SALIENCY DETECTION

Interactive Two-Stream Decoder for Accurate and Fast Saliency Detection ——ITSD Network

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01 Saliency Object Detection

- Target
 - "Salient object detection" or "salient object segmentation" is commonly interpreted in computer vision as a process that includes two stages:
 - 1) Detecting the most salient object
 - 2) Segmenting the accurate region of that object









Precision—Recall

$$P = \frac{TP}{TP + FN} \qquad R = \frac{TP}{TP + FP}$$

- F-measure
 - $\beta^2 = 0.3$

 $F_{\beta} = \frac{(1+\beta^2) \times Precision \times Recall}{\beta^2 \times Precision + Recall}$

• MAE(mean absolute error)

$$MAE = \frac{1}{W \times H} \sum_{x=1}^{W} \sum_{y=1}^{H} |S(x,y) - G(x,y)|$$



Images

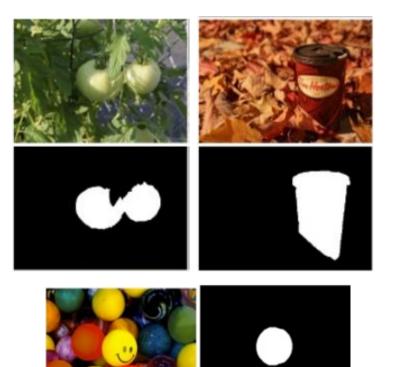
GT

Mask

03 Dataset

- DUTS: 10553 for train (DUTS-TR), 5019 for test (DUTS-TE)
- **SOD**: 300 images
- PASCAL-S: 850 images
- ECSSD: 1000 images
- HKU-IS: 4447 images
- **DUT-O**: 5168 images





• CVPR 2020

Motivation

Contour information largely improves the performance of saliency detection. However, the discussion on the correlation between saliency and contour remains scarce.

• Several works introduced contour into networks by proposing a boundary-aware objective function.

BASNet: Boundary-Aware Salient Object Detection

Xuebin Qin, Zichen Zhang, Chenyang Huang, Chao Gao, Masood Dehghan and Martin Jagersand University of Alberta, Canada {xuebin, vincent.zhang, chuang8, cgao3, masood1, mj7}@ualberta.ca

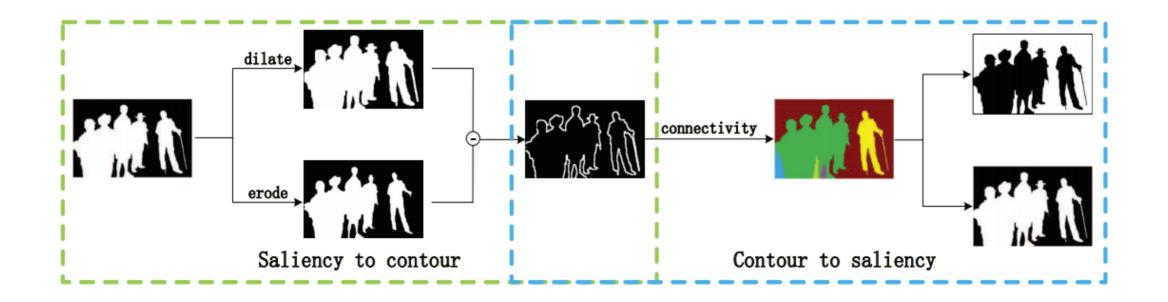
• Constructing a boundary-aware network becomes an impressive method in the saliency detection task.

A Simple Pooling-Based Design for Real-Time Salient Object Detection

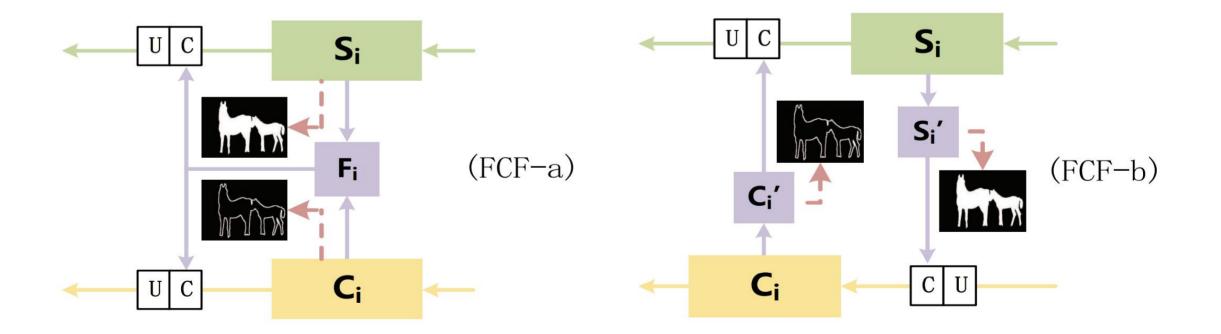
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Contribution

- Discuss the correlation between the saliency maps and corresponding contour maps.
- Propose a lightweight Interactive Two-Stream Decoder (ITSD) for saliency detection by exploring multiple cues of the saliency and contour maps.
- Develop an Adaptive ConTour (ACT) loss to improve the representation power of the learned network by taking advantage of hard examples.

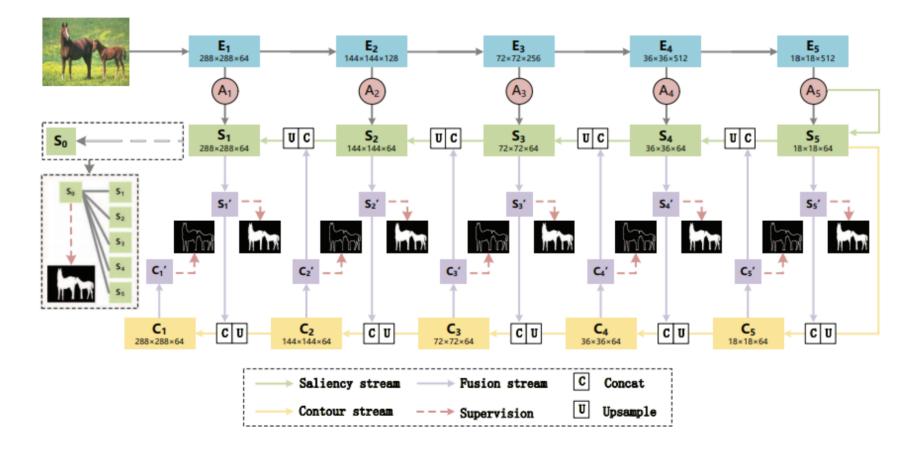


- Feature Correlation Fusion(FCF)
 - FCF-a: This simple module cannot guarantee that the fused features can be complementary to each branch.
 - FCF-b: These connections(S'_i and C'_i) to ensure the transferred features are related to their original branch.



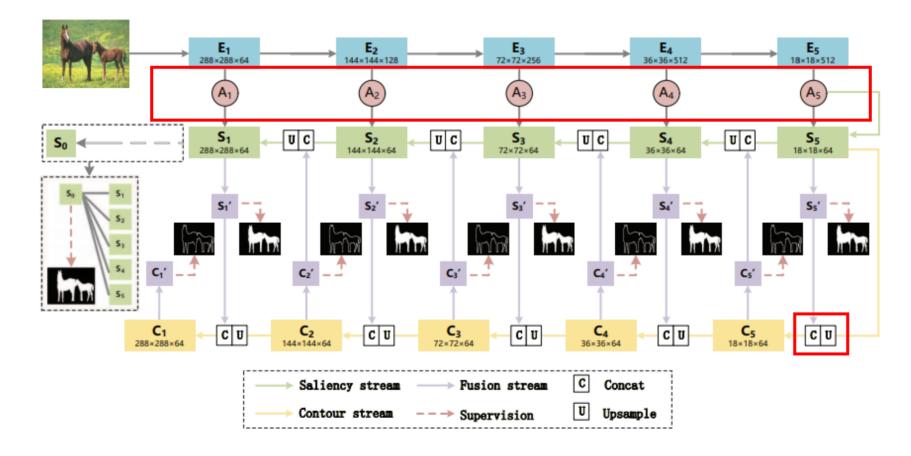
• Overall network architecture

- Feature encoder: VGG16 or ResNet50, pre-trained on ImageNet
- Attach a **channel pooling layer** to reduce feature channels and computation loads.



Channel pooling layer

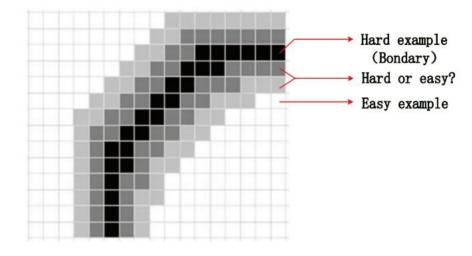
$$A_{i} = cp(E_{i}),$$
(1)
$$cp(X) = collect_{j \in [0, m-1]}(max_{k \in [0, \frac{n}{m} - 1]}X^{j \times \frac{n}{m} + k}),$$
(2)



• Loss for the contour branch

$$L_{bce}(x,y) = y \log(x) + (1-y) \log(1-x)$$
$$L^{c}(P^{c}, G^{c}) = -\frac{1}{n} \sum_{k=1}^{n} l_{bce}(p_{k}^{c}, g_{k}^{c})$$

• Loss for the saliency branch



 $L^{s}(P^{s}, G^{s}, G^{c}) = -\frac{1}{n} \sum_{k=1}^{n} (g_{k}^{c} \times m + 1) l_{bce}(p_{k}^{s}, g_{k}^{s}) \longrightarrow$ The definition of hard examples is ambiguous.

 $L^{s}(P^{s}, P^{c}, G^{s}, G^{c}) = -\frac{1}{n} \sum_{k=1}^{n} (\max(p_{k}^{c}, g_{k}^{c}) \times m + 1) l_{bce}(p_{k}^{s}, g_{k}^{s})$ Adaptive ConTour (ACT) loss

$$L(P^{s}, P^{c}, G^{s}, G^{c}) = \sum_{i=0}^{5} L^{s}(P_{i}^{s}, P_{i}^{c}, G_{i}^{s}, G_{i}^{c}) + \lambda \sum_{j=1}^{5} L^{c}(P_{j}^{c}, G_{j}^{c})$$

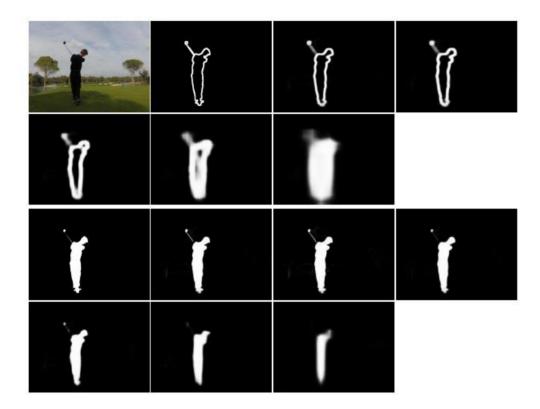
• Result

Method	FPS	SOD		PASCAL-S		ECSSD		HKU-IS		DUTS-TE		DUT-O	
		F_{β}^*	mae										
VGG-based													
RFCN [32]	9	.807	.166	.850	.132	.898	.095	.898	.080	.783	.090	.738	.095
Amulet [45]	16	.798	.145	.837	.099	.915	.059	.897	.051	.778	.085	.743	.098
UCF [46]	23	.803	.169	.846	.128	.911	.078	.886	.074	.771	.117	.735	.132
NLDF [24]	12	.842	.125	.829	.103	.905	.063	.902	.048	.812	.066	.753	.080
DSS [12]	25	.837	.127	.828	.107	.908	.062	.900	.050	.813	.064	.760	.074
CKT [18]	23	.829	.119	.850	.086	.910	.054	.896	.048	.807	.062	.757	.071
BMP [44]	22	.851	.106	.859	.081	.928	.044	.920	.038	.850	.049	.774	.064
PAGE [35]	25	.796	.110	.835	.078	.931	.042	.930	.037	.838	.051	.791	.066
PCA [22]	5.6	.855	.108	.858	.081	.931	.047	.921	.042	.851	.054	.794	.068
CTLoss [4]	26	.861	.109	.876	.079	.933	.043	.927	.035	.872	.042	.792	.073
EGNet [48]	9	.869	.110	.863	.076	.941	.044	.929	.034	.880	.043	.826	.056
RA [3]	35	.844	.124	.834	.104	.918	.059	.913	.045	.826	.055	.786	.062
AFNet [8]	45	.855	.110	.867	.078	.935	.042	.923	.036	.862	.046	.797	.057
CPD [37]	66	.850	.114	.866	.074	.936	.040	.924	.033	.864	.043	.794	.057
PoolNet [21]	32	.859	.115	.857	.078	.936	.047	.928	.035	.876	.043	.817	.058
ITSD (Ours)	48	.869	.100	.871	.074	.939	.040	.927	.035	.877	.042	.813	.063
					Res	Net-ba	sed						
BasNet [26]	70	.851	.114	.854	.076	.942	.037	.928	.032	.860	.047	.805	.056
CPD [37]	62	.852	.110	.864	.072	.939	.037	.925	.034	.865	.043	.797	.056
PoolNet [21]	18	.867	.100	.863	.075	.940	.042	.934	.032	.886	.040	.830	.055
EGNet [48]	7.8	.890	.097	.869	.074	.943	.041	.937	.031	.893	.039	.842	.052
SCRN [38]	32	.860	.111	.882	.064	.950	.038	.934	.034	.888	.040	.812	.056
ITSD (Ours)	43	.880	.095	.871	.071	.947	.035	.934	.031	.883	.041	.824	.061

FOOD

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• Result



Loss	EC	SSD	DUI	IS-TE	HKU-IS		
LUSS	F_{β}	MAE	F_{β}	MAE	F_{eta}	MAE	
F-score	.929	.043	.845	.050	0.915	.045	
BCE	.931	.040	.861	.046	0.921	.040	
CTLoss	.935	.040	.872	.045	0.925	.036	
ACT	.939	.039	.877	.042	0.927	.035	

Module	EC	SSD	DU	IS-TE	HKU-IS		
Wiodule	F_{eta}	MAE	F_{β}	MAE	F_{eta}	MAE	
U-shape	.919	.052	.842	.062	0.913	.048	
FCF-NoCS	.929	.043	.868	.045	0.921	.035	
FCF-a	.930	.041	.865	.046	0.919	.036	
FCF-b	.939	.040	.877	.042	0.927	.033	