

ReADS: A Rectified Attentional Double Supervised Network for Scene Text Recognition

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Introduction

Two main techniques adopted in scene text recognition for decoding

- Connectionist Temporal Classification (CTC)
 ✓ Better efficiency and easier to train
 ✗ Implicit semantic dependency modeling
- Attentional sequence recognition (Attn)
 - ✓ Better accuracy
 - **×** Overfitting on the limited data



Introduction

Our main contributions are three-fold:

- Both CTC and Attn are applied in our method but with different modules.
- An attention mechanism is applied in the encoder and a rectified module is also used in front of the encoder.
- Our proposed method achieves the state-of-the-art performance on both regular and irregular scene text benchmarks.



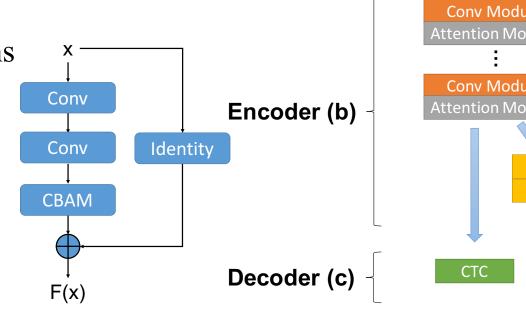
Method

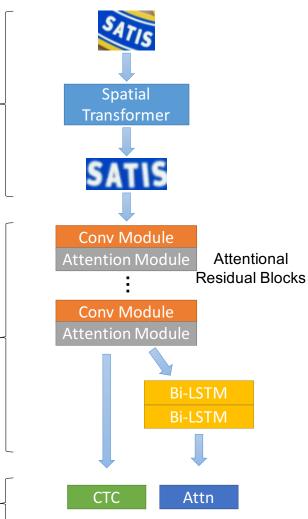
The ReADS is composed of three parts, the **rectifier**, the **encoder**, and the **Rectifier** (a) **decoder**.

Rectifier: An STN with a predicted TPS.

Encoder:

An attention mechanisms (CBAM) is adopted in the encoder and two branches is elaborate to extract features.





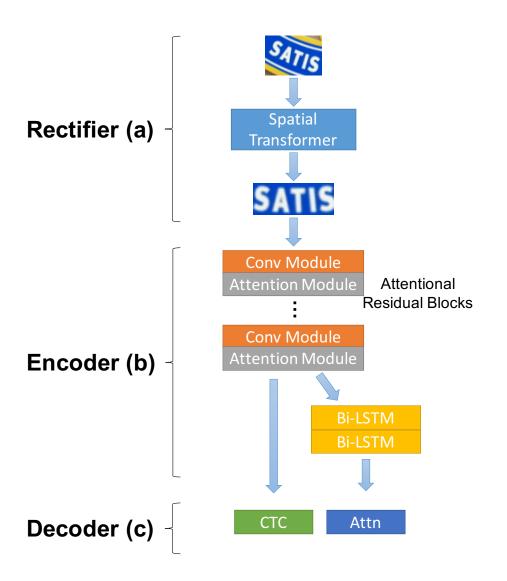


Method

Decoder:

We adopt two kinds of techniques in the decoding phase, namely CTC and Attn, to take both advantages of them. The CTC is responsible for recognition using inherent texture features, While Attn mainly focuses on semantic context modeling.

 $L_{total} = L_{Attn} + \lambda L_{CTC},$





Experiments

Our method gets five first, one second and one competitive results on a total of seven benchmarks.

Method	Regular Text				Irregular Text				
	IIIT5K	SVT	IC03	IC13	IC15-2077	IC15-1811	SVTP	CUTE	
Jaderberg et al. 2014 [4]	-	80.7	93.1	90.8	-	-	-	-	
Shi et al. 2016 [1]	78.2	80.8	89.4	86.7	-	-	-	-	
Shi et al. 2016 [16]	81.9	81.9	90.1	88.6	-	-	71.8	59.2	
Liu et al. 2016 [2]	83.3	83.6	89.9	89.1	-	-	73.5	-	
Gao et al. 2017 [3]	81.8	82.7	89.2	88.0	-	-	-	-	
Cheng et al. 2018 [21]	87.0	82.8	91.5	-	68.2	-	73.0	76.8	
Liu et al. 2018 [30]	83.6	84.4	91.5	90.8	60.0	-	73.5	-	
Shi et al. 2019 [17]	<u>93.4</u>	93.6	94.5	91.8	-	76.1	78.5	79.5	
Liao et al. 2019 [31]	92.0	82.1	-	91.4	-	-	-	78.1	
Zhan & Lu et al. 2019 [32]	93.3	90.2	-	91.3	-	76.9	<u>79.6</u>	<u>83.3</u>	
Luo et al. 2019 [18]	91.2	88.3	<u>95.0</u>	92.4	68.8	-	76.1	77.4	
Gao et al. 2019 [33]	89.9	87.2	93.3	92.9	<u>74.5</u>	-	76.4	70.8	
Baek et al. 2019 [34]	87.9	87.5	94.4	92.3	71.8	<u>77.6</u>	79.2	74.0	
Liu et al. 2019 [35]	85.2	85.5	92.9	90.3	65.7	71.8	74.4	-	
Wan et al. 2020 [36]	94.7	90.6	-	<u>93.9</u>	-	75.2	79.2	81.3	
Wang et al. 2020 [37]	90.5	82.2	-	-	-	-	-	<u>83.3</u>	
Ours	91.0	<u>91.2</u>	96.1	94.5	75.1	80.4	83.3	83.7	



Experiments

We conduct two sets of experiments for ablation studies. The first is to analyze the impact of some modules in the network. The second is to verify the effectiveness of double supervised branches.

Brar	Branches Regular Text			Irregular Text					
Attn	CTC	IIIT5K	SVT	IC03	IC13	IC15-2077	IC15-1811	SVTP	CUTE
	✓	88.6	87.3	92.4	90.3	72.1	76.5	77.1	78.8
\checkmark		91.0	90.6	94.3	93.3	75.7	80.2	84.2	82.3
✓	✓	91.0	91.2	96.1	94.5	75.1	80.4	83.3	83.7

Results of using different supervised branches

Мо	dules	Regular Text				Irregular Text				
Rectifier	Attentions	IIIT5K	SVT	IC03	IC13	IC15-2077	IC15-1811	SVTP	CUTE	
		89.4	87.6	94.8	93.1	70.4	75.0	76.7	80.2	
	✓	90.0	90.0	95.3	93.4	74.3	79.2	80.3	77.4	
✓		90.1	90.3	94.6	92.3	72.8	78.4	81.2	83.7	
\checkmark	✓	91.0	91.2	96.1	94.5	75.1	80.4	83.3	83.7	

Results of using different modules



Future work

- We plan to explore stronger attention mechanisms especially for irregular text.
- Merging predictions from CTC and Attn branches is another interesting topic.
- We will combine these two techniques for better results.

Thanks for listening !