

Enhanced Ultrasound Localization Microscopy with Spatio-Temporal Deep Learning

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Outline

- 1 Introduction
- 2 Proposed approach
- 3 Numerical Results

Introduction

Clinical Context

- **Non-invasive stroke diagnosis:**

Avoid MRI and CT-scan constraints.

- **Surgical management of cerebral gliomas:**

Infiltrating gliomas have no clear boundary with healthy tissue.
May be located close to or within “functional” brain areas

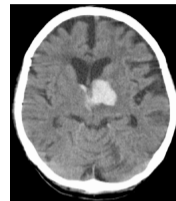


Figure 1: CT-scan with hemorrhage in the left thalamus.

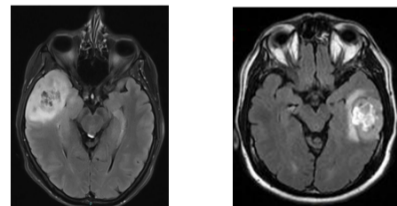


Figure 2: Diffuse high-grade gliomas.

Experimental procedure

- Contrast enhanced ultrasound:
 - Preparation and installation
 - Microbubble injection
- Ultrafast Ultrasound Imaging:
 - High pulse repetition frequency
 - Beamforming (DAS)

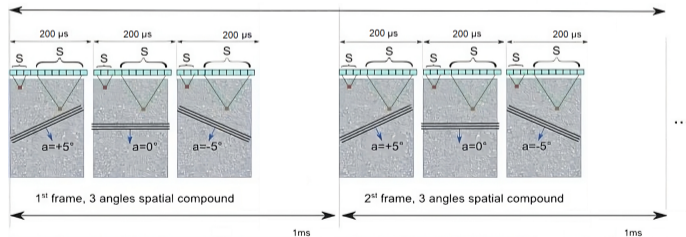
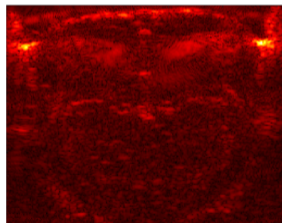
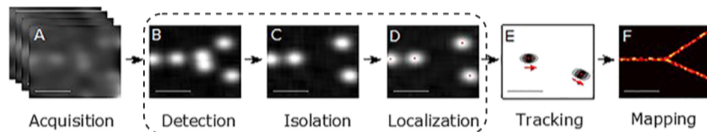
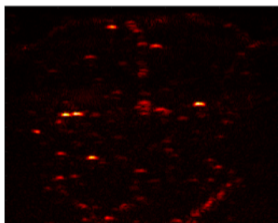


Figure 3: An US acquisition at a compounded frame rate of 1,000 Hz with 3 tilted plane waves $[-5^\circ, 0^\circ, +5^\circ]$.

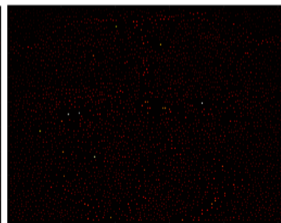
ULM Pipeline



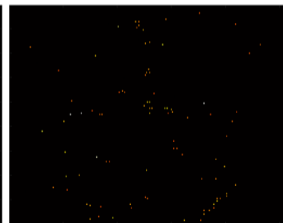
Bmode IQ



Clutter Filtered



Regional Max

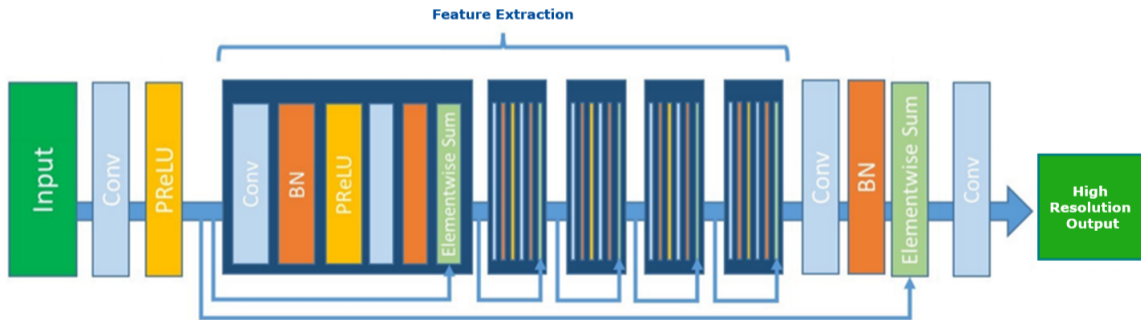


Amp Filtering

Proposed approach

ULM CNNs limitations

- Scarcity of labeled In Vivo data.
- Use of high-resolution grid.



US simulation from MRI

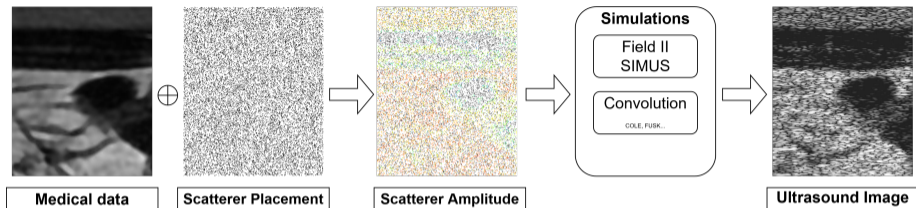


Figure 4: Standard scatterer based ultrasound simulation.

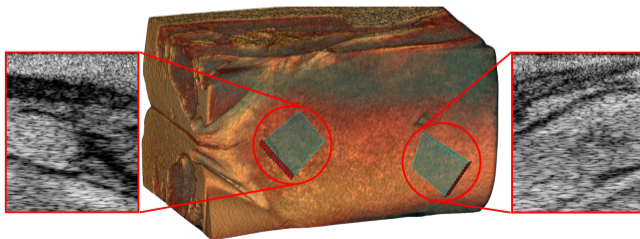
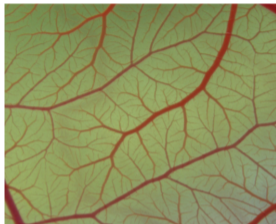
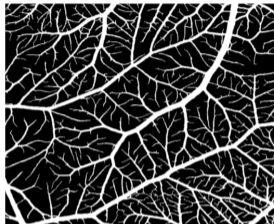


Figure 5: Simulated US images using MRI volume slices.

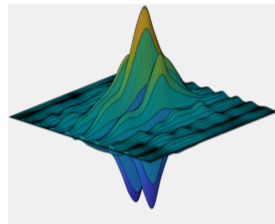
CAM simulation data



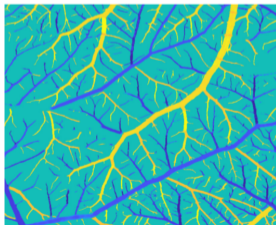
CAM image



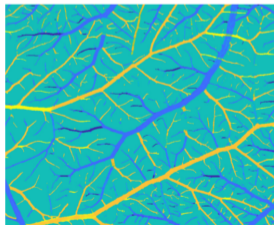
Segmented Vessels



Extracted PSF



X displacement map



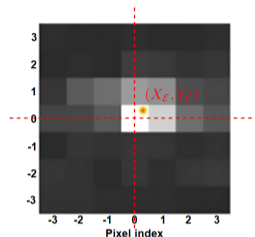
Y displacement map



Bmode US frame

Proposed Method

- Output Representation:



- Network Loss function:

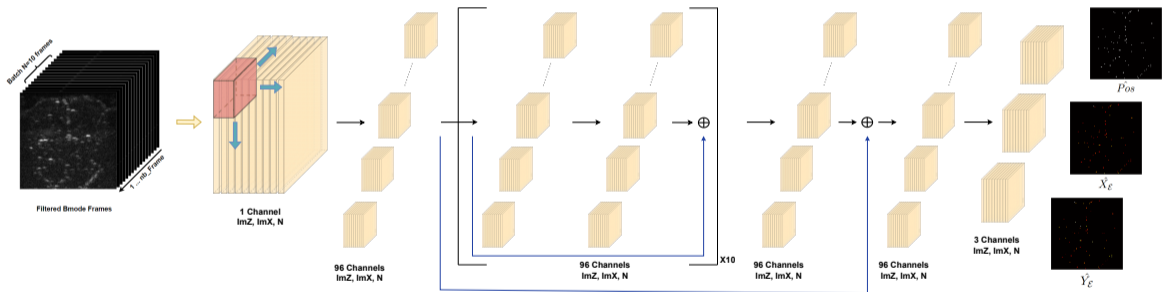
$$Loss = L_{pos} + L_{loc} \quad (1)$$

$$L_{pos} = \left\| H \circledast Pos - H \circledast \hat{Pos} \right\|_F^2 \quad (2)$$

$$L_{loc} = \frac{1}{2} \left\| X_{\mathcal{E}} - \hat{X}_{\mathcal{E}} \right\|_F^2 + \frac{1}{2} \left\| Y_{\mathcal{E}} - \hat{Y}_{\mathcal{E}} \right\|_F^2 \quad (3)$$

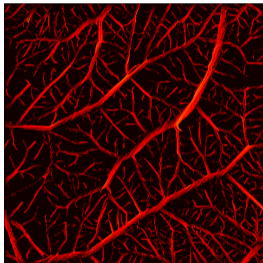
3DML-ResNet Architecture

Proposed 3DML-ResNet:

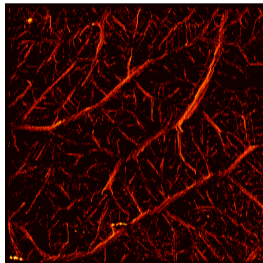


Numerical Results

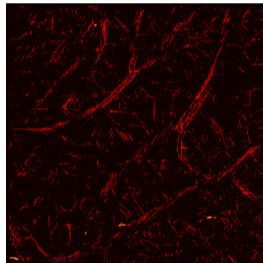
CAM data Rendering



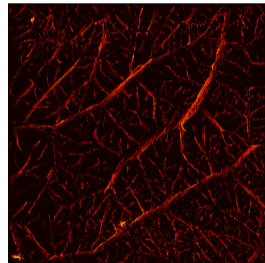
(a) Ground Truth



(b) RS ULM [Hei+22]

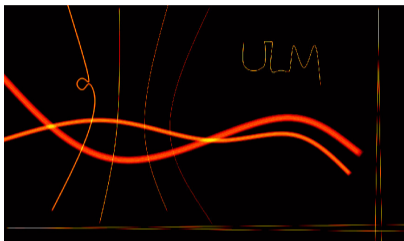


(c) mSPCN [Liu+20]

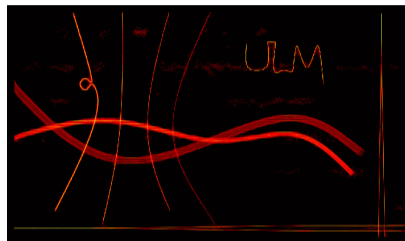


(d) 3DML-ResNet

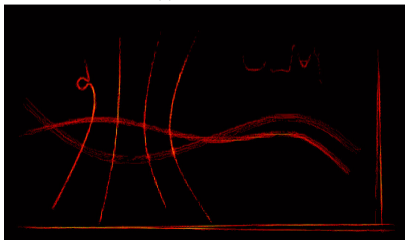
In Silico PALA Results



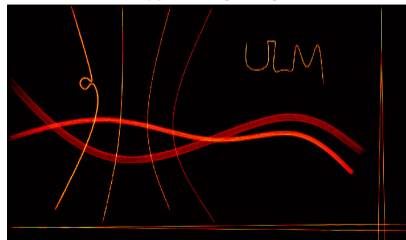
(a) Ground Truth



(b) RS ULM [Hei+22]



(c) mSPCN [Liu+20]



(d) 3DML-ResNet

Metrics

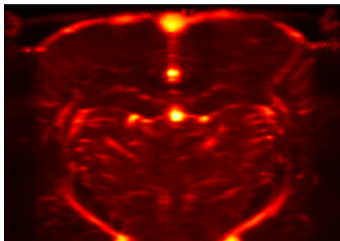
- **PALA In Silico [Hei+22] metrics comparison:**

	RS ULM	mSPCN	3DML-ResNet (Ours)
SSIM [%]	84.37	84.14	91.40
RMSE	7.043	9.440	6.616
Jaccard Index [%]	24.15	20.54	47.53

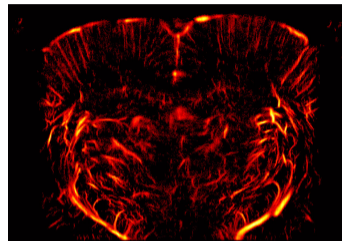
- **CAM Data [Che+23] metrics comparison:**

	RS ULM	mSPCN	3DML-ResNet (Ours)
SSIM [%]	40.34	42.02	54.43
RMSE	2.009	2.892	1.764
Jaccard Index [%]	8.13	5.80	14.29

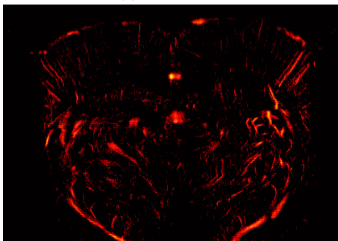
In Vivo Rat Brain PALA Results



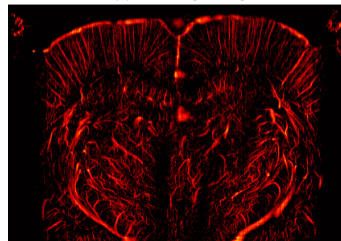
(a) Power Doppler



(b) RS ULM [Hei+22]



(c) mSPCN [Liu+20]



(d) 3DML-ResNet

Thank you!

Questions ?

References

- [Hei+22] B. Heiles et al. “Performance benchmarking of microbubble-localization algorithms for ultrasound localization microscopy”. In: *Nat. Biomed. Eng.* 6 (2022), pp. 605–616. DOI: 10.1038/s41551-021-00824-8.
- [Liu+20] Xin Liu et al. “Deep Learning for Ultrasound Localization Microscopy”. In: *IEEE TMI* 39.10 (2020), pp. 3064–3078. DOI: 10.1109/TMI.2020.2986781.
- [Che+23] Xi Chen et al. “Localization Free Super-Resolution Microbubble Velocimetry Using a Long Short-Term Memory Neural Network”. In: *IEEE TMI* 42.8 (2023), pp. 2374–2385. DOI: 10.1109/TMI.2023.3251197.