MMCFormer: Missing Modality Compensation Transformer for Brain Tumor Segmentation

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https://github.com/mindflow-institue/MMCFormer

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1. Introduction

Gliomas, a type of brain tumor originating from glial stem cells, pose a significant threat to human life. Magnetic Resonance Imaging (MRI) is commonly used to diagnose brain tumors, as it provides valuable insights into tissue properties through different contrasts. Multi-modal MRI, which combines various imaging modalities, is particularly useful in this regard. However, the absence of certain MRI modalities in clinical settings can lead to incomplete brain tumor studies. To address this issue comprehensively, we introduce MMCFormer, a novel network designed to compensate for missing modalities in an end-to-end manner.

2. Contributions

- Our strategy builds upon 3D efficient transformer blocks and uses a co-training strategy to effectively train a missing modality network.
- To ensure feature consistency in a multi-scale fashion, MMCFormer utilizes global contextual agreement modules in each scale of the encoders.
- Furthermore, to transfer modality-specific representations, we propose to incorporate auxiliary tokens in the bottleneck stage to model interaction between full and missing-modality paths.
- Moreover, we include feature consistency losses to reduce the domain gap in network prediction and increase the prediction reliability for the missing modality path.

3. Method Architecture

MMCFormer deploys three feature-matching mechanisms to reduce the domain gap and to ensure knowledge distillation from the ``full modality" path into a ``missing modality" network.

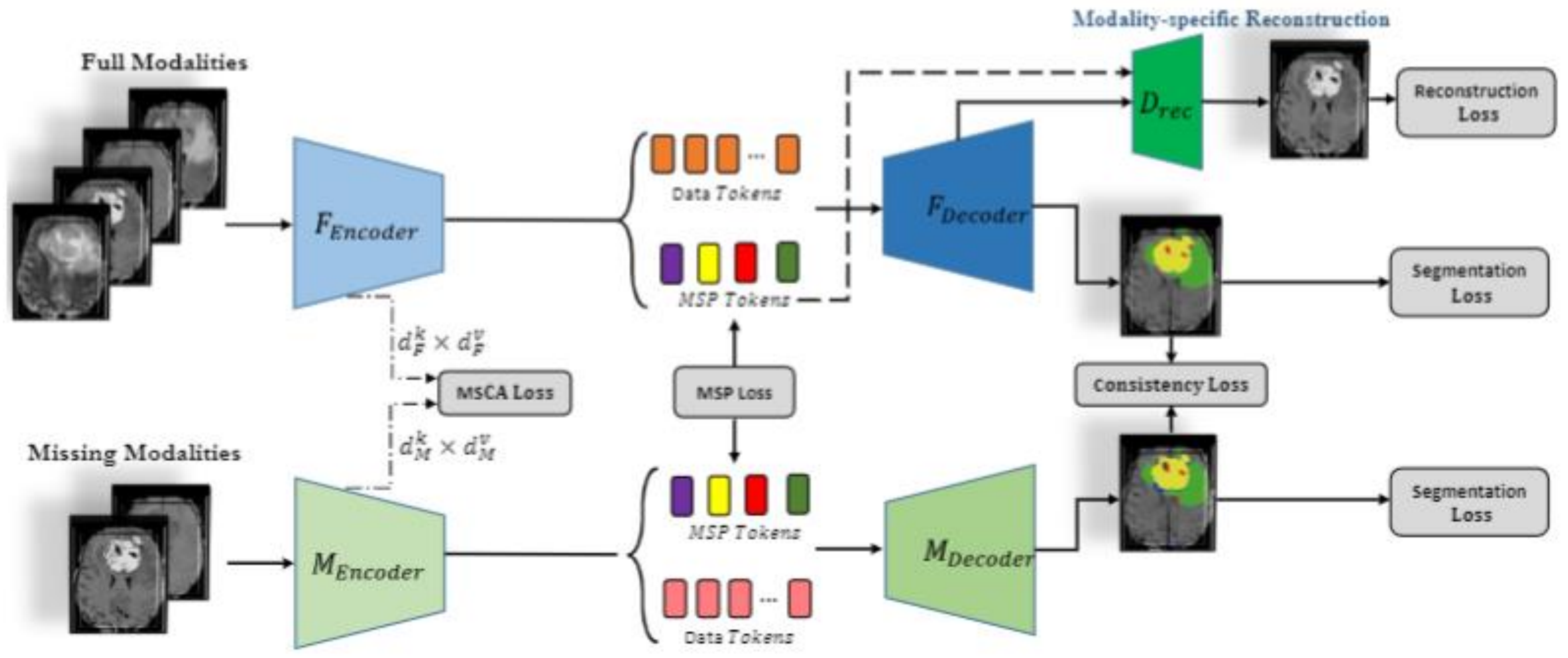

Fig. 2. The overview of the proposed MMCFormer

4. Loss Functions

Segmentation loss: $\mathcal{L}_{\text{seg}} = \alpha \mathcal{L}_{\text{dice}}\left(Y_f', Y\right) + \beta \mathcal{L}_{\text{dice}}\left(Y_m', Y\right)$

consistency loss: $\mathcal{L}_{Consistency}\left(S_f, S_m\right) = \sum_{i=1}^{c} \left|S_f^i - S_m^i\right|$

MSCA loss: $\mathcal{L}_{\text{MSCA}}\left(\text{GC}_f, \text{GC}_m\right) = 1 - \frac{\operatorname{tr}\left\{\text{GC}_f \text{GC}_m\right\}}{\left\|\text{GC}_f\right\| \left\|\text{GC}_m\right\|} \quad \in [0,1]$

MSP loss: $\mathcal{L}_{MSP}\left(MSP_f, MSP_m\right) = \sum_{i=1}^{M} \left|MSP_f^i - MSP_m^i\right|$

Recon loss: $\mathcal{L}_{recon} = \theta \underbrace{\left[1 - l_M(\tilde{p}) \cdot \prod_{j=1}^{M} cs_j(\tilde{p})\right]}_{\mathcal{L}_{\text{MS-SSIM}}} + (1-\theta).G_{\sigma_G^M} \cdot \underbrace{\frac{1}{N} \sum_{p \in P} \left|X_i(p) - Y'_{recon}(p)\right|}_{\mathcal{L}_{\ell_1}}$

5. Results

Table 1. Comparative results

Article	Dice score				
	T1	T1c	T2	FLAIR	AVG
Our Baseline	61.2	77.3	60.1	58.2	64.2
U-HeMIS (Havaei et al., 2016)	16.7	59.2	36.0	51.5	48.8
HVED (Dorent et al., 2019)	34.4	64.8	55.2	52.4	51.7
ACN (Wang et al., 2021)	**63.8**	80.3	64.6	65.3	68.5
SMU-net (Azad et al., 2022c)	63.3	80.9	65.3	68.4	69.4
nnU-Net(Isensee et al., 2019)	62.4	77.6	61.3	61.8	65.7
MMCFormer	63.6	**82.0**	**68.2**	**68.6**	**70.6**

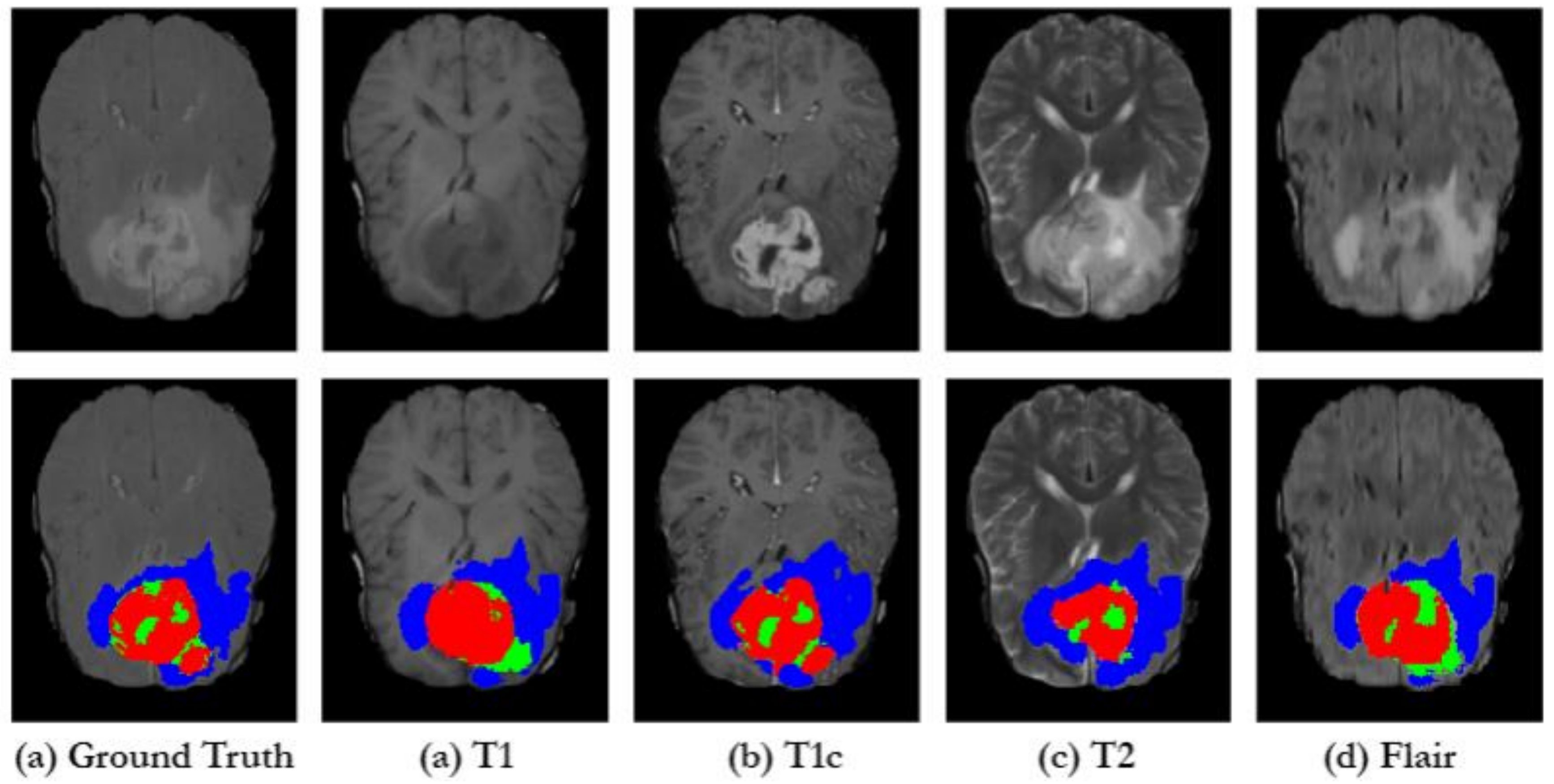

Fig. 2. Qualitative results using only a single modality

6. Conclusion

To address missing modality correction in an end-to-end manner, we proposed our MMCFormer model, which utilizes a co-training strategy to perform knowledge distillation from the full-modality network into a missing modality one. To preserve modality-specific features, we proposed MSP tokens in conjunction with the reconstruction head to distill more discriminative features to the ``missing modality" network. We also included a context agreement module to refine the feature representation in each scale of the co-training strategy.