

Reducing Volumetric Segmentation Errors through Inter-Slice Total Variation–Based Artifact Suppression

～From “Trash” to “Truth”: Eliminating Hidden 3D Errors in Medical Image Annotations～

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キーワード

Medical image segmentation, 3D artifact reduction, deep learning, MRI, brain tumor



研究概要

Both clinicians and medical artificial intelligence systems depend on manually annotated labels of anatomical structures and abnormalities in medical images. These annotations are often created slice by slice in a single viewing plane, with limited consideration of possible misalignment or inconsistency across adjacent slices. Although the resulting contours may appear accurate in the primary annotation plane, their three-dimensional reconstruction can reveal irregular boundaries, discontinuities, and step-like artifacts caused by insufficient cross-slice verification. Such hidden through-plane errors can substantially reduce the reliability of volumetric labels and compromise their use as ground truth for training and evaluating medical image segmentation models. In this study, we propose an automated method for detecting and correcting these inconsistencies by reconciling information across axial, sagittal, and coronal views. The proposed approach suppresses inter-slice artifacts while preserving the underlying anatomical structure, producing smoother and more anatomically plausible three-dimensional annotations. Experiments on the public UCSF-PDGM brain tumor MRI dataset using a standard nnU-Net segmentation framework demonstrate that the proposed method effectively reduces step-like volumetric artifacts while maintaining accurate tumor morphology.

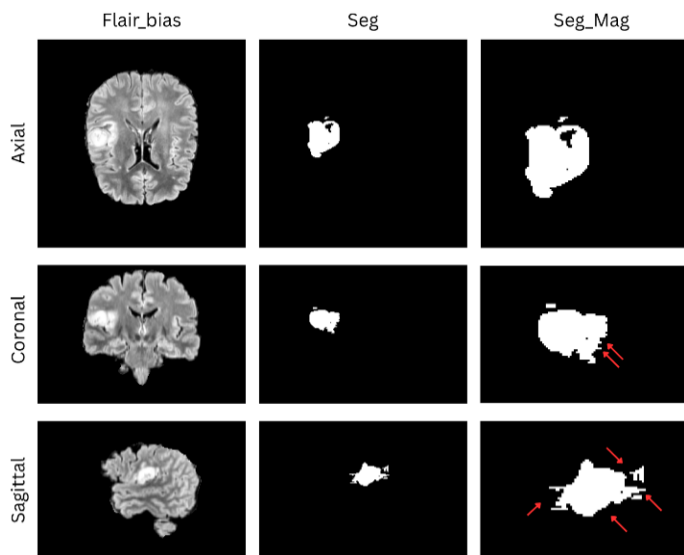


Figure 1 : Sample of UCSF-PDGM dataset with multiplanar views of subject UCSF-PDGM-0055 (Flair-bias, and tumor segmentation with 3X magnification)

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1. Turns “trash” into trustworthy data: recovers usable 3D ground truth from labels drawn in only one direction, no costly manual re-annotation. • Model agnostic and low-cost: an add-on training objective for standard networks (e.g., nnU-Net) that drops into existing medical-AI pipelines.
2. Broad application: any field stacking 2D slices into 3D MRI/CT diagnosis, surgical planning, radiotherapy, industrial CT, gains more reliable 3D labels.
3. More reliable downstream AI: smoother, anatomically coherent volumes make diagnosis and measurement more trustworthy.