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Metaball-Trained 3D Bubble Reconstruction CNN:

Cross-Validation via a Physics-Based Dataset (BubbleSH) and Encoder Structure Comparison

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1 Introduction

Background

Bubble volume and interfacial area affect thermal-hydraulic behavior relevant to nuclear reactor safety [1]. Non-intrusive two-view imaging offers a practical route to shape reconstruction.

Acquiring paired images and time-resolved 3D ground truth remains difficult. Deformed bubbles also challenge simple spherical or ellipsoidal approximations.

CNNs can learn reconstruction from synthetic Metaball shapes [2]. Testing on shapes from the same generator, however, does not establish transfer to physics-based bubble geometry.

Objective

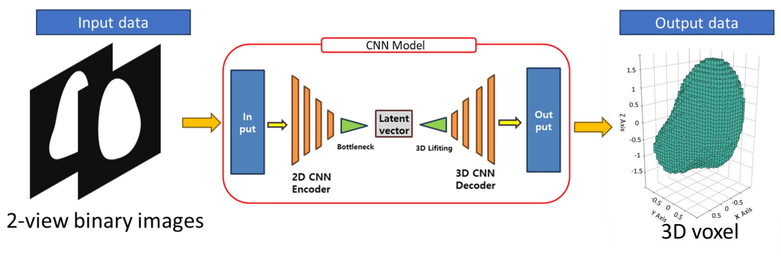
Evaluate Metaball-trained CNNs on an independent BubbleSH data set derived from numerical simulations. Compare single- and dual-encoder models using 3D overlap and errors in reconstructed volume and surface area.

2 Methodology

Training and evaluation

Metaball source dataset: 200,000 samples.
Input: two orthogonal silhouettes. Output: 128^3 voxels.
Evaluation: 1,000 Metaball and 1,000 BubbleSH shapes.

(a) Single encoder



(b) Dual encoder

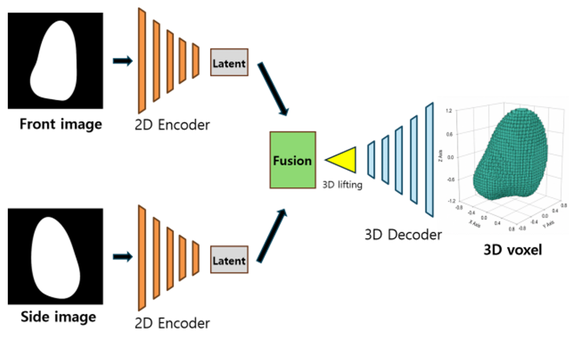
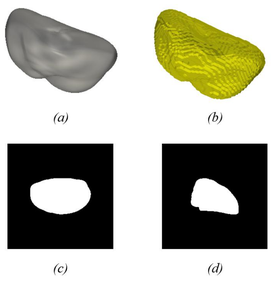


Fig. 1. Single: both views enter one encoder. Dual: separate encoders extract features before fusion and 3D decoding. Both models use the same Metaball source dataset.

BubbleSH reference preparation



BubbleSH contains simulation-derived bubble shapes [3]. Spherical harmonic coefficients define a mesh for silhouettes, voxel targets, and reference volume/area.

Fig. 2. Mesh, voxel reference and two silhouettes.

Evaluation metrics

$$\mathrm{Dice} = \frac{2|V_{\mathrm{pred}} \cap V_{\mathrm{truth}}|}{|V_{\mathrm{pred}}| + |V_{\mathrm{truth}}|} \qquad \mathrm{IoU} = \frac{|V_{\mathrm{pred}} \cap V_{\mathrm{truth}}|}{|V_{\mathrm{pred}} \cup V_{\mathrm{truth}}|}$$

V_{pred}, V_{truth}: predicted and reference occupied-voxel sets.
$|\cdot|$: voxel count. Both scores range from 0 to 1; higher is better.

References

[1] Ishii & Hibiki, Springer, 2006.
[2] Shin et al., KNS Spring Meeting, 2026.
[3] Ramesh et al., BubbleSH, arXiv:2607.07275, 2026.

3 Results and Discussion

3D reconstruction examples

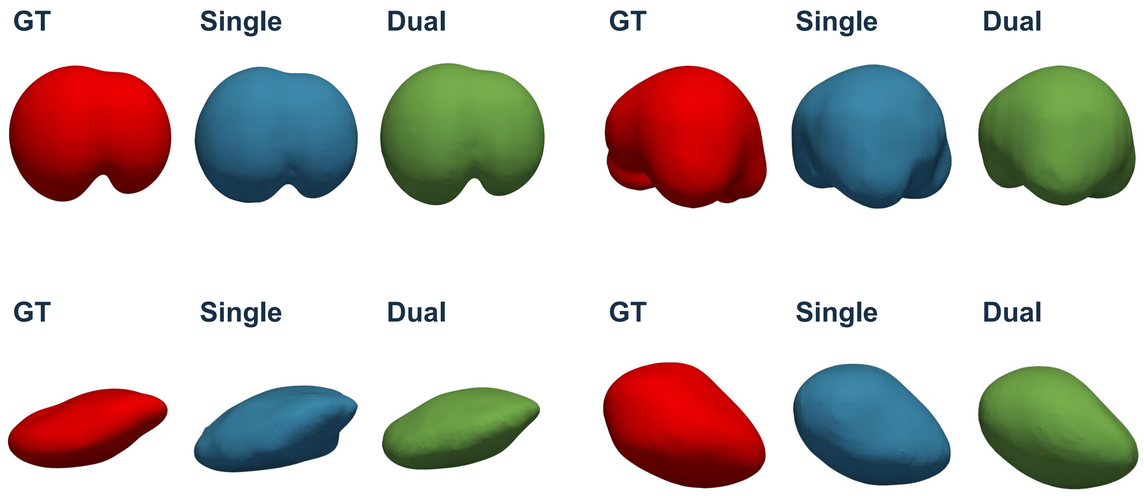


Fig. 3. Selected reconstructions of deformed shapes. Top: Metaball. Bottom: BubbleSH. GT (red), single encoder (blue), dual encoder (green).

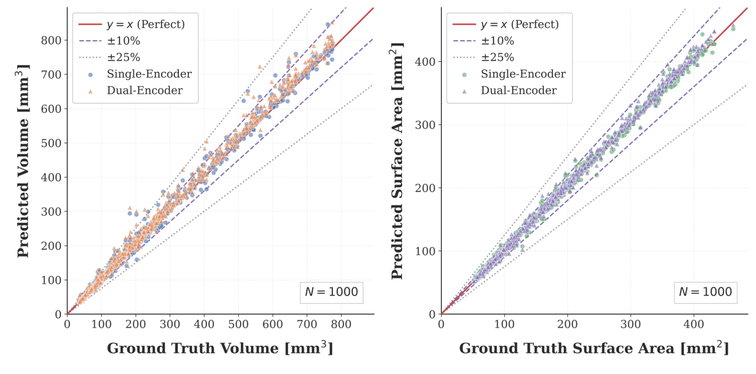
Quantitative comparison

Dataset / metric (%)	Single	Dual
Metaball: Dice	93.14 ± 5.19	93.34 ± 5.24
Metaball: IoU	87.57 ± 8.51	87.92 ± 8.55
Metaball: volume error	6.14 ± 5.90	6.15 ± 6.26
Metaball: area error	3.31 ± 2.52	3.11 ± 2.42
BubbleSH: Dice	89.77 ± 3.18	90.61 ± 3.23
BubbleSH: IoU	81.59 ± 5.08	82.98 ± 5.20
BubbleSH: volume error	6.43 ± 4.56	5.05 ± 3.80
BubbleSH: area error	4.11 ± 3.00	3.27 ± 2.59

Table 1. Mean ± SD (%), N = 1,000. Dice and IoU are scaled by 100.
Both models perform similarly on Metaball. On BubbleSH, the dual model achieves higher mean overlap and lower mean volume/area errors.

Volume and surface area comparison

(a) Metaball



(b) BubbleSH

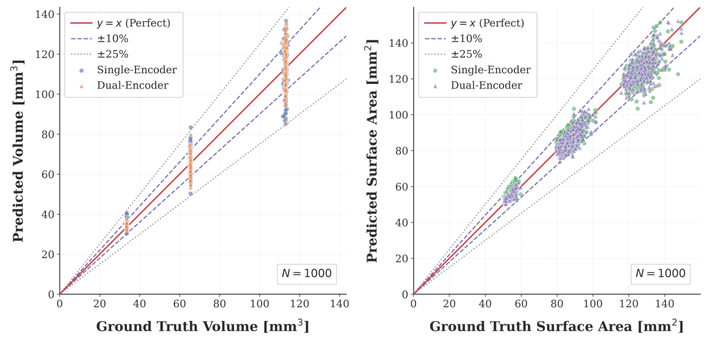


Fig. 4. Predicted versus reference volume (left) and surface area (right).

4 Conclusions

Both models transfer to BubbleSH. On BubbleSH, the dual model gives higher mean overlap and lower mean volume/area errors. Two-view shape ambiguity remains a limitation.

5 Acknowledgments

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