Abstract

Scene text removal (STR) contains two processes: text localization and background reconstruction. Through integrating both processes into a single network, previous methods provide an implicit erasure guidance by modifying all pixels in the entire image. However, there exists two problems: 1) the implicit erasure guidance causes the excessive erasure to non-text areas; 2) the one-stage erasure lacks the exhaustive removal of text region. In this paper, we propose a ProgrEssively Region-based scene Text eraser (PERT), introducing an explicit erasure guidance and performing balanced multi-stage erasure for accurate and exhaustive text removal. Firstly, we introduce a new region-based modification strategy (RegionMS) to explicitly guide the erasure process. Different from previous implicitly guided methods, RegionMS performs targeted and regional erasure on only text region, and adaptively perceives stroke-level information to improve the integrity of non-text areas with only bounding box level annotations. Secondly, PERT performs balanced multi-stage erasure with several progressive erasing stages. Each erasing stage takes an equal step toward the text-erased image to ensure the exhaustive erasure of text regions. Compared with previous methods, PERT outperforms them by a large margin without the need of adversarial loss, obtaining SOTA results with high speed (71 FPS) and at least 25% lower parameter complexity. Code is available at https://github.com/wangyuxin87/PERT.

1. Introduction

As one of the most important mediums in information interaction, scene text contains quite a lot of sensitive and private information [5][15][2][9]. To prevent these private messages from being used in illegal ways, Scene Text Removal (STR) task aims to remove the texts in the scene images and fill in the background information correspondingly. Benefiting from the development of Generative Adversarial Networks (GANs) [6][7], recent STR methods achieve promising results with various solutions [4][33]. However, there are still two problems to be solved.

The first problem is the excessive erasure problem, which makes the poor integrity of non-text regions. Recent methods [33][4] simply use paired images to train the model, integrating text localization and background reconstruction into a single network. However, since the text instances are sparse and exist in partial areas of scene images, such implicit erasure guidance that modifies all pixels in the entire image is not suitable for STR task. Though EraseNet [10] additionally uses a mask branch to enhance the text location perceiving, the pixel-wise reconstruction on the entire image is still performed under an implicit erasure guidance. As shown in red box of Fig. 1(b), such implicit erasure guidance has limited capability to maintain the integrity of non-text areas. In this paper, we are the first to argue that the explicit erasure guidance is the key, which provides targeted and regional erasure on only text regions to prevent modifying non-text areas.

The second problem is the inexhaustive erasure problem, resulting in the remnants of text traces. Early methods [13][33] achieve text removal through a one-stage erasure, which has limited capability to obtain exhaustive erasure of text regions. Though recent methods [17][10] design a multi-stage eraser to refine the coarse erased image, due
to the different learning difficulty caused by the same text-
erased image supervision, it is difficult to balance the net-
work architecture between the coarse and refinement stage.
Thus, such imbalanced multi-stage erasure will leave some
traces of text regions in the removal result (blue box of Fig.
1(b)). Based on the above analyses, how to construct the
balanced multi-stage erasure needs to be explored.

In this paper, we propose a novel ProgrEssively Region-
based scene Text eraser (PERT) to handle above two prob-
lems from following two aspects: introducing an explicit
erasure guidance and constructing the balanced multi-stage
erasure. As shown in Fig. 2, PERT consists of several eras-
ing blocks. Instead of integrating text localization and back-
ground reconstruction into a heavy network, we construct a
lightweight decoupled structure of text localization network
(TLN) and background reconstruction network (BRN) in
each erasing block (shown in Fig. 3). 1) The explicit era-
sure guidance. As the text region predicted by TLN is a
natural erasure guidance, we propose a new region-based
modification strategy (RegionMS) to explicitly guide the
BRN to only modify the predicted text regions. As back-
ground textures are directly inherited from the original im-
age. RegionMS regards scene text removal as a targeted
and regional erasure process to prevent the modification of
non-text areas. Since the reconstruction learning on the fi-
nal erased image aims to learn the stroke-level reconstruc-
tion rules, RegionMS enables TLN to adaptively perceive
stroke-level information to further ensure the integrity of
non-text areas (Fig. 1(c)) with only bounding box level annota-
tions (Fig. 1(d)). 2) The balanced multi-stage erasure. To balance the network architecture and learning
difficulty among different stages, we firstly construct a
balanced erasure structure by sharing the parameters of
each erasing block (shown in Fig. 2). Then, through only
supervising the output of last erasing stage, PERT learns
to adaptively balance the learning difficulty among differ-
ent erasing stages, where each erasing stage aims to take
an equal step toward text-erased image (shown in Fig. 3).
As parameters are shared among all erasing blocks, PERT
is able to achieve exhaustive erasure with a light structure.
In addition, to further improve the erasure performance, we
propose a new Region-Global Similarity Loss (RG loss) to
consider the feature consistency and visual quality of era-
sure results from both local and global perspective. Com-
pared with previous methods, PERT obtains more exhaus-
tive erasure of text regions while maintaining the integrity
of non-text areas. Without the need of adversarial loss,
PERT outperforms existing methods by a large margin with
high speed (71 FPS) and at least 25% lower parameter com-
plexity.

The proposed method has several novelties and advan-
tages: 1) To best of our knowledge, we are the first to
propose an explicit erasure guidance in STR task. Fur-
therefore, we also provide qualitative visualization to prove
how it prevents the erasure of non-text regions and why it
is more suitable for STR task. 2) Through designing a bal-
anced erasure structure and supervising only the last erasing
stage, PERT effectively balances the learning difficulty and
network structure among different erasing stages, obtaining
exhaustive erasure of text regions with a light architecture.
3) A new RG loss is proposed to improve the feature con-
sistency and visual quality of erasure results. The SOTA re-
results on both synthetic and real-world datasets demonstrate
the effectiveness of our method.

2. Related Work

Early STR methods [8, 20] mainly cascade the conven-
tional text localization and background reconstruction pro-
cesses for text removal. With the deep learning emerging as
the most promising machine learning tool [19, 30, 21, 14],
recent STR methods try to integrate the two independent
processes into a single architecture by end-to-end training
the network with paired images. Nakamura et al. [13] im-
plement a patch-based skip-connected auto-encoder for text
removal. Under the premise of reducing the consistency of
removal image, the coarse erasure result is obtained by
taking the patch-level images as inputs. MTRNet [18] con-
catenates the text location map with original image to im-
prove the erasure performance. As texts are sparse in the
scene image [16, 22, 29], such implicit erasure guidance by
modifying all the pixels in the entire image will cause the
excessive erasure to non-text regions. Benefiting from the
development of GANs [1, 35, 32], recent methods attempt
to adopt adversarial loss to improve the erasure visuality.
Though the adversarial loss significantly increases the train-
ing difficulty, the impressive improvement in visual quality
makes it popular in STR task. Following the structure of
cGAN [12], Ensnet [33] designs a local-aware discrimina-
tor to ensure the consistency of the erased regions. EraseNet
[10] and MTRNet++ [17] further construct a refinement-
network to optimize the coarse output from the first era-
sing stage. Following these methods [10, 17], our method
falls into multi-stage eraser, but we try to balance the learn-
ing difficulty and network structure among different stages.
Compared with previous methods, PERT effectively han-
dles the excessive and inexhaustive erasure problems from

Figure 2. The pipeline of PERT. $I_{out}^{t}$ is the erased image from $t^{th}$
erasing stage.
Figure 3. The architecture of erasing block. $I^t_{out}$ means the output from stage $t$, which has the same resolution of the original image $I_{original}$. $Mask^t_i$ is the mask map generated from TLN in stage $t$. MRM means Multi-scale Reconstruction Module.

the aspects of introducing explicit erasure strategy and constructing balanced multi-stage erasure.

3. Our Approach

3.1. Pipeline

The pipeline of PERT is shown in Fig. 2, which cascades $T$ lightweight erasing blocks. Through iteratively implementing erasing block on the erased image from previous stage, the output of the last erasing block is used as the final erasure result. To eliminate the effect of text characteristic losing, we concatenate the original image $I_{original} \in \mathbb{R}^{H \times W \times 3}$ with $I^t_{out} \in \mathbb{R}^{H \times W \times 3}$ ($H$ and $W$ are height and width respectively) to generate the input of $t^{th}$ erasing block (shown in Fig. 3). For the first erasing stage, we concatenate $I_{original}$ with itself as the input.

3.2. Lightweight Erasing Block

Inspired by the manual erasure process that firstly locating text regions and then performing regional modification, we design a decoupled structure in each erasing block. As shown in Fig. 3, the erasing block contains a text localization network (TLN) for text location prediction and a background reconstruction network (BRN) for background textures reconstruction. Backbone network are shared by both TLN and BRN for feature extraction, which contains two convolution layers and five residual blocks [3].

As text instances have large-variance scales, generating the robust representation of multi-scale texts is necessary for accurate scene text detection [23, 24]. Inspired by PSP Module [34] which obtains promising performance in long-range dependency capture, we implement a PSP Module in TLN for robustly representing multi-scale texts. To reduce the computation cost, we only gradually up-sample the feature map to 1/4 size of the original image (bilinear interpolation is employed), and directly resize it to the same size of input image. Mask map $Mask^t_i \in [0, 1]$ is generated through a sigmoid layer, where $t$ is the stage number. In the training stage, we supervise $Mask^t_i$ with the bounding box level annotations.

In order to learn the robust reconstruction rules of background textures, BRN is expected to contain two characteristics: 1) Modeling low-level texture information for background and foreground texture perception. 2) Capturing high-level semantics for feature representation enhancement. Thus, we construct BRN with skip connections to perceive low-level structures from shallow layers, and employ a relative deep network for high-level semantics capture. As the background reconstruction is a more challenging task than text localization, we use the deconvolution operation in the up-sampling layer to enhance the feature representation ability. Furthermore, the Multi-scale Reconstruction Module (MRM) is constructed to predict multi-scale erasure results ($P^1_{out}$ and $P^2_{out}$), which is only implemented in the training stage for performance boosting [33].

Instead of integrating the text localization and background reconstruction into an heavy network, our decoupled structure effectively reduces the parameter size, which only needs two lightweight network for localization and reconstruction respectively (detailed in Sec. 4.4).
3.3. Region-based Modification Strategy

Different from previous implicit erasure guidance methods [33][10], which modify all the pixels in the entire image, we provide an explicit erasure guidance for targeted and regional erasure. Such explicit erasure guidance is achieved by a region-based modification strategy (RegionMS).

RegionMS is formulated in Eq. (1). Firstly, to sample the candidate erasure areas, we use the text mask map $Mask^t \in [0, 1]$ to filter reconstructed image $I^t$ from BRN. Thus, BRN will only modify the pixels in the predicted text regions. Relatively, to prevent the erasure of non-text areas, we preserve the background textures by performing element wise product between $(1 - Mask^t)$ and original image $I_{original}$. It is worth mentioning that RegionMS is also employed in MRM to generate multi-scale predictions ($P^1_{out}$ and $P^2_{out}$), and the corresponding mask map is directly resized from $Mask^t$.

$$I^t_{out} = Mask^t \times I^t + (1 - Mask^t) \times I_{original} \quad (1)$$

To better illustrate the significance of RegionMS in ensuring the integrity of non-text areas, we provide some visualization of $Mask^t$. The details about this part is available in Sec. 4.5.1.

3.4. Balanced Multi-stage Erasure

As the deep network can erase a large-range step for difficult cases while the shallow network provides a small-range one, due to the different learning difficulty caused by the same text-erased image supervision, it is difficult to balance the learning difficulty and network architecture in the multi-stage erasure [17][10]. Thus, we adopt the most straightforward approach by dividing the overall learning difficulty and total network structure into $T$ equal parts, where $T$ is an ablation study in Sec. 4.3.

Firstly, we construct a balanced erasure structure by implementing the erasing block with same structure in each erasing stage. To reduce the parameter complexity, we share the parameters among all erasing blocks. As the generation of text-erased image in $T$ different erasure degrees requires a lot of human costs, we simply supervise the output of only last erasing block, guiding the network to adaptively balance the learning difficulty among different stages. By doing these, a new balanced multi-stage erasure is obtained, where each erasing stage aims to take an equal step toward the text-erased image for exhaustive erasure (detailed in Sec. 4.5.1).

3.5. Training Objective

We use the original image $I_{original}$, text-removed ground-truth $I_{gt}$ and localization map $Mask_{gt}$ in bounding-box level (0 for non-text regions and 1 for text regions) to train PERT. The total loss contains two parts: localization loss and reconstruction loss. In order to adaptively balance the learning difficulty among different erasing stages, we only implement the reconstruction loss to the erased images ($I_{out}, P^1_{out}$ and $P^2_{out}$) in the final erasing stage. In contrast, we supervise the mask map ($Mask^t$) in each erasing stage to guarantee an accurate erasure guidance.

3.5.1 Localization loss

We use dice loss defined in [25] to guide the learning process of TLN. As shown in Eq. (2), $p_i$ is the prediction and $y_i$ is the ground-truth.

$$L_{loc} = 1 - \frac{2\sum_i p_i y_i}{\sum_i p_i + \sum_i y_i} \quad (2)$$

3.5.2 Reconstruction loss

Benefiting from the RegionMS and balanced multi-stage erasure, the simple similarity losses are sufficient to train PERT.

1) Region-Global Similarity Loss (RG loss). The RG loss is newly proposed in this paper to consider the feature consistency and visual quality of erasure results from both local and global perspective. RG loss contains two parts (shown in Eq. (3): region-aware similarity (RS) loss and global-aware similarity (GS) loss.

$$L_{RG} = L_{RS} + L_{GS} \quad (3)$$

$$L_{RS} = \sum_{i=1}^{2} \alpha_i \| (P^i_{out} - I_{i,gt}) \cdot Mask_{i,gt} \|_1 + \sum_{n=1}^{2} \beta_i \| (P^i_{out} - I_{i,gt} - \cdot Mask_{i,gt}) \|_1 + \alpha \| (I_{out} - I_{gt}) \cdot Mask_{gt} \|_1 + \beta \| (I_{out} - I_{gt}) \cdot (1 - Mask_{gt}) \|_1 \quad (4)$$

As shown in Eq. (4), RS loss takes multi-scale predictions $P^i_{out}$ into consideration. $Mask_{i,gt}$ and $I_{i,gt}$ are generated by directly resizing the mask map $Mask_{gt}$ and text-erased image $I_{gt}$. The RS loss assigns the pixels in text region with a higher weight. To be specific, we set $\alpha, \alpha_1, \alpha_2 = 13, 10, 12$ and $\beta, \beta_1, \beta_2 = 2, 0.8, 1$ respectively.

Different from RS loss, GS loss aims to penalize the consistency and enhance the visual quality from a global view. We firstly down-sample $n = 3$ activation maps $\phi_n(I_{out}) \in R^{H_n \times W_n}$ from the $4^{th}, 9^{th}, 16^{th}$ layer of pre-trained VGG16 network to $F^n_{out} \in R^{Sm \times Sm}$ through max-pooling (the same process to $I_{gt}$). Inspired by the pair-wise Markov random field, which is widely used to improve the spatial labeling contiguity, we compute the pair-wise similarities between ground-truth and predicted features. Let $\gamma^n_{ij}$ denotes the similarity between the $j^{th}$ pixel and $i^{th}$ pixel in...
feature $F^n$ (shown in Eq. [5]). $\gamma_{ij}^{n,\text{out}}$ means the similarity from $F_{\text{out}}^n$.

$$\gamma_{ij}^{n} = (F_{i}^{n})^TF_{j}^{n}/(\|F_{i}^{n}\|_2\|F_{j}^{n}\|_2) \quad (5)$$

In our experiments, we set $S_m = 8, 4$ and $1$ when $m = 1, 2$ and $3$, which means we calculate the pair-wise similarities in three different scales ($\gamma_{ij}^{n,m}, m = 1, 2, 3$) for each feature $\phi_n(I)$. Finally, the GS loss is formulated in Eq. [6]

$$L_{GS} = \sum_{n=1}^{3} \sum_{m=1}^{3} \left( \frac{1}{S_m \times S_m} (\gamma_{ij}^{n,m,\text{out}} - \gamma_{ij}^{n,m,\text{gt}})^2 \right) \quad (6)$$

2) Negative SSIM Loss [28]. This loss is used to analyse the degradation of structural information:

$$L_{ssim} = -SSIM(I_{\text{out}}, I_{\text{gt}}) \quad (7)$$

3) VGG Loss. Inspired by previous STR methods [33, 10], we also adopt VGG loss ($L_{\text{vgg}}$) to improve the erasure results. The details can be obtained in the previous methods [33, 10].

Finally, the total loss function is formulated in Eq. [8]

$$L = L_{\text{loc}} + L_{\text{RG}} + L_{\text{ssim}} + L_{\text{vgg}} \quad (8)$$

4. Experiments
4.1. Datasets and Evaluation
4.1.1 Datasets
We conduct the experiments following the setup of [10]. We train PERT on the only official training images of SCUT-Syn [33] or SCUT-EnsText [10], and then evaluate the model on the corresponding testing sets, respectively. Details of these two datasets can be found in the previous works [33, 10].

4.1.2 Evaluation
To comprehensively evaluate the erasure results of our method, we use both Image-Eval (PSNR, MSSIM, MSE, AGE, pEPs and pCEPs) and Detection-Eval (precision (P), recall (R), F-measure(F), TIoU-precision (TP), TIoU-recall (TR), TIoU-F-measure(TF)). Details about Image-Eval and Detection-Eval can be found in the previous works [11, 10]. A higher PSNR and SSIM or lower MSE, AGE, pEPs, pCEPs, P, R, F, TP, TR and TF represent better results.

4.2. Implementation Details
Data augmentation includes random rotation with maximum degree of $10^\circ$ and random horizontal flip with a probability of 0.3 during training stage. PERT is end-to-end trained using Adam optimizer. The learning rate is set to $1e-3$. The model is implemented in Pytorch and trained on 2 NVIDIA 2080Ti GPUs.

To share the parameters among different stages, we iteratively use the same erasing block in all stages. As the gradient will accumulate on the same erasing block, the simple loss.backward() & optimizer.step() are used for parameter updating. Details are available in our submitted code.

4.3. Ablation Study
4.3.1 The region-based modification strategy
As shown in Tab. [1] through introducing an explicit erasure guidance, the proposed PERT significantly improves the erasure performance by 0.66, 0.33, 0.0002, 0.3931, 0.0016 and 0.0008 in PSNR, MSSIM, MSE, AGE, pEPs and pCEPs respectively. We attribute this remarkable improvement to two reasons: 1) The RegionMS provides targeted and regional modification on only text-region textures without changing pixels in non-text areas, ensuring the integrity of text-free regions. 2) The RegionMS reduces the learning difficulty of reconstruction process, helping BRN to focus on targeted reconstruction rules of text regions without considering non-text areas. The qualitative visualization are detailed in Sec. 4.5.1

4.3.2 The balanced multi-stage erasure
As shown in Tab. [2] the one-stage erasure ($T = 1$) has a limited capability to reconstruct background textures. When we increase the number of erasing stages step-by-step, the balanced multi-stage erasure increases the performance on all metrics, and the relative increases are 1.85, 0.59, 0.0003, 0.5361, 0.0092 and 0.0034 in PSNR, MSSIM, MSE, AGE, pEPs and pCEPs respectively. Benefiting from sharing parameters among all erasing blocks, PERT step-by-step refines the erasure result with ZERO parameter size increase.

4.3.3 The Region-Global similarity loss
The RG loss penalizes the feature consistency and enhances the visual quality from both local and global views. As shown in Tab. [3] the RG loss achieves the improvement by 0.52, 0.1, 0.0001, 0.1556, 0.0026 and 0.0020 in PSNR, MSSIM, MSE, AGE, pEPs and pCEPs respectively. Benefiting from the balanced multi-stage erasure and RegionMS, the simple similarity losses are sufficient to train PERT without the need of adversarial loss.

4.4. Comparison with State-of-the-Art Methods
The quantitative results on SCUT-EnsText dataset are shown in Tab. [4]. The state-of-the-art performance demonstrates that the proposed PERT outperforms existing meth-
Table 1. Ablation studies about the RegionMS.

| Model         | PSNR | MSE   | pEPs | pCEPs |
|---------------|------|-------|------|-------|
| w/o RegionMS  | 32.59| 0.0016| 0.0152| 0.0096|
| w/ RegionMS   | 33.25| 0.0014| 0.0136| 0.0088|

Table 2. Ablation studies about the number of erasing stages. Param means parameter.

| T  | PSNR | MSE   | pEPs | pCEPs | Param size |
|----|------|-------|------|-------|------------|
| T = 1 | 31.40| 0.0017| 0.0228| 0.0122| 14.0M      |
| T = 2 | 32.72| 0.0016| 0.0160| 0.0104| 14.0M      |
| T = 3 | 33.25| 0.0014| 0.0136| 0.0088| 14.0M      |

Table 3. Ablation studies about the RG loss.

| Model       | PSNR | MSE   | pEPs | pCEPs |
|-------------|------|-------|------|-------|
| w/o RG loss | 32.73| 0.0015| 2.3389| 0.0162|
| w/ RG loss  | 33.25| 0.0014| 2.1833| 0.0136|

4.4.1 Model size and speed

We compare the parameter size between PERT and existing methods in Tab. 6. We attribute our low parameter complexity to following two reasons: 1) the decoupled erasure structure reduces the network learning difficulty, which only needs two lightweight networks for detection and reconstruction without constructing a heavy network to achieve both functions simultaneously. 2) PERT shares the parameters among all erasing blocks. As shown in Tab. 6, PERT effectively reduces the model size by at least 25% from existing multi-stage erasers [17, 10] without performance decrease. The speed comparison is shown in Tab. 7. Without the need of adversarial loss, PERT effectively reduces the training time. In the testing stage, PERT also obtains the comparable speed and achieves real-time inference. Based on the above analyses, PERT obtains a better balance among the erasure performance, parameter complexity and inference speed.

4.5. Quantitative Analysis

4.5.1 The significance of explicit erasure guidance

We summarize the reasons why RegionMS is more suitable for STR task into two aspects: 1) As the reconstruction learning (Eq. 3) on final erasure result $I_{out}^{t}$ aims to learn the stroke-level reconstruction rules, RegionsMS promotes TLN to perceive stroke-level information (Fig. 4(e)) with only bounding box level annotations (Fig. 4(d)). On the one hand, for text areas with large character spacing, TLN generates the stroke-level mask map to further reduce the modification of background textures. On the other hand, TLN predicts region-level mask map for the text areas with small character spacing, as the region-level mask map only covers little background textures. Thus, such explicit erasure guidance is able to guide an accurate erasure by implementing targeted and regional modification on stroke-level text regions. 2) RegionMS reduces the learning difficulty in BRN, where texture reconstruction of text-free areas is not considered, resulting in a coarse reconstruction (shown in Fig. 5).
| Method              | PSNR | MSSIM | MSE  | AGE  | pEPs | pCEPs | P    | R     | F    | TP   | TR   | TF   |
|---------------------|------|-------|------|------|------|-------|------|-------|------|------|------|------|
| Original images     | -    | -     | -    | -    | -    | -     | 79.4 | 69.5  | 74.1 | 61.4 | 50.9 | 55.7 |
| Pix2Pix [4]         | 26.6993 | 88.56 | 0.0037 | 6.0860 | 0.0480 | 0.0227 | 69.7 | 35.4  | 47.0 | 52.0 | 24.3 | 33.1 |
| STE [13]            | 25.4651 | 90.14 | 0.0047 | 6.0069 | 0.0533 | 0.0296 | 40.9 | 5.9   | 10.2 | 28.9 | 3.6  | 6.4  |
| EnsNet [33]         | 29.5382 | 92.74 | 0.0024 | 4.1600 | 0.0307 | 0.0136 | 68.7 | 32.8  | 44.4 | 50.7 | 22.1 | 30.8 |
| EraseNet [10]       | 32.2976 | 95.42 | 0.0015 | 3.0174 | 0.0160 | 0.0090 | 53.2 | 4.6   | 8.5  | 37.6 | 2.9  | 5.4  |
| EraseNet* [10]      | 32.0486 | 95.47 | 0.0015 | 3.2751 | 0.0169 | 0.0098 | 58.3 | 3.8   | 7.1  | 42.1 | 2.3  | 4.4  |
| PERT                | **33.2493** | **96.95** | **0.0014** | **2.1833** | **0.0136** | **0.0088** | 52.7 | 2.9   | **5.4** | 38.7 | 1.8  | **3.5** |

Table 4. Comparisons between previous methods and proposed PERT on SCUT-EnsText. * means our reimplementation.

| Method              | PSNR | MSSIM | MSE  | AGE  | pEPs | pCEPs | P    | R     | F    | TP   | TR   | TF   |
|---------------------|------|-------|------|------|------|-------|------|-------|------|------|------|------|
| Pix2Pix [4]         | 26.76 | 91.08 | 0.0027 | 5.4678 | 0.0473 | 0.0244 |      |       |      |      |      |      |
| STE [13]            | 25.40 | 90.12 | 0.0065 | 9.4853 | 0.0553 | 0.0347 |      |       |      |      |      |      |
| EnsNet [33]         | 37.36 | 96.44 | 0.0021 | 1.73  | 0.0069 | 0.0020 |      |       |      |      |      |      |
| EraseNet [10]       | 38.32 | 97.67 | **0.0002** | 1.5982 | 0.0048 | **0.0004** |      |       |      |      |      |      |
| EraseNet* [10]      | 37.70 | 97.34 | 0.0003 | 1.8044 | 0.0059 | 0.0009 |      |       |      |      |      |      |
| PERT                | **39.40** | **97.87** | **0.0002** | **1.4149** | **0.0045** | **0.0006** |      |       |      |      |      |      |

Table 5. Comparisons between previous methods and proposed PERT on SCUT-Syn. * means our reimplementation.

4.5.2 The significance of balanced multi-stage erasure

By designing a balanced erasure structure and only supervising the last erasing stage, PERT performs a balanced
Figure 5. The visualization of reconstructed images from BRN in different stages. Output is the erased image from RegionMS in the last stage.

Figure 6. The comparison of convergence in the training stage between PERT and baseline model.

4.5.3 The significance in training

We visualize the PSNR value on the SCUT-EnsText during training. The baseline model is implemented with adversarial loss and constructed without balanced multi-stage erasure and RegionMS. As shown in Fig. 6, PERT obtains a better (33.24 vs 31.86) and faster (80 epoch vs 120 epoch) convergence.

4.5.4 Limitation

As shown in Fig. 7, our method fails when TLN provides an inaccurate detection result (detecting non-text region or missing detecting text region). However, this problem also exists in previous methods (EraseNet [10] for example). It is worth mentioning that our method reduces the impact of this problem to a certain extent (e.g., the erasure result of character “H” in Fig. 7). Furthermore, the proposed PERT provides a solution for this issue by embedding the latest detection branch [31], [27] to improve the quality of mask map.

5. Conclusion

This paper proposes a simple but strong scene text eraser named PERT. Based on the explicit erasure guidance and balanced multi-stage erasure, we qualitatively and quantitatively verify that PERT effectively handles the excessive and inexhaustive erasure problems in STR task. The simplicity of PERT makes it easy to develop new scene text removal models by modifying the existing ones or introducing other network modules. Extensive experiments demonstrate that the proposed method achieves state-of-the-art performance on both synthetic and real-world datasets while maintaining a low complexity. In the future, we will develop this work to the end-to-end text edit task.

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