

Automatic Brain Segmentation for PET/MR Dual-Modal Images Through a Cross-Fusion Mechanism 有代码

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研究背景与意义

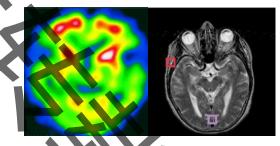




医学影像分析要求



PET/MR成像系统具有优势



现有的方法存在局限性

存在的问题?

依赖人工手动标注,费时费力,并且对图像的质量和噪声敏感

传统的方法

无法整合PET和MR 两种模态的信息

基于单模态深度学习的方法



MRI

融合方法简单 (拼接两种模态信息)

融合双模态信息的方

法: 分割区域有限和

融合双模态信息的方法

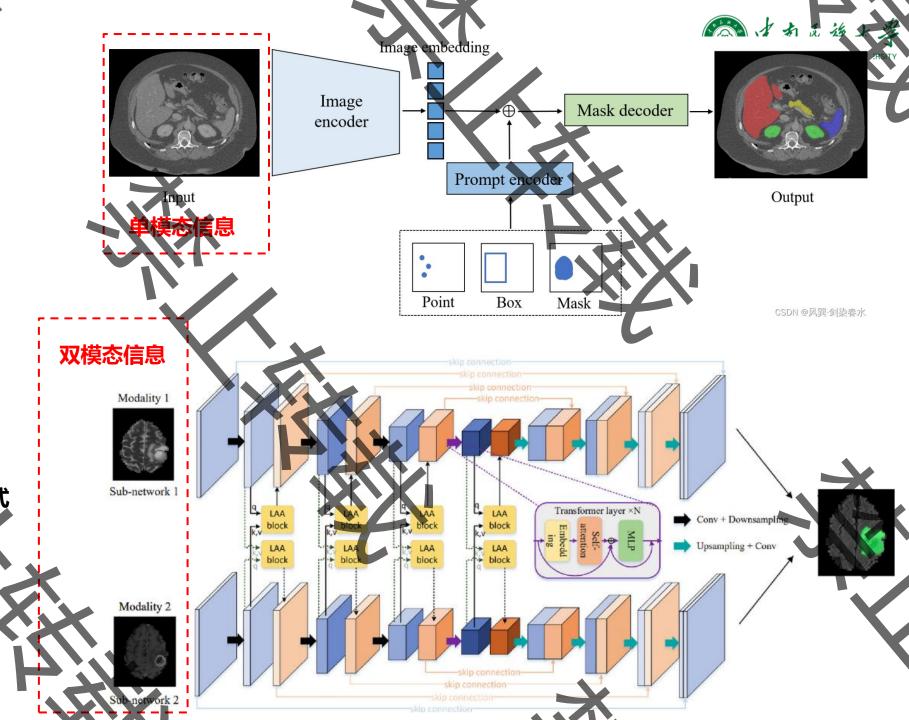


研究现状

单模态医学图像分割方法

未充分利用PET的<mark>功能代谢信息</mark>与 MR的高分辨率<mark>结构信息</mark>的互补性

 双模态融合的方法 分割目标区域较少,模态融合方式 较为简单(如通道拼接)

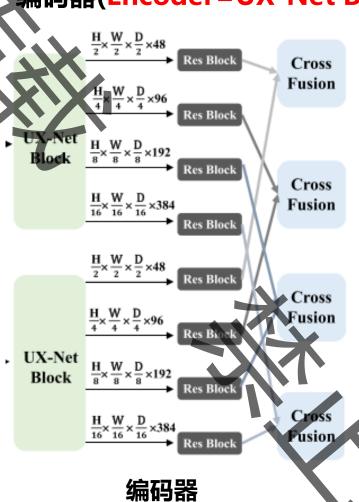


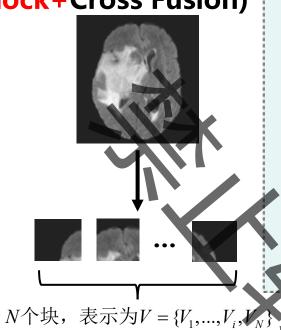
研究方法 残差块 $H\times W\times D$ H×W×D×48 H×W×D×48 Res Block Mask PET Res Block Cross **Fusion** Hidden Feature $\frac{H}{4} \times \frac{W}{4} \times \frac{D}{4} \times 96$ ➤ Res Block UX-Net Block $\frac{H}{8} \times \frac{W}{8} \times \frac{D}{8} \times 192$ → Res Block $\frac{H}{4} \times \frac{W}{4} \times \frac{D}{4} \times 192$ Res Block $\frac{H}{4} \times \frac{W}{4} \times \frac{D}{4} \times 192$ Cross Concatenation $\frac{H}{16} \times \frac{W}{16} \times \frac{D}{16} \times 384$ Fusion Res Block Res Block $\times \frac{W}{2} \times \frac{D}{2} \times 48$ Residual Block Res Block $\frac{H}{8} \times \frac{W}{8} \times \frac{D}{8} \times 384$ Cross **Fusion** Out Block → Res Block Out Block Res Block $\frac{H}{16} \times \frac{W}{16} \times \frac{D}{16} \times 768$ Cross Transpose Conv Fusion

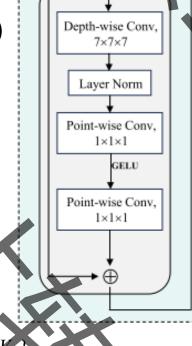
本文提出的分割网络结构

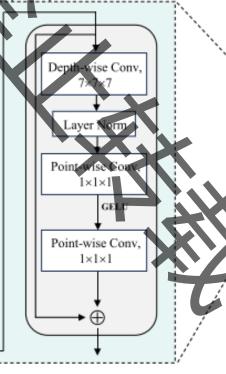
(a) The proposed segmentation network

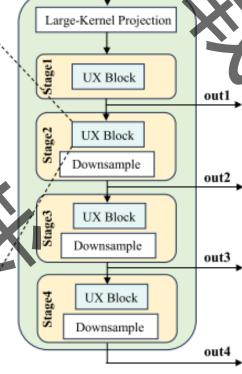
编码器(Encoder=UX-Net Block+Cross Fusion)











UX-Net Block

深度卷积

$$\hat{z_i^1} = LN(DWC(V_i))$$

$$z_{i}^{1} = PWC\left(GELU\left(PWC\left(\hat{z}_{i}^{1}\right)\right)\right) + V_{i}$$

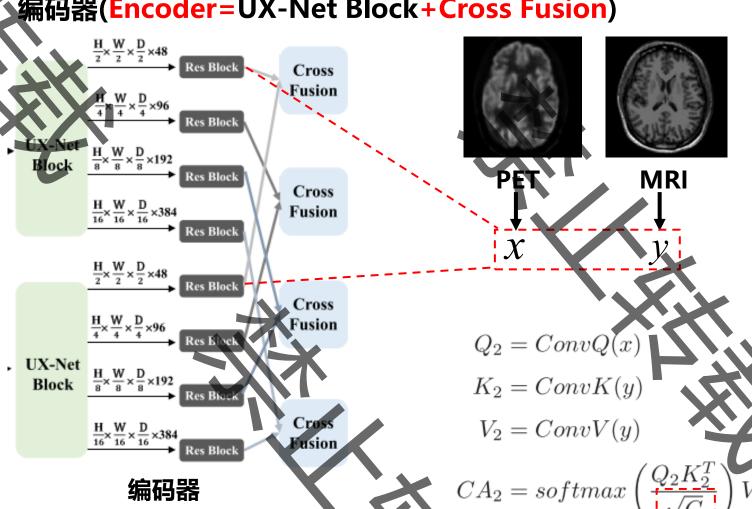
点卷积

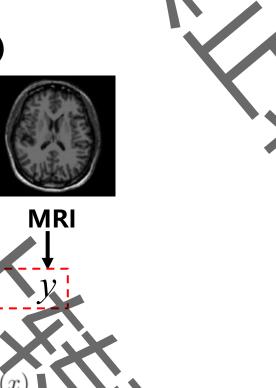
 $z_i^2 = LN(DWC(z_i^1))$

$$z_{i}^{2} = PWO\left(GELU\left(PWC\left(\hat{z_{i}^{2}}\right)\right)\right) + z_{i}^{1}$$



编码器(Encoder=UX-Net Block+Cross Fusion)

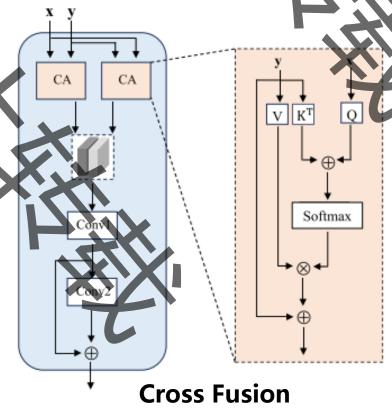




$$CA_2 = softmax \left(\frac{Q_2 K_2^T}{\sqrt{C}}\right) V_2 + y$$

 $= Conv3 \left(concat \left(CA_1, CA_2 \right) \right)$

Conv4(f) + f



缩放因子



解码器(Decoder)

以第三层解码器为示例:

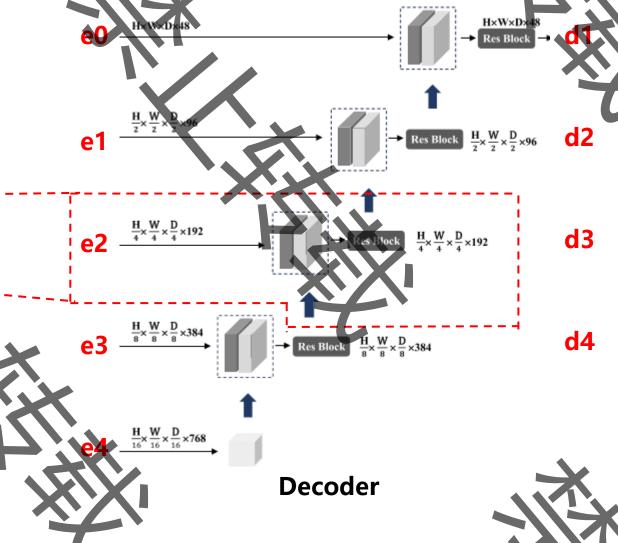
 $u_3 = upsampling(d_4)$

 $d_3 = ResBlock\left(concat\left(e_2, u_3\right)\right)$

 $e_0 = ResBlock\left(concat\left(x_1, x_2\right)\right)$

 $d_1 = decoder1(e_0, d_2)$

 $out = OutBlock(d_1)$ 最终结果



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Loss Function

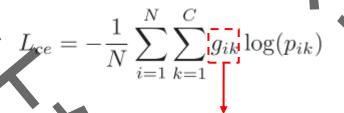
Dice系数损失和交叉熵损失

$$L_{dice} = 1 - \frac{1}{C} \sum_{k=1}^{C} \frac{2 \sum_{i=1}^{N} p_{ik} g_{ik}}{\sum_{i=1}^{N} p_{ik} + \sum_{i=1}^{N} g_{ik}}$$

第i个像素的k类预测结果

> 混合损失函数

$$L = L_{dice} +$$
 起多数



真实值中第i个像素的k类值



实验设置



数据集

 \mathbf{x} \mathbf{x} 自110名受试者的PET/MR脑图像,尺寸大小为256 \mathbf{x} 256 \mathbf{x} 256,所有的图像已经配准(不公开)

对比的方法

- > 基于Transformer: 3DUXNET(2022), SwinUNETR(2021), UNETR(2021), nnFormer(2021)
- ➤ 基于CNN: UNet3D(2016), NestedUNet(2018), ResUNet(2018), VNet(2016)

评估指标

$$Dice = \frac{2 \times TP}{2 \times TP + FP + FN}$$

$$\frac{\text{IoU}}{Jaccard} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}}$$

$$Precession = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

豪斯多夫距离

$$H(A,B) = \max \left(\sup_{a \in A} \inf_{b \in B}, \sup_{a \in A} \inf_{a \in A} d(b,a) \right)$$

$$Sensitivity = \frac{TP}{TP + FN}$$

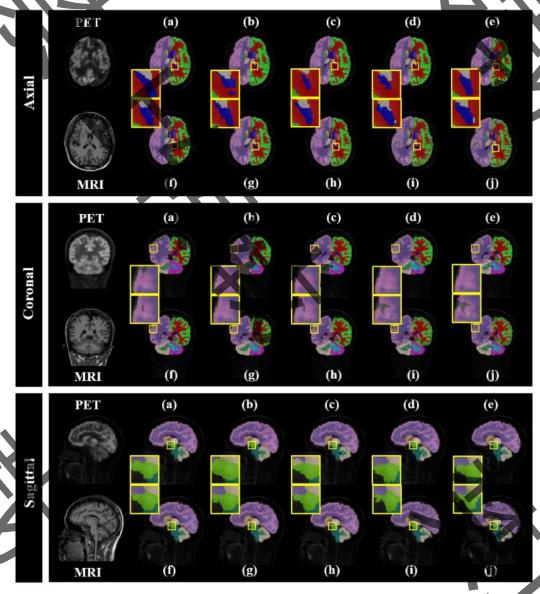
实验结果

总体的实验结果

Model	Dice	Jaccard	Sensitivity	Precision	HD
NestedUNet	0.5244 ± 0.0007	0.4119 ± 0.0006	0.4912 ± 0.0005	0.5572 ± 0.0009	10.6827 ± 1.4764
ResUNet	0.5391 ± 0.0005	0.4193 ± 0.0004	0.5184 ± 0.0009	0.5639 ± 0.0007	11.6593 ± 1.3235
VNet	0.5703 ± 0.0004	0.4458 ± 0.0003	0.5382 ± 0.0006	0.5818 ± 0.0005	10.7833 ± 0.4714
nnFormer	0.6342 ± 0.0004	0.5117 ± 0.0004	0.6105 ± 0.0006	0.6403 ± 0.0003	9.0837 ± 0.3506
UNETR	0.7081 ± 0.0002	0.5879 ± 0.0003	0.6978 ± 0.0004	0.6850 ± 0.0002	8.0191 ± 0.2780
SwinUNETR	0.7280 ± 0.0003	0.6114 ± 0.0004	0.7214 ± 0.0004	0.7032 ± 0.0002	6.3914 ± 0.1746
UNet3D	0.7376 ± 0.0003	0.6164 ± 0.0003	0.7353 ± 0.0005	0.7111 ± 0.0002	6.2792 ± 0.1564
3DUXNET	0.7499 ± 0.0003	0.6319 ± 0.0003	0.7524 ± 0.0006	0.7206 ± 0.0003	5.9680 ± 0.1578
Ours	0.8573 ± 0.0001	0.7668 ± 0.0002	0.8500 ± 0.0001	0.8326 ± 0.0003	4.4885 ± 0.1485

最优

- (a) NestedUNet. (b) ResUNet. (c) VNet. (d) nnFormer. (e) UNETR.
- (f) SwinUNETR. (g) UNet3D. (h) 3DUXNET. (i) Ours. (j) GT



全脑分割实验可视化

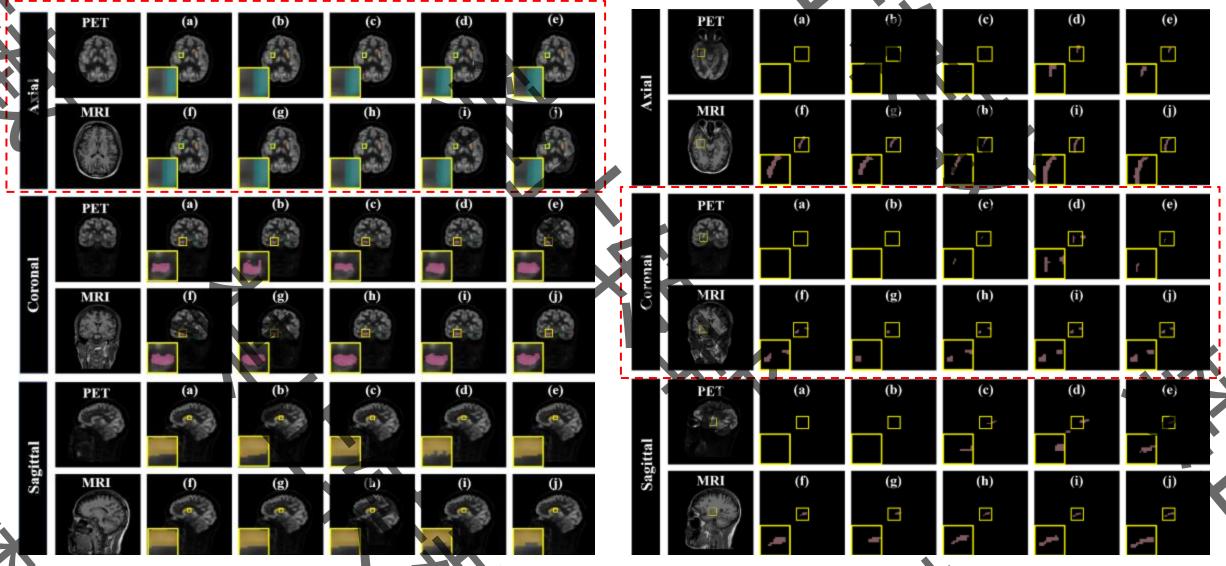
实验结果

脑部特定区域的分割

- (a) NestedUNet. (b) ResUNet. (c) VNet.
- (f) SwinUNETR. (g) UNet3D. (h) 3DUXNET. (i) Ours.







壳核,海马体和尾状核区域分割

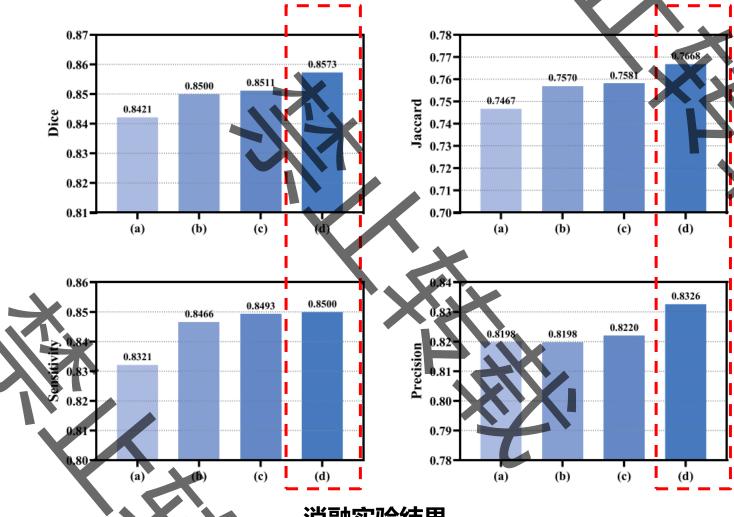
侧脑室区域分割

一致性和相关性分析 脑 Brain-Stem SUV 干 NestedUNet ResUNet VNet nnFormer 3DUXNET GTOurs Left-Hippocampus 左 海 马 体 suv NestedUNet ResUNet nnFormer UNETR SwinUNETR UNet3D 3DUXNET VNet

ResUNet VNet nnFormer 右脑白质 ·致性和相关性分析 Ours 3DUXNET SwinUNET Ours PCC = 0.93y = 0.92x10 NestedUNet ResUNet UNETR 5-15 PCC = 0.62 10 15 10 15 0 SUV 10 **SUV SUV** SUV UNet3D SwinUNETR 3DUXNET Ours 10 SHV VNet ResUNet 15 PCC = 0.92 15 PCC = 0.95 SUV. 5-5 10 SUV SUV 5 10 SUV 右丘脑 3DUXNET SwinUNETR UNet3D 10 SUVSUV

总体的消融实验



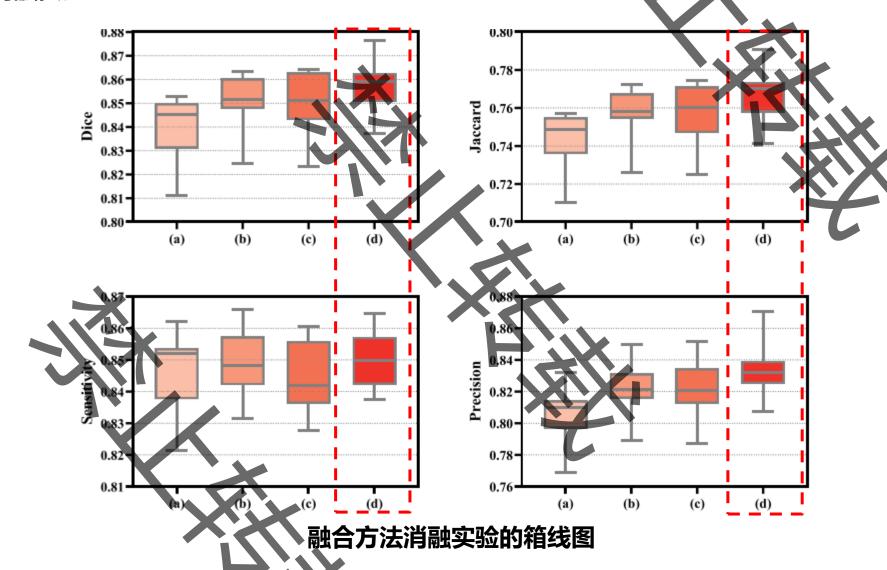


消融实验结果

实验结果

融合方法的消融实验













本文提出了一种基于交叉融合机制的自动脑分割方法,该方法整合了多模态PET和MR信息以实现精确的全脑分割,并且该方法有利于脑部疾病的临床诊断和分析。未来将探索该方法在其他模态图像(MR/CT、MR/SPECT等)处理任务中的应用。

