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Radiomics-Driven Volumetric Active Surface Optimization (R-VASO): Overcoming Low-Contrast Segmentation Failures In Deep Learning Auto-Contouring

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ABSTRACT

Deep learning auto-segmentation can improve clinical contouring efficiency, but AI-generated contours may still show jagged boundaries, spill-over, and slice-to-slice inconsistency, especially in low-contrast abdominal CT images. Conventional 2D active contour post-processing depends on intensity gradients and may fail when adjacent tissues have similar Hounsfield units. This study proposes **Radiomics-Driven Volumetric Active Surface Optimization (R-VASO),** a 3D contour-refinement framework that uses organ-specific radiomic texture gradients instead of intensity gradients to drive contour convergence. Using 20 abdominal CT cases with expert-verified contours, R-VASO improved Dice Similarity Coefficient from 0.84 ± 0.06 to 0.92 ± 0.03, reduced 95% Hausdorff Distance, decreased inter-slice centroid jitter from 3.5 mm to 1.4 mm, and reduced z-axis contour flicker. These findings suggest that R-VASO can improve the clinical reliability of AI-generated contours in low-contrast regions while reducing manual editing burden.

INTRODUCTION

AI-based auto-segmentation is increasingly used in radiotherapy and medical imaging workflows. However, deep learning models commonly generate voxel-wise probability maps, which may produce irregular contours, boundary spill-over, and discontinuous anatomy between adjacent axial slices. Traditional active contour refinement relies on image intensity gradients. This approach becomes unreliable in low-contrast CT regions where organ boundaries are weak or where neighboring tissues have similar HU values. Radiomic texture features provide an alternative form of contrast because tissues with similar intensity may still have different local texture patterns. R-VASO was developed to refine AI-generated contours by combining radiomics-based boundary guidance with 3D volumetric surface regularization. Instead of treating each axial slice independently, R-VASO converts the contour into a 3D surface mesh and applies forces that improve both boundary accuracy and z-axis consistency.

METHODS AND MATERIALS

A dataset of 20 abdominal CT images with expert-verified contours was used. Initial deep learning segmentations were generated using a U-Net architecture. These raw AI contours served as the input for the R-VASO refinement process. The R-VASO workflow included two major steps. First, an organ-specific radiomic potential field was generated. For each target organ, radiomic features such as GLCM entropy or correlation were evaluated to identify the texture signature that best separated the organ from adjacent soft tissue. This created a texture-contrast map in regions where intensity contrast was limited. A gradient vector flow field was then computed from the radiomic feature maps to guide contour evolution. Second, the initial deep learning contours were converted into 3D triangular meshes. Each mesh evolved under two forces: an external radiomic potential force that pulled the contour toward texture-defined anatomical boundaries, and an internal mean-curvature-flow constraint that minimized surface energy. This 3D constraint regularized the contour along the z-axis and reduced discontinuities between adjacent slices.Performance was evaluated using Dice Similarity Coefficient, 95% Hausdorff Distance, inter-slice centroid jitter, visual assessment of contour leakage, z-axis flicker, and estimated manual editing reduction.

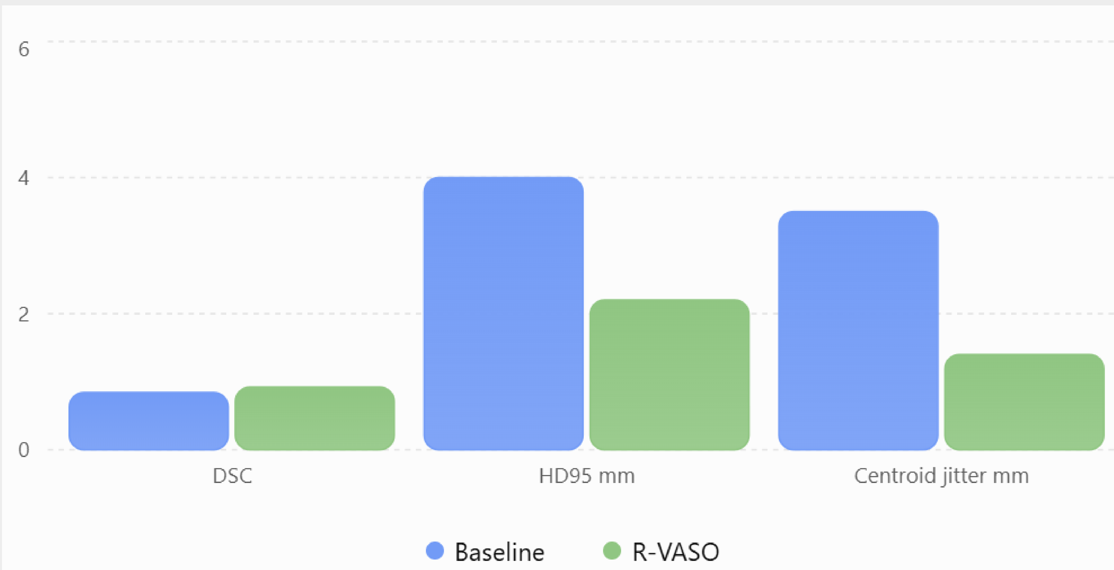
RESULTS

R-VASO improved AI-generated contours compared with raw deep learning segmentation and standard HU-based active contour refinement. Dice Similarity Coefficient improved from 0.84 ± 0.06 for raw deep learning contours to 0.92 ± 0.03 after R-VASO refinement. The 95% Hausdorff Distance was reduced by an average of 1.8 mm, with R-VASO achieving an HD95 of 2.2 mm. Inter-slice centroid jitter decreased from 3.5 mm with standard active contour refinement to 1.4 mm with R-VASO. Qualitatively, standard active contours failed to correct leakage in isodense regions because intensity gradients were insufficient. R-VASO used radiomic texture gradients to retract leaked boundaries and better align the contour with the organ surface. The 3D mean-curvature-flow constraint reduced inter-slice discontinuities and produced smoother, clinically acceptable 3D meshes. In low-dose or noisy conditions, R-VASO maintained stronger segmentation accuracy, with DSC remaining at 0.92, while standard active contour performance degraded to 0.84.

Table 1. Quantitative contour refinement performance

Metric	Raw DL / Standard AC	R-VASO	Interpretation
Dice Similarity Coefficient	0.84 ± 0.06	0.92 ± 0.03	Improved overlap with expert contours, better robustness
95% Hausdorff Distance	~4.0 mm	2.2 mm	Reduced boundary error
Centroid jitter	3.5 mm	1.4 mm	Improved slice-to-slice stability
Manual editing time	Baseline	~40% reduction	Lower clinical editing burden

Chart 1 R-VASO contour refinement performance



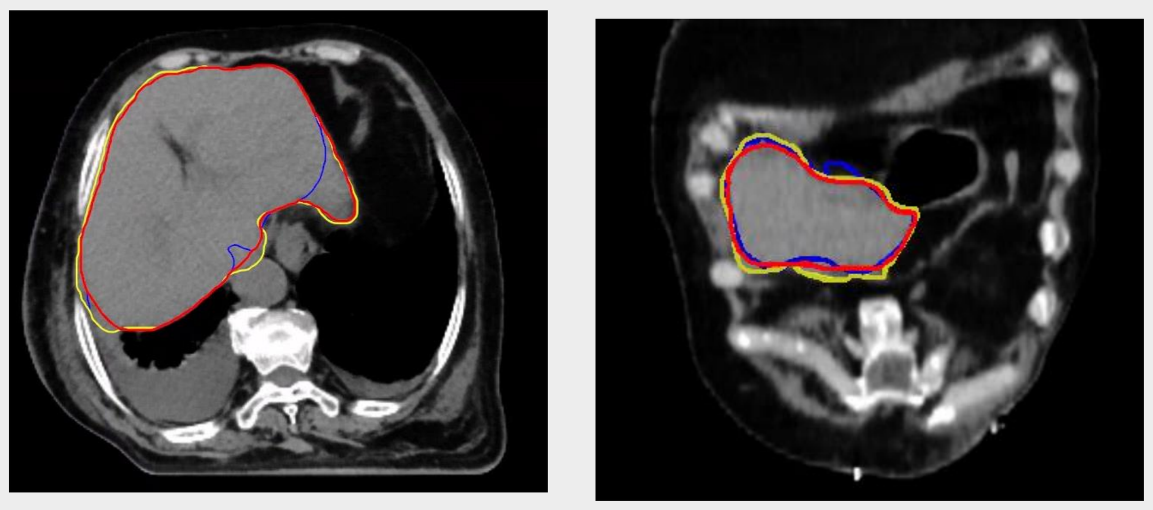


Figure 1. Contour illustration. The blue, yellow, and red lines line are the original ML contour, HU-based active contour, and R-VASO based active contour respectively.

DISCUSSION

The results demonstrate that R-VASO addresses two important limitations of conventional contour post-processing: weak image-intensity gradients and poor slice-to-slice consistency. Standard active contours are driven by HU-based edge information and may fail when neighboring organs have similar brightness. In contrast, R-VASO uses local radiomic texture differences to create a more informative boundary-driving force. The 3D mesh-based design is also important. Many post-processing methods operate slice by slice, which can lead to z-axis flicker and discontinuous anatomy. R-VASO applies a mean-curvature-flow constraint to the full 3D surface, allowing adjacent slices to stabilize local contour errors. This produces smoother, more anatomically consistent volumetric contours. The main limitation is that the reported evaluation used only 20 abdominal CT cases. Future work should validate the method on larger multi-institutional datasets, additional organs, and different imaging protocols. Additional comparisons with modern 3D deep learning segmentation models would also strengthen the evidence.

CONCLUSIONS

R-VASO provides a promising 3D post-processing framework for improving AI-generated contours in low-contrast CT anatomy. By combining radiomic texture-driven forces with volumetric surface-energy regularization, R-VASO improved DSC, reduced HD95, decreased inter-slice jitter, suppressed z-flicker, and may reduce manual editing time by approximately 40%. These findings support R-VASO as a practical contour-refinement strategy for clinical auto-segmentation workflows where low tissue contrast remains a major failure mode.

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