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

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Overview

Introduction

- Early diagnosis of **brain tumors** is important in clinical diagnosis and treatment planning[1].
- **Multi-modal images** can provide the complimentary information to improve the segmentation accuracy.

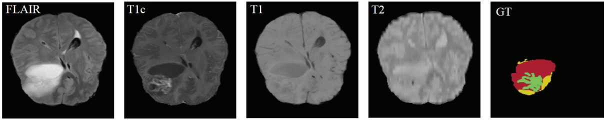
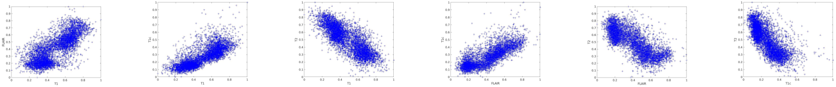


Figure: Example of data from a training subject. From left to right: FLAIR, T1c, T1, T2 images, and the ground truth labels. Red: Necrotic and Non-enhancing tumor, yellow: edema, green: enhancing tumor, black: healthy tissue and background.

[1] Tongxue Zhou, Su Ruan, and Stéphane Canu. "A review: Deep learning for medical image segmentation using multi-modality fusion". In: *Array* (2019), p. 100004.

Introduction

- **Motivation:** A strong correlation between multi MR modalities[2], since the same scene is observed by different modalities.
- **Our proposal:** A novel **correlation constraint block** to discover the latent multi-source correlation and help the **segmentation**.



(a) (b) (c) (d) (e) (f)

Figure: Joint intensity distributions of MR images: (a) T1-FLAIR, (b) T1-T1c,(c) T1-T2, (d) FLAIR-T1c, (e) FLAIR-T2, (f) T1c-T2. The intensity of the first modality is read on abscissa axis and that of the second modality on the ordinate axis.

[2] Jerome Lapuyade-Lahorgue, Jing-Hao Xue, and Su Ruan. "Segmenting multi-source images using hidden Markov fields with copula-based multivariate statistical distributions". In: *IEEE Transactions on Image Processing* 26.7 (2017), pp. 3187–3195.

Proposed Network Architecture

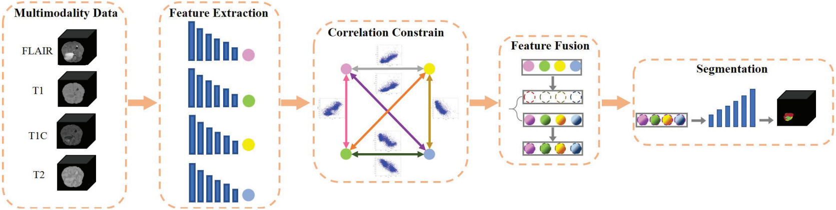


Figure: The pipeline of the proposed method, consisting of feature extraction, correlation constrain and fusion block, 4 color circles represent 4 modality feature representations.

Detailed Network Architecture

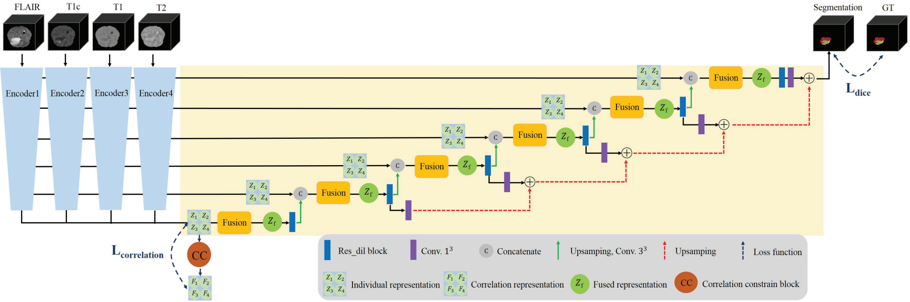


Figure: Overview of our proposed segmentation network framework.

Modeling the Multi-source Correlation

- LC block: to discover the latent correlation.
- Correlation constraint loss (KL based): to constrain the correlation between modalities.
- Equation 1: $F_j(X_j|\theta_j) = \alpha_i \odot Z_i(X_i|\theta_i) + \beta_i, (i \neq j)$

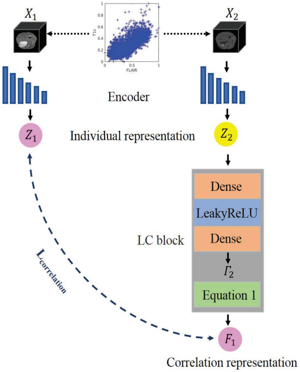


Figure: Architecture of Correlation Constrain (CC) block.

Dual Attention Fusion Block

- Dual Attention Fusion Block: **modality** attention module and **spatial** attention module[3].
- To **weight** the feature representations of the four modalities based on their **contributions** to the final segmentation.

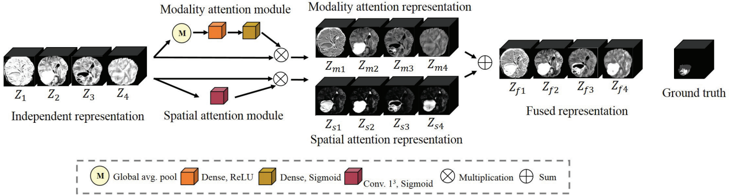


Figure: The architecture of the proposed dual attention fusion block.

[3] Abhijit Guha Roy, Nassir Navab, and Christian Wachinger. "Concurrent spatial and channel 'squeeze & excitation'in fully convolutional networks". In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer. 2018, pp. 421–429.

Implementation Details

- **Dataset**: BraTS2018
  - 285 training data
  - T1, FLAIR, T1c and T2
  - Whole Tumor, Tumor Core and Enhancing Tumor
- **Pre-processing**
  - Crop and resize: $240 \times 240 \times 155$ to $128 \times 128 \times 128$
  - Bias Field Correction: correct the distortion of MRI data
  - Intensity Normalization
- **Loss function**
  - $L_{total} = L_{dice} + 0.1 L_{correlation}$.

Quantitative Results

Table: Evaluation of our proposed method on Brats 2018 training 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 Distance		
	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**

Qualitative Results

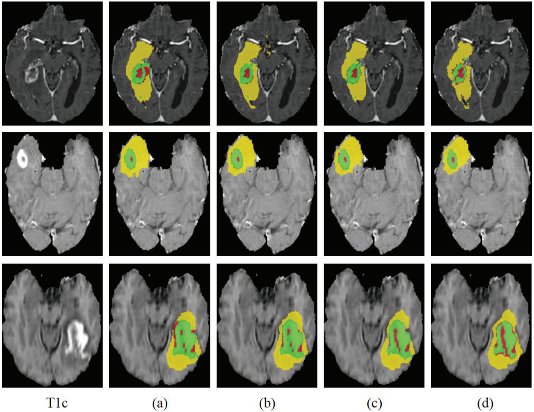


Figure: Visualization of the segmentation results. (a) Baseline (b) Baseline with fusion block (c) Proposed method with fusion block and correlation constraint (d) Ground truth. Red: necrotic and non-enhancing tumor core; Yellow: edema; Green: enhancing tumor.

Qualitative Results

- The correlation constrain block can constrain the network to emphasize the interested tumor region for segmentation.

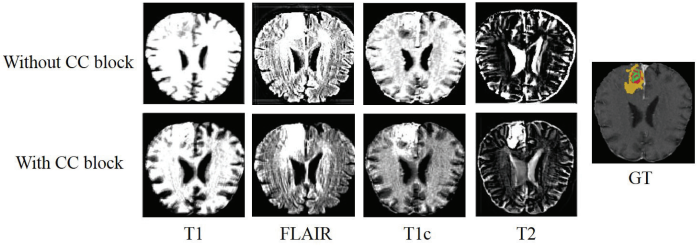


Figure: Visualization of feature maps in the layer before output.

Conclusion

- A 3D multimodal brain tumor segmentation network guided by a multi-source correlation constraint.
- The experimental results demonstrated the **effectiveness** of our method.
- To investigate **other methods** to describe the multi-source correlation representation.
- To valid our method in other **segmentation datasets**.

References

Jerome Lapuyade-Lahorgue, Jing-Hao Xue, and Su Ruan. "Segmenting multi-source images using hidden Markov fields with copula-based multivariate statistical distributions". In: *IEEE Transactions on Image Processing* 26.7 (2017), pp. 3187–3195.

Abhijit Guha Roy, Nassir Navab, and Christian Wachinger. "Concurrent spatial and channel 'squeeze & excitation'in fully convolutional networks". In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer. 2018, pp. 421–429.

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Thanks for your attention