Code

Paper

CMSA-Net: Causal Multi-scale Aggregation with Adaptive Multi-source Reference for Video Polyp Segmentation

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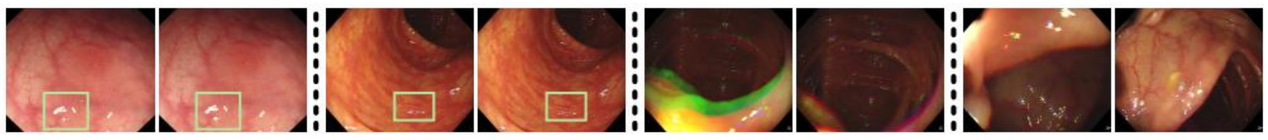
Clinical Problem

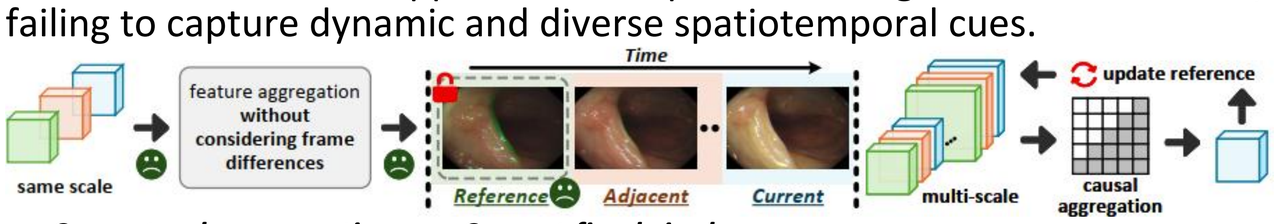
Challenge 1: Weak semantic discrimination, caused by the low contrast between polyps and background.
Challenge 2: Large spatio-temporal variations across frames.



Weak semantic discrimination *Large spatio-temporal variation*

Motivation

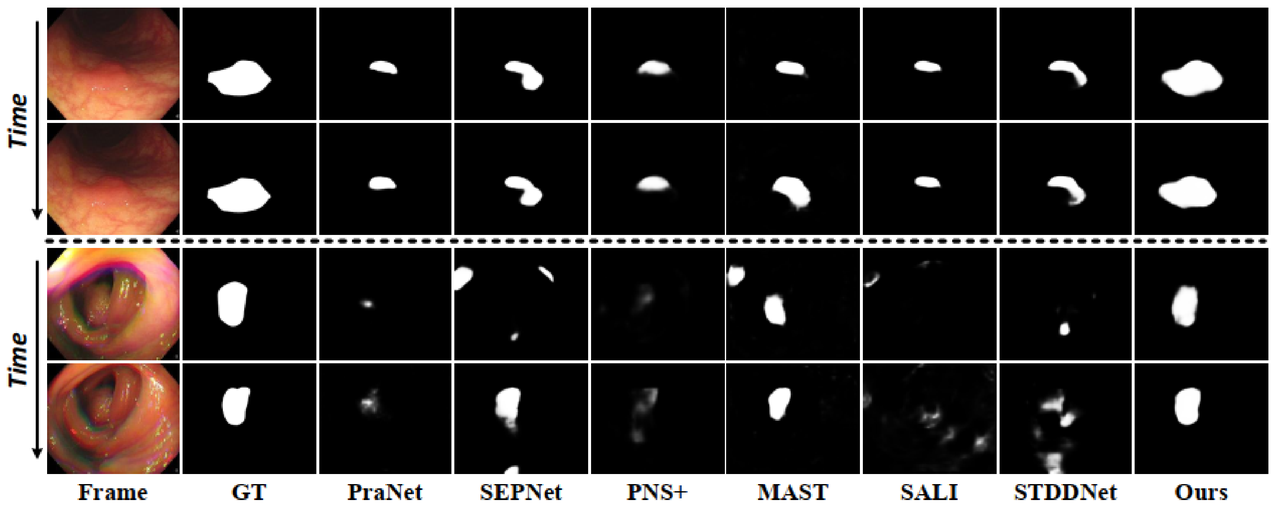
Limitation 1: Existing feature fusion methods for polyp semantic learning , which ignore multi-scale information and intrinsic identity relationships.
Limitation 2: Current approaches adopt a fixed single-source reference, failing to capture dynamic and diverse spatiotemporal cues.



Current polyp semantic learning method *Current fixed single-source reference method* *Our Method*

These observations motivate a more adaptive spatio-temporal modeling paradigm for video polyp segmentation:
1. **Multi-scale semantic modeling** is needed to distinguish low-contrast polyps from visually similar backgrounds.
2. **Frame-aware temporal propagation** is required to preserve useful historical information while suppressing noisy or inconsistent cues.
3. **Adaptive reference updating** is necessary to handle evolving target appearance and maintain reliable temporal guidance.

Qualitative Comparisons



CMSA-Net produces more accurate and complete masks in challenging cases with low contrast and large inter-frame variations.

Ablation Study

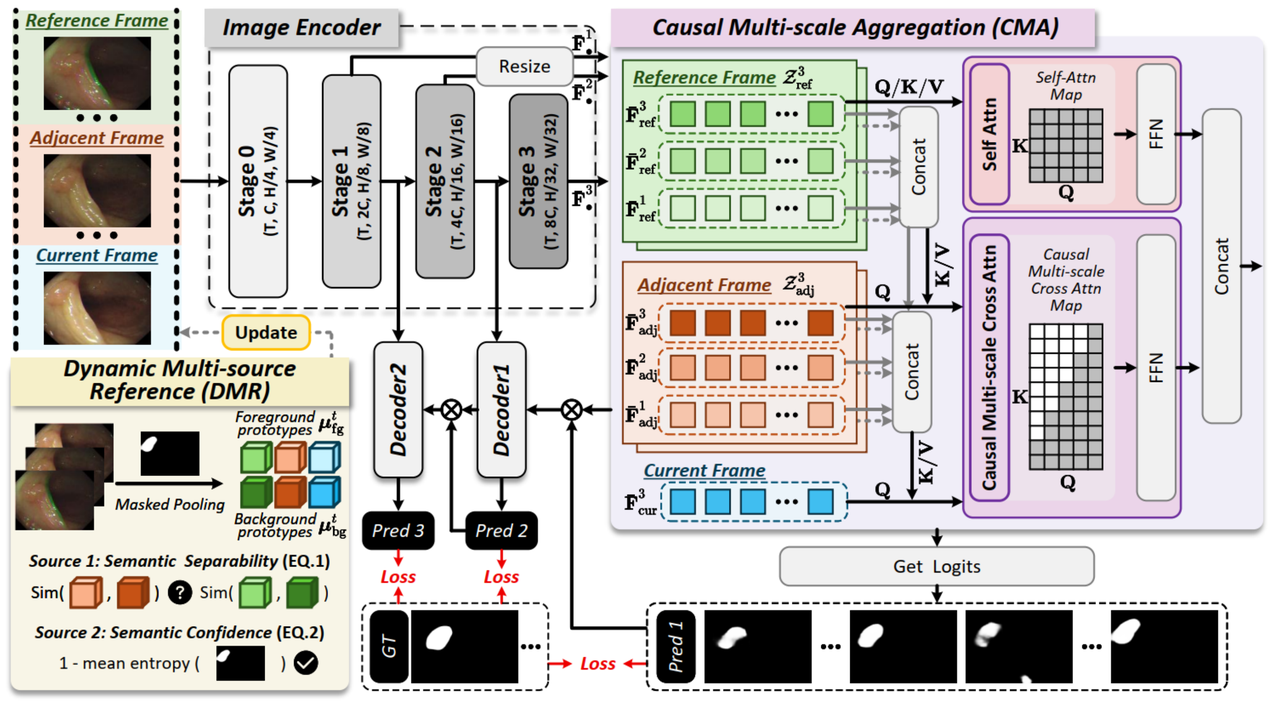
CMSA-Net balances accuracy and efficiency, with real-time speed.

Efficiency	PraNet	ACSNet	SEPNet	PNS+	SALI	STDDNet (R)	STDDNet (P)	Ours (R)	Ours (P)
GFLOPs ↓	78.89	130.52	75.12	68.58	86.58	75.17	64.18	73.36	59.42
Param. (M) ↓	30.50	29.45	25.96	9.8	82.73	38.16	29.67	29.61	25.79
FPS ↑	42	21	33	64	10	45	36	47	38

Ablation results show that removing CMA, DMR, or both significantly degrades performance, confirming their complementary contributions.

Methods	SUN-SEG-Easy-Seen					SUN-SEG-Easy-Unseen					SUN-SEG-Hard-Seen					SUN-SEG-Hard-Unseen				
	S_α	E_ϕ^{mn}	F_β^w	Dice	IoU	S_α	E_ϕ^{mn}	F_β^w	Dice	IoU	S_α	E_ϕ^{mn}	F_β^w	Dice	IoU	S_α	E_ϕ^{mn}	F_β^w	Dice	IoU
CMSA-Net	**95.1**	**97.5**	**91.6**	**92.6**	**87.6**	**86.7**	**90.3**	**79.3**	**80.3**	**72.6**	**92.3**	**95.6**	**87.1**	**88.9**	**82.1**	**87.3**	**91.0**	**79.6**	**81.3**	**73.7**
w/o CMA	92.4	94.8	87.2	88.5	82.1	78.1	79.5	64.4	65.2	56.5	88.5	92.1	81.3	83.1	74.9	76.4	78.2	61.8	62.9	54.4
w/o DMR	93.8	96.2	89.1	90.3	84.7	80.2	81.6	67.5	68.8	60.3	90.4	94.2	84.8	86.6	79.1	79.1	80.2	65.3	67.0	58.4
w/o CMA+DMR	90.6	92.9	84.0	85.3	79.0	72.5	72.1	55.1	55.8	47.6	85.8	89.5	77.7	79.2	71.0	71.6	71.5	53.4	54.8	46.3
w/o Multi-scale	93.2	95.8	88.6	89.7	83.9	83.5	86.9	75.1	76.2	67.4	89.8	93.5	84.2	86.1	78.4	82.9	87.5	74.1	75.8	67.1
w/o Causal Attn	94.2	96.9	90.1	91.3	85.6	84.5	88.2	76.8	78.1	69.8	91.2	95.2	85.9	87.7	80.5	85.3	89.4	76.7	78.5	70.2
w/o Multi-source	94.0	96.7	89.9	91.1	85.5	86.7	90.7	79.7	80.9	73.0	91.0	95.0	85.6	87.5	80.3	86.9	89.9	78.4	80.4	72.6

Method Overview



Our method introduces **CMSA-Net**, which integrates **Causal Multi-scale Aggregation (CMA)** and **Dynamic Multi-source Reference (DMR)**.
CMA aggregates multi-scale temporal cues from reference and adjacent frames under a causal constraint, enhancing current-frame polyp semantics while avoiding feature contamination.
DMR adaptively updates reliable multi-source references according to semantic separability and prediction confidence, providing robust and efficient guidance for real-time video polyp segmentation.

Quantitative Comparisons

We evaluate CMSA-Net on four **SUN-SEG** subsets: Easy-Seen, Easy-Unseen, Hard-Seen, and Hard-Unseen.
CMSA-Net consistently outperforms state-of-the-art image- and video-based methods, especially on challenging Hard/Unseen cases. These results demonstrate its robustness to low contrast and large spatio-temporal variations while maintaining real-time inference efficiency.

Quantitative comparison on SUN-SEG-Easy

Method	Publication	Backbone	SUN-SEG-Easy-Seen (%)						SUN-SEG-Easy-Unseen (%)					
			S_α ↑	E_ϕ^{mn} ↑	F_β^w ↑	Dice↑	IoU↑	MAE↓	S_α ↑	E_ϕ^{mn} ↑	F_β^w ↑	Dice↑	IoU↑	MAE↓
COSNet [16]	TPAMI'19	-	84.5	83.6	72.7	73.0	64.8	3.4	65.4	60.0	43.1	42.3	34.2	7.3
PCSA [11]	AAAI'20	-	85.2	83.5	68.1	70.9	60.4	3.9	68.0	66.0	45.1	45.0	35.3	7.8
2/3D [19]	MICCAI'20	-	89.5	90.9	81.9	82.9	75.6	2.1	78.6	77.7	65.2	65.6	57.0	4.4
PraNet [7]	MICCAI'20	Res2Net-50	91.8	94.2	87.7	88.3	82.5	2.0	78.1	78.8	66.3	66.5	58.2	5.2
ACSNet [27]	MICCAI'20	ResNet-34	92.0	94.2	87.4	88.2	82.8	1.7	77.2	76.6	63.0	63.8	56.4	4.6
SANet [22]	MICCAI'21	Res2Net-50	91.6	93.3	86.6	87.2	82.0	1.8	75.0	72.8	59.0	59.3	52.4	5.2
SEPNet [20]	TCSVT'24	PVTv2-B2	93.1	96.2	88.3	89.6	83.4	1.7	82.9	88.3	73.5	75.1	66.6	4.2
PNS [13]	MICCAI'21	Res2Net-50	90.6	91.0	83.6	84.1	78.3	2.0	76.7	74.4	61.6	61.8	54.5	4.8
PNS+ [14]	MIR'22	Res2Net-50	91.7	92.5	84.8	85.5	78.7	2.1	80.6	79.8	67.6	67.8	59.1	4.4
MAST [3]	Arxiv'24	PVTv2-B2	92.5	96.2	87.8	89.3	82.7	1.6	83.2	89.4	74.9	77.0	67.4	3.7
SALI [12]	MICCAI'24	PVTv2-B2	90.2	93.2	84.9	85.8	78.9	2.4	73.1	75.2	58.7	59.2	50.2	6.3
SALI [12]	MICCAI'24	PVTv2-B5	90.7	93.7	85.1	86.2	79.6	2.2	77.1	82.1	64.6	65.6	56.8	5.5
STDDNet [4]	ICCV'25	Res2Net-50	93.5	96.0	89.7	90.5	85.0	1.5	81.7	83.0	72.1	72.4	64.3	3.7
STDDNet [4]	ICCV'25	PVTv2-B2	94.1	96.9	90.5	91.5	86.1	1.4	86.0	**90.3**	78.6	80.1	72.4	3.4
Ours	-	Res2Net-50	94.5	97.3	90.5	91.9	86.5	1.2	84.4	90.1	75.3	77.5	69.2	3.5
Ours	-	PVTv2-B2	**95.1**	**97.5**	**91.6**	**92.6**	**87.6**	**1.1**	**86.7**	**90.3**	**79.3**	**80.3**	**72.6**	**2.9**

Quantitative comparison on SUN-SEG-Hard

Method	Publication	Backbone	SUN-SEG-Hard-Seen (%)						SUN-SEG-Hard-Unseen (%)					
			S_α ↑	E_ϕ^{mn} ↑	F_β^w ↑	Dice↑	IoU↑	MAE↓	S_α ↑	E_ϕ^{mn} ↑	F_β^w ↑	Dice↑	IoU↑	MAE↓
COSNet [16]	TPAMI'19	-	78.5	77.2	62.6	63.3	54.1	4.6	67.0	62.7	44.3	43.8	35.3	7.0
PCSA [11]	AAAI'20	-	77.2	75.9	56.6	58.5	47.9	5.7	68.2	66.0	44.2	45.0	35.1	8.0
2/3D [19]	MICCAI'20	-	84.9	86.9	75.3	76.4	67.1	3.5	78.6	77.5	63.4	64.4	55.8	4.4
PraNet [7]	MICCAI'20	Res2Net-50	88.4	91.9	83.1	83.9	76.6	3.1	78.7	80.2	66.7	67.5	58.7	5.3
ACSNet [27]	MICCAI'20	ResNet-34	87.2	91.0	80.6	82.0	74.8	3.6	76.2	77.6	61.0	62.4	54.7	5.3
SANet [22]	MICCAI'21	Res2Net-50	87.4	90.5	81.0	82.0	74.8	3.3	75.3	73.6	59.0	59.5	52.7	5.5
SEPNet [20]	TCSVT'24	PVTv2-B2	89.4	94.0	83.5	85.7	77.6	3.4	84.7	89.5	74.5	77.4	68.4	3.9
PNS [13]	MICCAI'21	Res2Net-50	87.0	89.2	78.7	79.6	72.1	3.3	76.7	75.5	60.9	61.5	53.9	5.0
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MAST [3]	Arxiv'24	PVTv2-B2	89.2	94.2	83.2	85.3	76.7	2.6	85.6	91.3	77.2	79.9	70.8	3.1
SALI [12]	MICCAI'24	PVTv2-B2	86.8	90.9	79.9	81.0	72.6	3.4	72.8	75.9	56.9	57.9	48.7	6.8
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Ours	-	Res2Net-50	**92.7**	**96.1**	**87.1**	**89.8**	**83.0**	**1.8**	85.1	89.8	75.0	78.0	69.5	3.6
Ours	-	PVTv2-B2	92.3	95.6	**87.1**	88.9	82.1	1.9	**87.3**	**91.0**	**79.6**	**81.3**	**73.7**	**2.9**

Acknowledgments

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Conclusion

CMSA-Net integrates CMA and DMR for robust video polyp segmentation. It outperforms SOTA methods on SUN-SEG, especially in hard cases, while ensuring real-time efficiency.

https://github.com/wangtong627/CMSA-Net

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