Row-Column Scanned Neural Signed Distance Fields for Freehand 3D Ultrasound Imaging Shape Reconstruction

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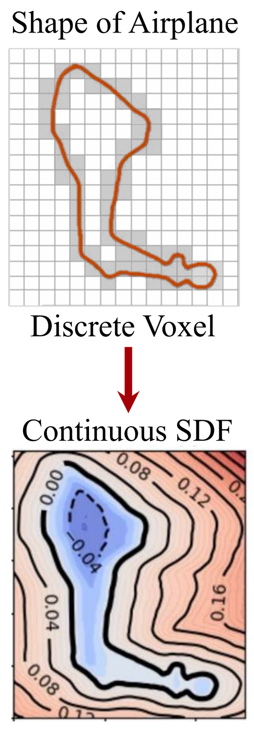
Introduction

Background

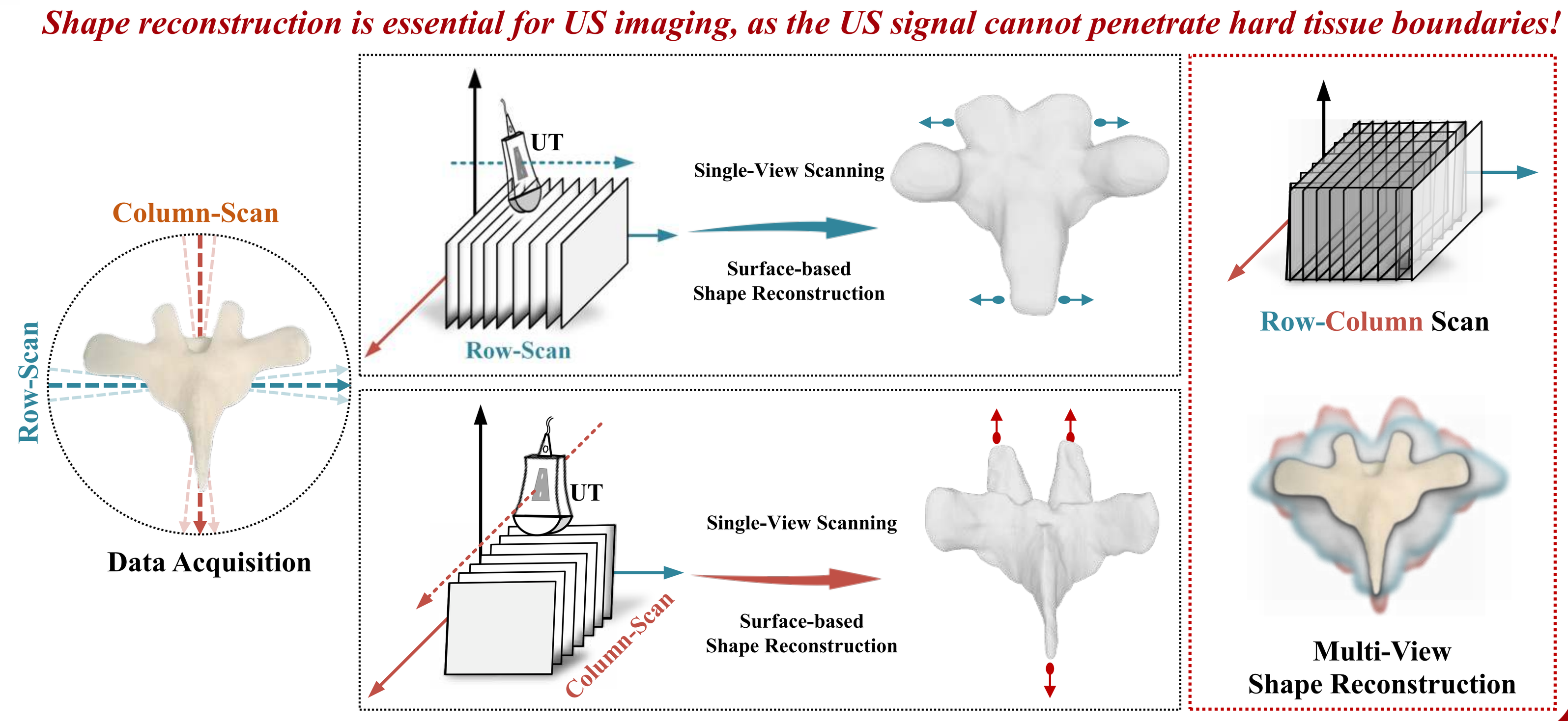
- Multi-view ultrasound scanning provides:
  - Complex anatomical shapes.
  - Comprehensive spatial understanding.
  - Complementary directional information.
- Implicit neural representation:
  - Resolution-agnostic.
  - Memory-efficient.
  - Continuous representation.

Challenges

- ❑ Freehand 3D ultrasound (US) imaging:
  1) View-dependent issue.
  2) Elevational thickness issue.
  3) Discrete voxel resolution.
- ❑ Shape reconstruction:
  - > Point-based: non-uniform.
  - >> Volume-based: poor geometry.
  - >>> Surface-based: limited view.



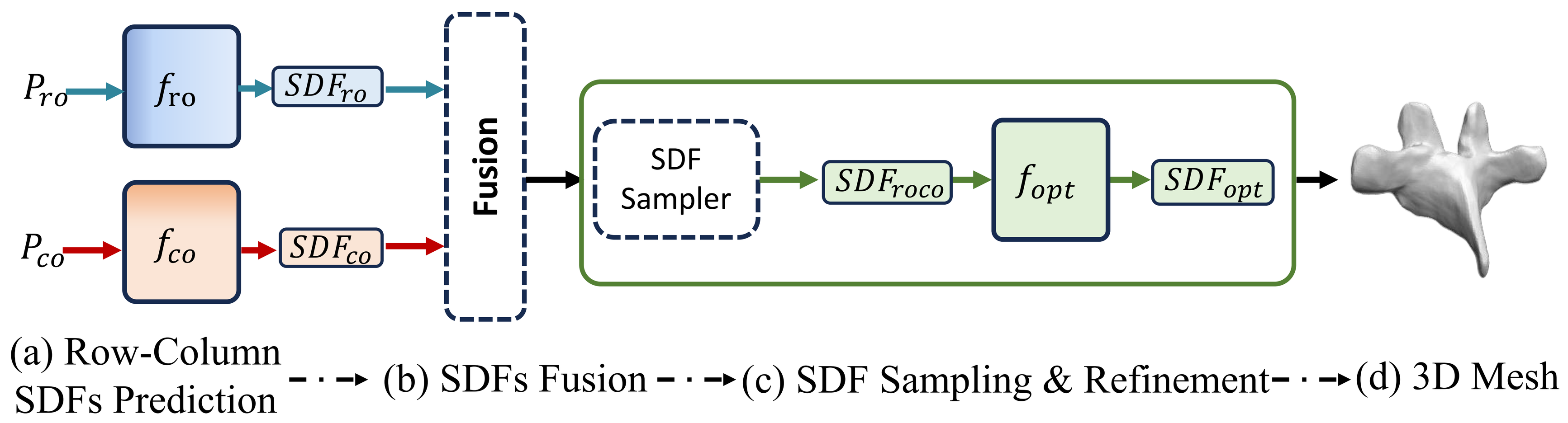
Shape reconstruction is essential for US imaging, as the US signal cannot penetrate hard tissue boundaries!



Methodology

RoCoSDF: Row-Column neural Signed Distance Function

- Separately encode the shape from each view. ✓ **Decoupled views**
- Implicitly fuse a distance field from multile views. ✓ **High-quality geometry**
- Without requiring ground truth shape supervision. ✓ **Self-supervised learning**



(a) Row-Column Neural SDFs Prediction

Neural SDF. An MLP ($f_\theta(\mathbf{x})$) neural network can be trained as an SDF to map any 3D point to its corresponding SDF value. The surface $\mathcal{S}$ can be represented by the zero-level-set of neural SDFs, $f_\theta(\cdot) = 0$.

Row-Column Neural SDFs. Two MLPs neural networks are utilized to predict the row-column neural SDFs for row-scan and column-scan, respectively.

$$SDF_{ro}(\mathbf{x}) = f_{ro}(\mathbf{x})$$

$$SDF_{co}(\mathbf{x}) = f_{co}(\mathbf{x})$$

(b) SDFs Fusion

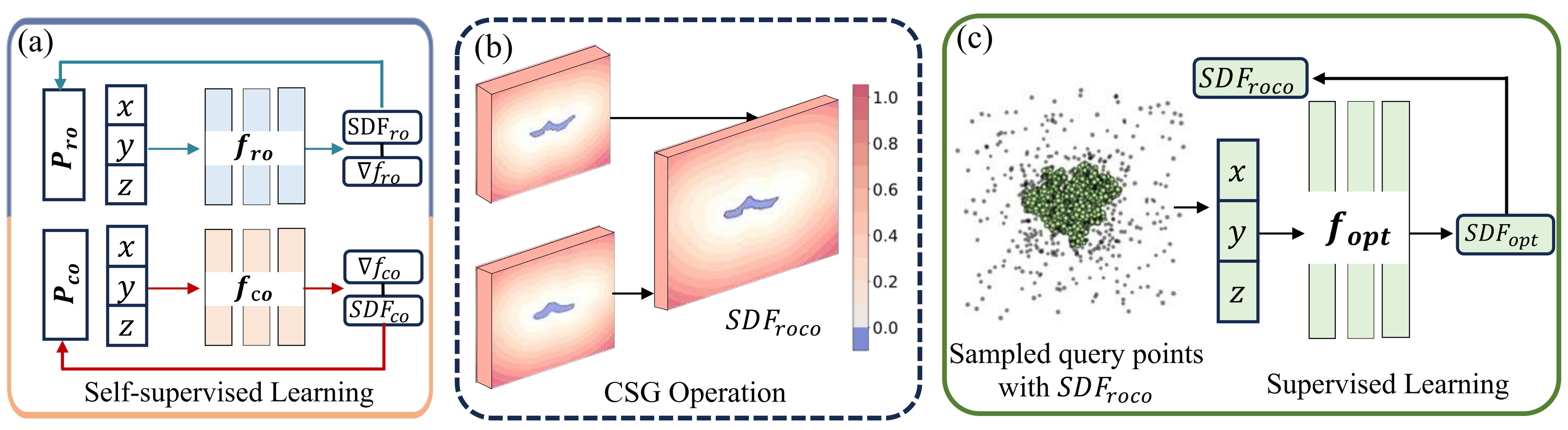
Constructive Solid Geometry (CSG). Adopt intersection boolean operation.

$$\text{Intersection } f_{ro} \cap f_{co} : SDF_{roco} = \max(SDF_{ro}, SDF_{co})$$

(c) SDF Sampling & Refinement

SDF Sampler. 1) Directly sample query points and SDF values using SDF_{roco}. 2) Sample more aggressively near the zero-level-set of SDF_{roco}.

Refinement. Train a third MLP f_{opt} to optimize the fused SDF field.



Model Training

The networks are trained using two learning strategies:

1) f_{ro} and f_{co} are trained by a series of **self-supervised loss functions with an non-manifold regularizer**, since there are no ground truth SDFs available.

2) f_{opt} is trained by a **supervised loss with an manifold regularizer.** SDF_{roco} is used as pseudo ground truth for the supervision. For more detailed definition of loss functions, please refer to our full paper.

Experiments and Results

Experimental Setup

A total of 24 scans and 12 shapes are collected from:

1) Two transducers in configuration of freehand 3D US imaging.
2) Six computer-aided designed (CAD) vertebra phantoms.

Quantitative Results

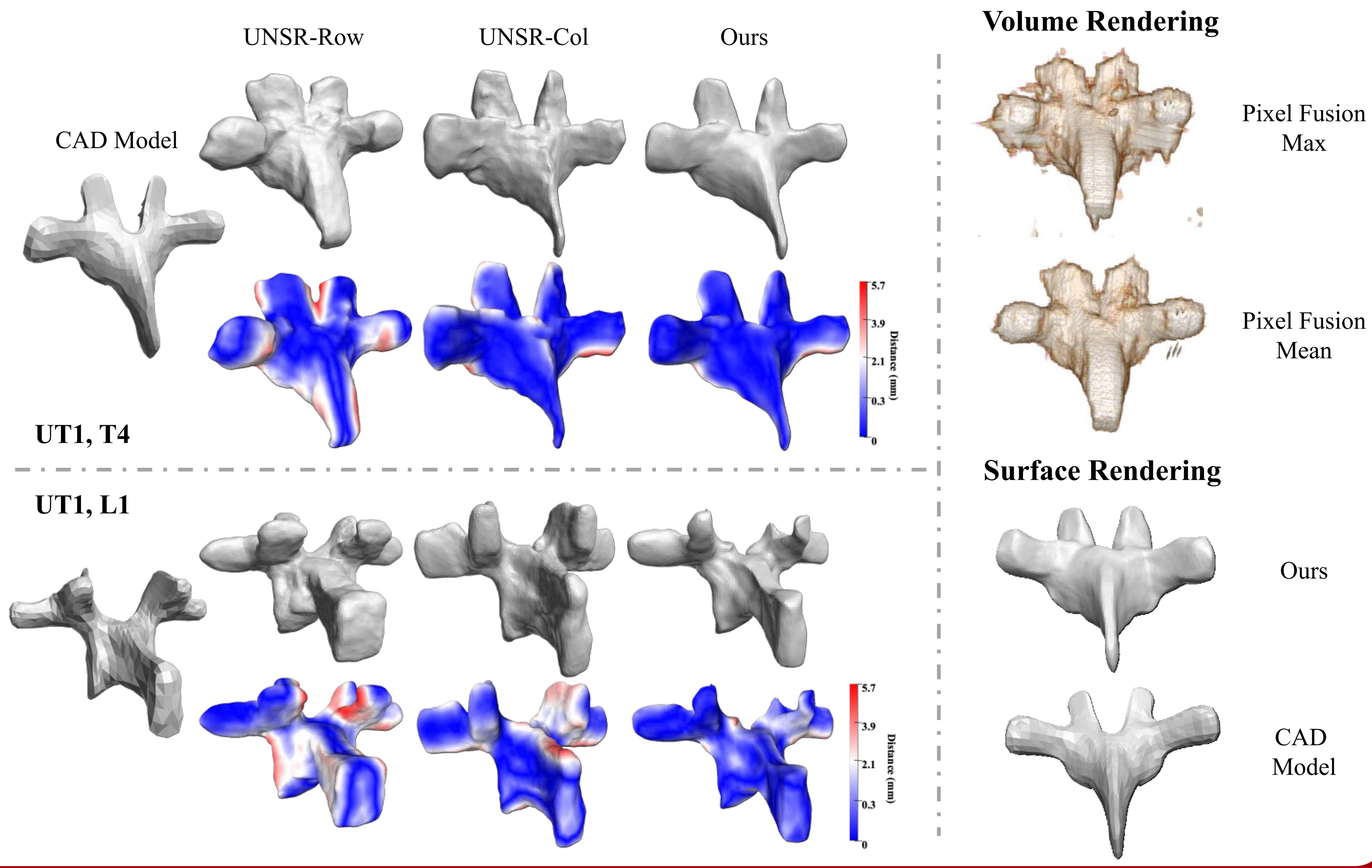
Table 1. Performance comparison of our approach with the baseline on two datasets.

Transducer	Methods	CD (mm)	HD (mm)	MAD (mm)	RMSE (mm)
UT1	UNSR [4] (Row)	2.16 ± 0.16	5.21 ± 1.77	1.84 ± 0.14	2.25 ± 0.17
	UNSR [4] (Col)	2.11 ± 0.18	5.82 ± 0.80	1.78 ± 0.17	2.25 ± 0.21
	RoCoSDF(Ours)	$\mathbf{1.75 \pm 0.09}$	$\mathbf{4.08 \pm 0.74}$	$\mathbf{1.34 \pm 0.05}$	$\mathbf{1.70 \pm 0.03}$
UT2	UNSR [4] (Row)	2.40 ± 0.62	5.22 ± 2.47	1.97 ± 0.67	2.39 ± 0.86
	UNSR [4] (Col)	2.54 ± 0.63	7.53 ± 2.45	2.25 ± 0.69	2.97 ± 0.95
	RoCoSDF(Ours)	$\mathbf{2.03 \pm 0.36}$	$\mathbf{4.87 \pm 2.80}$	$\mathbf{1.53 \pm 0.47}$	$\mathbf{1.92 \pm 0.74}$

* **CD:** Chamfer Distance; **HD:** Hausdorff Distance; **MAD:** Mean Absolute Distance; **RMSE:** Root Mean Square Error

- For row-scan, ~25% MAD and 22% RMSE reduction over UNSR ($p < 0.01$).
- For col-scan, ~29% MAD and 30% RMSE reduction over UNSR ($p < 0.01$).

Qualitative Results



Conclusion

- We present RoCoSDF, a novel neural-SDF-based framework for multi-view freehand 3D US shape reconstruction from row-column scanned data.
- A coarse-to-fine optimization strategy is designed to solve the view-dependent issue and elevational thickness issue with additional surface regularizers.
- ■ **Applications:** Medical augmented reality. US-guided surgical navigation.

References

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