Double Supervised Network with Attention Mechanism for Scene Text Recognition

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Abstract. In this paper, we propose Double Supervised Network with Attention Mechanism (DSAN), a novel end-to-end trainable framework for scene text recognition. It incorporates one text attention module during feature extraction which enforces the model to focus on text regions and the whole framework is supervised by two branches. One supervision branch comes from context-level modelling and another comes from one extra supervision enhancement branch which aims at tackling inexplicit semantic information at character level. These two supervisions can benefit each other and yield better performance. The proposed approach can recognize text in arbitrary length and does not need any predefined lexicon. Our method outperforms the current state-of-the-art methods on three text recognition benchmarks: IIIT5K, ICDAR2013 and SVT reaching accuracy 88.6%, 92.3% and 84.1% respectively which suggests the effectiveness of the proposed method.

1 Introduction

Scene text contains rich and high-level semantic information, it is crucial for scene understanding and is widely used in many applications such as robot navigation, vehicle license plate recognition. Scene text understanding usually involves two steps, text detection and text recognition. In this paper, we focus on text recognition which directly convert text images into text strings. Since the development of deep learning technology, scene text recognition has attracted much attention from the community and it has become a hot topic in computer vision. Although Optical Character Recognition (OCR) technology has been quite successful, it is mainly aimed at neat document texts. However, due to the complexity of natural scenes, such as variable text shapes and fonts, complicated background, blur and uneven illumination, scene text recognition is still challenging. Figure 1 shows some quite difficult examples.

In this paper, we present a novel and efficient framework for lexicon-free scene text recognition. It can recognize text in arbitrary length. Different from existing methods, this method treat the contextual semantic information in text from two perspectives. It contains two supervision branches to tackle explicit and inexplicit contextual semantic information respectively. These two supervisions have mutually reinforcing effects and they are jointly trained together. In addition, one text attention module is integrated in the entire framework which
enforces the model to pay more attention to text regions. Without bells and whistles, the proposed approach outperforms the state-of-the-art methods on several benchmarks.

Our main contributions are summarized as follows:

– We present Double Supervised Network with Attention Mechanism (DSAN), an end-to-end trainable network for lexicon-free scene text recognition which is supervised by two branches and can recognize text in arbitrary length.
– We design a novel text attention mechanism module from perspective of global features of entire image. This dedicated text attention module is integrated in the feature backbone ResNet [1] which makes the feature extraction procedure selectively focus on text regions.
– We use two-layer bidirectional LSTM [2][3] to do context-level modelling.
– We add one supervision enhancement branch on the extracted feature representations to tackle inexplicit contextual semantic information at character level. This branch can force the model to obtain finer feature for each character and we do some ablation experiments to demonstrate the significance of this branch.
– We conduct experiments on three benchmarks and compare with other state-of-the-art methods, the result suggests the effectiveness of the proposed approach.

![Difficult Examples](image-url)

**Fig. 1.** Difficult Examples. (a) uneven illumination (b)(c) variable fonts (d) complicated background (e) variable font sizes (f) blur
2 Related Work

In recent years, a lot of methods for scene text recognition have been proposed \cite{4,5}. Generally, these approaches can be divided into two categories, character-based and word-based.

Traditional approaches are character-based which means they recognize scene text character by character \cite{6,7,8,9}. These methods first detect the position of individual character, then classify each one and finally aggregate classification results together. They rely much on character detector and character classifier. \cite{9} uses HOG voting to do character detection and random forest classifier for character classification based on Strokelets and HOG features. However, due to the lack of contextual relationship between characters, it is difficult to recognize words totally correct at character level. Thus, some methods combine explicit language models are proposed to enforce recognition accuracy. \cite{10} uses neural network as character classifier based on HOG features, and then uses beam search algorithm combined with N-gram language model to generate output. \cite{11} uses a complex CNN network which includes segmentation, correction and character recognition, then utilizes Hidden Markov Language Model with predefined lexicon to generate final recognition results. Nevertheless, the explicit language model increases training complexity.

Recently, a lot of works have been proposed to directly recognize word. \cite{12} regards scene text recognition as a large-scale (90k) image classification problem and each word has a corresponding class. Although this approach performs well on some benchmarks which have large lexicons, it depends on predefined lexicon and can not be generalized to new words. At the same time, it can not apply to many other languages, such as Chinese, since the combination of Chinese characters has thousands of ways. Advanced studies treat scene text recognition as sequence recognition problem which usually has an encoder-decoder structure. \cite{13} models scene text recognition as a deep sequence labelling problem. \cite{14} proposed an end-to-end trainable neural network for image-based sequence recognition which uses a framework composed of CNN, RNN and CTC. \cite{15} also adopts sequence prediction scheme but further combines spatial transformer network (STN) to deal with irregular texts. Most recently, attention mechanism has been widely used in image recognition, allowing the model to select the most important image features. \cite{16} presents recursive recurrent neural networks with attention modelling for scene text recognition. \cite{17} finds that attention model sometimes cannot accurately associate each feature vector with the corresponding target region in the input image and they call this phenomenon attention drift. They put forward FAN to deal with this problem and draw back the drifted attention by using extra character location information.

Regarding scene text recognition as sequence recognition problem has become current mainstream method which usually use Recurrent Neural Network to capture contextual semantic information and we call this context-level modelling. Although some texts in natural scene images do have explicit semantic information, such as English words, many of scene texts just are simple concatenation of characters without explicit contextual relationship, such as Figure 1(c). At this
point, just using context-level modelling usually does not handle decently. At the same time, the attention mechanisms in the existing text recognition methods are only used in RNN and just applied in one time step.

Inspired by these existing methods, we present an end-to-end trainable framework called Double Supervised Network with Attention Mechanism which can recognize text in arbitrary length and does not need any predefined lexicon. It inherits merits from both traditional methods and advanced methods. It tackles both explicit and inexplicit contextual semantic information in text. Firstly, it extracts feature representations through ResNet backbone, and during feature extraction, one text attention module is integrated which makes the model focus on text regions. Then two branches follows, dealing with explicit and inexplicit semantic information respectively. These two branches constitute two supervisions on the entire framework and they are trained jointly together. The experiment results suggest these two supervisions can benefit each other and improve the total performance a lot.

Fig. 2. The proposed framework consists of three parts: text attention-based feature extraction, context-level modelling branch and one extra supervision enhancement branch. Extracted feature sequences will be input to two branches to do context-level modelling and character-level modelling respectively.
3 Methods

The whole proposed framework for scene text recognition is diagrammed in Figure 2. It is an end-to-end trainable network which consists of three parts and contains supervisions from two branches. Feature representations of each image are extracted through ResNet-34 backbone. As far as we know, there are few works using ResNet in text recognition. ResNet does play an important role in text recognition, it enriches feature representations. Furthermore, one dedicated text attention module is integrated to make the model focus on text regions. The final extracted features are then reshaped to feature sequences and fed into two branches. One branch is Context-level Modelling Branch which uses two-layer bidirectional LSTM to capture contextual semantic information and another branch is Supervision Enhancement Branch which is composed of character classifiers and mainly aimed at tackling inexplicit semantic information at character level. These two branches are trained jointly together. Section 3.1 introduces the network architecture which contains four key components and section 3.2 exhibits the final objective function which is a multi-task loss.

3.1 Network Architecture

**Feature Extraction with Text Attention** Attention mechanism can make model pay more attention to the most important features of the image. [16] [17] use attention mechanism in the language modelling part but they are applied to each time step of RNN alone, as shown in the Figure 3(a), where A stands for attention.

![Fig. 3.](image)

(a) Previous attention mechanism. (b) Proposed Text Attention Module. One 3x1 with stride 1x1 same convolution followed by a sigmoid activation function. The circle dot operation is broadcast elementwise product operation.
Different from these methods, we design attention mechanism from the perspective of global features of the entire image which means it can selectively focus on features of interest from global information. The dedicated text attention module is integrated in the feature extraction procedure which enforce the model to focus on text regions.

Feature representations of each image are extracted through ResNet-34 backbone, denoted as FeatureBackbone. The height and width of FeatureBackbone both are $\frac{1}{8}$ of the input image and the number of channels is 512. After acquiring FeatureBackbone, text attention module is applied on it. As shown in Figure 3(b), in text attention module, we adopt one 3x1 with stride 1x1 same convolution on feature maps and followed by a sigmoid activation function. We call the output of text attention module AttentionMask which has the same resolution with FeatureBackbone but only has one channel. Then weighted feature representations are obtained through broadcast elementwise product operation (due to different channel numbers) on FeatureBackbone and AttentionMask. In Figure 4, we show some heatmap examples of AttentionMask and its corresponding input images. These heatmaps exactly demonstrate that Text Attention Module do focus the model on text regions. The text areas in the image are highly activated while other areas are in a relatively low activation state. In Figure 4(a) the gaps between characters are low active and in Figure 4(b) the edge portion of the image is selectively ignored.

Fig. 4. Heatmap examples of AttentionMask and corresponding input images.
In the text attention module, it actually does a feature filtering process, enhancing feature columns with semantic information while suppressing redundancies and clutter.

Finally, the weighted feature representations are reshaped to feature sequences. Suppose the final feature maps have the size of $H \times W \times D$, where $H$, $W$, $D$ are height, width and depth respectively. Then we follow Map-to-Sequence operation in [14] to convert feature maps into $W$ feature sequences, each sequence has $HD$ dimensions. The Map-to-Sequence operation actually splits the feature maps apart by column in the left-to-right order, and flattens them into sequence. Each feature sequence corresponds to one image region. Then these feature sequences with attention mechanism will be fed into two branches simultaneously.

**Context-level Modelling Branch** Due to the high-level semantic information in text, context-level modelling is of great importance to text recognition. For text, contexts from both forward direction and backward direction are useful and important. Thus, extracted feature sequences are fed into two-layer bidirectional LSTM to do context-level modelling. Two-layer BLSTM is effective to capture bidirectional long-term dependence contextual semantic information. The output sequence of BLSTM is $h = (h_1, h_2, ..., h_W)$, where $W$ is input sequence length. Then each output sequence will put into a fully connected layer and followed by a softmax classifier over the alphabet.

Therefore, this branch finally will generate probability distributions over the alphabet for each feature sequence, then the probability distributions will input to transcription layer to generate output label. The transcription layer will be described in the following.

**Supervision Enhancement Branch** For texts in natural scenes, some of them do have explicit semantic information, such as English words. However, some of them just are simple combinations of characters without explicit contextual relationship between characters, just doing context-level modelling for these texts usually does not handle decently. Meanwhile, text with identical meaning may have different present forms in pictures, such as different fonts, sizes and colors, which means finer feature does matter. Therefore, we propose supervision enhancement branch to tackle this problem which does character-level modelling for texts and aims at obtaining finer features for each character.

Extracted feature sequences are fed into a classification layer which consists of character classifiers. Each feature sequence corresponding to one image region is classified over the alphabet with a softmax classifier. Finally, the classification probability distributions are input to transcription layer. This branch does not consider contextual relationship between feature sequences, each feature sequence is independent. Therefore this branch can take most advantage of each sequence and learn finer feature for each character.

We do ablation experiments in section 4.4 to show supervision enhancement branch and context-level modelling branch have mutually reinforcing effects which can improve the total performance a lot.
Transcription Layer In the transcription layer, we use Connectionist Temporal Classification (CTC) as decoder to generate final output label [18]. Following the strategy in [18], sequence label with the highest probability is directly selected. Without predefined lexicon, CTC will simply output the character with the highest probability at each time stamp and concatenate them together, then repeated ones and blanks are removed. The transcription procedure can be denoted as follows:

$$l = B(\arg\max_{\pi} p(\pi|y))$$ (1)

where $$p(\pi|y) = \prod_{t=1}^{T} y_{\pi_t}^{t}$$ is the probability of outputting $$\pi_t$$ at time stamp $$t$$, $$T$$ is sequence length, $$y = (y_{1}, y_{2}, ..., y_{T})$$ is the input sequence and $$\pi$$ is the output sequence. $$B$$ is a mapping function which remove the repeated characters and blanks. $$l$$ is the final predicted label. Due to the simple procedure, the computation cost of transcription layer is trivial.

3.2 Loss Function

The entire network is supervised by two perspectives and loss comes from two branches. The objective function can be interpreted as follows which is a multi-task loss:

$$L = L_{context} + \lambda L_{char}$$ (2)

The full loss are divided into two categories: context-level modelling loss $$L_{context}$$ and character-level modelling loss $$L_{char}$$ from supervision enhancement branch. Both $$L_{context}$$ and $$L_{char}$$ are CTC loss. CTC loss is defined as: $$L_{CTC} = -ln p(\pi|y)$$, $$p(\pi|y)$$ is the probability of inputting $$y$$ and outputting $$\pi$$. Minimizing CTC loss actually is maximizing probability of outputting correct label. $$\lambda$$ is a hyperparameter which is used to trade off the weight of these two terms. We do ablation experiments in section 4.4 to choose the best $$\lambda$$. Finally, $$\lambda$$ is set to 0.1 in DSAN.

4 Experiments

Experiments are conducted on three standard benchmarks without predefined lexicon and compared with current state-of-the-art methods. Section 4.1 introduces the used datasets, section 4.2 shows implementation details, section 4.3 demonstrates the results of our method and section 4.4 conducts some ablation experiments to show the validity of our key components.

4.1 Datasets

IIIT 5K-Words (IIIT5K) [16] contains 2000 word images in its train set and 3000 word images in its test set.
ICDAR 2013 [20] (IC13) test set contains 233 scene images. Word images are cropped from them. We discard images that have non-alphanumeric characters and the resulting word test dataset contains 1015 text images.

Street View Text [6] (SVT) is harvested from Google Street View. It contains 249 street view images, 647 word images are cropped. Images often have low resolution and are challenging to be recognized.

Synthetic Word Dataset [21] (Synth90k) contains 9 million synthetically generated word images. We used 800,000 images for model’s pretraining.

SynthText in the Wild [22] (SynthText) contains 800,000 synthetic images for scene text detection. We cropped 720,000 word images for model’s pretraining. These text images are diverse and play an important role in the training process.

Char74k [23] contains 74k single-character images. We use 6439 character images that obtained from natural scenes for model’s pretraining. This dataset is used to enhance the model’s ability to recognize single character.

4.2 Implementation Details

All the experiments are conducted on MXNet [24] framework and the workstation has a 3.2GHz Intel i7-6800K CPU, 32G RAM, a GTX 1080Ti GPU and Ubuntu 14.04 OS.

Training We pretrain the model with 1.5 million synthetic word images and 6k scene character images, then finetune on each standard benchmark dataset. The batch size is set to 32. The height of each image is resized to 32 and the width is scaled according to the aspect ratio. The alphabet size is 37 with 26 English characters and 10 numbers. For two-layer BLSTM, 256 memory blocks are used.

For optimization, gradient descent with momentum is used, the $\beta$ is 0.9 [25]. The learning rate is initialized as 0.1 and then divided by 10 after each epoch, the pretraining procedure takes 4 epochs. During finetune procedure, dropout [26] is used in two-layer BLSTM to avoid overfitting. The input of the first layer and output of the second layer is dropout with probability 0.5.

Data augmentation Data augmentation is applied to the three standard benchmarks. Random rotation and random zoom-out are used. Random rotation: each image is randomly rotated 0-3 degrees to the left and right respectively. Random zoom-out: each image is randomly zoomed out to 0.9-1.0 times of the original size. Consequently, the dataset is expanded to 4 times of the original size.

Testing During testing time, each input image is scaled as training time does.

4.3 Results

Table 1 shows accuracy results of the proposed method on three benchmarks compared with some state-of-the-art methods. Baseline results just use ResNet-
34 backbone and context-level branch without text attention module and supervision enhancement branch.

| Method                  | IIIT5K | IC13 | SVT |
|-------------------------|--------|------|-----|
| Photo-OCR [10]          | –      | 87.6 | 78  |
| CharNet [27]            | –      | 82.4 | 71.7|
| CRNN [28]               | 78.2   | 86.7 | 80.8|
| RARE [15]               | 81.9   | 88.6 | 81.9|
| STN-OCR [29]            | 86     | 90.3 | 79.8|
| R²AM [14]               | 78.4   | 90.0 | 80.7|
| Jaderberg et al. [12]   | –      | 90.8 | 80.7|
| Baidu IDL [30]          | –      | 89.9 | –   |
| baseline                | 83.3   | 88.9 | 75.7|
| DSAN (simple)           | 84.7   | 88.8 | 78.8|
| DSAN                    | **88.6** | **92.3** | **84.1**|

Table 1. Accuracies on IIIT5K, IC13 and SVT benchmarks. Here all the results do not use any lexicon. DSAN is the results using transcription layer from context-level modelling branch and DSAN (simple) uses transcription layer from supervision enhancement branch.

In the entire framework, there are two transcription layers, we use transcription layer from context-level modelling branch as the output of DSAN. The last row of Table 1 is the results of DSAN. The accuracy results reach 88.6%, 92.3% and 84.1% on IIIT5K, IC13 and SVT respectively. These accuracies substantially outperform other state-of-the-art methods which demonstrates the effectiveness of DSAN.

Furthermore, we argue that during testing time, we can even leave out context-level modelling branch and just use the transcription layer from supervision enhancement branch, and we use DSAN (simple) to represent this simple version. This version simply does character classifications based on feature representations. The accuracies are shown in the penultimate row of Table 1. The results are also good which suggests that double supervision can promote the performance of feature extraction backbone a lot.

Table 2 shows average time cost for predicting one image by these two transcription layers separately. It is obvious that the simple version can reduce more than half of the time cost.
Some correct recognition results examples are shown in Figure 5. The first row illustrates results on IIIT5K, the second row exhibits images from IC13 and the last row is SVT. These images are quite challenging but are all recognized totally correct which indicates the validity of the proposed approach.

Fig. 5. Scene text recognition results by DSAN. All these images are recognized correctly. gt stands for ground truth.

| Methods      | Time Cost |
|--------------|-----------|
| DSAN (simple)| 3ms       |
| DSAN         | 7ms       |

**Table 2.** Average time cost for predicting one image by two transcription layers separately.

### 4.4 Ablation Experiments

In this section, we do two ablation experiments to show the performance improvements brought by our key components: supervision enhancement branch and text attention module, the results indicate the validity of our approach.

**The Effect of Supervision Enhancement Branch** In our method, \( \lambda \) controls the weight of context-level modelling branch and supervision enhancement branch. Table 3 shows the effect of parameter \( \lambda \) on accuracies. In this part, we discard text attention module and just use ResNet-34 as backbone.
Table 3. Accuracy results on three benchmarks with different $\lambda$.

| $\lambda$ | IIIT5K | IC13 | SVT  |
|----------|--------|------|------|
| 0        | 83.3   | 88.9 | 75.7 |
| 0.05     | 87.5   | 91.2 | 81.9 |
| 0.1      | 88.3   | 92.0 | 82.4 |
| 0.15     | 86.4   | 90.5 | 80.5 |

$\lambda = 0$ means character classifiers are not working which is equivalent to no supervision enhancement branch. From the results, we can see that supervision enhancement branch can improve overall performance a lot and the whole network achieves relatively high performance with $\lambda = 0.1$. Compared to $\lambda = 0$, accuracy was improved 5% on IIIT5K, 3.1% on ICDAR2013 and 6.7% on SVT which indicates the effectiveness of supervision enhancement branch.

Figure 6 shows some real images that are identified wrong without supervision enhancement branch, but recognized totally correct with $\lambda = 0.1$.

![Fig. 6. Some real images that are correctly recognized with $\lambda = 0.1$. gt stands for ground truth. Red character represents incorrectly recognized character without supervision enhancement branch.](image)

Text images in the left column do not have explicit semantic information, they just are simple concatenation of characters, while the right ones contain
explicit contextual relationship between characters. It can be observed that the supervision enhancement branch not only enforces the recognition accuracy for text without explicit semantic information, but also further promotes the model’s ability to capture contextual relationship. The results further confirm the mutual reinforcing effects of our two branches.

**The Effect of Text Attention Module** Table 4 shows the effect of text attention module. In this part, the weight of supervision enhancement branch $\lambda$ is set to 0.1.

| Method | Dataset | IIIT5K | IC13 | SVT |
|--------|---------|--------|------|-----|
| DSN    | 88.3    | 92.0   | 82.4 |
| DSAN   | 88.6    | 92.3   | 84.1 |

Table 4. The effect of text attention module on accuracy results. DSN represents double supervised network without text attention module.

Compared to DSN, accuracy was improved 0.3% on IIIT5K, 0.3% on IC-DAR2013 and 1.7% on SVT. We can see that text attention module can improve the performance especially for SVT dataset which contains low-quality and challenging street view images. This is consistent with the intention of designing text attention module to suppress redundant features and clutter.

**5 Conclusions**

We present Double Supervised Network with Attention Mechanism (DSAN), an end-to-end trainable framework for scene text recognition which is supervised by two branches and is integrated with one text attention module. It outperforms state-of-the-art methods on three benchmarks and can recognize text in arbitrary length without any predefined lexicon. In the future, we will explore to extend this framework into multi-level supervised which may take more low-level features into consideration and will consider to combine detection and recognition into one end-to-end framework.

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