Efficient and accurate arbitrary-shaped text detection with pixel aggregation network (PAN)

ICCV 2019

Kim Bochan

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Scene Text Detection

Figure 8. Detection results on CTW1500.

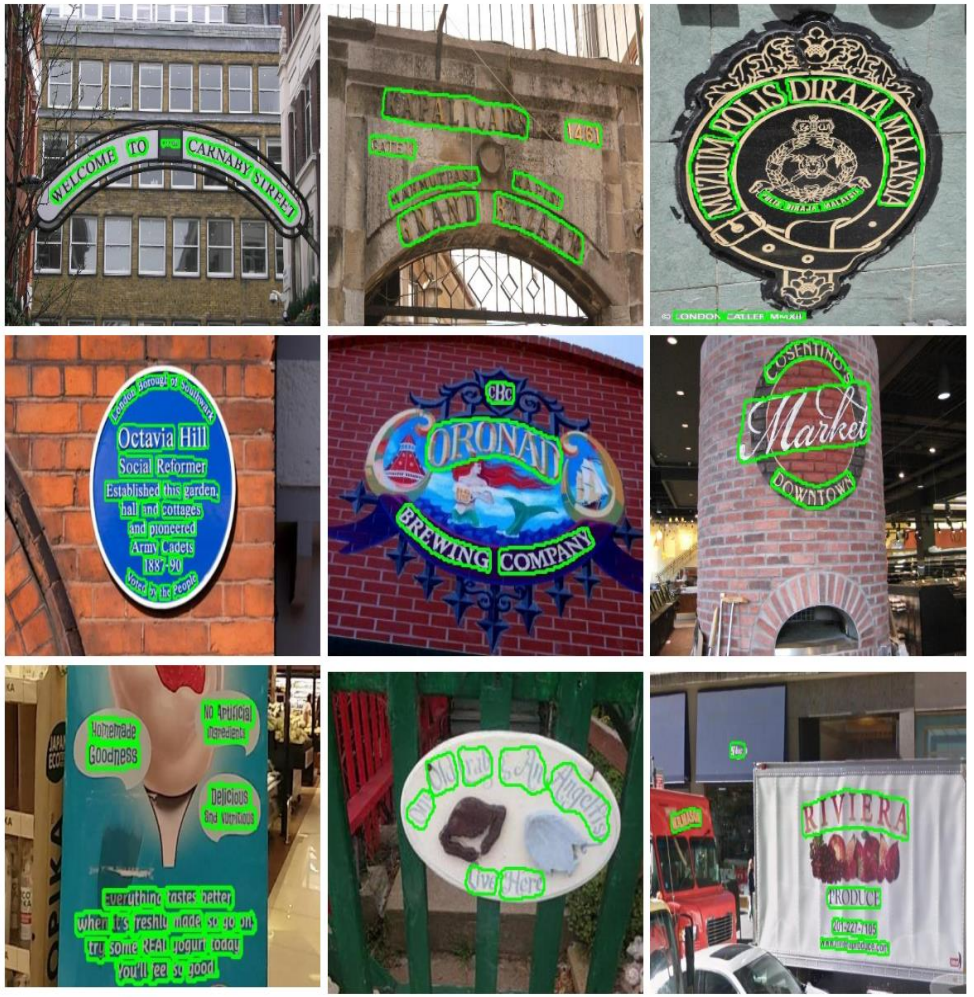


Figure 9. Detection results on Total-Text.

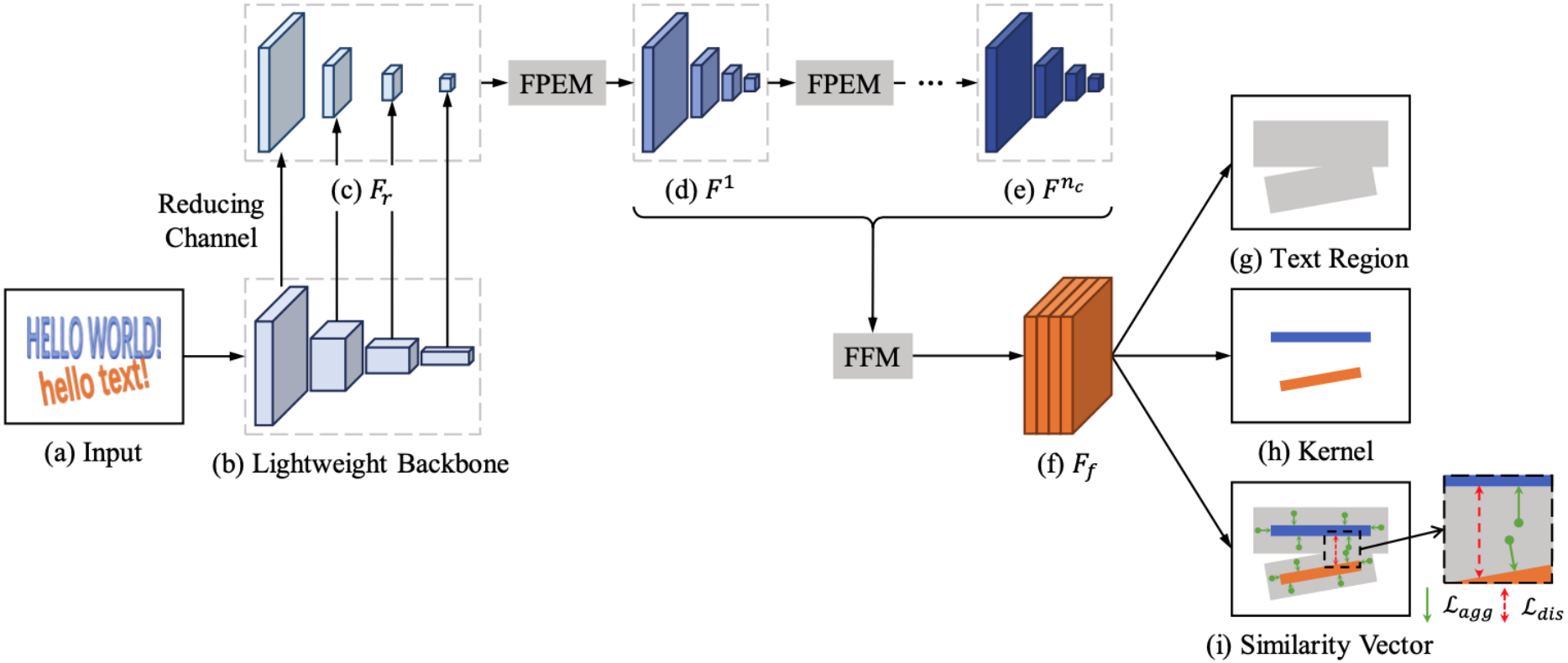
FPS

Method	Ext	R	P	F	FPS
SegLink* [28]	-	23.8	30.3	26.7	-
EAST* [49]	-	36.2	50.0	42.0	-
Lyu *et al.*[24]	✓	55.0	69.0	61.3	-
TextSnake [23]	✓	74.5	82.7	78.4	-
MSR [43]	✓	74.8	83.8	79.0	4.3
PSENet [33]	-	75.1	81.8	78.3	3.9
PSENet [33]	✓	78.0	84.0	80.9	3.9
Wang *et al.*[35]	-	76.2	80.9	78.5	-
TextDragon [6]	✓	74.2	84.5	79.0	-
TextField [41]	✓	79.9	81.2	80.6	6
PAN [34]	-	79.4	88.0	83.5	**39.6**
LOMO [46]	✓	75.7	**88.6**	81.6	4.4
LOMO† [46]	✓	79.3	87.6	83.3	-
CRAFT [2]	✓	79.9	87.6	83.6	-
Ours	-	**83.9**	86.9	**85.4**	3.8

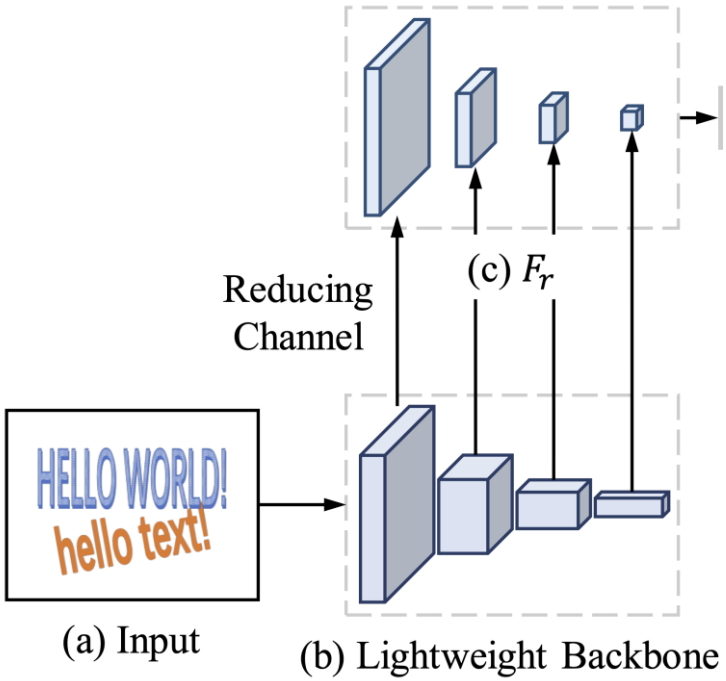
Method	Ext	R	P	F	FPS
EAST [49]	✓	73.5	83.6	78.2	13.2
Liao et al. [15]	✓	79.0	85.6	82.2	6.5
Lyu et al. [25]	✓	70.7	**94.1**	80.7	3.6
FOTS [20]	✓	82.0	88.8	85.3	7.8
PixelLink [4]	-	81.7	82.9	82.3	7.3
MSR [43]	✓	78.4	86.6	82.3	4.3
PSENet [33]	-	79.7	81.5	80.6	1.6
PSENet [33]	✓	84.5	86.9	85.7	1.6
PAN [34]	-	77.8	82.9	80.3	**26.1**
TextDragon [6]	✓	81.8	84.8	83.1	-
LOMO [46]	✓	83.5	91.3	87.2	3.4
TextField* [41]	✓	83.9	84.3	84.1	1.8
Liu *et al.* [21]	✓	83.8	89.4	86.5	-
Tian *et al.* [32]	✓	85.0	88.3	86.6	3
CRAFT [2]	✓	84.3	89.8	86.9	-
Wang *et al.* [35]	-	83.3	90.4	86.8	-
Wang *et al.*† [35]	-	86.0	89.2	**87.6**	-
Ours	-	**86.1**	87.6	86.9	3.5

Architecture

(Light)Backbone +
Feature Pyramid Enhancement Module(FPEM) +
Feature Fusion Module(FFM) +
Pixel Aggregation(PA)



Architecture – backbone

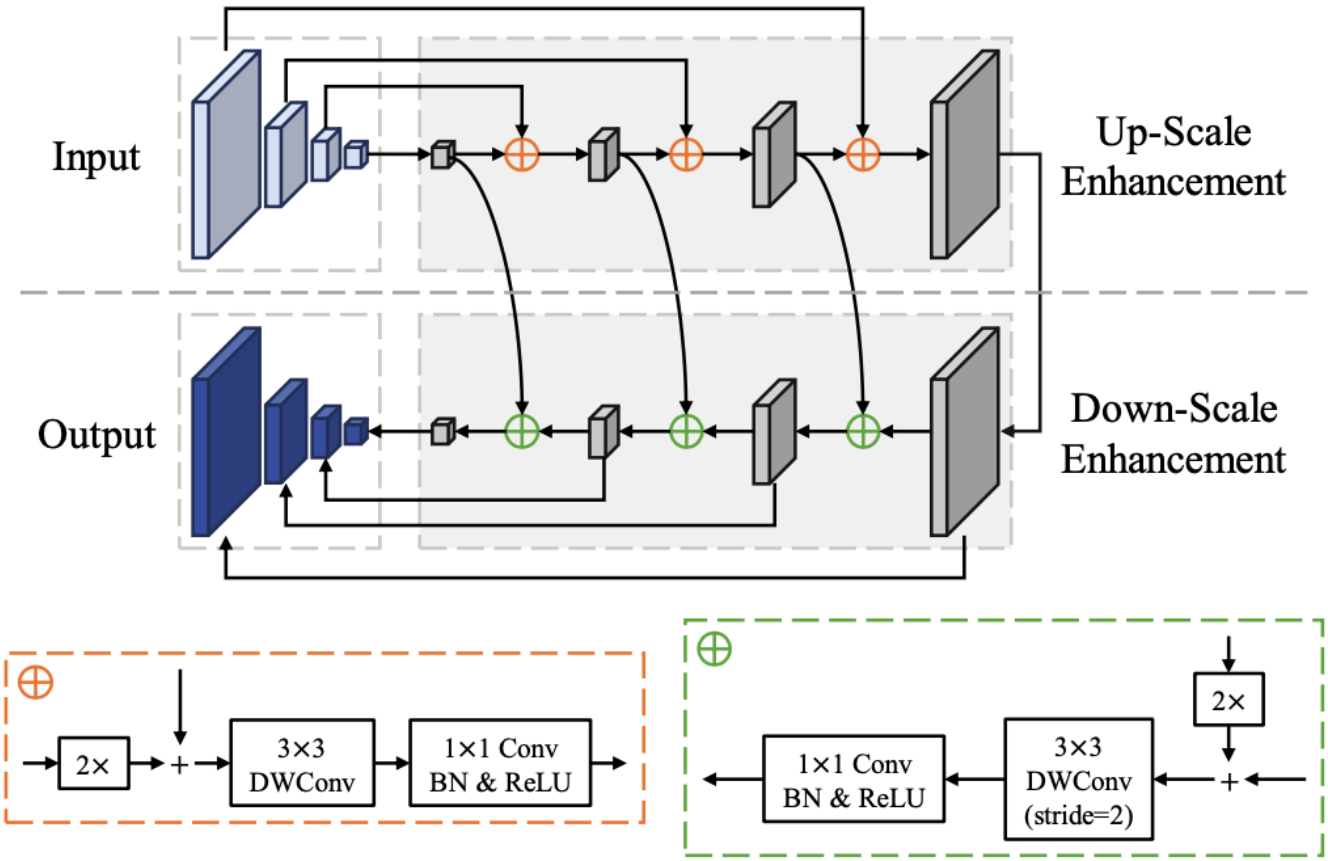


1. Resnet18

2. 4 feature maps generated by conv2, conv3, conv4, and conv5 stages of backbone (4, 8, 16, 32 strides)

3. 1×1 conv to reduce the channel to 128

Architecture – FPEM

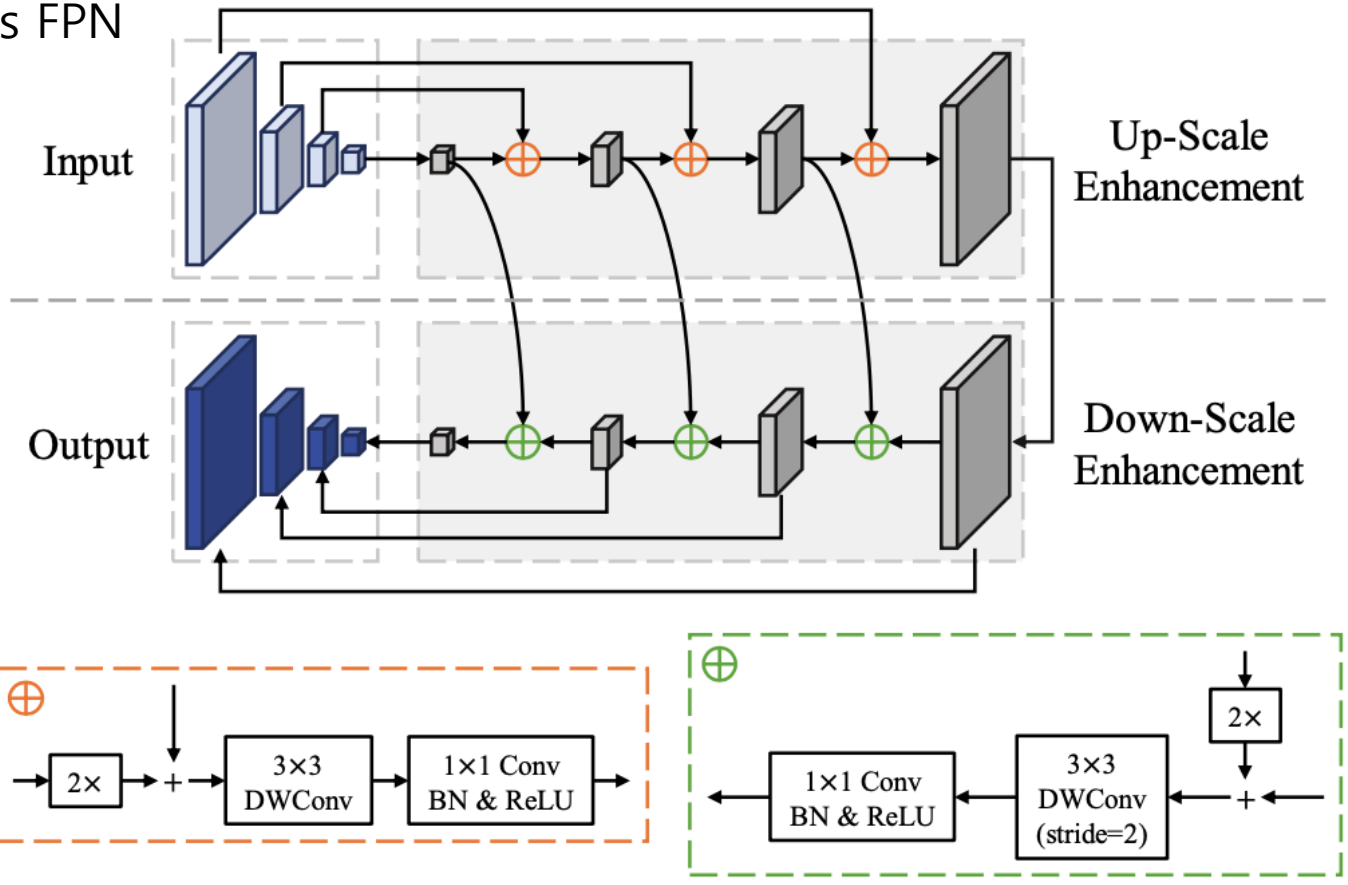


1. U-shaped with two phases, up-scale & down-scale enhancement
    1. enhancement is iteratively conducted on [4, 8, 16, 32] strides

2. Depthwise Separable Conv(DWConv)
    1. small computation overhead

Architecture - FPEM

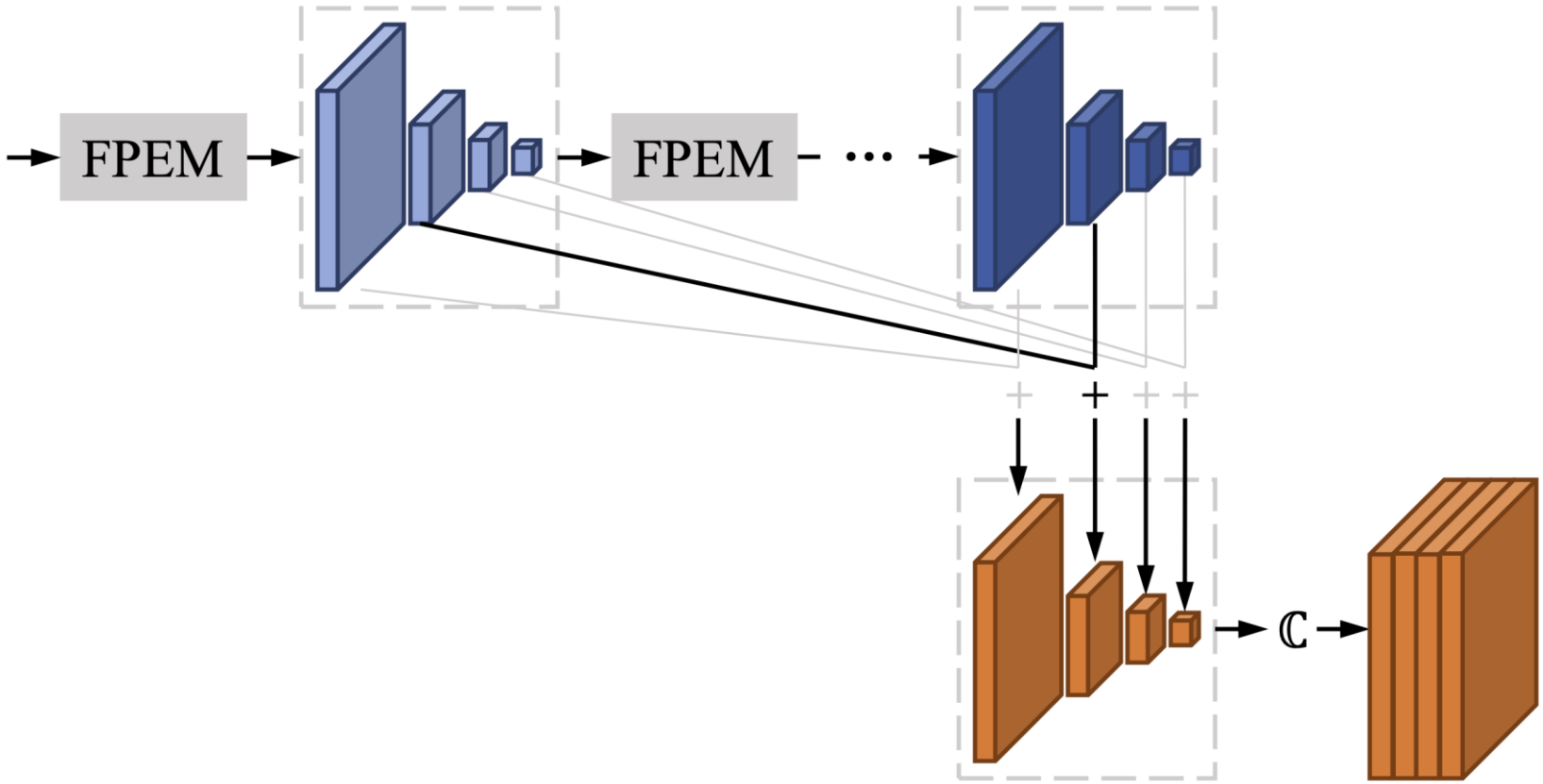
FPEM vs FPN



1. Fully Cascadable
    1. as n_c increased, feature map of different scales are fused
    2. receptive field more bigger

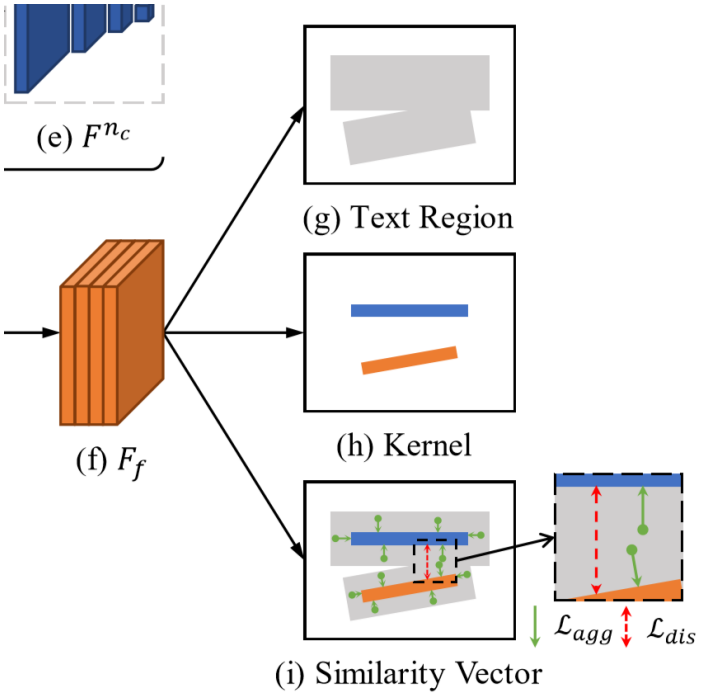
2. Computationally cheap
    1. 1/5 FLOPS of FPN

Architecture - FFM



1. Combine the corresponding-scale feature maps by element-wise addition
2. Feature maps after addition are upsampled and concatenated into a final feature map (4×128 channels)

Architecture - PA



Text regions lying closely are often overlapping
-> need to merge text region pixels to kernels

1. Distance between the **text pixel** and kernel of the same text instance should be small.
-> Aggregation Loss

2. **Kernels** of different text instances should maintain enough distance.
-> Discrimination Loss

Architecture - PA

1. Aggregation Loss

$$\mathcal{L}_{agg} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{|T_i|}\sum_{p\in T_i} ln(\mathcal{D}(p, K_i) + 1)$$

$$\mathcal{D}(p, K_i) = max(\|\mathcal{F}(p) - \mathcal{G}(K_i)\| - \delta_{agg}, 0)^2$$ (δagg = 0.5)

N: number of text instances

T : text instance

p: pixel

K: kernel

F(p): similarity vector of pixel p

g(k): similarity vector of kernel k, calculated as $\sum_{q\in K_i}\mathcal{F}(q)/|K_i|$

Architecture – PA

2. Discrimination Loss

Try to keep the distance among the kernels not less than δdis (δdis = 3)

$$\mathcal{L}_{dis} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} ln(\mathcal{D}(K_i, K_j) + 1),$$

$$\mathcal{D}(K_i, K_j) = max(\delta_{dis} - \|\mathcal{G}(K_i) - \mathcal{G}(K_j)\|, 0)^2.$$

Full Objective

$$\mathcal{L}_{tex} = 1 - \frac{2\sum_i P_{tex}(i) G_{tex}(i)}{\sum_i P_{tex}(i)^2 + \sum_i G_{tex}(i)^2},$$

$$\mathcal{L}_{ker} = 1 - \frac{2\sum_i P_{ker}(i) G_{ker}(i)}{\sum_i P_{ker}(i)^2 + \sum_i G_{ker}(i)^2},$$

$$\mathcal{L} = \mathcal{L}_{tex} + \alpha \mathcal{L}_{ker} + \beta(\mathcal{L}_{agg} + \mathcal{L}_{dis}),$$

1. Dice Loss
2. tex, ker : binary map
3. GT of kernel map is generated by shrinking original GT polygon
    1. methods followed by PSENet
4. Online Hard Example Mining(OHEM, ratio=3)
5. alpha=0.5, beta=0.25

Result Visualization

(a) Final Result (b) Predicted Text Region (c) Predicted Kernel (d) Predicted Similarity Vector

(e) CTW1500 (f) Total-Text (g) ICDAR 2015 (h) MSRA-TD500

1. Dimension of similarity vector is reduced to 3, 2 by PCA

Post Processing

(a) Final Result (b) Predicted Text Region (c) Predicted Kernel (d) Predicted Similarity Vector

(e) CTW1500 (f) Total-Text (g) ICDAR 2015 (h) MSRA-TD500

i) Finding the connected components in the kernels' segmentation result, and each connected component is a single kernel.

i) For each kernel K_i, merging its neighbor text pixel in predicted text regions while the Euclidean distance of their similarity vectors is less than d(=6).

i) Repeating step ii) until there is no eligible neighbor text pixel.

Training Details

1. Dimension of similarity vector = 4
2. SGD
3. Two training strategies
    1. From scratch(36K)
        1. lr = 10-3, "poly" lr strategy
    2. Pre-training on SynthText(50K) and finetuning(36K)
        1. lr = 10-3, weight decay = 5X10-4, Nesterov momentum = 0.99, He init
4. random scale, random horizontal flip, random rotation and random crop

Ablation Study - FPEM

Influence of the number of cascaded FPEMs

#FPEM	GFLOPS	ICDAR 2015		CTW1500	
		F	FPS	F	FPS
0	**42.17**	78.4	**33.7**	78.8	**49.7**
1	42.92	79.9	29.5	80.4	44.7
2	43.67	80.3	26.1	81.0	39.8
3	44.43	80.4	23.0	81.3	35.2
4	45.18	**80.5**	20.1	**81.5**	32.4

Table 1. The results of models with different number of cascaded FPEMs. "#FPEM" means the number of cascaded FPEMs. "F" means F-measure. The FLOPS are calculated for the input of $640 \times 640 \times 3$.

1. Satureaed after n_c = 2
2. Set default as n_c = 2

Ablation Study - FPEM

Effectiveness of FPEM

#FPEM	GFLOPS	ICDAR 2015		CTW1500	
		F	FPS	F	FPS
0	**42.17**	78.4	**33.7**	78.8	**49.7**
1	42.92	79.9	29.5	80.4	44.7
2	43.67	80.3	26.1	81.0	39.8
3	44.43	80.4	23.0	81.3	35.2
4	45.18	**80.5**	20.1	**81.5**	32.4

Method	ICDAR 2015		CTW1500	
	F	FPS	F	FPS
ResNet18 + 2 FPEMs + FFM	80.3	**26.1**	81.0	**39.8**
ResNet50 + PSPNet [56]	**80.5**	4.6	**81.1**	7.1

1. With FPEM, can make about 1.5% improvement on F-measure while bringing tiny extra computation
1. Can reach almost same performance with huge model
    1. 5 times faster
    2. Model size is only 12.25M

Ablation Study - FFM

Effectiveness of FFM

#	Backbone	Fuse	PA	ICDAR 2015		CTW1500	
				F	FPS	F	FPS
1	ResNet18	FFM	✓	80.3	26.1	81.0	39.8
2	ResNet18	-	✓	79.7	**26.2**	80.2	**40.0**
3	ResNet18	Concat	✓	80.4	22.3	81.2	35.9
4	ResNet18	FFM	-	79.3	26.1	79.8	39.9
5	ResNet50	FFM	✓	81.4	16.7	**81.6**	26.0
6	VGG16	FFM	✓	**81.9**	6.6	81.5	10.1

1. F-measure drop 0.6%-0.8% when the FFM is removed
2. Proposed FFM can achieve performance comparable to the direct concatenation

Ablation Study - PA

Effectiveness of PA

#	Backbone	Fuse	PA	ICDAR 2015		CTW1500	
				F	FPS	F	FPS
1	ResNet18	FFM	✓	80.3	26.1	81.0	39.8
2	ResNet18	-	✓	79.7	**26.2**	80.2	**40.0**
3	ResNet18	Concat	✓	80.4	22.3	81.2	35.9
4	ResNet18	FFM	-	79.3	26.1	79.8	39.9
5	ResNet50	FFM	✓	81.4	16.7	**81.6**	26.0
6	VGG16	FFM	✓	**81.9**	6.6	81.5	10.1

1. set β to 0
2. F-measure of the model without PA (Table #4) drops over 1%

Ablation Study - backbone

Effectiveness of backbone

#	Backbone	Fuse	PA	ICDAR 2015		CTW1500	
				F	FPS	F	FPS
1	ResNet18	FFM	✓	80.3	26.1	81.0	39.8
2	ResNet18	-	✓	79.7	**26.2**	80.2	**40.0**
3	ResNet18	Concat	✓	80.4	22.3	81.2	35.9
4	ResNet18	FFM	-	79.3	26.1	79.8	39.9
5	ResNet50	FFM	✓	81.4	16.7	**81.6**	26.0
6	VGG16	FFM	✓	**81.9**	6.6	81.5	10.1

1. ResNet50 and VGG16 can bring over 1% improvement on ICDAR 2015 and over 0.5% improvement on CTW1500.

2. The reduction of FPS brought by the heavy backbone is apparent

Results

CTW 1500 – Curved TD (Polygon)

Method	Ext.	Venue	CTW1500			
			P	R	F	FPS
CTPN* [47]	-	ECCV'16	60.4*	53.8*	56.9*	7.14
SegLink* [42]	-	CVPR'17	42.3*	40.0*	40.8*	10.7
EAST* [58]	-	CVPR'17	78.7*	49.1*	60.4*	21.2
CTD+TLOC [31]	-	ICDAR'18	77.4	69.8	73.4	13.3
PSENet-1s [24]	-	CVPR'19	80.6	75.6	78.0	3.9
PAN-320	-	-	82.2	72.6	77.1	**84.2**
PAN-512	-	-	83.8	77.1	80.3	58.1
PAN-640	-	-	84.6	77.7	81.0	39.8
TextSnake [35]	✓	ECCV'18	67.9	85.3	75.6	-
PSENet-1s [24]	✓	CVPR'19	84.8	79.7	82.2	3.9
PAN-320	✓	-	82.7	77.4	79.9	**84.2**
PAN-512	✓	-	85.5	**81.5**	83.5	58.1
PAN-640	✓	-	**86.4**	81.2	**83.7**	39.8

Results

Total Text – Curved TD (Polygon)

Method	Ext.	Venue	Total-Text			
			P	R	F	FPS
SegLink* [42]		CVPR'17	30.3*	23.8*	26.7*	-
EAST* [58]	-	CVPR'17	50.0*	36.2*	42.0*	-
DeconvNet [2]	-	ICDAR'18	33.0	40.0	36.0	-
PSENet-1s [24]	-	CVPR'19	81.8	75.1	78.3	3.9
PAN-320	-	-	84.0	71.3	77.1	**82.4**
PAN-512	-	-	86.7	78.4	82.4	57.1
PAN-640	-	-	88.0	79.4	83.5	39.6
TextSnake [35]	✓	ECCV'18	82.7	74.5	78.4	-
PSENet-1s [24]	✓	CVPR'19	84.0	78.0	80.9	3.9
SPCNet [50]	✓	AAAI'19	83.0	82.8	82.9	-
PAN-320	✓	-	85.6	75.0	79.9	**82.4**
PAN-512	✓	-	**89.4**	79.7	84.3	57.1
PAN-640	✓	-	89.3	**81.0**	**85.0**	39.6

Results

ICDAR 2015 – Arbitrary oriented dataset(most commonly used dataset)

Method	Ext.	Venue	ICDAR 2015			
			P	R	F	FPS
CTPN [47]	-	ECCV'16	74.2	51.6	60.9	7.1
EAST [58]	-	CVPR'17	83.6	73.5	78.2	13.2
RRPN [38]	-	TMM'18	82.0	73.0	77.0	-
DeepReg [17]	-	ICCV'17	82.0	80.0	81.0	-
PixelLink [3]	-	AAAI'18	82.9	81.7	82.3	7.3
PAN	-	-	82.9	77.8	80.3	**26.1**
SegLink [42]	✓	CVPR'17	73.1	76.8	75.0	-
SSTD [16]	✓	ICCV'17	80.2	73.9	76.9	7.7
WordSup [19]	✓	CVPR'17	79.3	77.0	78.2	-
Lyu et al. [37]	✓	CVPR'18	**94.1**	70.7	80.7	3.6
RRD [28]	✓	CVPR'18	85.6	79.0	82.2	6.5
MCN [32]	✓	CVPR'18	72.0	80.0	76.0	-
TextSnake [35]	✓	ECCV'18	84.9	80.4	82.6	1.1
PSENet-1s [24]	✓	CVPR'19	86.9	84.5	85.7	1.6
SPCNet [50]	✓	AAAI'19	88.7	**85.8**	**87.2**	-
PAN	✓	-	84.0	81.9	82.9	**26.1**

Results

MSRA-TD500 - Long straight TD (Quadrangle)

Method	Ext.	Venue	MSRA-TD500			
			P	R	F	FPS
EAST [58]	-	CVPR'17	87.3	67.4	76.1	13.2
RRPN [38]	-	TMM'18	82.0	68.0	74.0	-
DeepReg [17]	-	ICCV'17	77.0	70.0	74.0	1.1
PAN	-	-	80.7	77.3	78.9	**30.2**
SegLink [42]	✓	CVPR'17	86.0	70.0	77.0	8.9
PixelLink [3]	✓	AAAI'18	83.0	73.2	77.8	3.0
Lyu et al. [37]	✓	CVPR'18	87.6	76.2	81.5	5.7
RRD [28]	✓	CVPR'18	87.0	73.0	79.0	10
MCN [32]	✓	CVPR'18	**88.0**	79.0	83.0	-
TextSnake [35]	✓	ECCV'18	83.2	73.9	78.3	1.1
PAN	✓	-	84.4	**83.8**	**84.1**	**30.2**

Results

Time consumption comparison

Method	F	Time consumption (ms)			FPS
		Backbone	Head	Post	
PAN-320	77.10	**4.4**	**5.4**	**2.1**	**84.2**
PAN-512	80.32	6.4	7.3	3.5	58.1
PAN-640	**81.00**	9.8	10.1	5.2	39.8

1. Time costs of backbone and segmentation head are similar, and the time cost of post-processing is half of them.

1. Measured on 1 1080Ti GPU and 2.20GHz GPU with PyTorch

Results - robustness analysis

Cross-dataset results on word-level and line-level datasets

Annotation	Train Set→Test Set	P	R	F
Word	SynthText → ICDAR 2015	65.9	46.9	54.8
	SynthText → Total-Text	69.1	40.8	51.3
	ICDAR 2015 → Total-Text	72.0	57.8	64.1
	Total-Text → ICDAR 2015	77.6	65.5	71.1
Text Line	CTW1500 → MSRA-TD500	76.6	73.1	74.8
	MSRA-TD500 → CTW1500	82.4	69.1	75.2

1. still competitive

Results - robustness analysis

Results comparison on CTW1500 with other (high efficiency) segmentation methods

Methods	Ext.	F (%)	FPS
BiSeNet (ResNet18) [54]	-	78.8	25.9
CU-Net-2 (m=128, n=32) [46]	-	76.4	39.3
Ours (ResNet18 + 2FPEM + FFM)	-	**81.0**	**39.8**

1. They make prediction on 1/8 feature map

2. Our method enjoys obviously better accuracy (+2.2% and +4.6%) at the similar speed

개인적 소감

1. 속도 하나는 독보적이다

2. 속도를 중점적으로 focus하면서 성능도 최대한 지킬려고 노력한 느낌
   - 아키텍쳐 설계도 합리적이고 속도에 비해 성능도 나쁘지 않음

3. Training method(PA) 는 좀 애매한 느낌 (robust 할 수 있을까?)
   1) 가령 한 이미지에 text instance 가 엄청 많으면 4d-similarity vector 로 다 표현하게 학습할 수 있을까?
   2) text box를 binary segmentation 하는게 맞는건지 잘 모르겠음
   3) kernel을 정의하기 애매한 text나 이미지들도 wild 에선 존재할 듯

-> 속도는 빠르고 그 속도는 가성비 좋은 아키텍쳐 디자인에서 온 것 같으니 PA는 빼고 아키텍쳐만 한번 갖다 써볼까..

Q & A

감사합니다.