

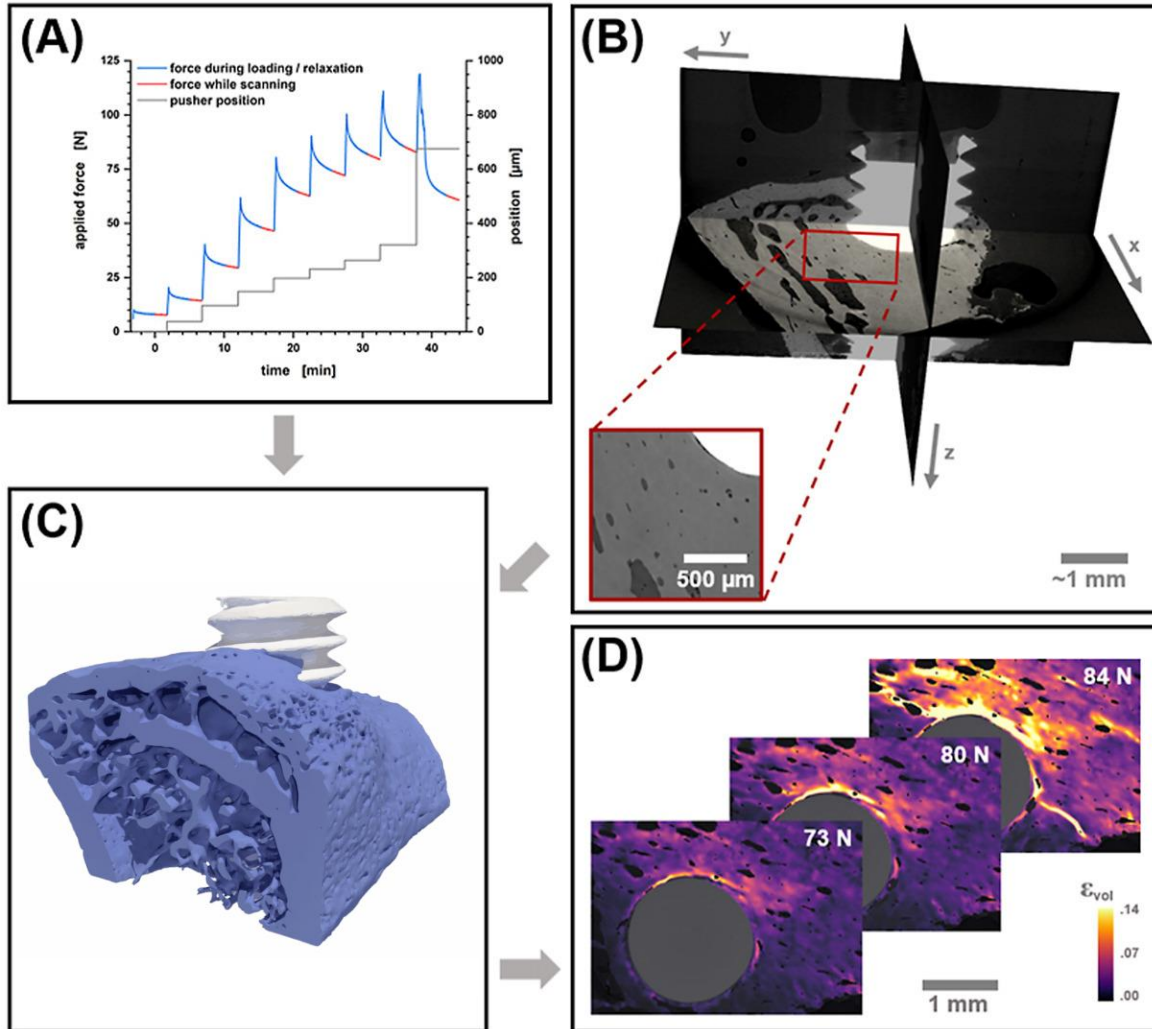
# VoIRAFv2: Volumetric Optical Flow Network for Digital Volume Correlation

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Helmholtz-Zentrum Hereon

22.11.2024

# Digital Volume Correlation (DVC)



Push-out experiment and DVC analysis with a titanium screw as an example (Bruns, 2023).

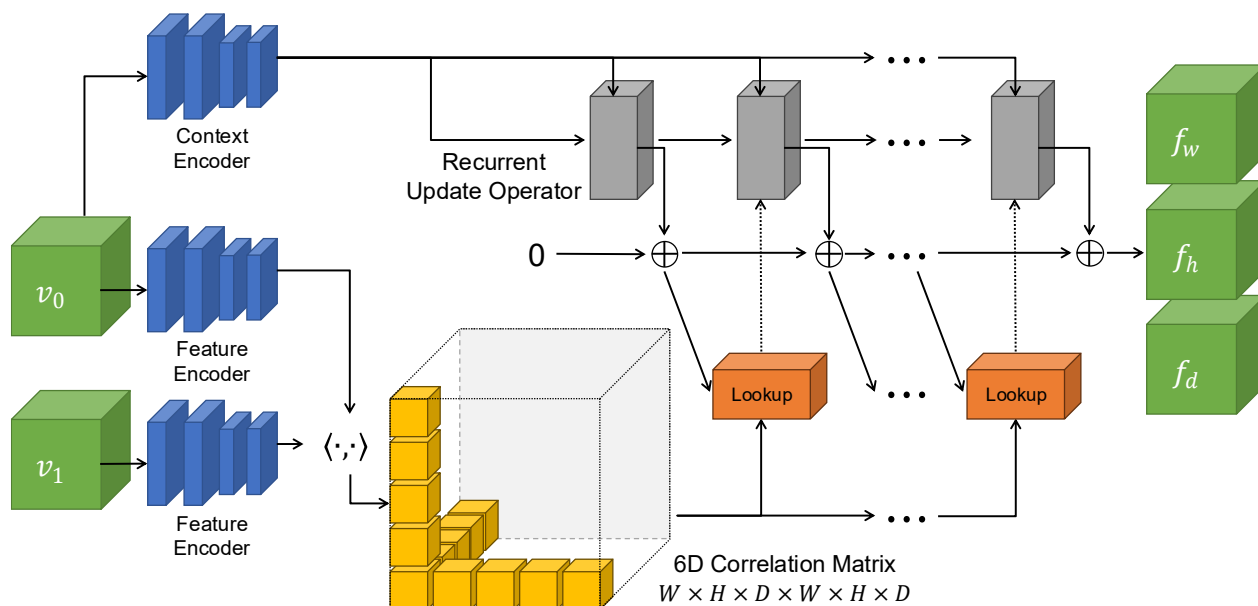
## DVC:

- Estimate the local, 3D displacement field between consecutive volumes
- To track bone deformation and strain

## Challenges and motivations:

- Optical Flow: estimate the displacement (motions) fields of intensities, i.e. *flow field*
- ML optical flow can outperform classical iterative approaches
- *Network-based DVC approach*
  - Rely heavily on computing powers of GPUs, limited by GPU memory size

# VoRAFT: Volumetric Optical Flow Network



VoRAFT consists of three major parts: feature encoders, a 6D correlation matrix and recurrent 3D update operators.

## Contributions:

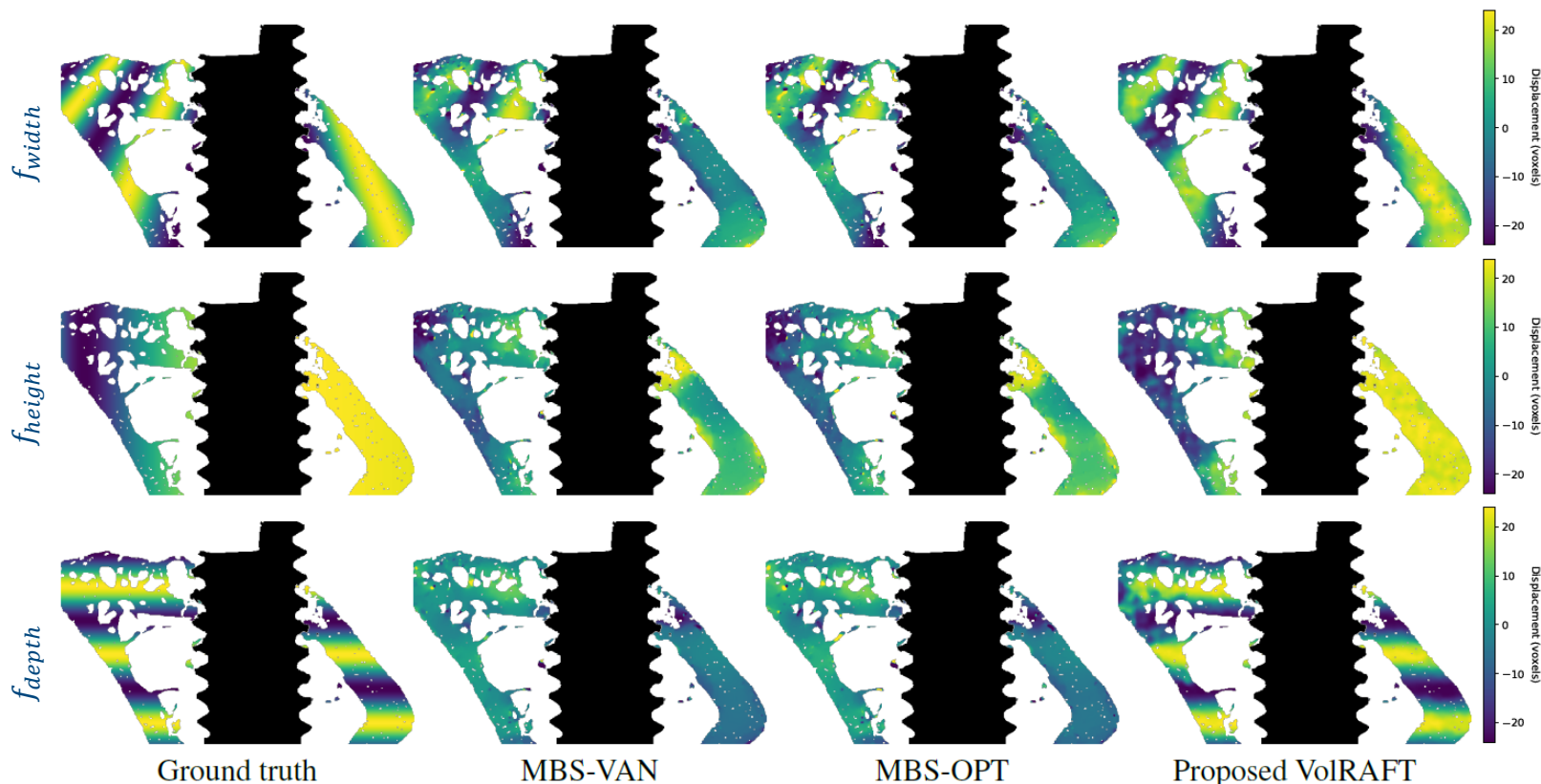
- Supervised machine learning approach for DVC to estimate 3D displacement fields between consecutive volumes.
- Extension of the optical flow network, RAFT (Teed, 2020), from 2D images to 3D volumes.
- Generation of synthetic displacement fields and application to the measured SR $\mu$ CT volumes for training, validation and testing.
- Comparison to iterative methods [2] for bone-implant loading scenarios based on SR $\mu$ CT volumes.

## Publications:

- 2024 CVPR Workshop Paper
- <https://github.com/hereon-mbs/VoRAFT>

# VoRAFT

## Experimental Results: Synthetic Datasets



- VoRAFT generally resembles the Star displacement field
- However, VoRAFT can obtain block-based artifacts near the edge of homogeneous region due to patch-based inference methods

Sample	Disp. class	MBS-VAN	MBS-OPT	VoRAFT
PEEK_4w_5L	Star	20.686	24.406	<b>4.968</b>
PEEK_4w_5L	Curve	<b>0.680</b>	0.714	1.276
PEEK_4w_5L	Random	<b>0.187</b>	0.250	0.456
PEEK_4w_5L	Sphere	1.045	1.178	<b>0.880</b>
PEEK_4w_5L	Overall	1.195	1.406	<b>0.882</b>
*Mg-5Gd_4w_103L	*Star	20.526	20.136	<b>5.748</b>
Mg-5Gd_4w_103L	Curve	<b>0.356</b>	0.413	0.440
Mg-5Gd_4w_103L	Random	<b>0.140</b>	0.152	0.339
Mg-5Gd_4w_103L	Sphere	1.569	2.081	<b>0.855</b>
Mg-5Gd_4w_103L	Overall	1.149	1.280	<b>0.944</b>
Ti_4w_5R	Star	21.262	19.805	<b>4.426</b>
Ti_4w_5R	Curve	<b>0.923</b>	0.997	1.270
Ti_4w_5R	Random	0.313	<b>0.229</b>	0.307
Ti_4w_5R	Sphere	3.103	2.236	<b>1.078</b>
Ti_4w_5R	Overall	1.928	0.946	<b>0.706</b>

\* MBS-OPT is empirically optimized by this dataset.

### Comparison of End-Point-Error (EPE):

- Compare to iterative optical-flow-based DVC method (MBS-VAN)
- VoRAFT Generally performs better in displacement fields with strong and significant divergence and curl

# VoRAFTv2: Volumetric Optical Flow Network

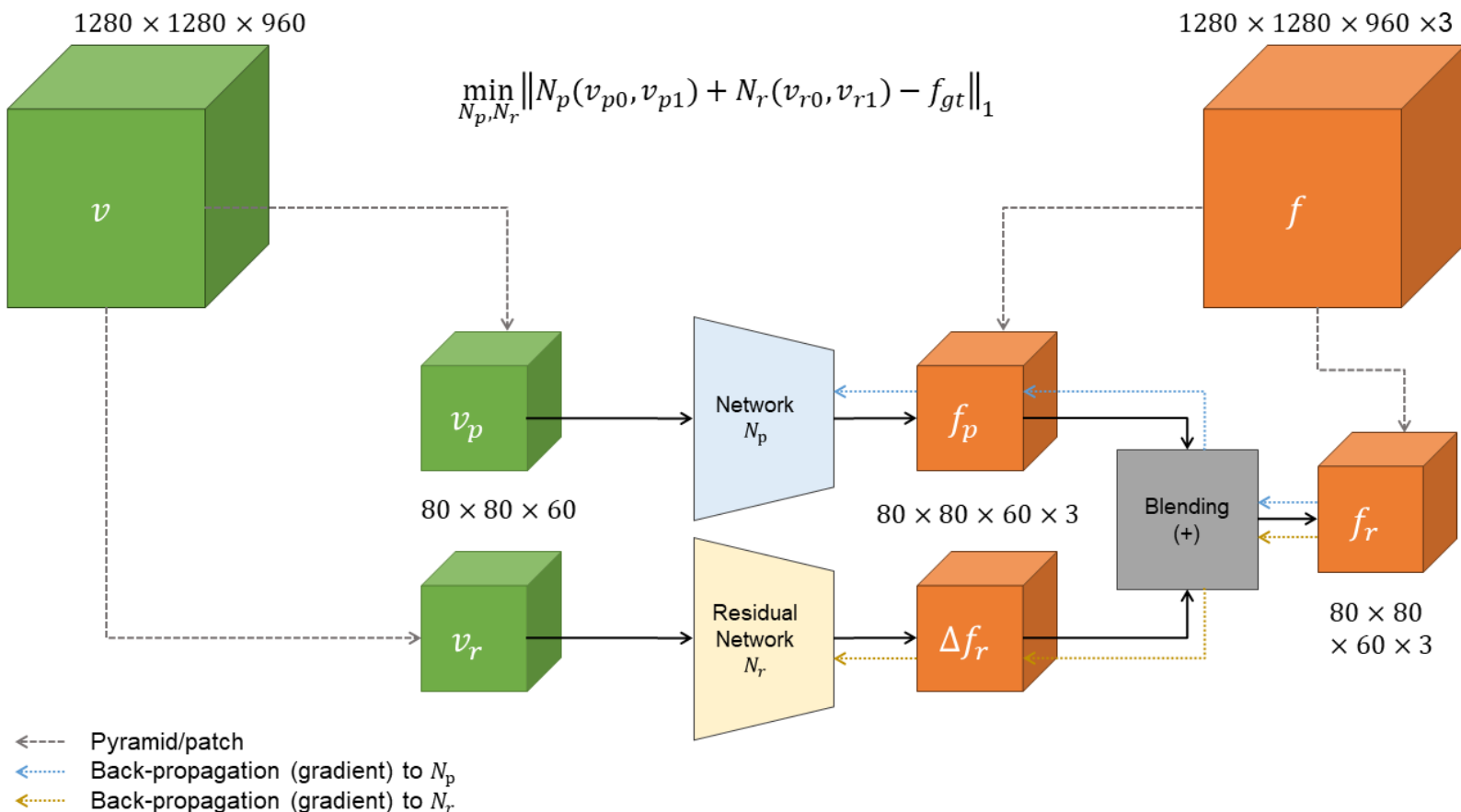
## Challenges:

- Artifacts
  - Patch-based blending at the boundary
- GPU memory
  - Memory requirement is huge for tensors at [B, C, H, W, D] dimensions for 6 matrices (i.e. v0, v1, mask, fw, fh, fd)
- Storage
  - Large storage (much larger than 20TB) for patch-based .npy files with overlapping area
- Data: synthetic flow field
  - More realistic

## Motivations/ideas:

- Multi-scale pyramid blending by “learning-the-residual”
- Smarter choice of sampling position for inference
- Pyramid-and-patch approach to minimize data-loading for full-size volume accessing during training
- Dynamic data-loading to access partial data by full-size data files.
- Generate flow-fields by iterative methods and extract principal components

# VoRAFTv2: Volumetric Optical Flow Network



## Multiscale Volumes:

- $v_p$ : 16-folding from  $[1280, 1280, 960]$  to  $[80, 80, 60]$
- $v_r$ : local patches of  $[80, 80, 60]$

## Networks:

- $N_p$  and  $N_r$  are both RAFT, but might change  $N_r$  to residual architecture.

## Blending:

- Rescale/upsample  $f_p$  back to full-size volume at each local patch position
- Sum of local patches  $\Delta f_r$  to corresponding  $f_p$

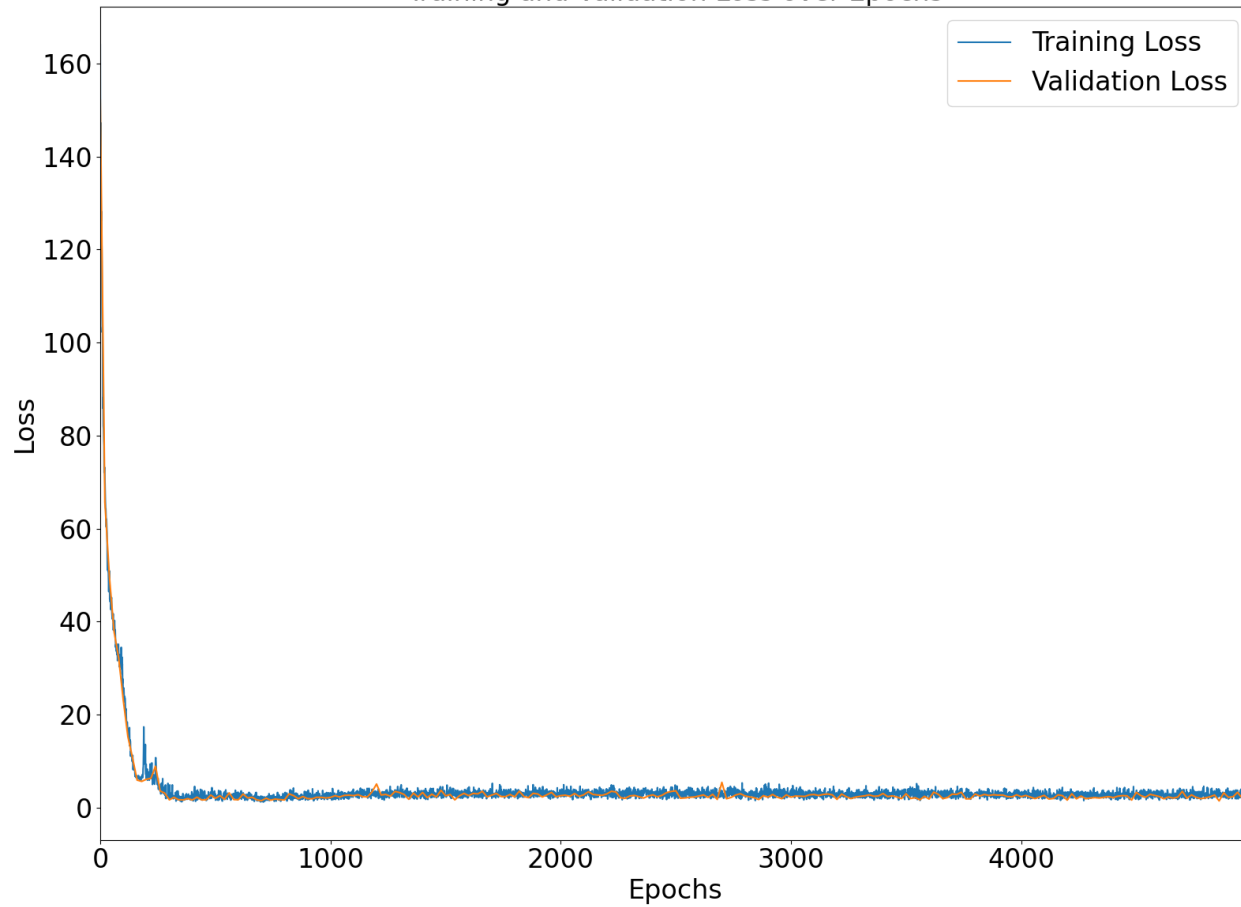
## Optimization:

- Alternative minimization: for each epoch, Step 1 minimize  $N_p$ , Step 2 minimize  $N_r$

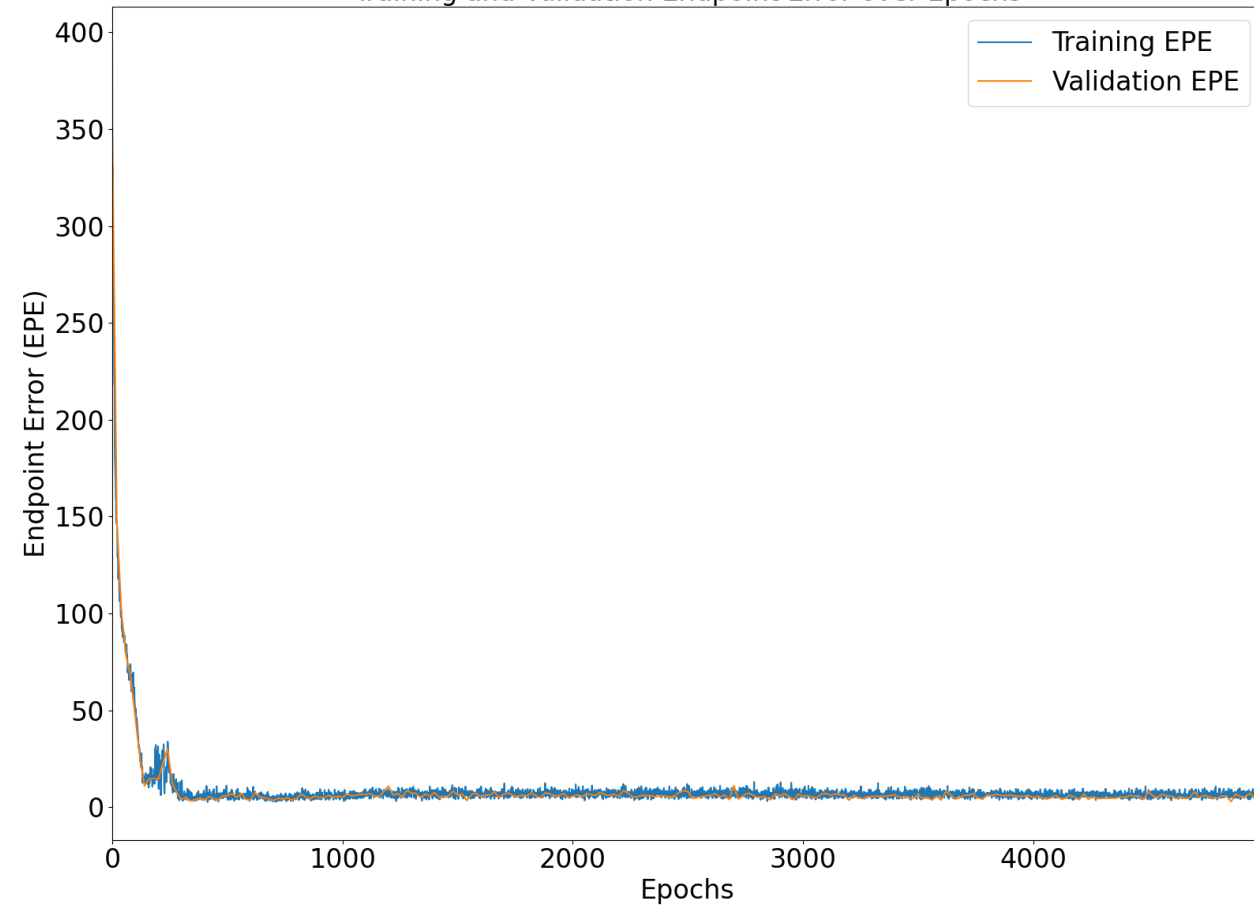
# VoIRRAFTv2

## Training

Training and Validation Loss over Epochs



Training and Validation Endpoint Error over Epochs



**~12 days training for 5000 epochs**

# VoRAFTv2: Volumetric Optical Flow Network

## Summary:

- Developing volumetric optical flow network for SRCT images/volumes
- Large volume size => need patches => solve artifacts problem
- Large datasets of patches => over 20TB storage => solve by dynamic loading
- Small patch size => long training time => solve by better & more GPU
- **Memory. Memory. Memory!**

## Acknowledgement

### Hereon

- Stefan Bruns
- Diana Krüger
- D.C. Florian Wieland
- Felix Beckmann
- Jörg Hammel
- Regine Willumeit-Römer

## Reference:

1. Lu, Yu, et al. "Biodegradable magnesium alloys for orthopaedic applications." *Biomaterials translational* 2.3 (2021): 214.
2. Bruns, Stefan, et al. "On the material dependency of peri-implant morphology and stability in healing bone." *Bioactive Materials* 28 (2023): 155-166.
3. Teed, Zachary, and Jia Deng. "RAFT: Recurrent All-Pairs Field Transforms for Optical Flow." *European Conference on Computer Vision (ECCV)*. 2020.
4. Wong, Tak Ming, et al. "VoRAFT: Volumetric Optical Flow Network for Digital Volume Correlation of Synchrotron Radiation-based Micro-CT Images of Bone-Implant Interfaces." *CVPR Workshop* (2024).

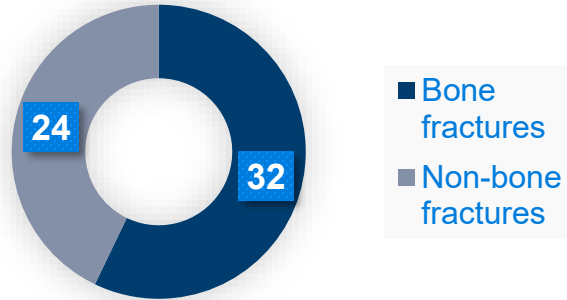
# Appendix

Further information



# Metallic Biomaterial: Bone Implants

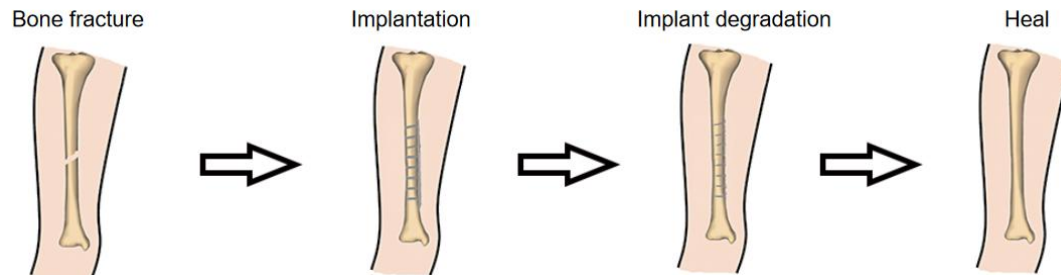
Annual medical treatment cost  
for trauma in US  
(Billion dollars)



Data from (Tsakiris, 2021)

## Bone implants:

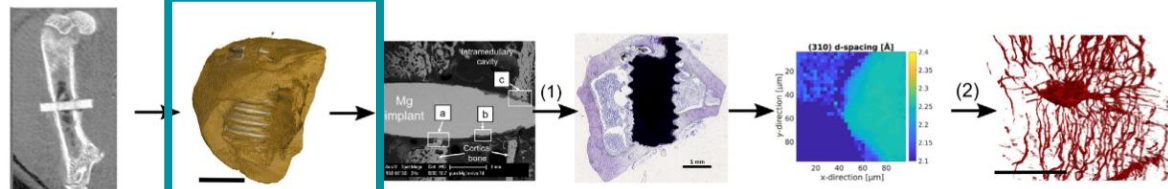
- Bone undergoes the most transplants among organs, estimated to be over 3 million surgeries worldwide annually (Tsakiris, 2021)
- Traditional implants (e.g. Titanium):
  - Permanent
  - Need secondary surgery
- Magnesium implants:
  - Bio-degradable
  - Reduce patient's pain, surgery risk and medical cost



Degradation of the magnesium-based implant in bone fracture healing.  
Illustration from (Lu, 2021), used under CC BY 4.0 License.

# Synchrotron Radiation-based Computed Tomography

Sample processing pipeline for a multi-scale investigation of implant osseointegration



Synchrotron radiation- based techniques		MicroCT, 3D XRD/SAXS		SAXS, XRD, XRF		TXM, NFHT, Ptychography
Laboratory measurements	<i>In vivo</i> CT, MRI, PET	MicroCT	SEM+EDX	Histology		
Obtained information	longitudinal implant degradation and osseointegration, inflammation	Implant degradation, Osseointegration, 3D morphology for scattering, 3D ultrastructure	Bone implant interface and chemical composition	Detailed information on biology	Bone ultrastructure, chemical information	Lacuno-calicular network
Sample processing		Explantation, fixation, optional: embedding, critical point drying	Cutting in half	Thin sectioning (cut-and-grind or laser cutting)	Mounting on kapton film/tape	Focussed ion beam milling

Sample processing pipeline for the multiscale investigation of implant osseointegration covering all hierarchical levels of bone. Figure from (Zeller-Plumhoff, 2021).

Zeller-Plumhoff, Berit, et al. "Utilizing synchrotron radiation for the characterization of biodegradable magnesium alloys—from alloy development to the application as implant material." *Advanced Engineering Materials* 23.11 (2021): 2100197.

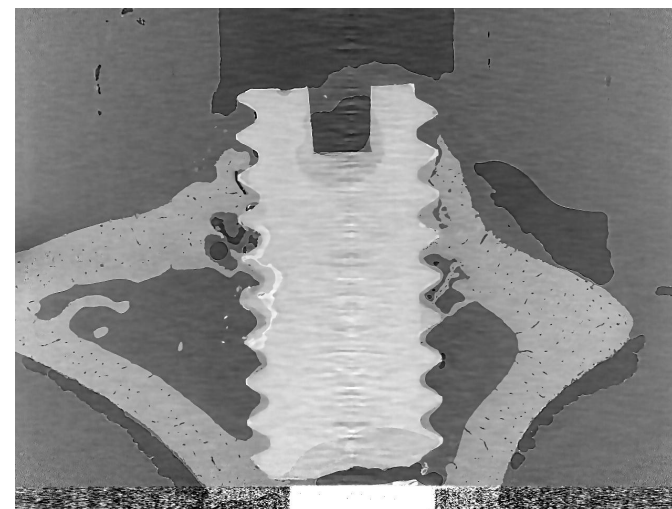
Bruns, Stefan, et al. "On the material dependency of peri-implant morphology and stability in healing bone." *Bioactive Materials* 28 (2023): 155-166.

## Helmholtz-Zentrum Hereon outpost at DESY:

- Operating synchrotron radiation imaging beamlines PETRA III at DESY, Hamburg
- Materials science researches and experiments utilizing X-ray micro-/nano-meters tomography

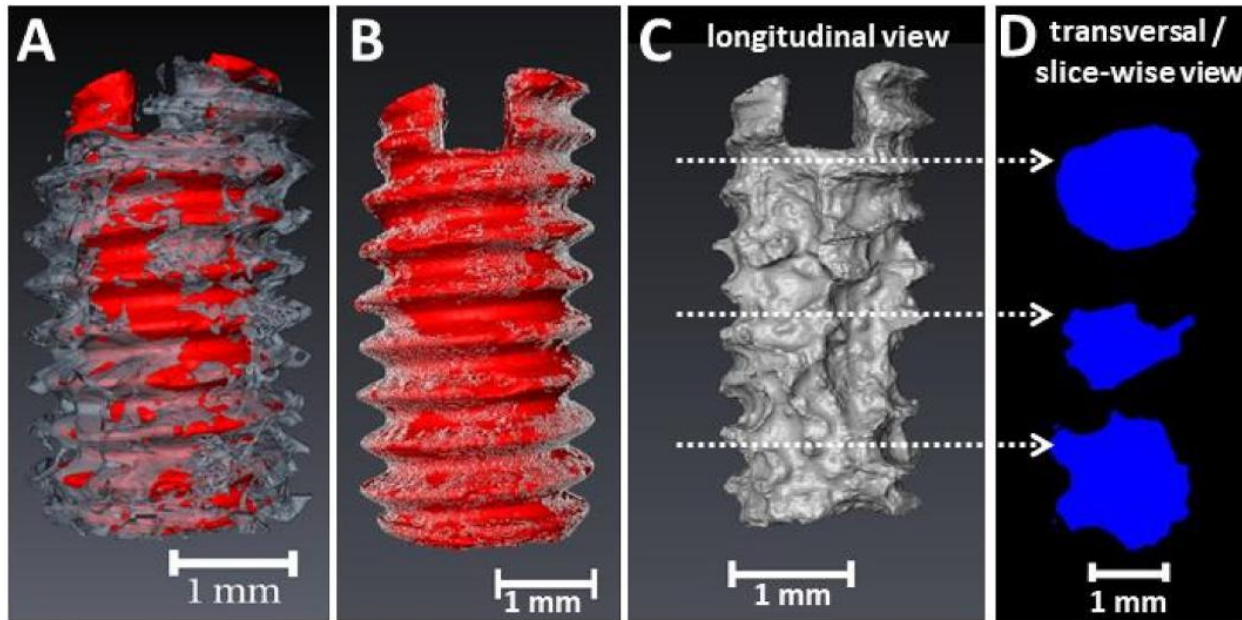
## In situ push-out experiment:

- $\mu$ CT: voxel size 5.1  $\mu$ m
- Attenuation contrast



Tomogram of in situ compression of biodegradable bone implant (Bruns, 2023)

# Metallic Biomaterial: Bio-degradable Mg-Alloy



Mg-10Gd implant after 8 weeks in vivo degradation: screw and the surrounding bone (A), the Bone-to-Implant contact (B) and the residual screw (C). Figure from (Krüger, 2021).

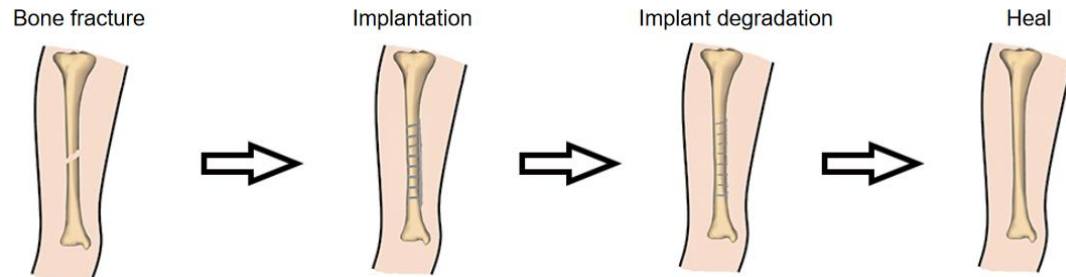
## Study of degradation:

- Composition of implants
  - How degradation is changed
  - How implant change bone properties
  - Different degradation media
- Mechanical properties of implants
  - Stress and strains
  - Implant stability: push-out/pull-out tests
  - Treatment: heat, extruded, etc.
- Modeling
  - Degradation
  - Composition of degradation layers

# Degradation Study of Bio-degradable Material using SR $\mu$ CT

## Bio-degradable implants:

- Reduce patient's pain, surgery risk and medical cost



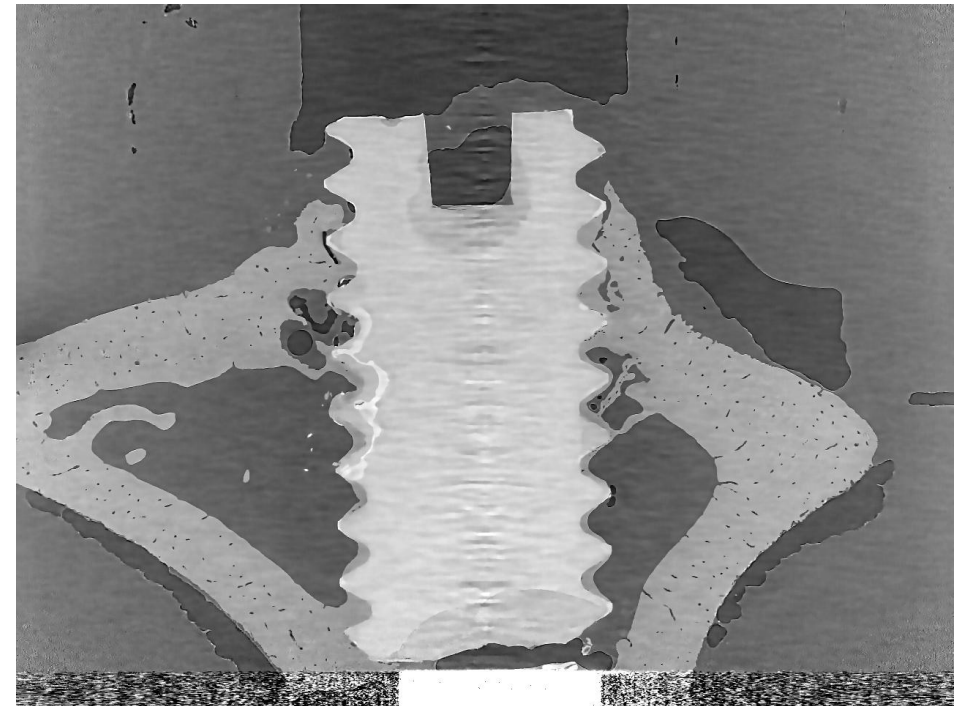
Degradation of the magnesium-based implant in bone fracture healing.  
Illustration from (Lu, 2021), used under CC BY 4.0 License.

## Study of implant stability (osseointegration):

- Push-out tests

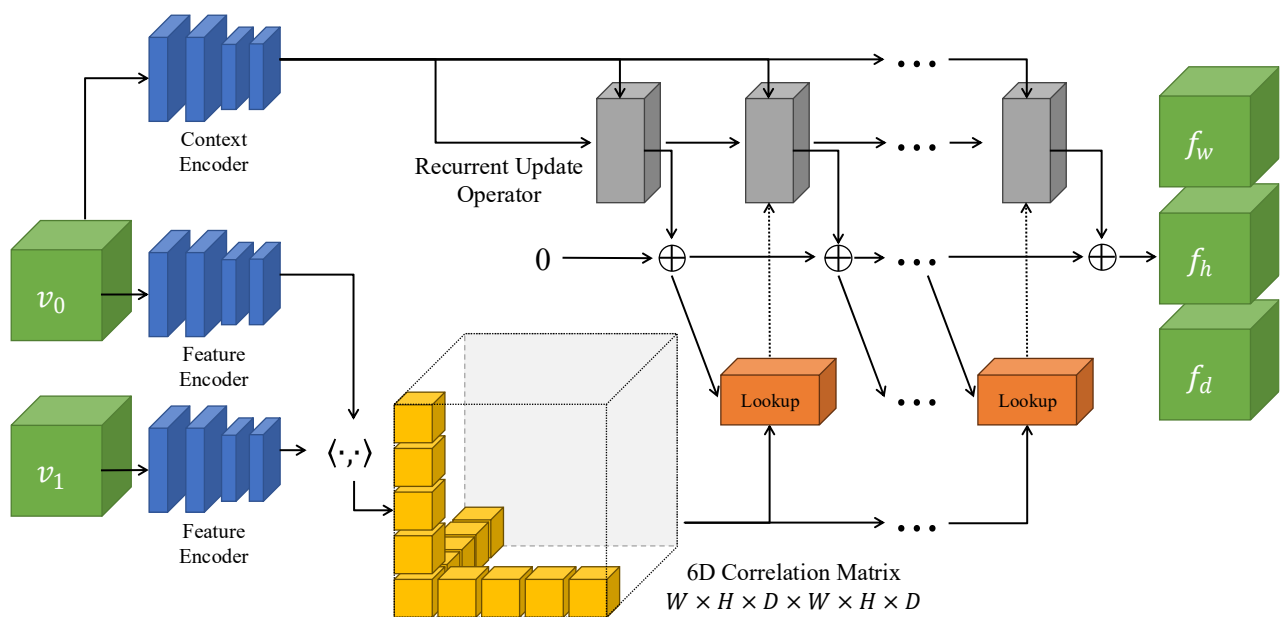
## In situ push-out experiment:

- $\mu$ CT: voxel size 5 $\mu$ m
- Attenuation contrast



Tomogram of in-situ compression of biodegradable bone implant (Bruns, 2023)

# VoRAFT: Volumetric Optical Flow Network



## Patch-based approach:

- Splits full volumes (1280 x 1280 x 960) into patches (80 x 80 x 60) for training and inference

## Feature/Context encoders:

- Convolutional layers

## 6D Correlation Matrix:

- Dot product to compute the similarity on multiscale pyramid

## Correlation Lookup Operators:

- Generate feature maps by indexing from correlation pyramid

## 3D Recurrent Update Operators:

- Predict a sequence of displacement field

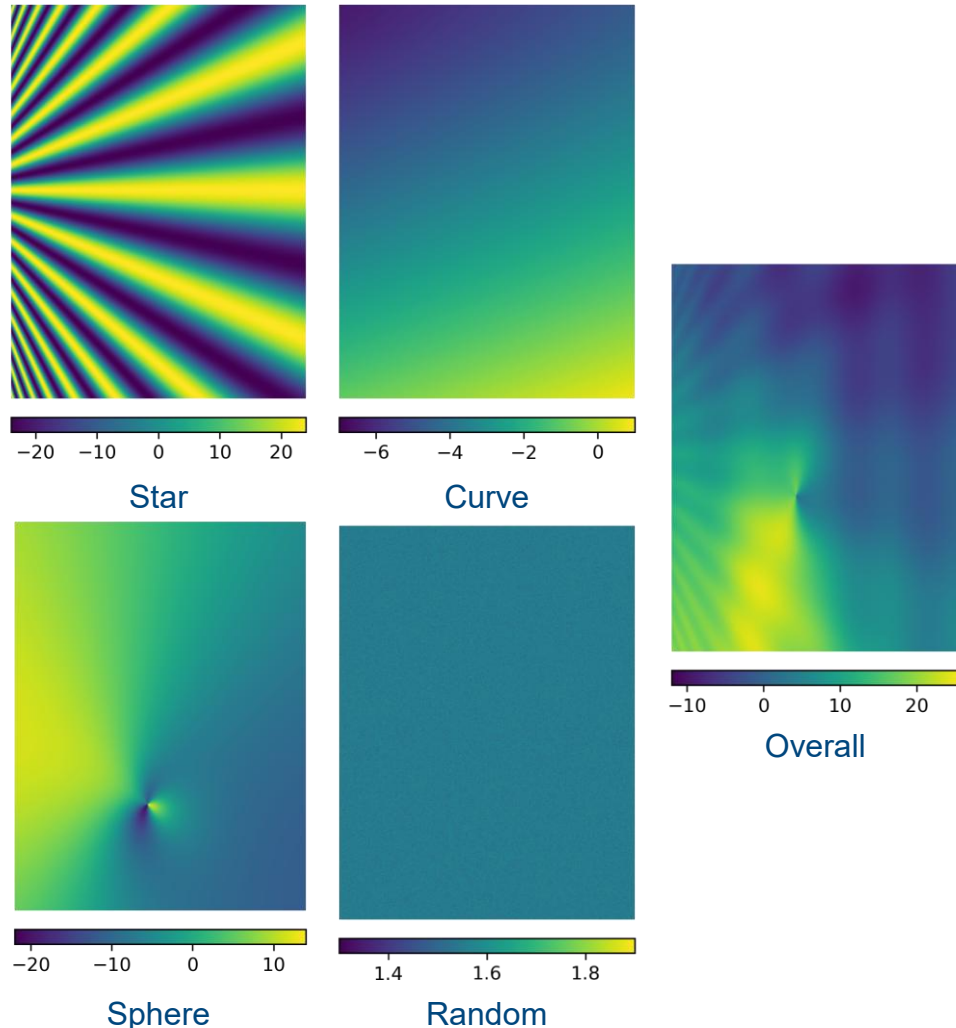
## Supervised Loss with a foreground mask:

- Foreground segmentation mask ( $v_m$ ) for region-of-interest
- L1-distance of mini-batch  $\mathbf{b}$  :

$$\min_{\theta} \sum_{\mathbf{b}} \sum_{k=1}^N \gamma^{N-k} \cdot v_m \cdot \|f_{gt}^{\mathbf{b}} - f_k^{\mathbf{b}}(\theta)\|_1$$

# VoRAFT

## Synthetic 3D Displacement Field



### Measured CT datasets (in total 39):

- Bone + Screw samples: Titanium (Ti), Magnesium Gadolinium alloy (Mg-10Gd, Mg-5Gd), Polyetheretherketone (PEEK)
- Denoised, Registration, Segmentation

### Synthetic 3D displacement fields (in total 23):

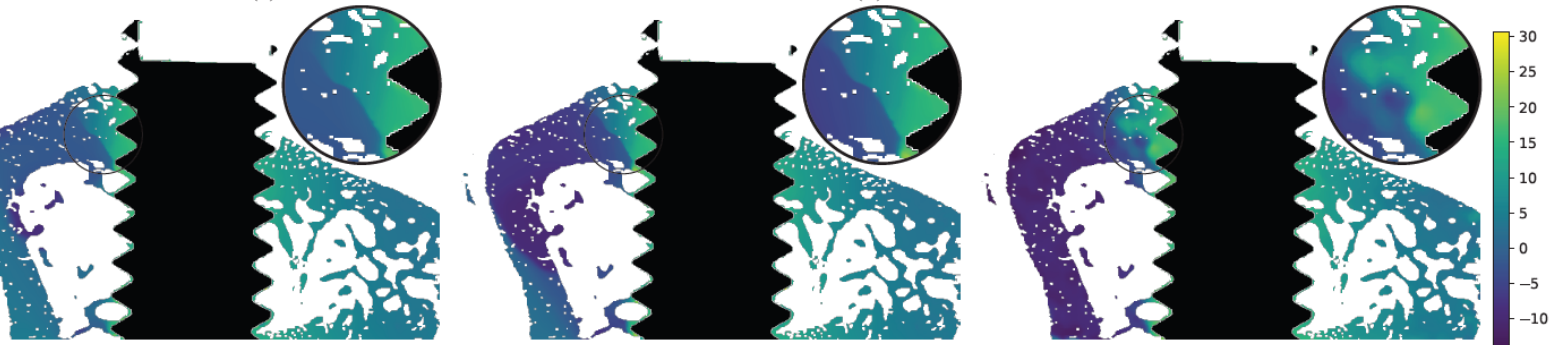
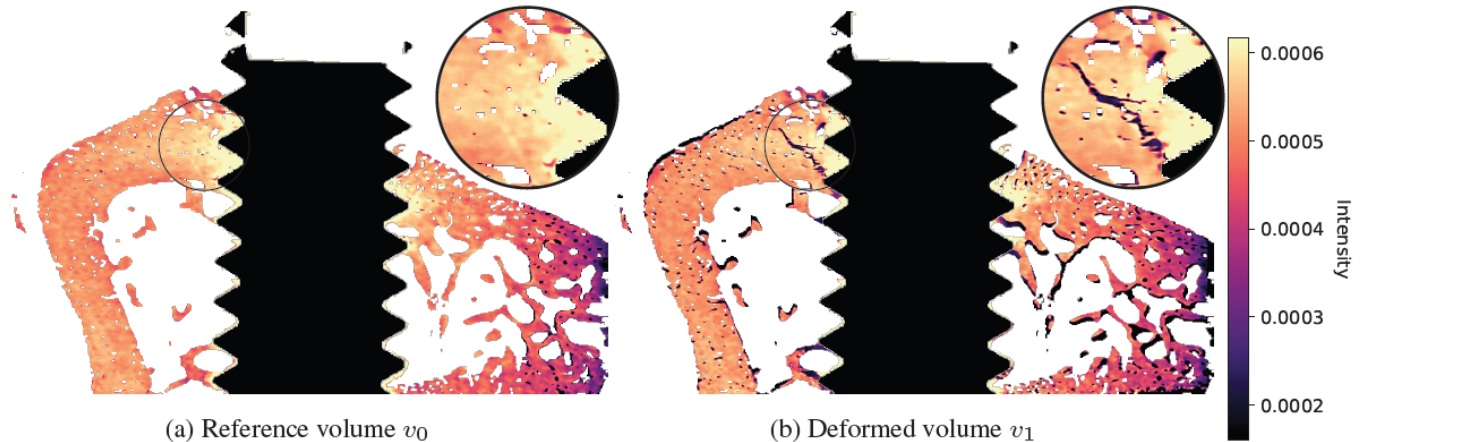
- 4+1 classes: star, curve, sphere, random, overall
- Random data augmentation:
  - rotation by 3D angles, permutation of the axes order, addition of noise,
  - generation of random flow parameters, e.g.: amplitudes, spatial frequencies, non-linearity

### Synthetic datasets (in total 897):

- 828 datasets for training and validation
- Exclude 3 samples (69 datasets) for testing the generalization

# VoRAFT

## Experimental Results: Measurement Datasets



(c) Displacement fields (in voxels) at the height-direction  $f_h$

### Measurement datasets by Titanium:

- VoRAFT estimates the structure of displacement fields correctly
- Samples are unknown in the training set
- VoRAFT roughly estimate displacement for discontinuous and sharp structures in the fracture

# VoRAFT

## Hyperparameter

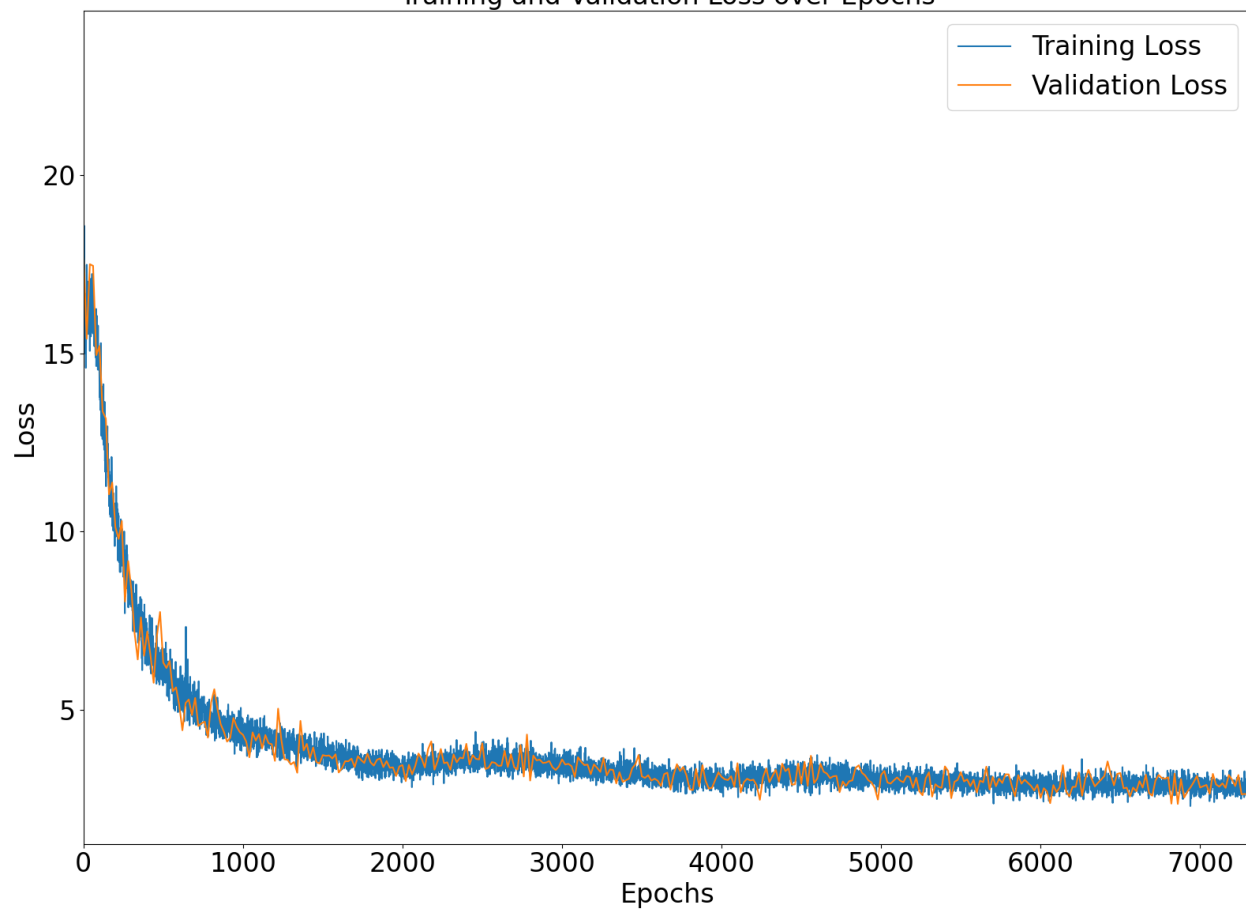
Hyperparameter		RAFT-S	VoRAFT
Size of image/volume-patches		$512 \times 384$	<b><math>80 \times 80 \times 60</math></b>
Size of flow/displacement-patches		$2 \times 512 \times 384$	<b><math>3 \times 80 \times 80 \times 60</math></b>
Optimizer		AdamW [21]	AdamW [21]
Learning rate		$2e-5$	$2e-5$
Number of epochs		100000	<b>10000</b>
Maximum range of displacement		400	<b>24</b>
(Mini-)Batch size $\mathbf{b}$	Eq. (3)	6	<b>18</b>
Recurrent iterations $N$	Eq. (3)	12	12
Weights of loss $\gamma$	Eq. (3)	0.8	0.8
Levels of correlation matrix $L$		4	4
Gradient-norm clipped		$[-1, 1]$	$[-1, 1]$
Number of learnable parameters		1M	2.95M

Table 1. Comparison of hyperparameters and the number of learnable parameters between the RAFT-S model and our proposed VoRAFT approach. We take the default setting of hyperparameters from the source code of RAFT as a reference. The changed hyperparameters are highlighted.

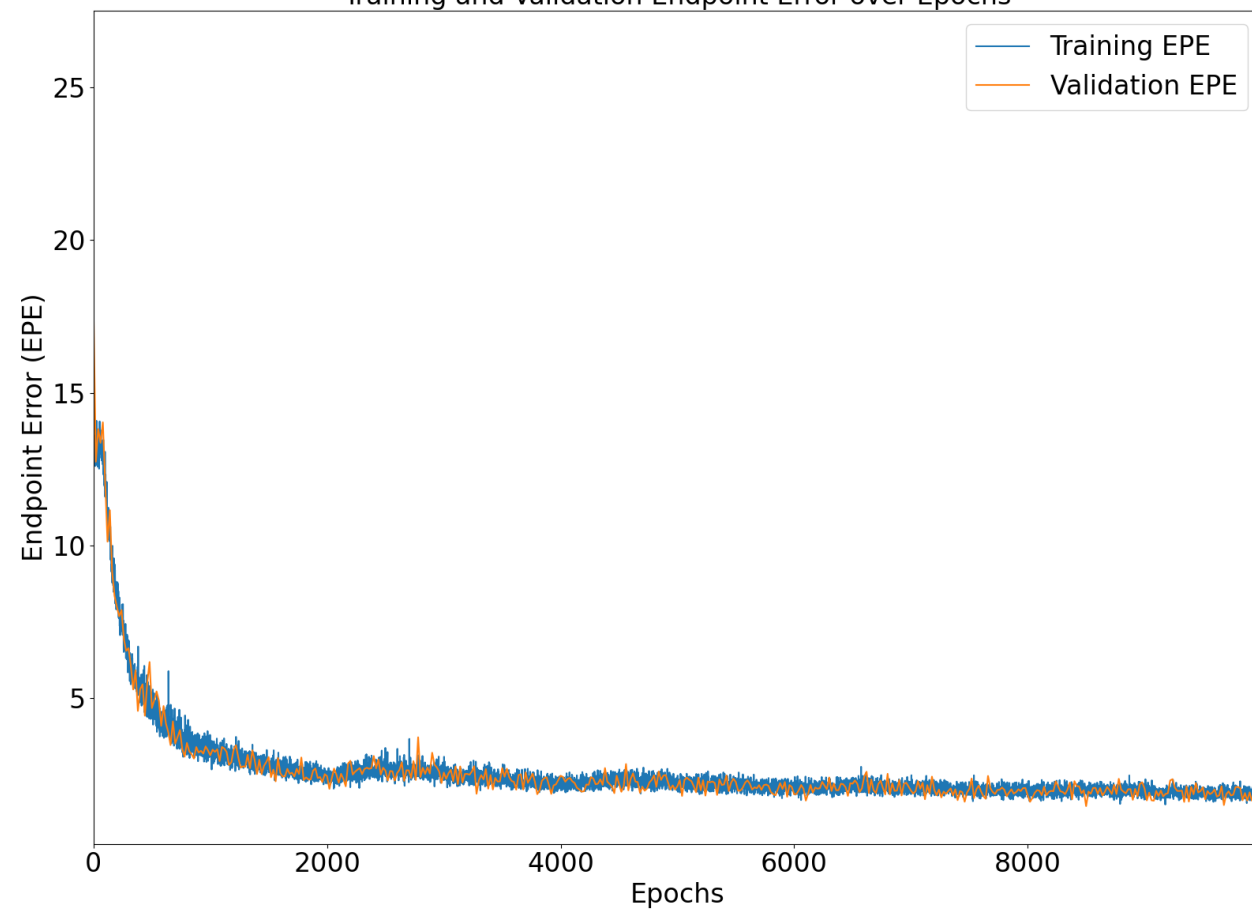
# VoIRAFt

## Training

Training and Validation Loss over Epochs

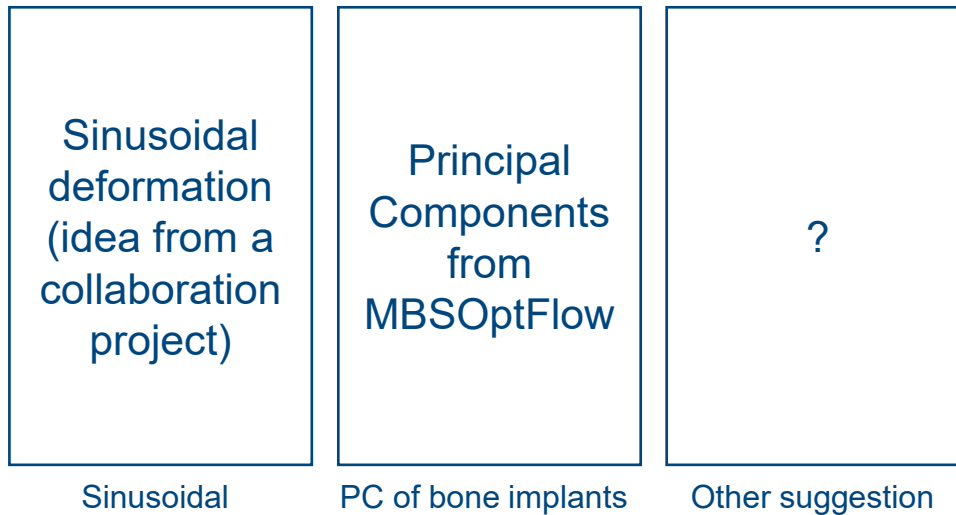
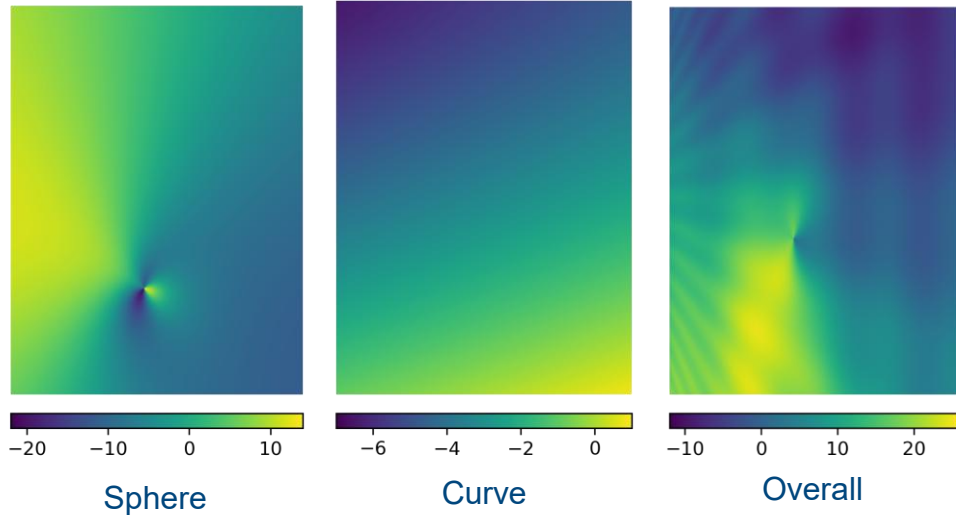


Training and Validation Endpoint Error over Epochs



# VoIRAFtV2

## Synthetic 3D Displacement Field



### Synthetic fields:

- Sphere: for divergence and curl
- Curve: for tensile test
- Overall: for mixture of structures
- Sinusoidal: sinusoidal deformation (idea from wood sample)
- Principal Components of bone implants:
  - Use MBSOptFlow to estimate realistic deformation
  - Extract main features of flow fields by PCA
  - Need to determine the size of PC, i.e. 80x80x60 or 1280x1280x960
- Other suggestions?

# VoRAFT: Volumetric Optical Flow Network for Digital Volume Correlation of SR $\mu$ CT Images of Bone-Implant Interfaces

## Summary

- Provides insight into application of SOTA computer vision approaches to address classical challenges in materials science research
- Can be improved by its inference method
- Can be potentially applied to other materials and experimental data
- Source code and trained network are available on GitHub: <https://github.com/hereon-mbs/VoRAFT>

## Reference:

1. Lu, Yu, et al. "Biodegradable magnesium alloys for orthopaedic applications." *Biomaterials translational* 2.3 (2021): 214.
2. Bruns, Stefan, et al. "On the material dependency of peri-implant morphology and stability in healing bone." *Bioactive Materials* 28 (2023): 155-166.
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