Motion Compensation for 4D Digital Subtraction Angiography via Deep Autofocus and Implicit Neural Model

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Acknowledgments

The Carnegie Center for Surgical Innovation carnegie.jhu.edu

Quantis Lab

Quantitative Imaging Systems: Physics, Algorithms, and Devices quantis.bme.jhu.edu

AIAI Lab

Advanced Imaging Algorithms and Instrumentation Laboratory aiai.jhu.edu

Collaborators

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Digital Subtraction Angiography (DSA)

3D-DSA in Interventional Neuroradiology

Critical to diagnosis and guidance of treatment

- Subarachnoid hemorrhage (>27k per year in the US [1])
- Stroke (over 101 million worldwide [2])
- Arterial Vascular Malformation (AVM)

Relies on 2D-DSA for temporal information

→ Limited by vessel overlap [3]

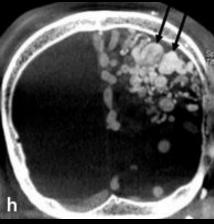
From 3D to 4D-DSA [4]

<u>Time-resolved 3D-DSA sequence</u>

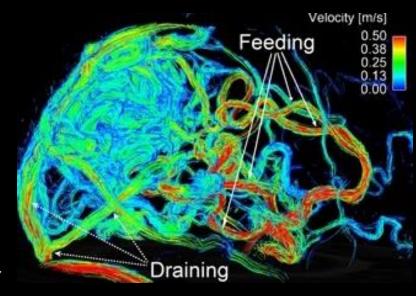
- Volumetric visualization + flow quantification
- Complements 3D-DSA
 - Diagnosis of AVMs [5]

Treatment of Intracranial Aneurysms [6]





DSA of Venous Aneurysm [7]



4D-DSA Flow Estimation [7]

^[1] J. Brisman, et al, New England Journal of Medicine, 2006.

^[2] Wolfe, C. D. A. The impact of stroke. Br Med Bull, 2000

^[3] K.L. Ruedinger, et al, AJNR, 2021

^[4] B.J. Davis, Implementation and Evaluation of 4D-DSA, 2023

Challenges to DSA Image Quality - Motion

3D/4D DSA Requirements

<u>Spatial alignment (Mask + Contrast)</u>

- No intra-scan inconsistent artifacts
- Perfect spatial registration

Challenges from Motion

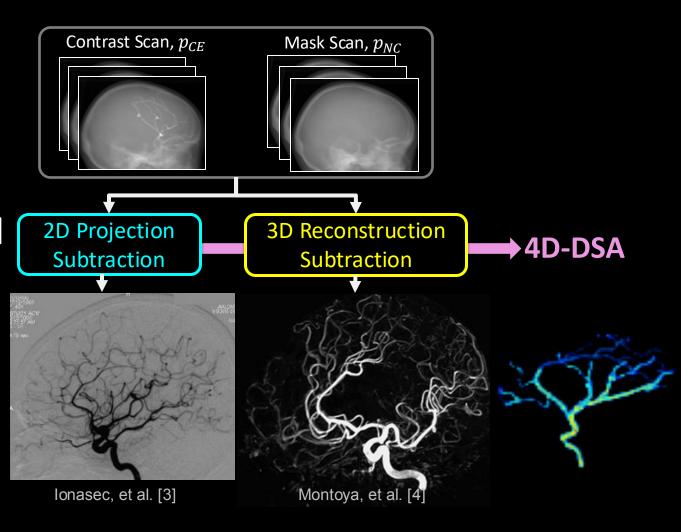
Prevalent source of artifacts in 4D-DSA [1] >82% CBCT (~6% severe) [2]

Moderate acquisition time (4-20 s)

Intra-scan patient motion (trajectory)

Two independent scans

- Inter-scan misalignment (global pose)
- → Joint estimation of intra and inter-scan motion



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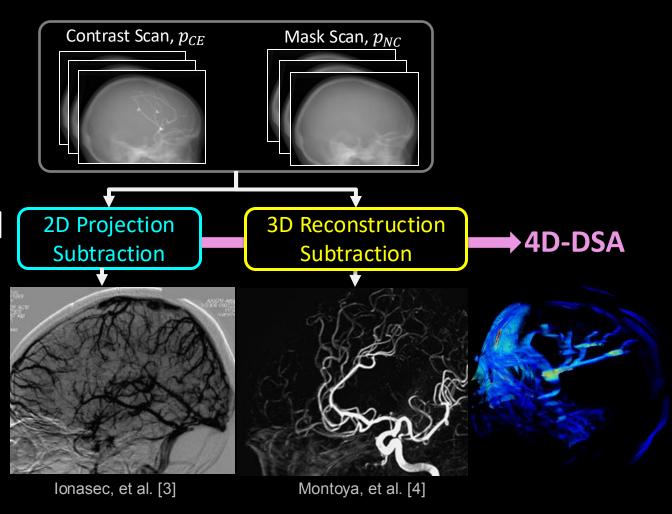
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Deep Autofocus in Interventional CBCT

Motion Compensation in CBCT

Immobilization and breath-holding → Not sufficient
Fiducial markers → Fit poorly with interventional workflow
Gating → Difficult for long scan - only one motion source
Tracking of prior image → Prior unavailable

Deep Autofocus Motion Compensation

Rigid motion compensation^{1,2,3} (extremity, brain/head) Deformable motion compensation (abdomen) ⁴ Learned deep autofocus metric

Anatomy-aware learned metrics ⁵ Adaptive Motion Models^{6,7}

→ Applicable to 4-DSA

Motion-Corrupted



Deep Autofocus³



^[1] J. Hahn, et al. Med. Phys. 44(11), 5795-5813, 2017.

^[2] A. Sisniega, et al. Phys. Med. Biol. 62(9), 3712-3734, 2017

^[3] H Huang et al 2022 Phys. Med. Biol. 67 125020

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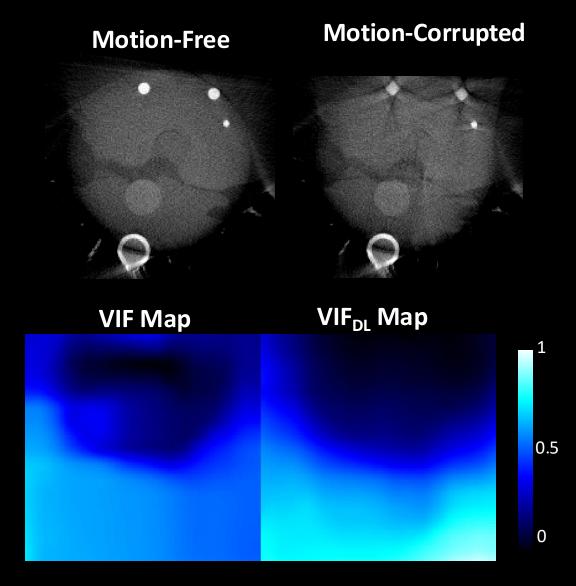
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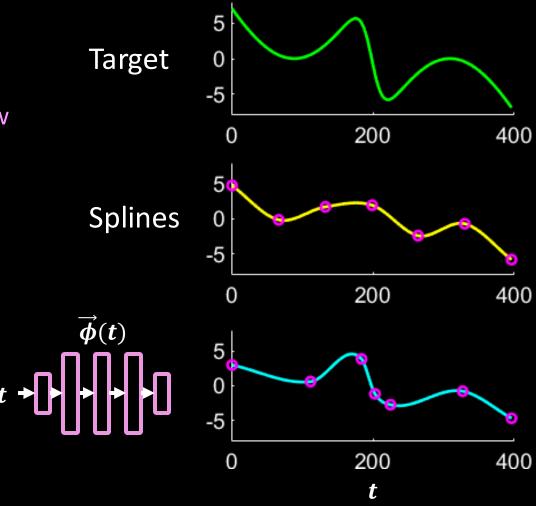
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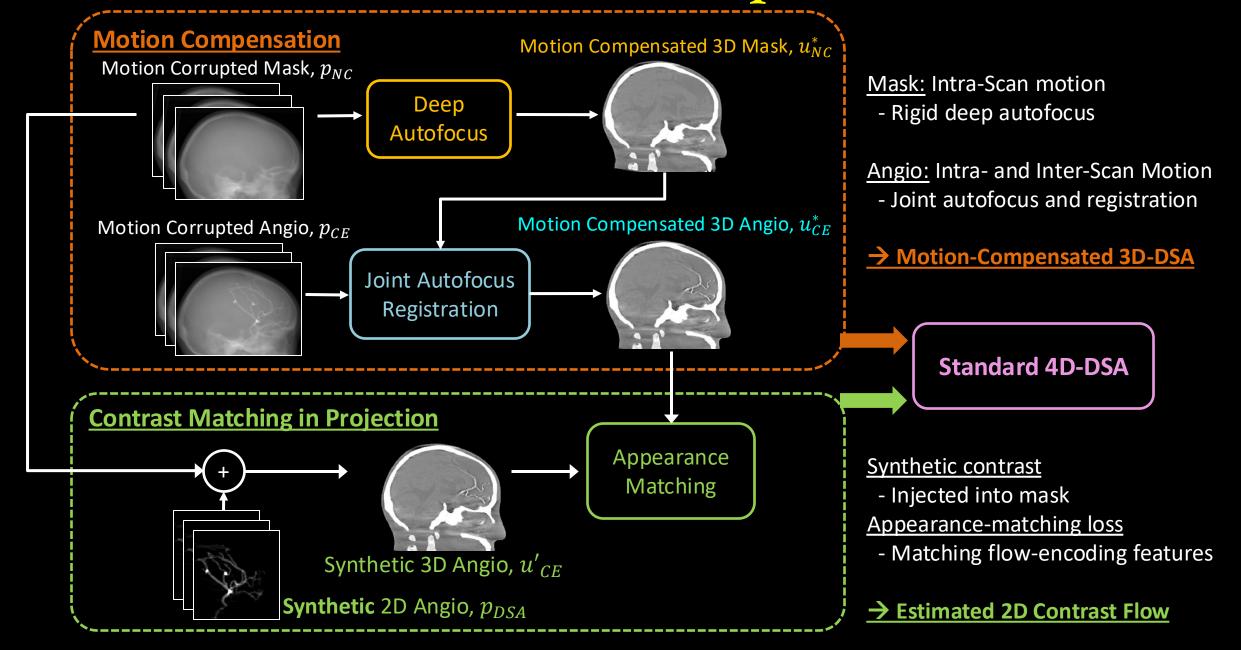


^[1] J. Hahn, et al. *Med. Phys.* 44(11), 5795-5813, 2017.

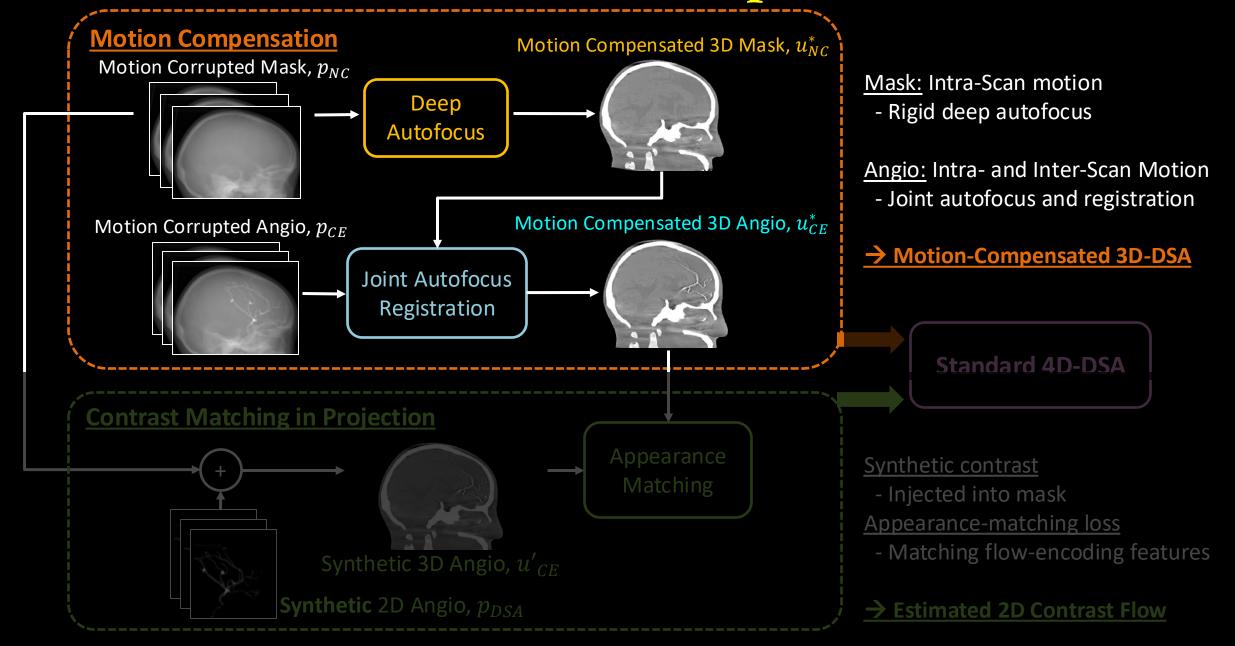
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Framework for Motion Compensated 4D-DSA



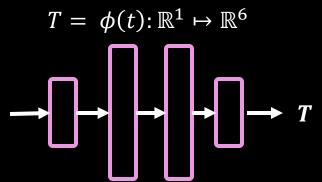
Framework for Motion Compensated 4D-DSA



Intra-Scan Motion in Mask: Deep Autofocus

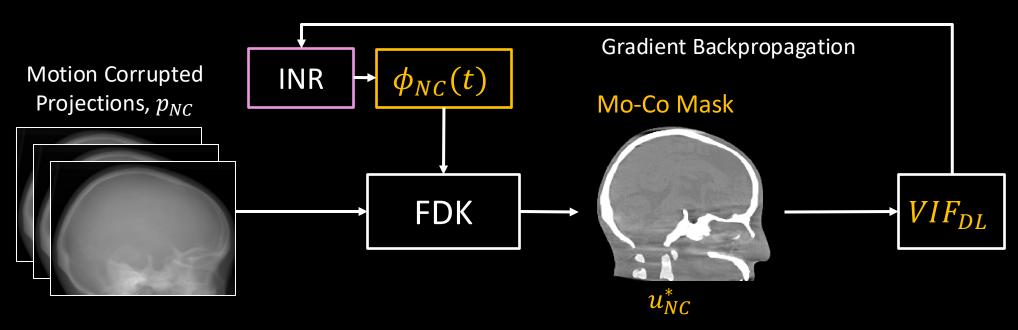
Deep Autofocus

- Anatomy-aware learned metric VIF_{DL} [1]
- Differentiable motion model
 - Implicit Neural Representation (INR)
- Gradient-based optimization [2]



Motion-Encoding INR

- Continuous function approximator
- $T = \phi(t)$ 6 DoF per projection
- Continuous input/output space
- Fully connected network3 hidden layers, 64 features each



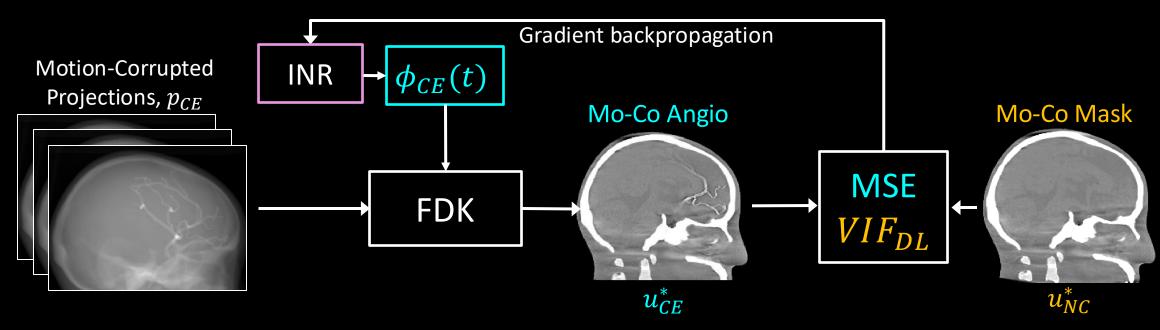
$$T_{NC}^* = \underset{\boldsymbol{\phi}}{\operatorname{argmin}} VIF_{DL}[FDK(p_{NC}, T)],$$

$$\boldsymbol{u}_{NC}^* = FDK(p_{NC}, \boldsymbol{T}_{NC}^*)$$

Motion and Pose in Angio: Reference Autofocus

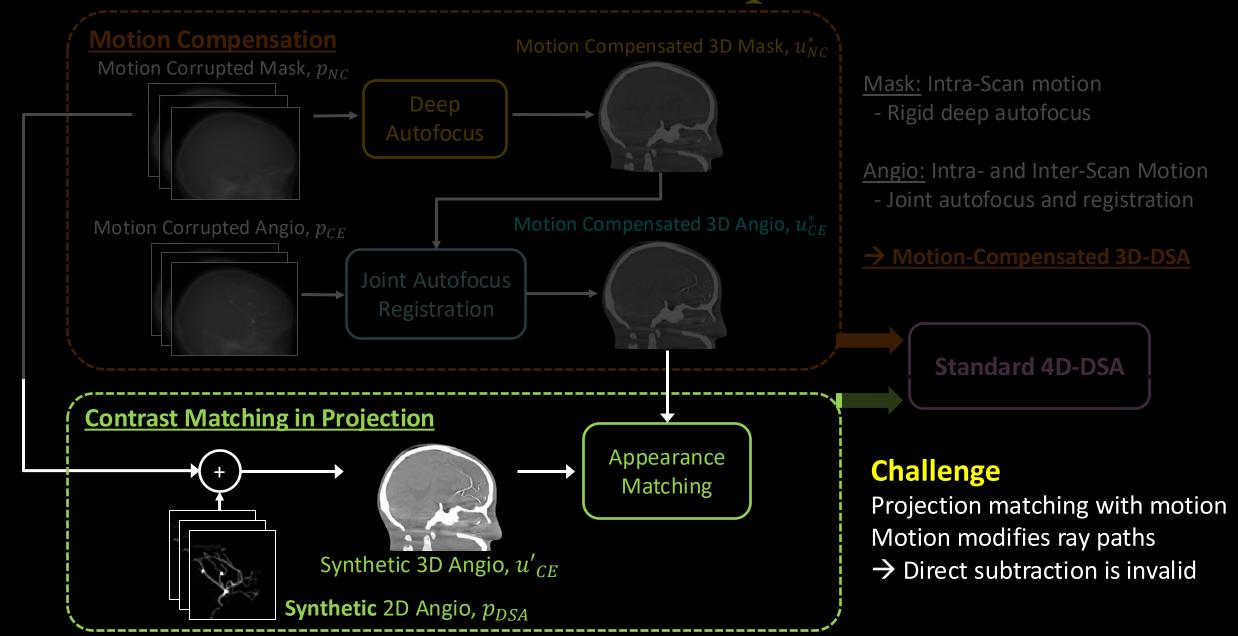
Joint Autofocus and Registration

- Motion compensated mask as reference
- Joint optimization:
 - Intra-scan motion with VIF_{DL}
 - Residual motion and registration with MSE vs reference



$$T_{CE}^* = \underset{\boldsymbol{\phi}}{\operatorname{argmin}} \|\boldsymbol{u}_{NC}^* - FDK(p_{CE}, \boldsymbol{T})\|^2, \qquad \boldsymbol{u}_{CE}^* = FDK(p_{CE}, \boldsymbol{T}_{CE}^*)$$

Framework for Motion Compensated 4D-DSA



Contrast Projection Estimation

INR for Contrast Synthesis

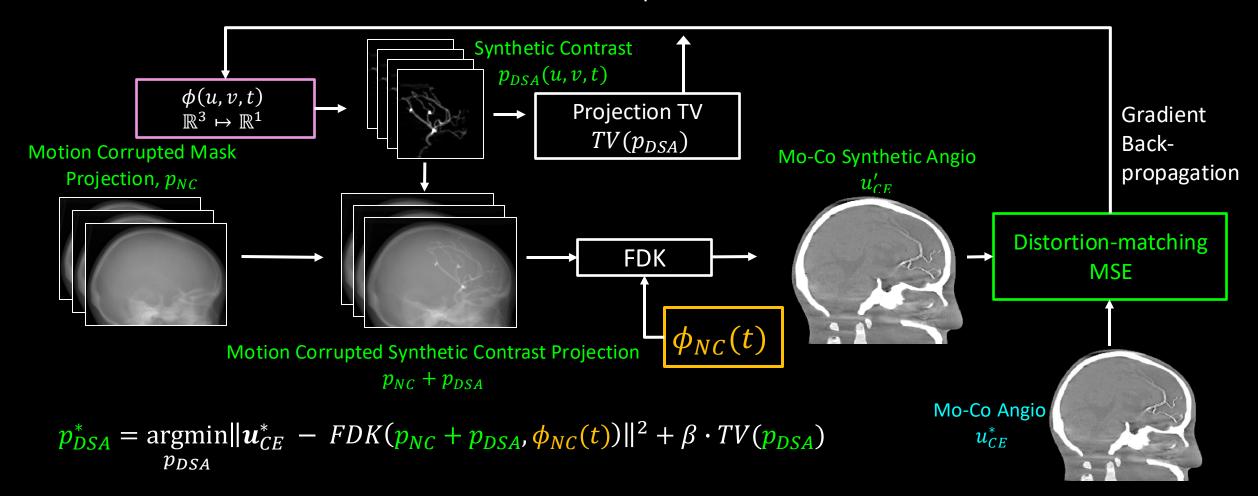
Map time-dependent pixel location to line integral values

→ Continuous multi-resolution transition

Distortion Matching Loss

Time-dependent contrast creates unique image features

→ Matching reconstruction "distortion" provides
temporal information



Validation Study

Simulation Phantom

CT scan of Kagaku phantom (Kyoto Kagaku, Japan)

- Contrast-enhanced vascularity:
 - Left-anterior and left-middle cerebral arteries
 - Internal carotid artery

Contrast Flow

Laminar Flow (2 cm/s during 12s scan)

Time-concentration modeled using gamma function [1]

Kagaku Phantom



Simulated Contrast Flow

Acquisition Geometry

Angle: 0° - 215° (304 projections)

<u>Detector:</u> 580x440 pixels (0.616x0.616 mm)

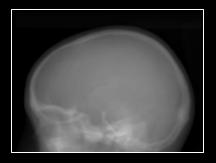
SAD: 750 mm SDD: 1200 mm

Motion Pattern

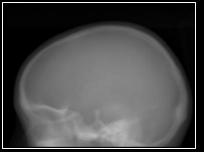
Amplitude: 2 – 6 mm

<u>Frequency</u>: 2 – 4 periods per scan

Inter-Scan Phase Shift: ~90 degrees (random)



Motion Corrupted Mask Projections



Motion Corrupted Contrast Projections

Evaluation

Motion Compensation Fidelity

Intra-scan Motion Compensation

SSIM of Mask and Angio volumes

Vascular Tree Integrity

DICE score of 3D-DSA

Contrast Projection Estimation Accuracy

Vasculature Detection

Precision and recall

Contrast Flow Accuracy

Pixel-wise mean average error (MAE)

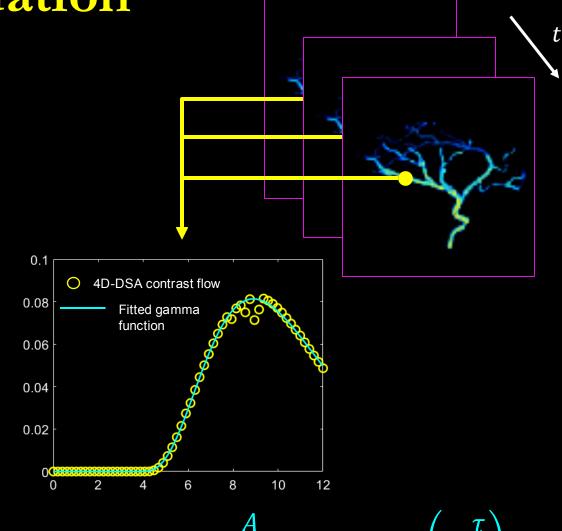
4D-DSA Quality

Contrast Flow Quantification

MAE of 4D-DSA

Contrast Time of arrival (TOA)

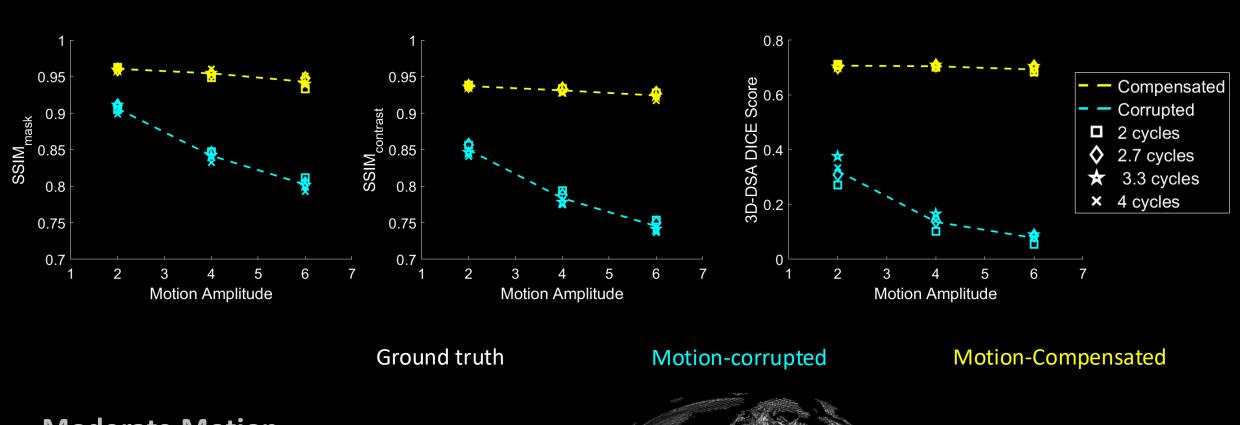
Fitting 4D-DSA to gamma function



$$\mu(t) = \frac{A}{(\alpha\beta \exp(-1))^{\alpha}} \tau^{\alpha} \exp\left(-\frac{\tau}{\beta}\right) H(\tau)$$

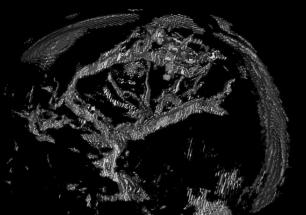
 $\tau(t) = (t - t_0)/\eta$, where t_0 is TOA

Motion Compensation Fidelity



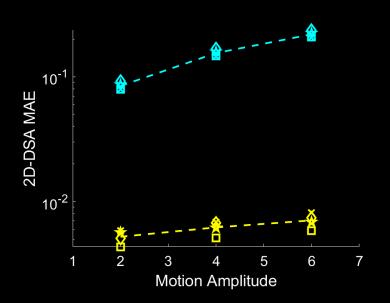
Moderate Motion (4mm, 2.6 cycles per scan)

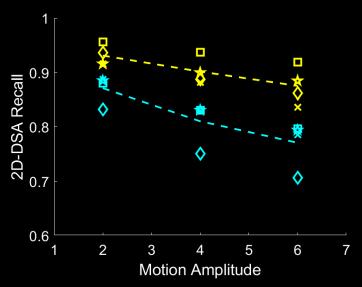


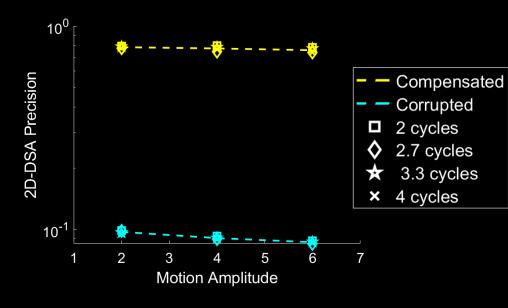




Contrast Projection Estimation Accuracy





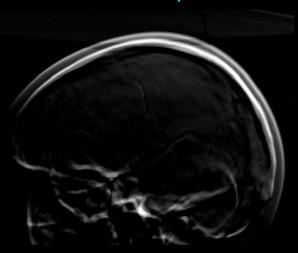


Ground truth

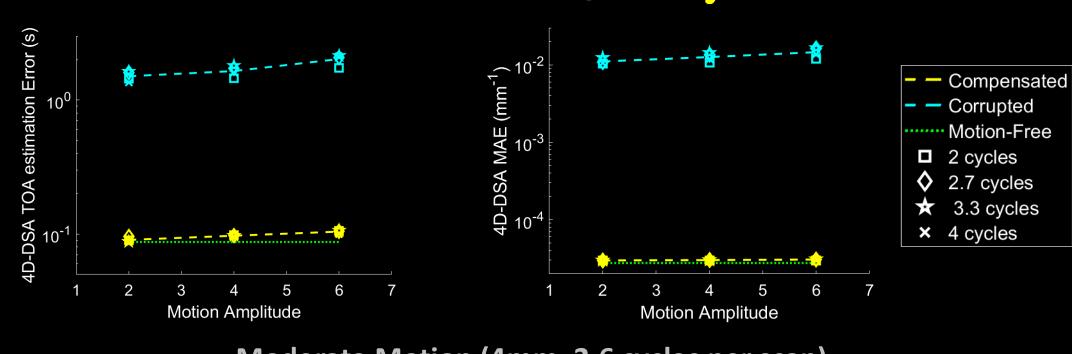
Motion-corrupted

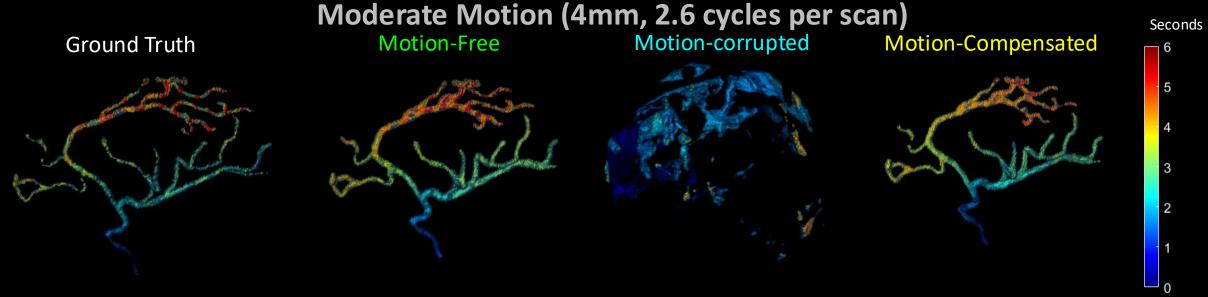
Motion-Compensated

Moderate Motion (4mm, 2.6 cycles per scan)



4D-DSA Quality





Conclusion ID-DSA Framework

Motion Compensated 4D-DSA Framework

Joint Deep Autofocus & Registration:

Learning-based metric, INR of motion trajectory

Contrast Projection Synthesis:

Appearance-matching loss, projection intensity encoded by INR

Simulation Study

3D-DSA:

SSIM increase: 11.8%

DICE score increase: ~3 times higher

Contrast Projection Estimation:

MAE reduction: 93.3%

False detection reduction: 88.2%

<u>4D-DSA</u>:

Estimated TOA error reduction: 94.8%

Ongoing Work

Application to clinical data

