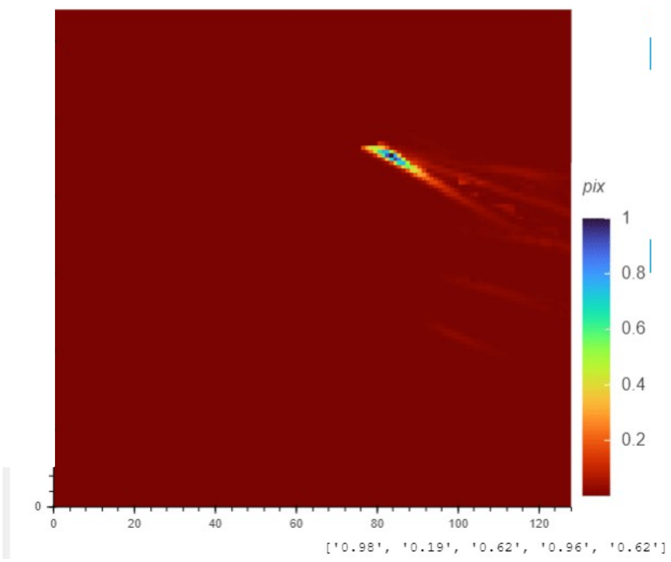

New simulated samples

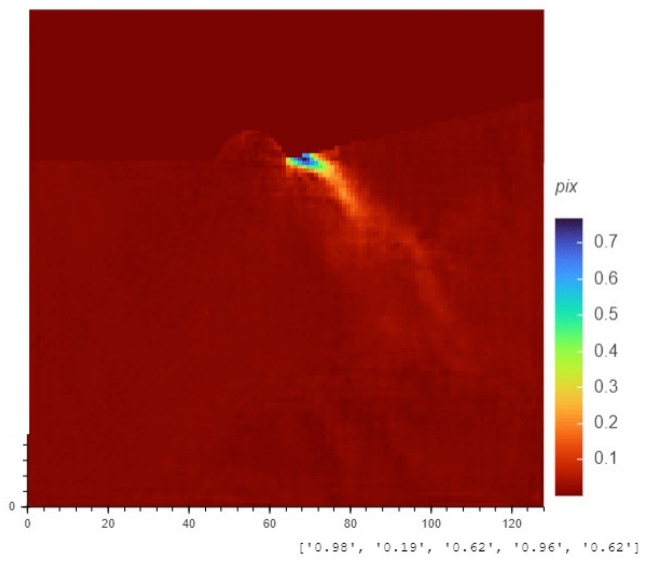
A point represents: simulated image + parametares vector

XS_{test}+YS_{test} → cU-NET → XE_{test}

New generated dataset

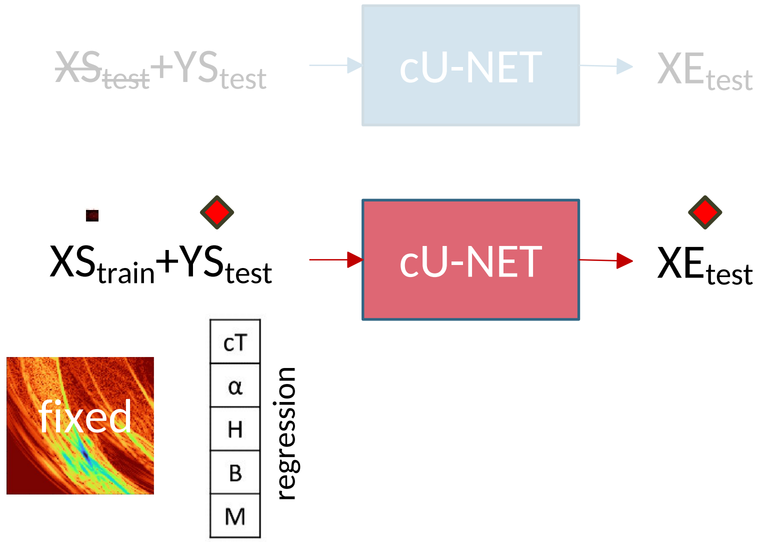
SIMULATION → EXPERIENCE

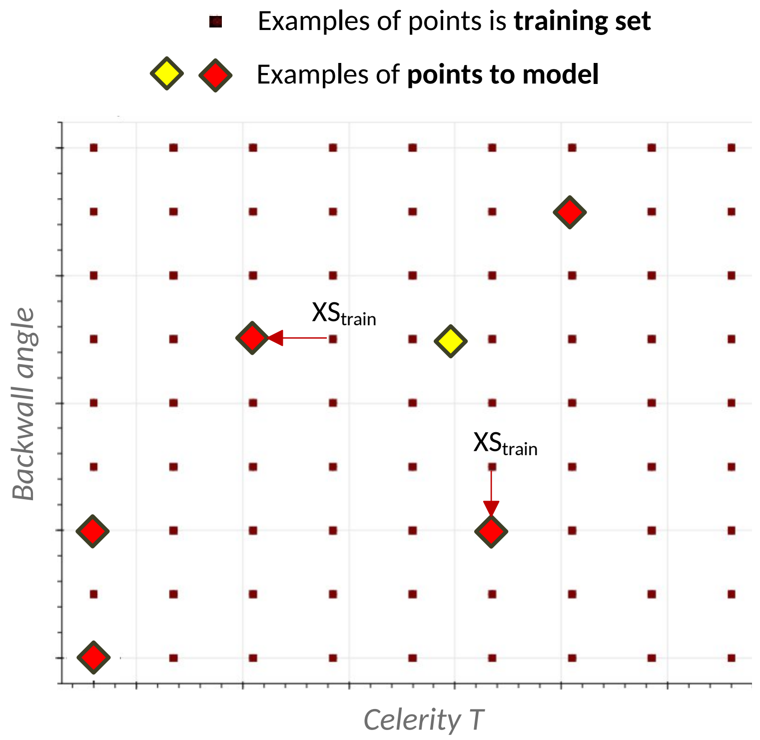




Conditional U-Net as generator on TFM data (supervised)
Results on Test: Surrogate model

cU-Net surrogate model - *regresion in parameter space (labels)*



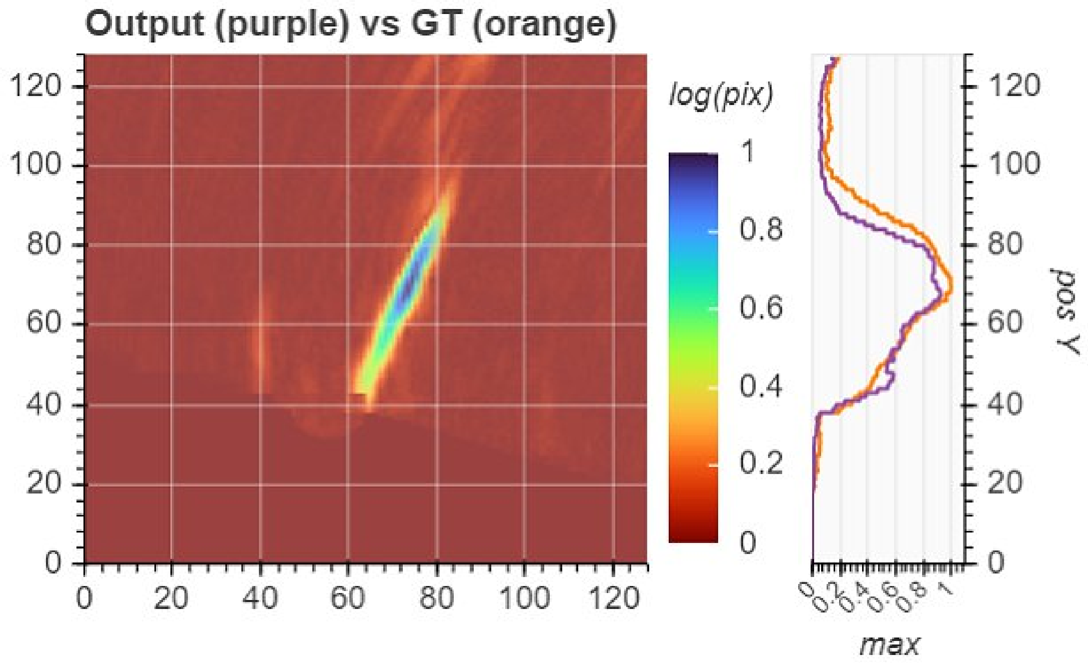


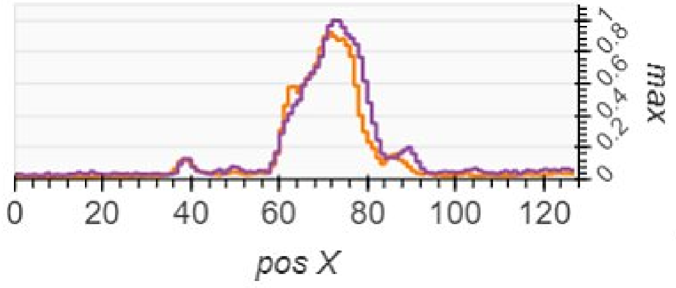
The neural network has a parametric input that modifies the input image in realtion to the input parameters.

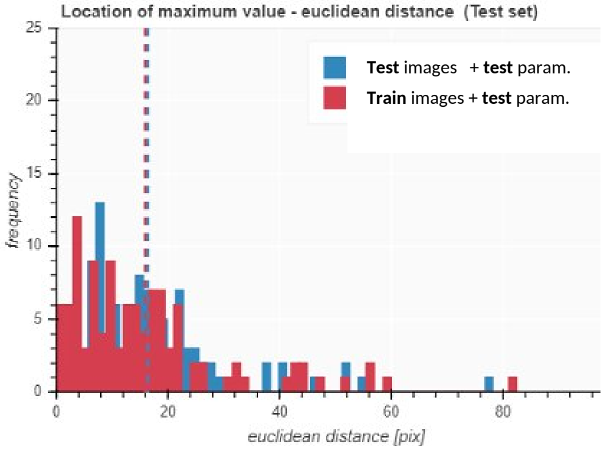
Can we sample the parameter space to generate **new images** related to **new labels**?

Conditional U-Net as generator on TFM data (supervised)
Generation error on reconstruction parameters regression

Echo localisation

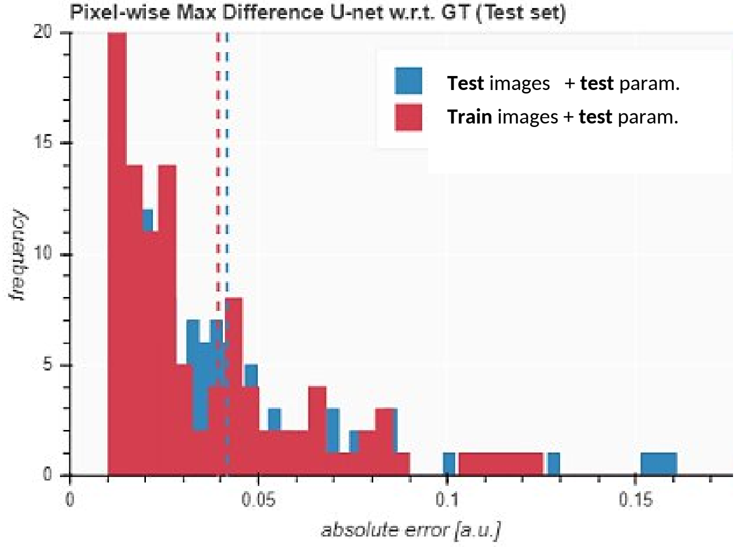


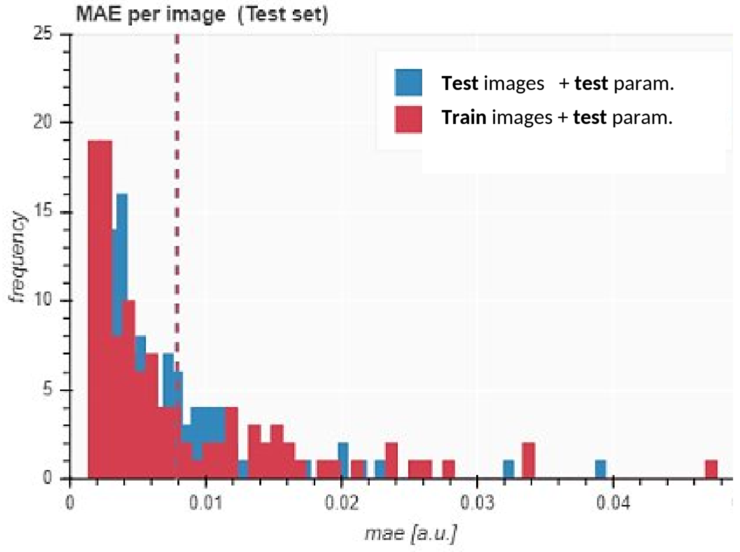




$XS_{train}+YS_{test}$ → cU-NET → XE_{test}

Echo amplitude





Conditional U-Net as generator on TFM data (supervised)

Generation by reconstruction parameters regression

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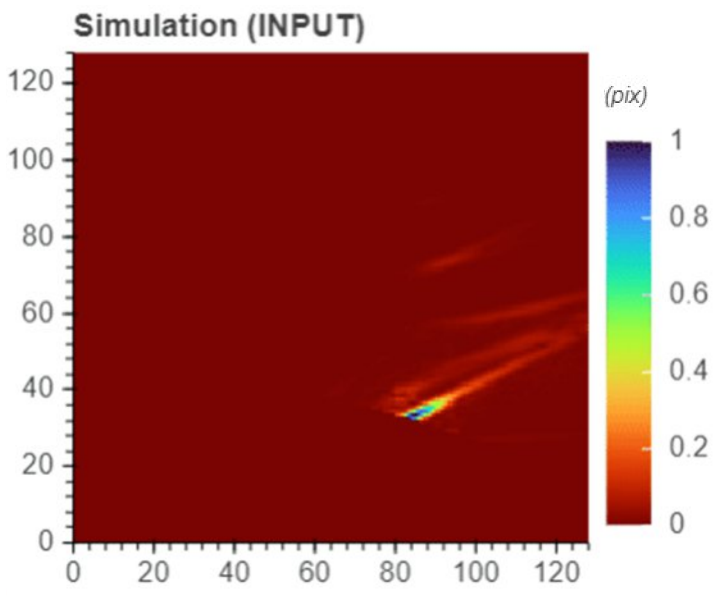
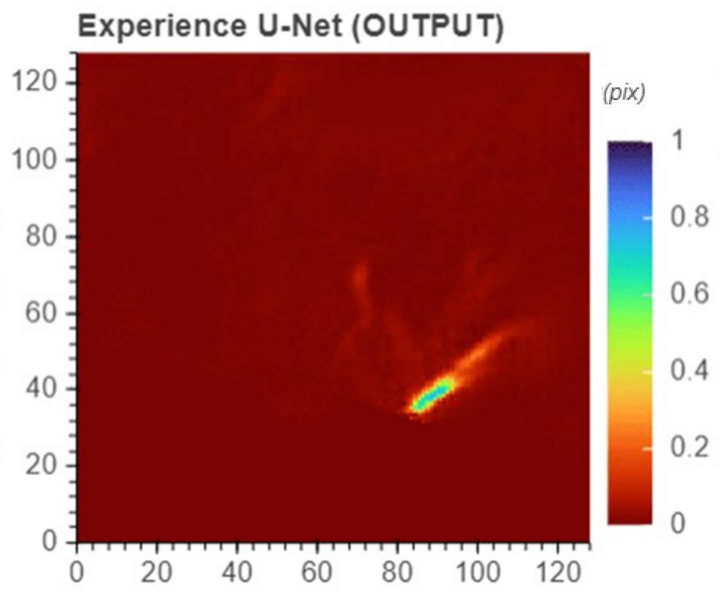
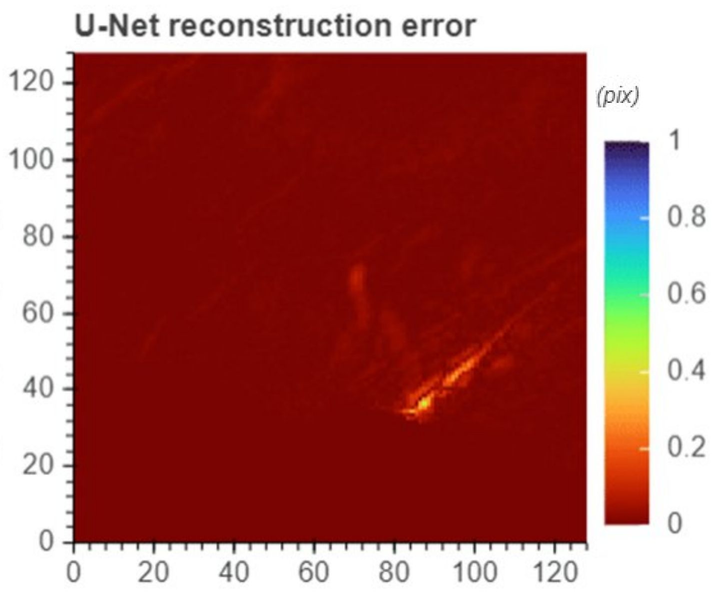
CentraleSupélec







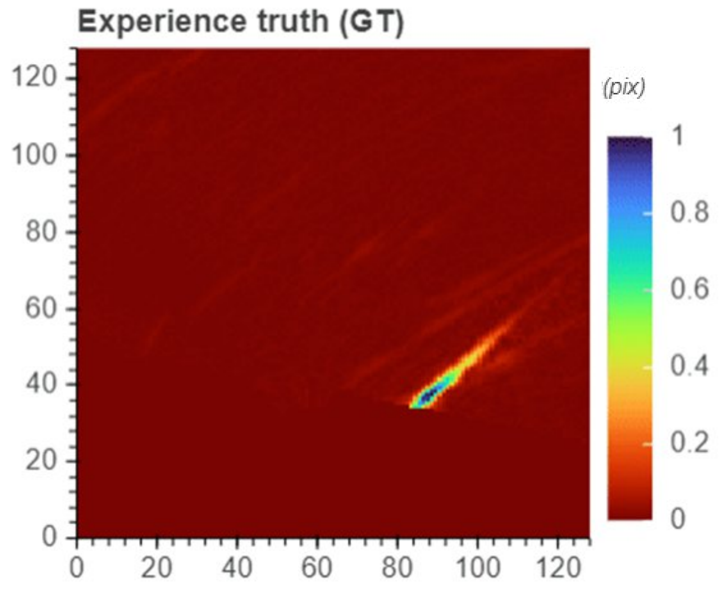
cT
α
H
B
M

Crack Length: **1**

Crack Angle: **1**

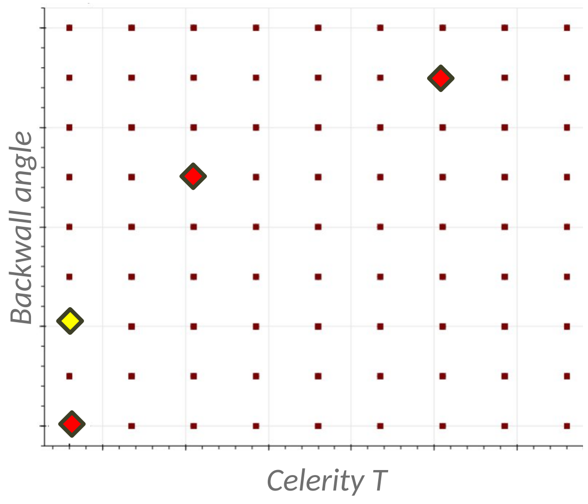
Celerity T: **0.03**

Backwall Slope: **0.25**



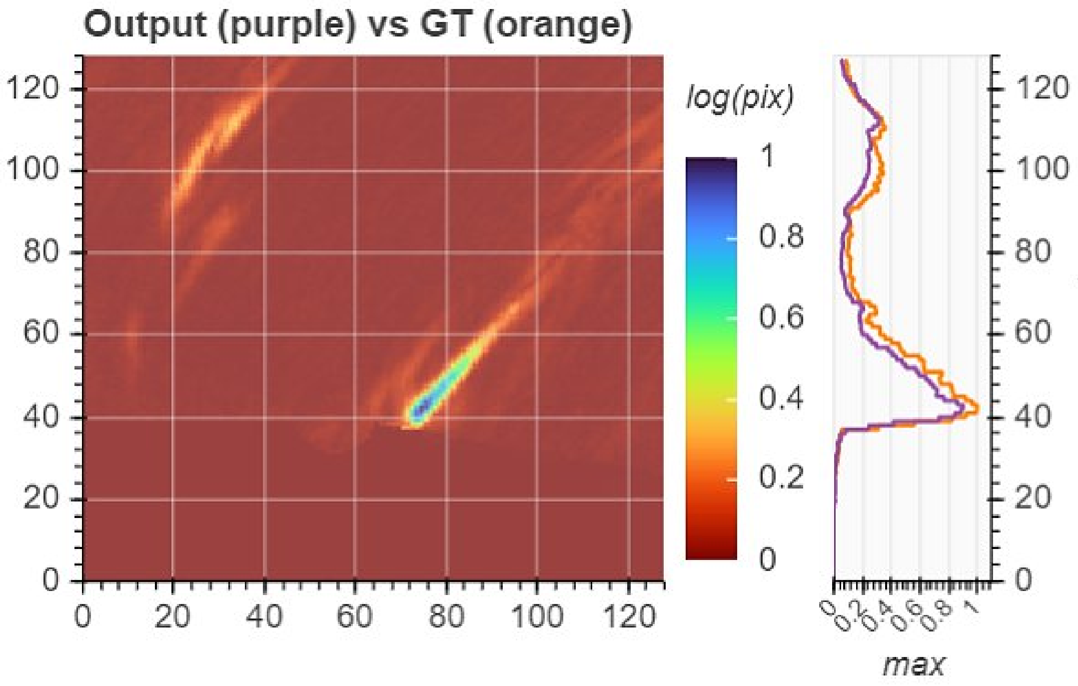
Examples of points is **training set**

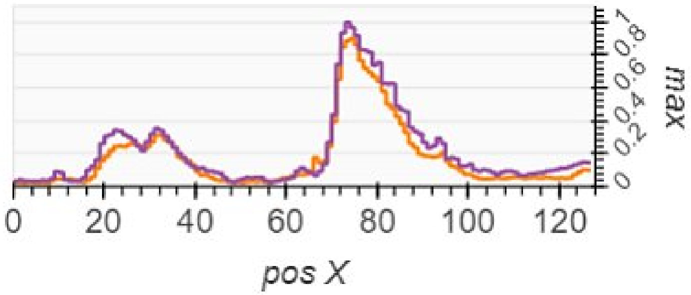
Modelling point



Generation error on flaw geometry regression

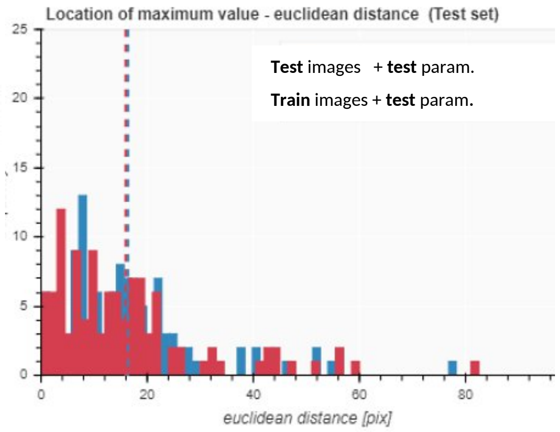
Echo localisation



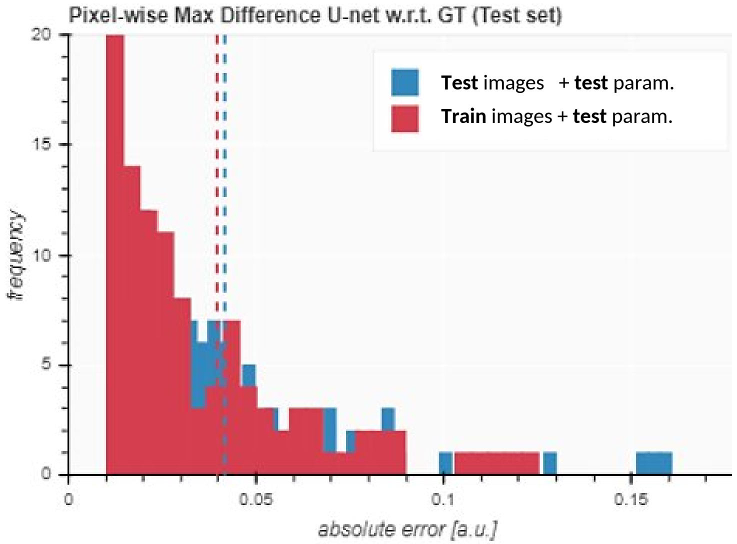


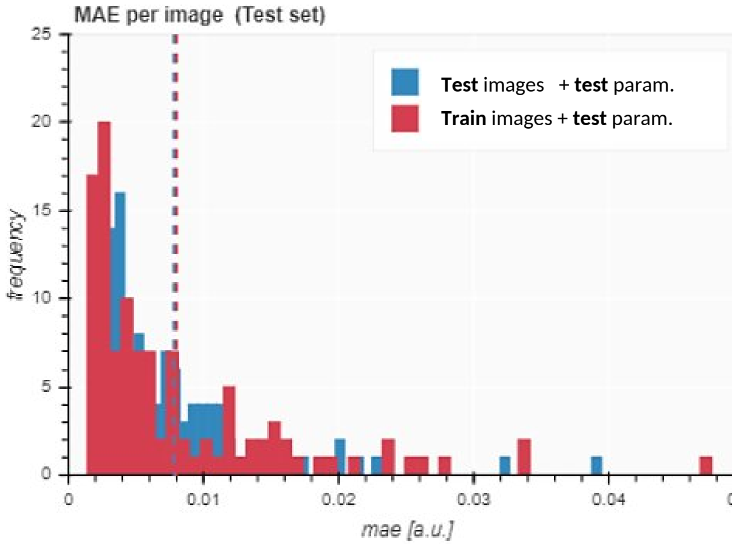
10 [mm] → ML → 3 [mm]

$XS_{train}+YS_{test}$ → cU-NET → XE_{test}



Echo amplitude



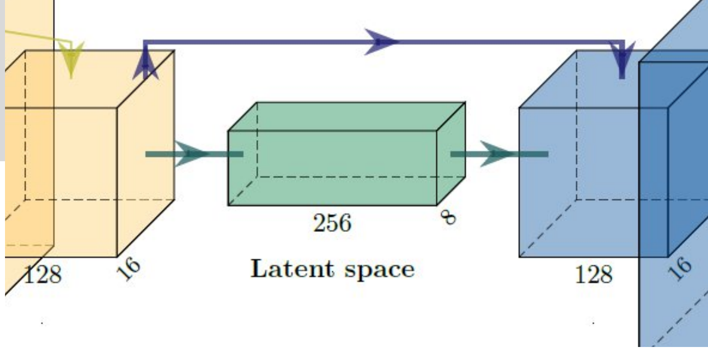


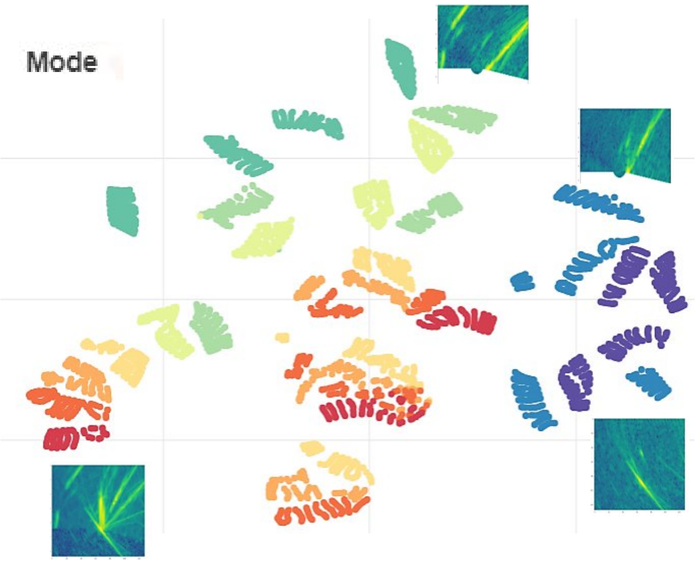
Conditional U-Net as generator on TFM data (supervised)

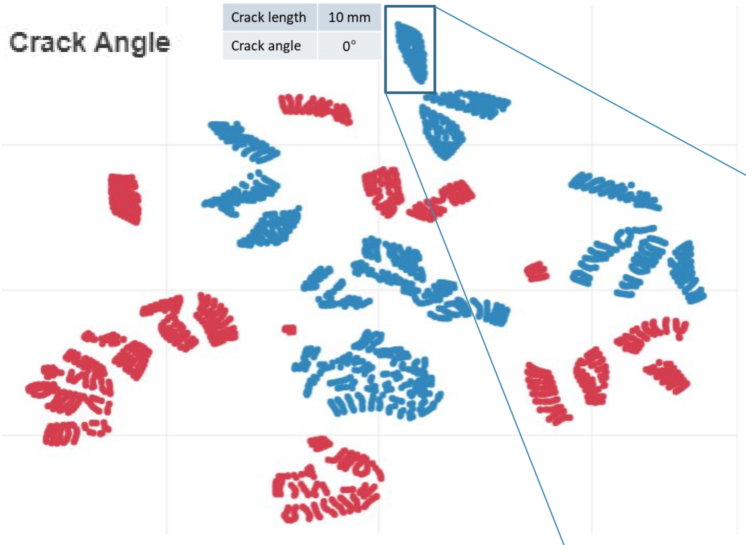
Features exploration

Latent space exploration

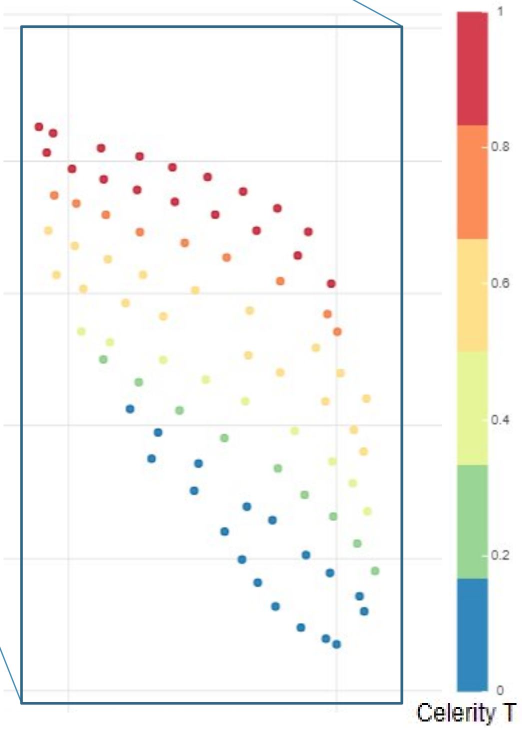
U-MAP representation 8x8x256 ☾ 2D

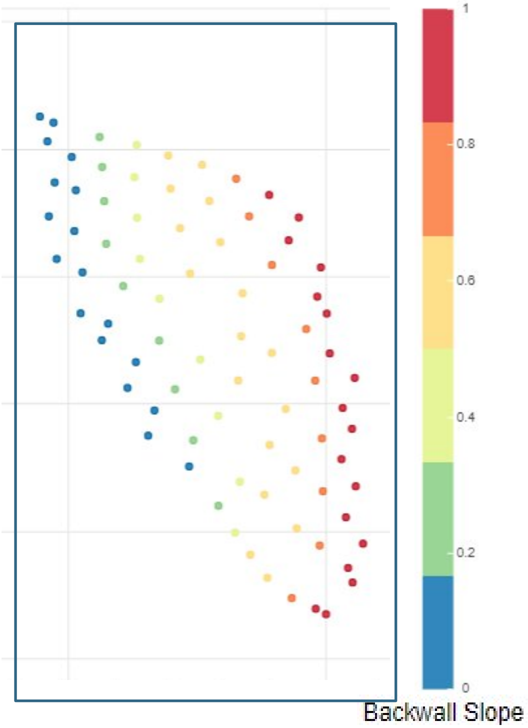






Crack length	10 mm
Crack angle	0°





UMAP constructs a high dimensional graph representation of the data then optimizes a low-dimensional graph to be as structurally similar as possible

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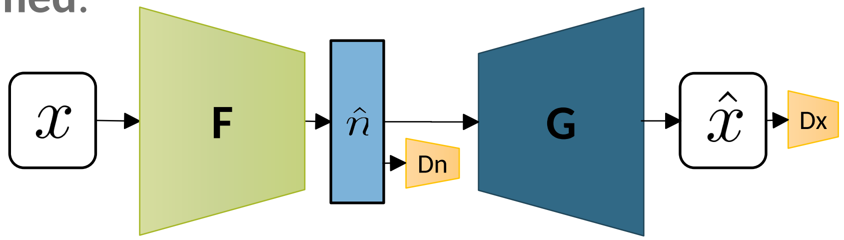
Conclusion

- **Multitask neural network**: 9 TFM reconstruction modes are learned. New modes requires DA or new training.
- The model takes as HF domain the experience. **Different degrees of data fidelity on HF side** can be considerer (e.g: FEM).
- A **novel application of ST and FiLM modules** is presented to learn parametric subrogated model on ML frame.
- Relation between NDT image features and the simulation parameter are learned by the model.
  The architecture is **not limited by the shape of the parameter vector**.
- Parametric **metamodeling** allows to generate **new "experimental" instances**, even without new simulation instances.
- Regression on label space provides **direct labelling for new data**.

Perspectives

- **cU-net as realistic data generator** for data-set creation provides the tool to have enogh data to train deeper models: GAN as variational inference tool to link two fidelity data domains (e.g.: simulation and experience)
- GAN approach is pertinent when **couples on each fidelity domain are not informed**.



GAN architecture

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Merci de votre attention

Thanks you for you attention

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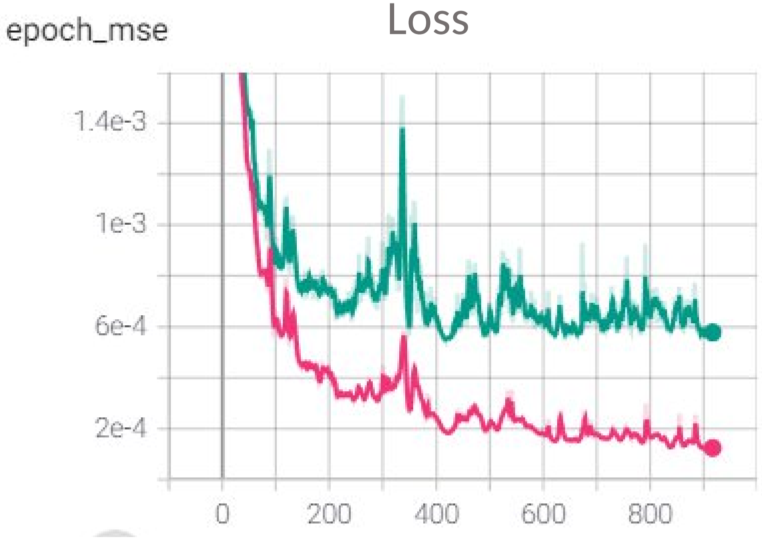
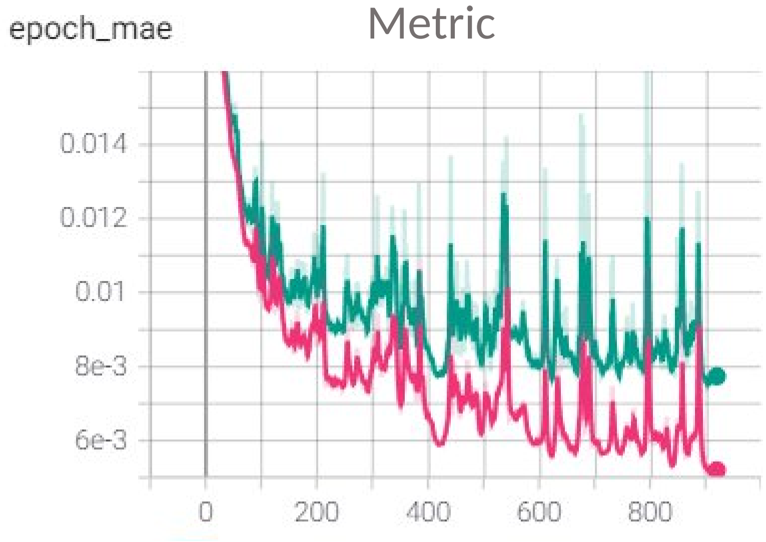
Training: best model

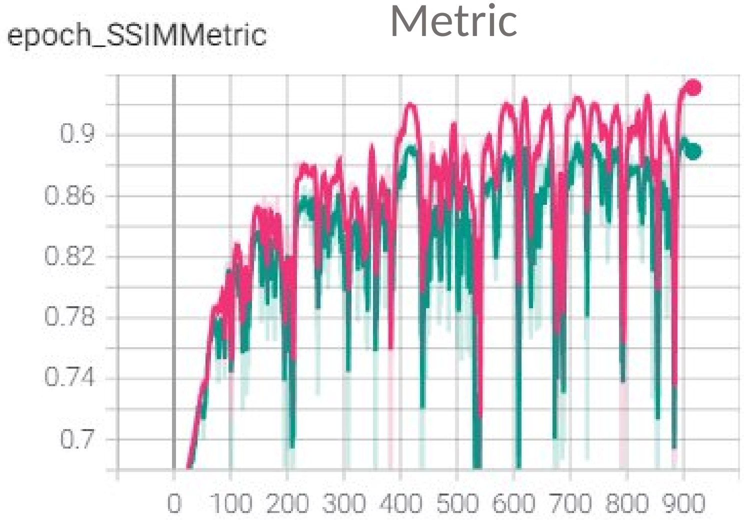
Loss

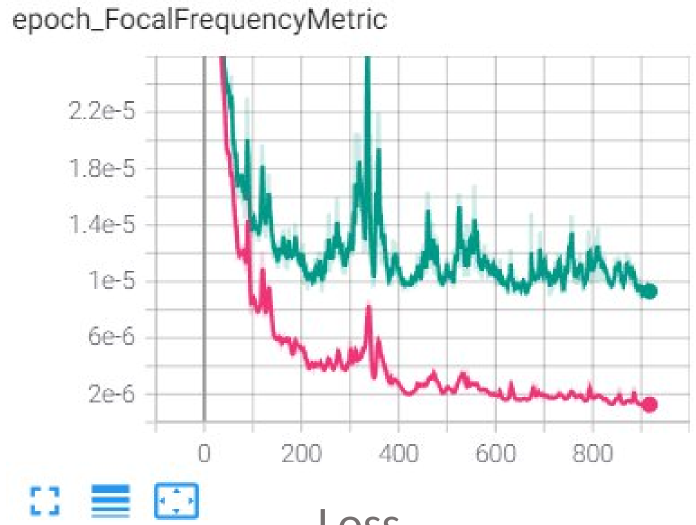


Metric



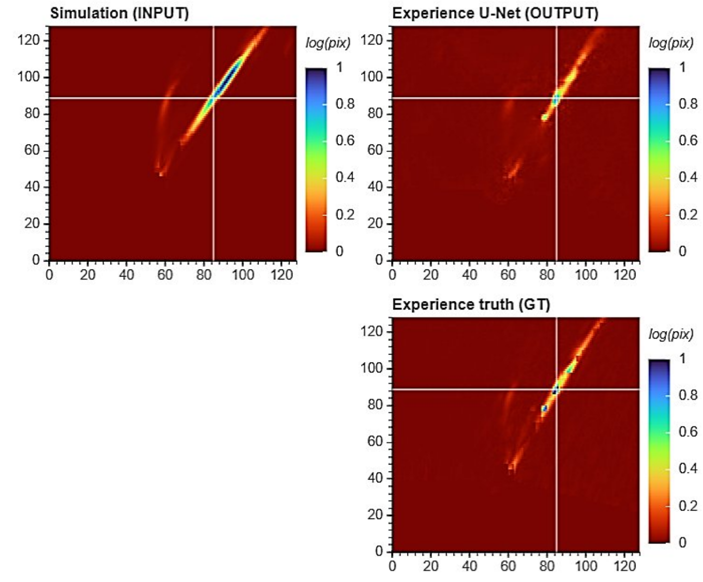
Metric





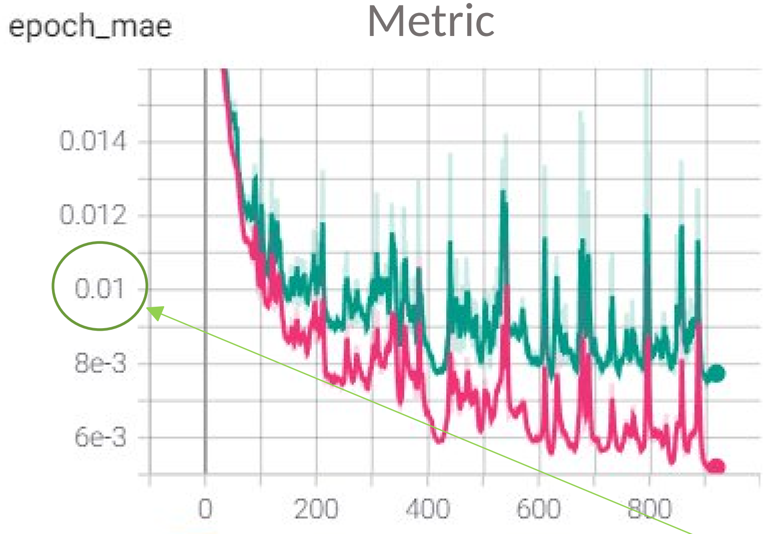
Loss

Training
Validation

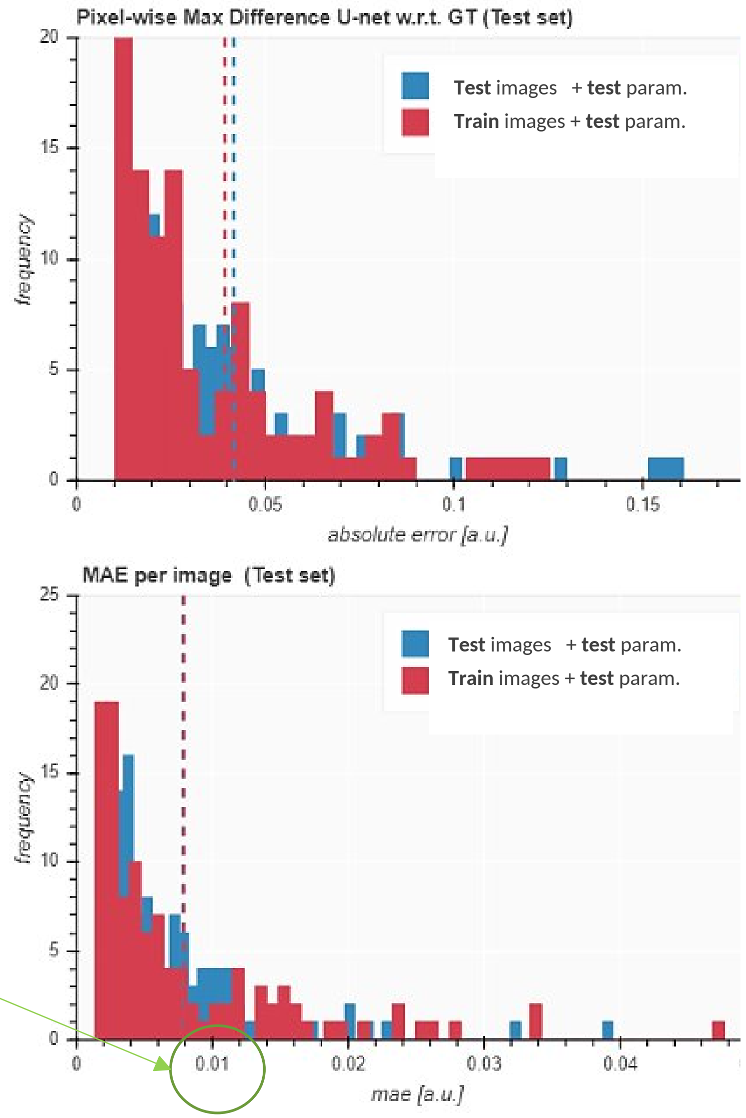


4h sur GPU
NVIDIA Quadro RTX 6000
Batch 128
22 GB on GPU

Metric



epoch_mae
0.014
0.012
0.01
8e-3
6e-3
0
200
400
600
800



Pixel-wise Max Difference U-net w.r.t. GT (Test set)
Test images + test param.
Train images + test param.
frequency
absolute error [a.u.]
MAE per image (Test set)
Test images + test param.
Train images + test param.
frequency
mae [a.u.]