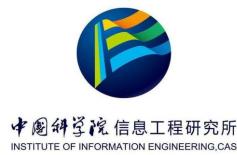


Gaussian Constrained Attention Network for Scene Text Recognition

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• Method

- Experiments
- Conclusion



• Attention Mechanism is the Mainstream Method in Scene Text Recognition

- > The model predicts corresponding alignments for every characters
- Inspired from Neural Machine Translation (NMT) and Image Caption (IC)



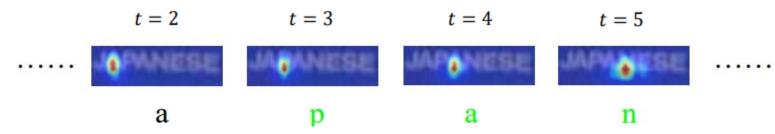
• Existing Methods does not Fully Use the Characteristic of Text Recognition

- > Different from NMT and IC, the attention weights in text recognition is concentrated
- > The attention weights seems like a Gaussian distribution
- Existing methods do not modify the attention operation for text recognition specifically





- Existing Attention Operation may Lead to Attention Diffusion
 - > Attention diffusion is the problem that the attention weights are not concentrated
 - > The noise features are introduced into the decoding and lead to wrong predictions



- Can We Introduce Gaussian Distribution into the Attention Operation?
 - > In this paper, we propose a Gaussian Constrained Refinement Module
 - > With refinement the attention weights become more concentrated and accurate



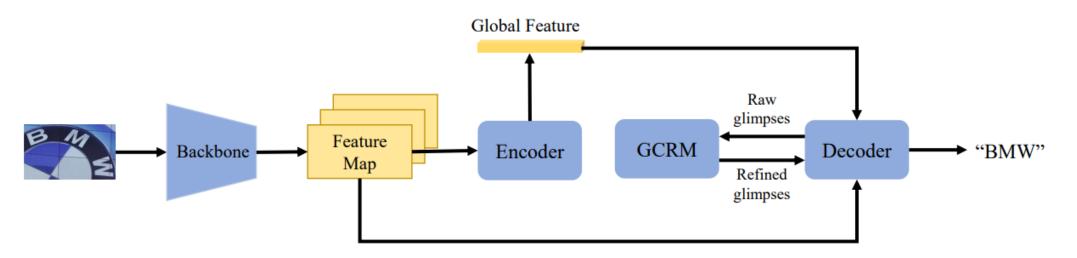


• Method

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Method: Framework

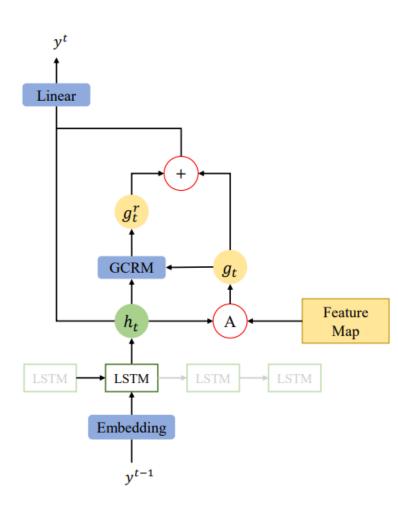




- ➢ Our Gaussian Constrained Attention Network is based on SAR^[1]
- > The proposed GCRM refines the raw attention weight to make it more concentrated and accurate
- ➢ The Backbone adopts a 31-layer ResNet
- ➤ The Encoder is a 2-layer LSTM

[1] H. Li, P. Wang, C. Shen, and G. Zhang, "Show, attend and read: A simple and strong baseline for irregular text recognition," in AAAI, 2019, pp. 8610-8617

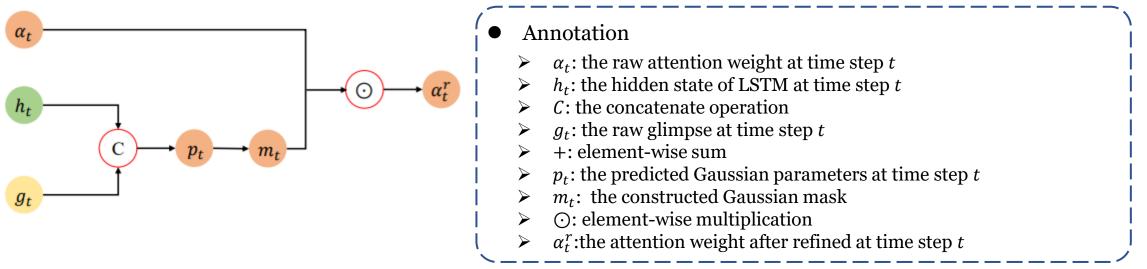
Method: Decoder



- Annotation
 - \succ y^t : the predicted character at time step t
 - > h_t : the hidden state of LSTM at time step t
 - A: the attention operation
 - g_t : the glimpse calculated attention weight and feature map
 - +: Element-wise sum
- > The attention-based decoder is combined with proposed GCRM
- In each iteration, the attention weight is calculated between feature map and the hidden state h_t , then the glimpse g_t is generated
- GCRM tries to refine the raw attention weight with the h_t and g_t , then generates the glimpse g_t^r with the refined attention weight
- > The final prediction is predicted based on h_t , g_t and g_t^r

Method: GCRM





→ GCRM predicts an additional Gaussian mask to refine the raw attention weight α_t

- Pipeline of the GCRM:
 - a) The Gaussian parameters p_t are first predicted by hidden state h_t and raw glimpse g_t
 - b) The Gaussian mask m_t is constructed with the predicted parameters p_t
 - c) The Gaussian mask m_t is applied to refine the raw attention weight α_t with element-wise multiplication





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Experiments

IIII ICPR20

Performance

Methods	IIIT5K	SVT	IC13	IC15	SVTP	CUTE
Shi et al. [13]	81.2	82.7	89.6	-	-	-
Shi et al. [50]	81.9	81.9	88.6	-	71.8	59.2
Lee et al. [49]	78.4	80.7	90.0	-	-	-
Yang et al. [36]	-	-	-	-	75.8	69.3
Cheng et al. [37]	87.4	85.9	93.3	70.6	-	-
Cheng et al. [52]	87.0	82.8	-	68.2	73.0	76.8
Liu et al. [57]	92.0	85.5	91.1	74.2	78.9	-
Bai et al. [65]	88.3	87.5	94.4	73.9	-	-
Liu et al. [66]	87.0	-	92.9	-	-	-
Liu et al. [67]	89.4	87.1	<u>94.0</u>	-	73.9	62.5
Shi et al. [18]	93.4	89.5	91.8	76.1	78.5	79.5
Liao et al. [53]	91.9	86.4	91.5	-	-	79.9
Zhan et al. [56]	93.3	90.2	91.3	76.9	79.6	83.3
Xie et al. [60]	-	-	-	68.9	70.1	82.6
Li et al. [26]	91.5	84.5	91.0	69.2	76.4	83.3
Luo et al. [25]	91.2	88.3	92.4	74.7	76.1	77.4
Yang et al. [54]	94.4	88.9	93.9	78.7	<u>80.8</u>	87.5
Wang et al. [58]	94.3	89.2	93.9	74.5	80.0	84.4
SAR-reproduced	93.0	86.7	90.8	76.1	77.0	83.7
GCAN (Ours)	94.4	<u>90.1</u>	93.3	<u>77.1</u>	81.2	<u>85.6</u>

- ➢ GCAN achieves best performance on 2 datasets and second best performance on 3 datasets
- ➢ GCAN is much better than our baseline SAR

ICPR 2020

Gaussian Constrained Attention Network for Scene Text Recognition

GCRM brings significant improvements with or without the character-level supervision Estimation perpendicute to estimate the Council of a state of a formalistic data of a state of the CODM

- > *Estimation* represents to estimate the Gaussian parameters instead of predicted by GCRM
- ➢ GCAN consumes less than **10ms** more during both training and inference compared with SAR

Experiments

Ablation Study

Methods	L_{att}	IIIT5K	SVT	SVTP	IC15
SAR-reproduced		93.0	86.7	77.0	76.1
SAR-reproduced	\checkmark	93.1	87.3	78.8	75.4
with Estimation		93.4	88.1	78.4	75.6
with Estimation	\checkmark	93.8	88.4	78.8	77.5
with GCRM		93.6	86.9	79.1	77.0
with GCRM	\checkmark	94.4	90.1	81.2	77.1

Methods	Training	Inference	
SAR-reproduced	67.9ms	45.4ms	
GCAN	75.5ms	54.3ms	



Gaussian Constrained Attention Network for Scene Text Recognition

Performance Comparison of Different Text Length

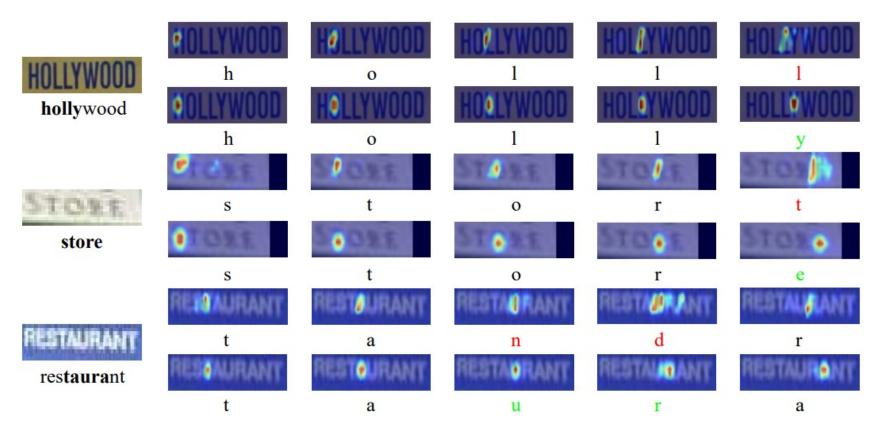
- 45.0% 40.0% 35.0% 30.0% Error Rate 25.0% 20.0% 15.0% 10.0% 5.0% 0.0% 2 8 10 12 >124 6 Label Length GCAN SAR SAR Char
- > The error rate on different length of text
- ➢ GCAN is more robust with longer text



Experiments

Visualization

Experiments



> The first line of each image is the attention weights of SAR, and the second line is from our GCAN

▶ With the proposed GCRM, the problem of attention diffusion is alleviated significantly

Gaussian Constrained Attention Network for Scene Text Recognition







• Method

• Experiments

• Conclusion





- In this paper we introduce the problem of attention diffusion
- We propose a novel Gaussian Constrained Refinement Module (GCRM)to deal with attention diffusion
- GCRM is flexible and can be applied into the most existing attention-based methods
- Combining GCRM and SAR, our Gaussian Constrained Attention Network achieves convincing performance
- In future, the specifical attention operation for text recognition is worth exploring



Gaussian Constrained Attention Network for Scene Text Recognition

Thanks for Your Watching !



