3D Medical Multi-modal Segmentation Network Guided by Multi-source Correlation Constraint

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Introduction

- Objective: To segment brain tumor using different modalities.
- Motivation: A strong correlation between multi MR modalities can be considered for improving the segmentation results.
- Proposal: A multi-modality segmentation network guided by multi-source correlation constraint.

Dataset

- BraTS 2018 dataset
- Training set: 285, Validation set: 66
- Input Modalities: T1, T1c, FLAIR, T2
- Volume Size: $240 \times 240 \times 155$
- Resolution: $1mm \times 1mm \times 1mm$
- Segmentation Classes: whole tumor, tumor core and enhancing tumor

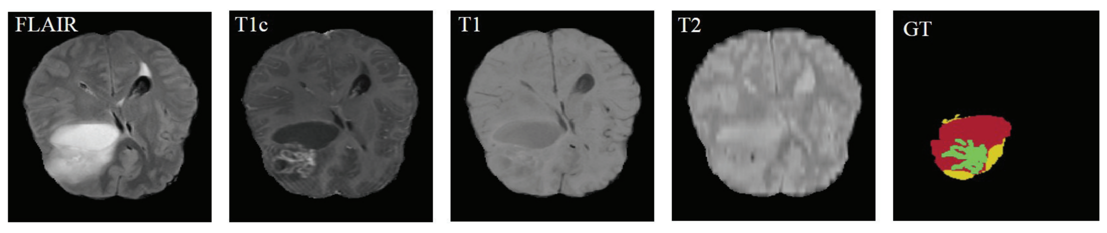

Figure 1. Input modalities and the ground truth. Red: necrotic and non-enhancing tumor core; Yellow: edema; Green: enhancing tumor.

Method

- Encoders → to extract individual feature representations
- Correlation Constrain block → to discover the correlation between modalities
- Feature Fusion → to fuse the feature representations via attention mechanism
- Decoders → to achieve the segmentation

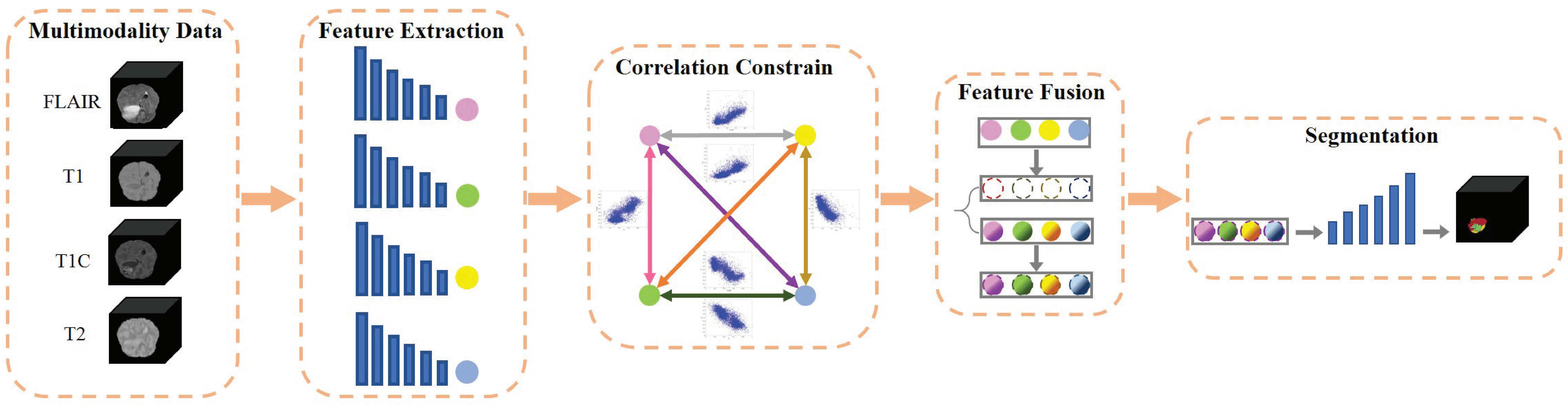

Figure 2. The pipeline of the proposed method, consisting of feature extraction, correlation constrain and fusion block, 4 color circles represent four modality feature representations.

Results

Table. Evaluation of our proposed method on BraTS 2018 dataset. (1) Baseline (2) Baseline+Dual attention fusion (3) Baseline+Dual attention fusion+Correlation constrain. ET, WT, TC denote enhancing tumor, whole tumor and tumor core, respectively.

Methods	Dice Score			Hausdorff (mm)		
	ET	WT	TC	ET	WT	TC
(1)	0.726	0.867	0.764	8.743	8.463	9.482
(2)	0.733	0.879	0.765	8.003	7.813	9.153
(3)	**0.747**	**0.886**	**0.776**	**7.851**	**7.345**	**9.016**

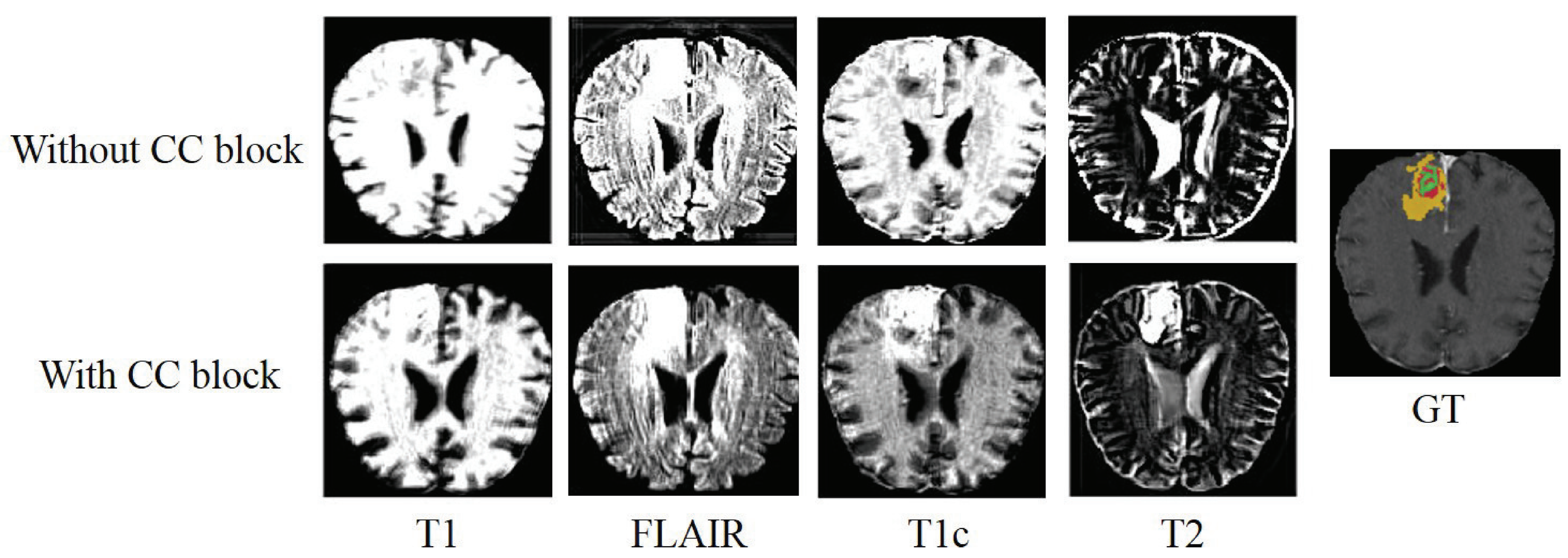

Figure 3. Visualization of the effectiveness of the proposed correlation constrain block. The first and second rows show the feature maps in the last layer (before output). The last column shows the ground truth, CC denotes the correlation constrain block.

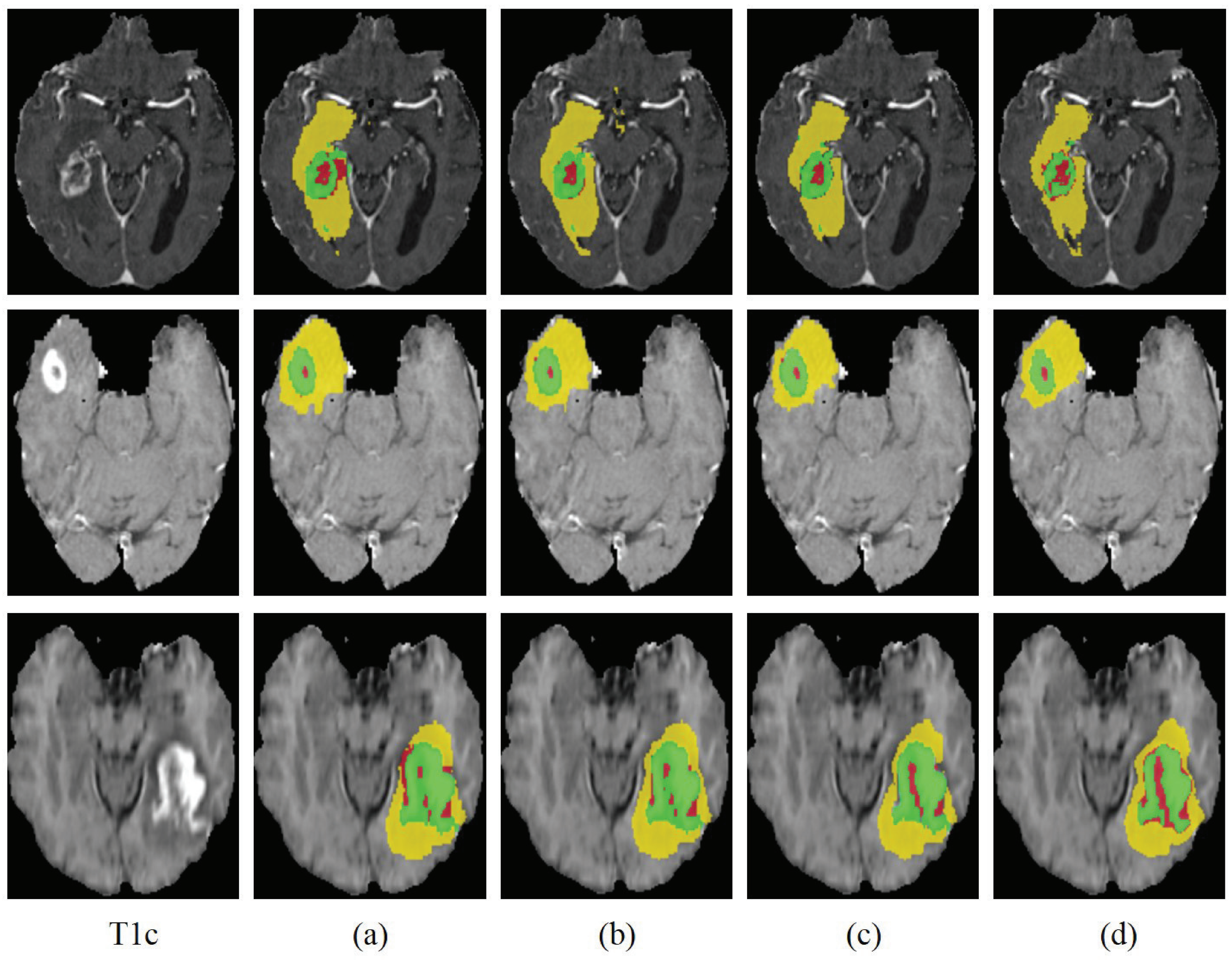

Figure 4. Visualization of several segmentation results. (a) Baseline (b) Baseline + Dual attention fusion (c) Baseline + Dual attention fusion + Correlation constrain (d) Ground Truth. Red: necrotic and non-enhancing tumor core; Yellow: edema; Green: enhancing tumor.

Conclusion

- A 3D multimodal brain tumor segmentation network guided by a multi-source correlation constrain is proposed.
- The multi-encoder based network is used to extract feature representations from different modalities.
- A correlation constrain block is introduced to exploit the latent multi-source correlation.
- A dual-attention fusion strategy is proposed to learn more useful feature representation to boost the segmentation result.
- The experiments evaluated on BraTS 2018 demonstrate the effectiveness of our method.

References

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