PSSTRNET: PROGRESSIVE SEGMENTATION-GUIDED SCENE TEXT REMOVAL NETWORK

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ABSTRACT

Scene text removal (STR) is a challenging task due to the complex text fonts, colors, sizes, and background textures in scene images. However, most previous methods learn both text location and background inpainting implicitly within a single network, which weakens the text localization mechanism and makes a lossy background. To tackle these problems, we propose a simple Progressive Segmentation-guided Scene Text Removal Network(PSSTRNet) to remove the text in the image iteratively. It contains two decoder branches, a text segmentation branch, and a text removal branch, with a shared encoder. The text segmentation branch generates text mask maps as the guidance for the regional removal branch. In each iteration, the original image, previous text removal result, and text mask are input to the network to extract the rest part of the text segments and cleaner text removal result. To get a more accurate text mask map, an update module is developed to merge the mask map in the current and previous stages. The final text removal result is obtained by adaptive fusion of results from all previous stages. A sufficient number of experiments and ablation studies conducted on the real and synthetic public datasets demonstrate our proposed method achieves state-of-the-art performance. The source code of our work is available at: https://github.com/GuangtaoLyu/PSSTRNet.

Index Terms— Scene text removal, segmentation, image inpainting, progressive process

1. INTRODUCTION

Scene text contains quite a lot of sensitive and private information. To prevent the private information in images from being used illegally, scene text removal(STR) is proposed to address this issue.

The well-known Pix2Pix[1] which used patch-GAN for image translation can be applied to the STR task. So, Scene Text Eraser(STE)[2] adopted its idea and used a single-scaled sliding window to remove the text in each patch independently. This method processed STR locally without considering the global context information. EnsNet[3] developed several designed loss functions and a lateral connection to further enhance the STR performance. However, these single stage-based STR methods may modify non-text pixels in images and result in excessive or inadequate inpainting results. MTRNet[4] employed conditional GAN and used the text segmentation results for inpainting region guidance. EraseNet[5] used a text detection branch to locate text regions and remove text from coarse to fine. However, the STR performance of those methods relay heavily on only one-shot text segmentation results. PERT[6] performed multi-stage text erasure in a progressive way[7] with explicit text region guidance. However, it could not get more accurate text regions in iteration stages, and the network was difficult to train.

In this paper, we propose a Progressive Segmentationguided Scene Text Removal Network (PSSTRNet) with very low computation costs. It is built on a very simple and small network, which has one feature-sharing encoder and two decoders to generate text segmentation and removal results individually. However, we find that single forward computing generates very coarse STR results. So, we input the text removal image to the network again to yield refined results progressively. A Mask Update module is added in the text segmentation branch for generating more precise text segmentation results. Additionally, we design an adaptive fusion method to make full use of the results of different iterations.

We conducted sufficient experiments on two datasets: SCUT-EnsText[5] and SCUT-syn[3]. Both the qualitative and quantitative results indicate that PSSTRNet can outperform previous state-of-the-art STR methods.

We summarize the contributions of this work as follows:

- We propose a novel STR network termed PSSTRNet. It decomposes the challenging STR task into two simple subtasks and processes text segmentation and background inpainting progressively.
- We design a Mask Update module and an adaptive fusion strategy to make full use of results from different iterations.
- Our proposed PSSTRNet is light-weighted and achieves SOTA quantitative and qualitative results on public synthetic and real scene datasets.

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Fig. 1. The overall architecture of PSSTRNet. TSB is the text segmentation branch that outputs a mask with $\frac{1}{4}$ size of input text image I_{in} . The mask is further corrected in the Mask-Update block. TRB is the text removal branch, and it outputs the temporary text removed result I_{temp} . Then, I_{temp} and I_{in} are merged in the Merge block to get correct text removed result I_{out}^i in current iteration. The final result is the adaptive fusion of results from all iterations.

2. PROPOSED METHOD

get a more complete text mask map M^i_{comp} .

2.1. Overall pipeline

As shown in Fig.1, the pipeline of our model consists of two branches: the text segmentation branch and the text removal branch. They share a lightweight encoder with 5 residual convolutional layers. PSSTRNet implements text segmentation and erasing process on the previous results iteratively, and merges all the results in each iteration as final output adaptively.

2.2. Text Segmentation Branch

The text segmentation branch contains a Text Region Positioning module (i.e., TRPM), an upsampling process, and a Mask Updating module(i.e. MUM). To reduce the computational cost, TRPM is designed to locate the unremoved text regions in text removal images from the output of the previous iteration. It outputs the expansion text mask with 1/4 size of the original image. Then, this mask goes through the upsampling process by two bilinear interpolations to get the mask owning the same size as the origin image. The size recovered expansion text mask is denoted as M_{temp}^i ($M_{temp}^i \in [0, 1]$, 1 for text region and 0 for non-text region). With the input of the previous text mask M^{i-1} and M_{temp}^i , MUM updates M^{i-1} and outputs the final text mask map(M^i) in i_{th} iteration. It includes a Merging block and a Correcting block. The Merging block merges M_{temp}^i and M^{i-1} through Eq.(1) to

In Correcting block[8],
$$M_{comp}^{i}$$
 is first multiplied with the origin text image I_{in} , to generate the text-attentive features I_t and the background-attentive features I_b , respectively. Then, we feed these two types of features into two parallel context exploration (CE) blocks to perform contextual reasoning for discovering the false-positive distractions I_{fp} and the false-negative distractions I_{fn} , respectively. The CE block consists

(1)

 $M_{comp}^{i} = max(M_{temp}^{i}, M^{i-1})$

of four dilation convolutions with different dilation rates of 1, 2, 3, 5. The outputs of all the four dilation convolutions are concatenated and then fused via a 1×1 convolution. Using such a design, the CE block gets the capability of exploring abundant context over a wide range of scales and thus can be used for context reasoning.

After context reasoning, we can correct the mask in the following way:

$$I_{in} = \text{NR}(I_{in} - \alpha I_{fp}),$$

$$I_{in} = \text{NR}(I_{in} + \beta I_{fn})),$$

$$M^{i} = \sigma(I_{in}).$$
(2)

where α and β are the learnable parameters that are initialized as 1. NR is batch normalization and ReLU operation. σ is the sigmoid function.

We use the element-wise subtraction operation to restrain the ambiguous backgrounds (i.e., false-positive distractions) and the element-wise addition operation to enhance the missing text regions (i.e., false-negative distractions). Then, we apply a sigmoid function to get a more precise text mask map M^i .

2.3. Text Removal Branch

Similarly, the text removal branch and the shared encoder are built on a simplified residual U-Net structure. The encoder has five convolution layers with kernel size k×k (k=7,5,3,3,3 in each layer in order). Each layer contains a batch normalization, a ReLU, and a residual block after convolution operation. With inputting the previous result I_{out}^{i-1} in i_{th} iteration, the output is defined as I_{out}^{i} .

The goal of STR is to remove the text areas while keeping the background areas unchanged. So, we merge the text regions of I_{out}^i , and non-text regions of I_{in} as the final output I_{out}^i of i_{th} iteration as in Eq.(3).

$$I_{out}^{i} = I_{in}^{i} * (1 - M^{i}) + I_{out} * M^{i},$$
(3)

Where I_{in} is the original text image.

Finally, after a specific number of iterations, the text regions can be extracted more accurately and the text erased cleaner. However, since the process of mapping RGB images to the latent features and mapping them back to the RGB space occurs in each iteration, it results in information distortion in every recurrence. To solve these problems, we merge the intermediate iteration outputs in an adaptive merging way as formulated in Eq.(4). The final output is I_{out} .

$$M' = \frac{\sum_{1}^{n} M^{i}}{n}$$

$$I'_{out} = \frac{\sum_{1}^{n} I^{i}_{out} * M^{i}}{n}$$

$$I'_{out} = (I'_{out} + \epsilon)/(M' + \epsilon)$$

$$I_{out} = I'_{in} * (1 - M') + I_{out} * M'$$
(4)

where ϵ is a smoothing factor and is set to be $1e^{-8}$

2.4. Loss Functions

We introduce several loss functions for PSSTRNet learning, including region content loss L_{rc} , perceptual loss L_p , style loss L_s and segmentation loss L_{seg} . Given the origin text image I_{in} , text-removed ground truth (gt) I_{gt} and the binary text gt mask M_{gt} , the text removal output of PSSTRNet in each iteration i_{th} is denoted as I_{out}^i and text segmentation result as M^i .

Region content Loss. We use L_1 loss as the region content loss for text and non-text region reconstruction:

$$L_{rc} = \gamma_1 * \sum_{i} ||M_{gt} \odot (I^i_{out} - I_{gt})||_1 + \gamma_2 * \sum_{i} ||(1 - M_{gt}) \odot (I^i_{out} - I_{gt})||_1.$$
(5)

where $\gamma_1 \gamma_2$ is set to be 50,10.

Perceptual Loss. We employ the perceptual loss[9] in Eq.(6). Φ_i is the activation map of the *i*-th layer of the VGG-16 backbone. H_n , W_n , and C_n denotes the height, width and channel numbers of feature maps outputted from n_{th} layer of VGG-16.

$$L_{p} = \sum_{i} \sum_{n} \frac{1}{H_{n}W_{n}C_{n}} ||\Phi_{i}(I_{out}^{i}) - \Phi_{i}(I_{gt})||_{1}$$
(6)

Style Loss. We compute the style loss [10] as Eq.(7), where G_n is the Gram matrix constructed from the selected activation maps.

$$L_s = \sum_i \sum_n \frac{1}{H_n W_n C_n} ||G_n(I_{out}^i)_T \cdot G_n(I_{out}^i) - G_n(I_{gt})^T \cdot G_n(I_{gt})||_1$$

$$(7)$$

Segmentation Loss. For learning of text segmentation module, L_{seg} in Eq.8 is formulated as dice loss [11].

$$L_{seg} = \sum_{i} 1 - \frac{2\sum_{x,y} (M^{i}(x,y) \times M_{gt}(x,y))}{\sum_{x,y} (M^{i}(x,y)^{2} \times M_{gt}(x,y))} * \gamma_{i} \quad (8)$$

where γ_i is set to be 1,2,3. (x, y) denotes each pixel coordinate in the image.

In Summary, the total loss for training PSSTRNet is the weighted combination of all the above loss functions.

$$L_{total} = 200 * L_s + 0.1 * L_p + L_{rc} + L_{seg}$$
(9)

3. EXPERIMENTS AND RESULTS

3.1. Datasets and Evaluation Metrics

SCUT-Syn. This synthetic dataset only includes English text instances, including 8,000 images for training and 800 images for testing. More details can be found in [12].

SCUT-EnsText. It contains 2,749 training images and 813 test images which are collected in real scenes. More descriptions refer to [5].

Evaluation Metrics: For detecting text on the output images, we employ a text detector CRAFT[13] to calculate recall and F-score. The lower, the better. Six alternative metrics are adopted for measurement the equality of the output images, i.e, PSNR, MSE, MSSIM, AGE, pEPs, and pCEPS[3]. A higher MSSIM and PSNR, and a lower AGE, pEPs, pCEPS, and MSE indicate better results.



Fig. 2. Comparison results with other SOTA methods on SCUT-EnsText and SCUT-Syn datasets.



Fig. 3. The results of different iterations on SCUT-EnsText and SCUT-Syn datasets. It_i is the M_{temp} of i_{th} iteration. Final represents the final STR results and final fused mask.



Fig. 4. The results of ablation study on SCUT-EnsText dataset.

3.2. Implementation Details

We train PSSTRNet on the training set of SCUT-EnsText and SCUT-Syn and evaluate them on their testing sets, respectively. The masks are generated by subtraction from the input images and the labels. We use dilated process for covering as much of the text area as possible. We follow [5] to apply data augmentation during the training stage. The model is optimized by adam optimizer. Experimentally, we set the iteration number to be 3. The learning rate is set to be 0.001. The learning rate decayed by 50% every 10 epochs. The PSSTR-Net is trained by a single NVIDIA GPU with a batch size of 6 and input image size of 256×256 .

Table 1. Ablation study results of different modules effect onSCUT-Text.

Iterations	PSNR	MSSIM	MSE	AGE	pEPs	pCEPs
1It.	32.97	96.41	0.0017	2.0742	0.0180	0.0105
2It.	34.09	96.40	0.0014	1.7788	0.0144	0.0077
3It.	32.44	95.56	0.0028	2.4506	0.0209	0.0125
4It.	32.15	95.69	0.0020	2.1221	0.0184	0.0100
2It.+AF	34.13	96.42	0.0014	1.7388	0.0142	0.0075
3It.+AF	34.65	96.75	0.0014	1.7161	0.0135	0.0074
4It.+AF	33.02	96.46	0.0017	2.0084	0.0177	0.0098

3.3. Ablation Study

In this section, we study the effect of the number of iterations and the adaptive fusion method on the SCUT-Text dataset. In total, we conduct seven experiments by designing the network with 1) one iteration (1It.), 2) two iterations (2It.), 3) three iterations (3It.), 4) four iterations (4It.), 5) two iterations with adaptive fusion(2It.+AF), 6) three iterations with adaptive fusion(3It.+AF), 7) four iterations with adaptive fusion(4It.+AF). All experiments use the same training and test settings.

Qualitative and quantitative results are illustrated in Fig.4 and table1, respectively. We can see that the network generates the best STR results with two iterations if only considering iteration times (i.e., comparing results in the first four experiments). This arises from that the information is lost in increasing iterations using encoder-decoder architecture. By adding an adaptive fusion strategy, the model with three iterations (3It.+AF) gets the best results. It is because adaptive fusion utilizes previous removal results and could also get more erased regions on text when increasing iterations. As shown in (b)(c)(d) of Fig.3, our method gets a roughly segmentation result at 1_{st} iteration and extracts the rest part of the text segments, and cleaner text removal results in the following iterations. However, We find that the style of intermediate result is distorted when increasing the iterative times to 4 or larger. The decreasing qualitative results of 7_{th} experiment 4It.+AF in table1 reflect this point.

3.4. Comparison with State-of-the-Art Approaches

We compare our proposed PSSTRNet with five state-ofthe-art methods: Pix2pix[1], STE[2], EnsNet[3], EraseNet[5] and PERT [6], on both SCUT-EnsText and SCUT-Syn datasets. We retrain all the models with the setting as official reported, but input the image of size 256×256 . The source code of PERT is not released currently, so we do not show its qualitative results.

Qualitative Comparison. As shown in the 1st row of Fig.2, our model can preserve more information in non-text areas while erasing text regions cleaner. Compared with other state-of-the-art methods, the results of our proposed PSSTR-Net have significantly fewer color discrepancies and blurriness, especially in 1st, 2nd, and 4th lines. It demonstrates our model could generate more semantically elegant results on text removal and background inpainting results.

Quantitative Comparison. As shown in Table 2 and 3, our method produces the best scores on most text removal

Method	Image-Eval							Detection-Eval(%)		
wiethou	PSNR ↑	MSSIM↑	MSE↓	AGE↓	pEPs↓	pCEPs↓	P↓	R↓	F↓	
Original Images	-	-	-	-	-	-	79.8	69.7	74.4	
Pix2pix	26.75	88.93	0.0033	5.842	0.048	0.0172	71.3	36.5	48.3	
Scene Text Eraser	20.60	84.11	0.0233	14.4795	0.1304	0.0868	52.3	14.1	22.2	
EnsNet	29.54	92.74	0.0024	4.1600	0.2121	0.0544	68.7	32.8	44.4	
EraseNet	32.30	95.42	0.0015	3.0174	0.0160	0.0090	53.2	4.6	8.5	
PERT(official)	33.25	96.95	0.0014	2.1833	0.0136	0.0088	52.7	2.9	5.4	
PSSTRNet(Ours)	34.65	96.75	0.0014	1.7161	0.0135	0.0074	47.7	5.1	9.3	

Table 2. Comparison with SOTA methods and proposed method on SCUT-EnsText. R: Recall; P: Precision; F: F-score.

 Table 3. Comparison with SOTA methods and proposed method on SCUT-Syn.

Method	PSNR ↑	MSSIM↑	MSE↓	AGE↓	pEPs↓	pCEPs↓	Parameters↓	Inference Time↓
Pix2pix	25.16	87.63	0.0038	6.8725	0.0664	0.0300	54.4M	2.96ms
Scene Text Eraser	24.02	89.49	0.0123	10.0018	0.0728	0.0464	89.16M	18.45ms
EnsNet	37.36	96.44	0.0021	1.73	0.0276	0.0080	12.4M	5.1 ms
EraseNet	38.32	97.67	0.0002	1.5982	0.0048	0.0004	19.74M	8.67ms
PERT(official)	39.40	97.87	0.0002	1.4149	0.0045	0.0006	14.00M	-
PSSTRNet(Ours)	39.25	98.15	0.0002	1.2035	0.0043	0.0008	4.88M	14.9ms

evaluation protocols for both SCUT-EnsText and SCUT-Syn datasets. Furthermore, our model has the minimum number of parameters, which only has about one-third of the parameters of PERT that also implements STR in a progressive way.

4. LIMITATION

As shown in the 3rd row of Fig.2 and Fig.4, there are still some texts that are not be removed. Besides, our model's inference time is longer than others since we apply iterative processes. Hence, there is still some improvement space of our method in terms of text detection and inference time. Combining our work with a better scene text detector may lead to better results.

5. CONCLUSION

In this paper, we present a light-weighted progressive network PSSTRNet for scene text removal in images. It is based on an encoder-decoder structure with a shared encoder and two decoder branches for progressive text segmentation and text removal respectively. A Mask Updated module is developed to gradually acquire more and more complete and accurate text masks for better guidance. Instead of using the output from the final iteration, we aggregate the results in each iteration by adaptive fusion. Experimental results indicate that the proposed method achieves state-of-the-art performance on both synthetic and real-world datasets while maintaining low complexity.

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