

Spatial Attention Is All You Need for Scene Text Recognition with Arbitrary Shapes

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Abstract. Scene text recognition with arbitrary shape is very challenging due to large variations in text shapes, fonts, colors, backgrounds, etc. Most state-of-the-art algorithms rectify the input image into the normalized image, then treat the recognition as a sequence prediction task. The bottleneck of such methods is the rectification, which will cause errors due to distortion perspective. In this paper, we find that the rectification is completely unnecessary. What all we need is the spatial attention. We therefore propose a simple but extremely effective scene text recognition method based on transformer [50]. Different from previous transformer based models [56,34], which just use the decoder of the transformer to decode the convolutional attention, the proposed method use a convolutional feature maps as word embedding input into transformer. In such a way, our method is able to make full use of the powerful attention mechanism of the transformer. Extensive experimental results show that the proposed method reasonably outperforms state-of-the-art methods on both regular and irregular text datasets. On one of the most challenging CUTE dataset whose state-of-the-art prediction accuracy is 89.6%, our model’s accuracy is 87.2% and outperforms 75% models, which is a pretty surprising result.

Keywords: Scene Text Recognition, Transformer, Spatial Attention

1 Introduction

Scene text recognition has been attracting increasing interest in computer vision due to its potential real-world applications, such as street sign recognition in the driverless vehicle, human computer interaction, assistive technologies for the blind and guide board recognition [41,61]. When the text in an image is horizontal or nearly horizontal, existing methods can achieve great performance. However, when the text is in arbitrary shapes or seriously distorted, recent state of the art methods still fail to correctly recognize the text. Some failure cases of the best model in [3] are shown in Figure 1. As we can see in Figure 1(a), when the text has light bend or lean, although the recognized text is wrong it still looks much like the ground truth. When the text has moderate bend or learn as shown in Figure 1(b), the recognized text is far from the ground truth. For the text with severe bend or lean as shown in Figure 1(c), the recognized text does not make any sense. For example, the “STARBUCKS” is recognized as “the” and “CLUB” is recognized as “i”.

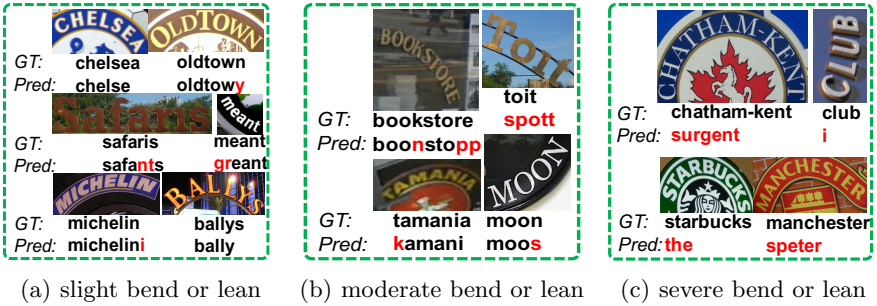


Fig. 1. Some failure cases of the best model in [3], whereas our method can predict all the failure cases accurately.

In the past few years, a huge number of efforts have been devoted to developing effective methods to approach scene text recognition with arbitrary shapes, which can be roughly grouped into three categories: rectification based methods, segmentation based methods and spatial attention based methods. Rectification based methods resort to a rectification module to rectify the text in irregular shapes into regular forms and then perform sequence recognition. Most rectification modules are based on spatial transform network (STN [22]). Although these methods recognize well the text in light distortion, they fail to recognize the text with severe distortion because the rectification modules are not able to rectify the severely distorted texts into regular ones especially when the background is complex. Rather than rectifying the text from arbitrary shapes into regular ones, segmentation based methods [29,33] directly segment the characters of the text and then classify the segmented characters by voting. A word formation module is finally used to group the characters to form the final word. The performance of these methods heavily rely on the segmentation accuracy, which face several challenges. First, the character segmentation needs the character-level annotations to supervise the training which is labor consuming. Second, a carefully designed post-processing algorithm is required to yield the text sequence from segmentation maps. Third, the order of the characters cannot be obtained from the segmentation maps. Very recently, spatial attention based methods have been proposed [28], which use Convolutional Neural Networks (CNNs) to encode a spatial attention, and a Long short-term memory (LSTM [18]) model to encode a holistic feature, then using another LSTM model to decode the holistic feature into a sequence of character by glimpsing the spatial attention. These methods do not need to rectify or segment the characters and therefore can be applied to recognize the text in arbitrary shapes. However, their performance is not good enough because spatial attention is not fully encoded due to the limited receptive fields of CNNs. In addition, the RNN decoder also loses partial spatial information.

In this paper, we find that neither rectification nor segmentation is needed for scene text recognition with arbitrary shapes. What all we need is spatial

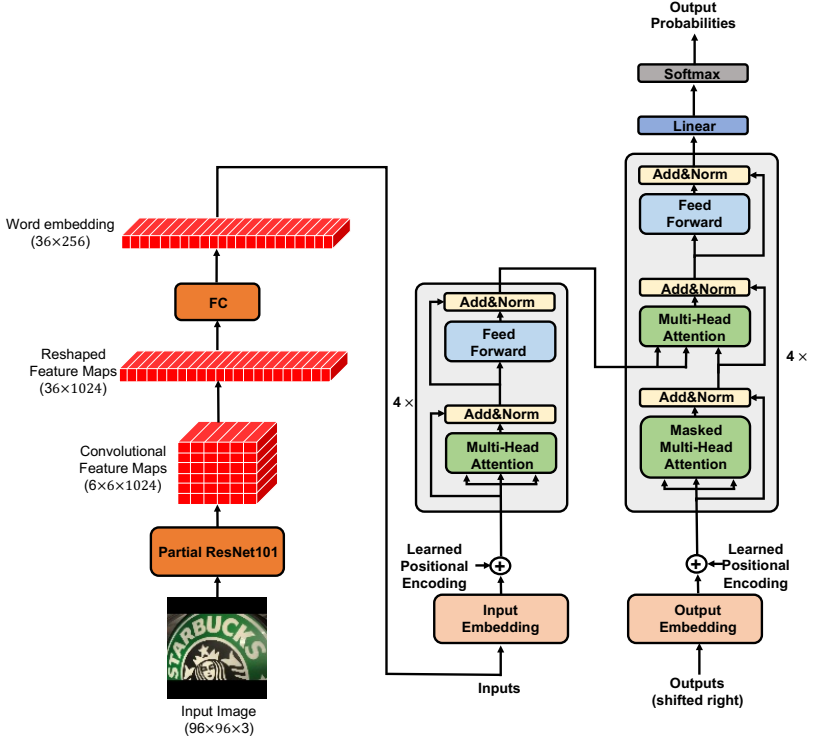


Fig. 2. Overview of the proposed Transformer OCR, which contains two cascade modules: the feature extractor module and the transformer module.

attention. Once the spatial attention is fully encoded, scene text recognition with arbitrary shapes can be effectively solved. Inspired by transformer [50], we propose a simple but extremely effective scene text recognition method as shown in Figure 2. Different from RNN based sequence-to-sequence model, the transformer adopts global attention to encode and decode. As illustrated in Fig 3, each encoded attention memory has the whole attention of the input image. For example, after transformer encoding, the letters “K” and “B” can accurately collect the spatial informations of the input. The order of the input sequence of the encoder is learnable, which is very suitable to realize spatial attention. Different from previous transformer based models [56,34], which just use the decoder of the transformer to decode the convolutional attention, the proposed method use a convolutional feature maps as word embedding input into transformer. In such a way, our method is able to make full use of the powerful attention mechanism of the transformer. Benefiting from the powerful spatial attention mechanism realized by the transformer, the proposed model performs really good on both regular and irregular text datasets.

The contributions of this paper are summarized below:

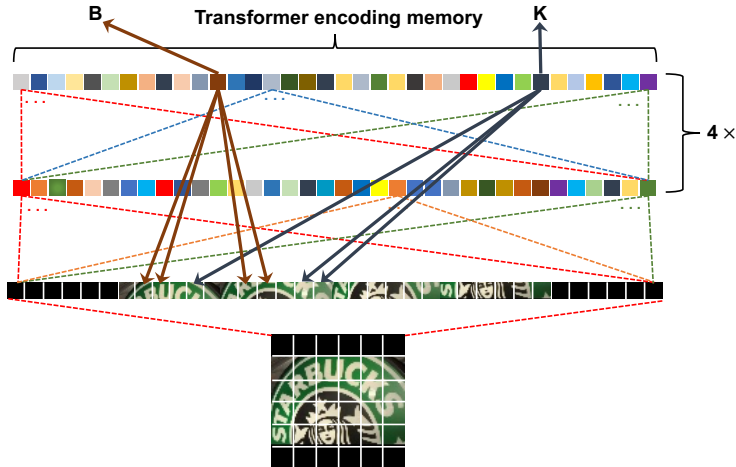


Fig. 3. Spatial attention realized by cross attention mechanism of transformer encoder.

- With a lot of experiments and analysis, we conclude that the rectification or segmentation stage of most existing methods is completely unnecessary. What all we need is the spatial attention. Based on this conclusion, we propose a simple but extremely effective scene text recognition method based on transformer [50].
- Extensive experimental results show that the proposed method significantly outperforms state-of-the-art methods by a very large margin on both regular and irregular text datasets. On one of the most challenging CUTE dataset, we outperform 75% models, which is a pretty surprising result.

2 Related Works

According to the shape of the text in an image, existing scene text recognition can be roughly grouped into two categorization: text recognition with regular shapes and text recognition with arbitrary shapes. In this section, we present a simple review on the related works.

2.1 Text Recognition with Regular Shapes

Regular scene text recognition aims to recognize the text in an image where the text is horizontal or nearly horizontal. Prior to the advent of deep learning, traditional methods usually use a three-stage framework [51,6,52,53,60,49,36,5]. They first use a character proposal extractor to locate all characters in the text. Then, a classifier is used to recognize the characters. Finally, the recognized characters are group into words. With the development of deep learning in computer vision, deep learning based methods [21,47,42,43,44,27,7,37,30,4,8,12] have been dominating scene text recognition in recent years. Roughly, scene text recognition algorithms based on deep learning can be divided into two main classes:

CTC [15] based CRNN [42,37] and RNN based attention OCR [55,46,11,10]. Although these methods achieve appealing performance on regular text recognition, they can not be applied to text recognition with arbitrary shapes because the order of the feature maps largely determines the order of the prediction result.

2.2 Text Recognition with Arbitrary Shapes

Arbitrary shape texts [58,38,8,43,44,31,57] include oriented or perspectively distorted text, curved text, even twisted text, etc. Different from text recognition with regular shapes, the order of the feature maps of a text image with arbitrary shapes is not consistent with the order of the text. Therefore, most state-of-the-art methods of text recognition with arbitrary shapes focus on how to normalize the image with irregular texts into an image with straight texts. However, the normalization is very difficult and always not robust due to large distortion of the texts. Therefore, most previous state-of-the-art methods are not enough effective and robust for text recognition with arbitrary shapes. Text recognition methods with arbitrary shapes are roughly grouped into three categories: rectification based methods, segmentation based methods and spatial attention based methods.

Rectification based methods Shi et al. [43] propose a robust text recognizer with automatic rectification (RARE), which is a carefully designed deep neural network and consists of a Spatial Transformer Network (STN) and a Sequence Recognition Network (SRN). An image is firstly rectified into a normalized image via a predicted Thin-Plate-Spline (TPS [54]) transformation for SRN. Yang et al. [57] propose a Symmetry-constrained Rectification Network (ScRN) based on the local attributes of text instances, such as center line, scale, and orientation. ScRN can generate better rectification results than previous methods and therefore achieves higher recognition accuracy.

Segmentation based methods Liao et al. [29] propose a character attention mechanism, which is realized by a semantic segmentation network. Combined with a word formation module, the proposed method can simultaneously recognize the script and predict the position of each character. Liao et al. [33] propose an end-to-end trainable neural network for spotting text with arbitrary shapes, in which both detection and recognition can be achieved directly from a two-dimensional space via semantic segmentation. Further, a spatial attention module is proposed to enhance the performance.

Spatial attention based methods Yang et al. [59] propose a spatial attention mechanism, which uses an auxiliary dense character detection module to select local 2D features. Nevertheless, the proposed method needs extra character-level annotations to supervise the attention network. Li et al. [28] modify the RNN

based attention OCR by introducing spatial attention. The proposed model, called SAR, saves the CNN output as spatial attention. At each time step of the decoding, an attention module gets a glimpse of the spatial attention. In this way, SAR achieves state-of-the-art performance on irregular text recognition benchmarks and comparable results on regular text datasets. Inspired by transformer [50], Lyu et al. [34] propose a 2D attentional scheme, which consists of a relation attention module and a parallel attention module. The proposed 2D attentional scheme transforms the irregular text with the 2D layout to character sequence directly. Nevertheless, experimental results indicate that the above 2D attentional scheme is not powerful as transforms itself. The above spatial attention is either constrained by RNN, which is not friendly to spatial information, or in a semantic segmentation manner, which needs an extra module to convert the segmentation to the final prediction. Another work inspired by transformer is proposed by Yang et.al [56], which just takes use of the decoder of the transformer to decode a convolutional attention and does not use the encoder of the transformer. Because it does not take full use of powerful attention mechanism of transformer, it leads to poor performance.

3 Proposed method

As illustrated in Figure 2, the proposed model consists of two major modules: feature extractor module and transformer [50] module. The feature extractor module is first used to generate feature maps from an input image. The feature maps are then fed to the transformer as input word embeddings.

3.1 Feature Extractor module

There are a lot of CNNs [45,48,17,19] can be used to extractor feature. Considering the complexity of the scene text and the dimension of transformer we used, we adopt the first four layers of ResNet-101 [17] as the feature extractor module. The architecture of the used network is presented in Table 1. In order to feed the feature maps into the transformer module, we must rearrange the two-dimensional feature maps produced by the feature extractor to one dimension. Generally speaking, the rearrangement will lose spatial informations of the original image. Fortunately, the transformer has the ability to learn the spatial informations.

The input RGB image is first resized to 96×96 resolution, and then fed to the partial ResNet-101. The output feature maps is a $6 \times 6 \times 1024$ tensor. Then we reshape the feature map into a 36×1024 matrix, followed by a fully connection layer to convert the reshaped features to a 36×256 tensor. Finally, we input the converted feature to the encoder of the transformer.

3.2 Transformer module

Transformer is a revolutionary model in natural language processing [50]. Benefiting from powerful attention mechanism, transformer outperforms most RNN

Table 1. Feature extractor model layer configuration from the first 4 layers of ResNet-101.

Layer name	Output size	Configuration
conv1	48×48	$7 \times 7, \text{stride } 2$
	24×24	$3 \times 3, \text{max pool, stride } 2$
layer1	24×24	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
layer2	12×12	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$
layer3	6×6	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$

based attention models by a large margin. Different from RNN based local attention, transformer has a global attention scope. As illustrated in Figure 2, the transformer has an encoder-decoder structure. The encoder maps the feature maps (x_1, \dots, x_{36}) produced by the feature extractor module to a sequence of continuous representations $z = (z_1, \dots, z_{36})$. Given z , the decoder then generates an output sequence (y_1, \dots, y_m) of symbols one element at a time. At each step, the model is auto-regressive, consuming the previously generated symbols as additional input when generating the next one.

In our model, the transformer encoder is composed of a stack of $N = 4$ identical layers, each of which has two sub-layers. The first sub-layer is a multi-head self-attention mechanism, and the second one is a position-wise fully connected feed-forward network. The decoder is also composed of a stack of $N = 4$ identical layers. Besides the two sub-layers in each encoder layer, the decoder inserts another sub-layer, which performs multi-head attention over the output of the encoder stack. Both the encoder and decoder employ a residual connection around each of the two sub-layers, followed by a layer normalization [2].

3.3 Positional Encoding

Since the transformer does not contain recurrence and convolution, it adds “positional encodings” to the input embeddings at the bottoms of the encoder and decoder stacks in order to make use of the order of the sequence. The positional encodings have the same dimension as the embeddings. Therefore, they can be summed. There are two choices of positional encodings: the learned positional encodings and the fixed positional encodings.

In our model, the input image is in a two-dimensional perspective. Therefore, the fixed positional encoding of one-dimension [13] is not suitable. We use learnable positional embedding instead in the proposed model. Different from the origin transformer model, there is no need to worry about the length of input sequence because our input image size is fixed in 36.

3.4 Spatial Attention

Benefitting from the powerful attention mechanism of the transformer, we realize spatial attention. Why not RNN based attention models? The main reason is that, RNN process input sequence one by one, this mechanism makes RNN more inclined to obtain local information. What's worse is that RNN has no ability to make up the loss of spatial information when convert two-dimensional feature maps to one-dimension. But transformer process the input sequence in a parallel manner, each single feature can have all the input attention. Although the rearrangement of feature maps from two-dimensional to one-dimensional will lose spatial information, the learned positional encodings is able to make up for the lose.

4 Experiment

4.1 Datasets

To demonstrate the effectiveness of the proposed method, we extensively evaluate the proposed method on 5 challenging datasets, which contain two datasets with regular texts and three datasets with irregular texts. The descriptions of the datasets are as follows.

IIIT5K-Words (IIIT5K) [35] is the dataset crawled from Google image searches, with query words that are likely to return text images, such as “billboards”, “signboard”, “house numbers”, “house name plates”, and “movie posters”. IIIT consists of 2,000 images for training and 3,000 images for evaluation. Each image is associated with a 50-word lexicon and a 1k-word lexicon.

Street View Text (SVT) [51] consists of 257 images for training and 647 images for evaluation. These images are collected from the Google Street View, many of which are heavily corrupted by noise, blur or in low resolution. Each image specifies a 50-word lexicon.

ICDAR 2015 (IC15) [24] was created for the ICDAR 2015 Robust Reading competitions. It contains 4,468 images for training and 2,077 images for evaluation, which are captured by Google Glasses under the natural movements of the wearer. Thus, many images are noisy, blurry, and rotated, and some are also of low resolution.

SVT-Perspective (SVTP) [38] is specifically proposed to evaluate the performance of perspective text recognition algorithms. It is collected from Google Street View and contains 645 images for evaluation. Many of the images contain perspective projections due to the prevalence of non-frontal viewpoints.

CUTE80 (CUTE) [39] is designed to evaluate curved text recognition. It is collected from natural scenes and contains 288 cropped images for evaluation. Many of these are curved text images.

It should be noted that the IIIT5k and SVT datasets have lexicons to constrain recognition results. For 50-word and 1k-word lexicon, the false prediction will be replace by the corresponding lexicon word, which has the least edit distance with the original prediction.

4.2 Implementation Details

The proposed method is implemented in PyTorch. Test images are first resized to 96×96 before fed to the network. The size of the feature map produced by the feature extraction network is $6 \times 6 \times 1024$. Then, a fully connection layer is used to align dimension of transformer input. The transformer has 4 layers 256 dimensional encode and the same size decoder. In total, 71 symbols are recognized, including digits, upper-case and lower-case letters, 8 punctuation marks and an end-of-sequence symbol (EOS).

Except ResNet-101 is pretrained from PyTorch model zoo, the rest of our model is trained from scratch on SynthText [16] from which we crop 4,004,986 sub-images, and RRC-ArT [9] which contains 36,897 Latin only text arbitrary shape text images, and training set of each dataset if it has. We used the Adam optimizer [25] and follow the same setup of OpenNMT [26]. In particular, we set $\beta_1 = 0.9$, $\beta_2 = 0.98$ and $\epsilon = 10^{-9}$. We also varied the learning rate over the course of training, according to $lrate = d_{model}^{-0.5} \cdot \min(step_num^{0.5}, step_num \cdot warmup_steps^{1.5})$, which means to increase the learning rate linearly for the first $warmup_steps$ training steps, and decrease the learning rate thereafter proportionally to the inverse square root of the step number. We used $warmup_steps = 4000$. All models are trained on a single NVIDIA Tesla P40 graphics card.

4.3 Compassions against state of the art methods

To demonstrate the effectiveness of the proposed method, we compare our method against a total of 29 methods including several state of the art methods such as rectification based methods [43,57], segmentation based methods [29,33] and spatial attention based methods [59,28,34,56]. The comparison results on five datasets are shown Table 2.

Performance on regular text recognition The datasets IIIT5K and SVT contains images with regular texts so we use them as the regular text dataset baseline to beat. As we can see from Table 2, when 50 lexicons are used on IIIT5K dataset, our model outperforms 7 out of 23 models. The largest improvement margin is 32.4% compared to 64.1% accuracy; when 1000 lexicons are used on IIIT5K dataset, our model performs equally or better than 14 out of 23 models. The largest improvement margin is 38.7% compared to 57.4% accuracy; when no lexicons are used on IIIT5K dataset, our model outperforms all 16 other models. The largest improvement margin is 17.4% compared to 78.4% accuracy. Similarly, our model has good performance on SVT dataset: when 50 lexicons are used on SVT dataset, our model outperforms equally or better than 14 out of 27 models. The largest improvement margin is 38.2% compared to 57.0% accuracy; when no lexicons are used on SVT dataset, our model outperforms all 17 other models. The largest improvement margin is 23.1% compared to 71.7% accuracy.

Performance on irregular text recognition The proposed method gives reasonable results when recognizing text with irregular shapes. As we can see

4.4 Compassions against other Transformer based methods

As illustrated in Table 2, we can see that our method is among the first-tier transformer based methods. The main reason is that the previous transformer based methods do not take use of the encoder of the transformer to encode the convolutional feature maps. In our opinion, the encoder of the transformer is the key of realizing spatial attention. Instead of using the transformer encoder, Yang et. al [56] use a 2D attention module in order to avoid losing spatial informations. Actually, there is no need to maintain a 2D attention module at all. Even if we reshape the 2D attention to 1D, the cross attention mechanism of the transformer encoder is able to recover spatial information even better than the specifically designed 2D attention module of [56].

4.5 Study on Spatial Attention

In order to illustrate how spatial attention recovers spatial information when recognizing texts with arbitrary shapes, we show the heat maps of the source attention (encoder memory) scores of the first layer of the decoder in Fig. 4. The first column is input images with rotation angles 0 , $\pi/2$, π and $3\pi/2$, respectively. From left to right are the letters appearing in the images. For example, the second column is the spatial position of the first letter “H”. It is obvious that our model can find the positions of the letters, which indicates that our model does realize spatial attention. It is because the transformer can accurately locate the letters even if they appears in arbitrary shapes, our method can predict the texts very precisely. We also find that the learned order of the text is reasonable. Whatever we rotate the input image, our model is not affected by the rotation.

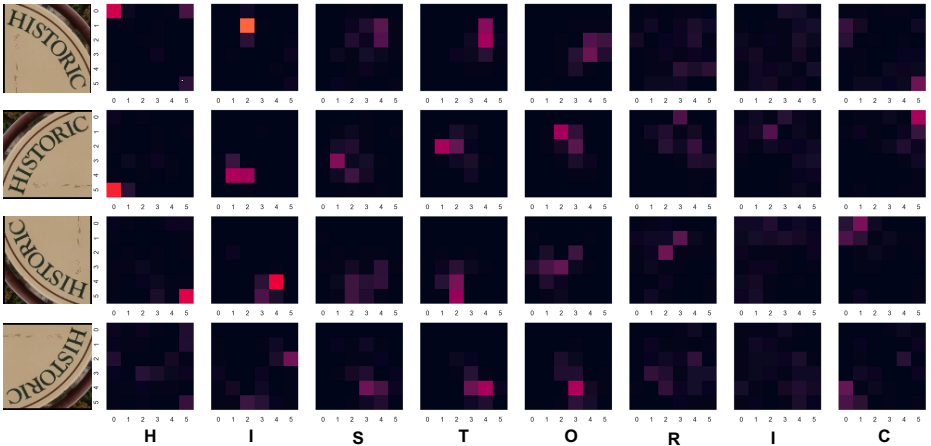


Fig. 4. Heat map of the source attention (encoder memory) score of the first layer of decoder. The left most column is input images with rotation angles respectively 0 , $\pi/2$, π and $3\pi/2$ radian. The rest columns are map to prediction letters one by one.

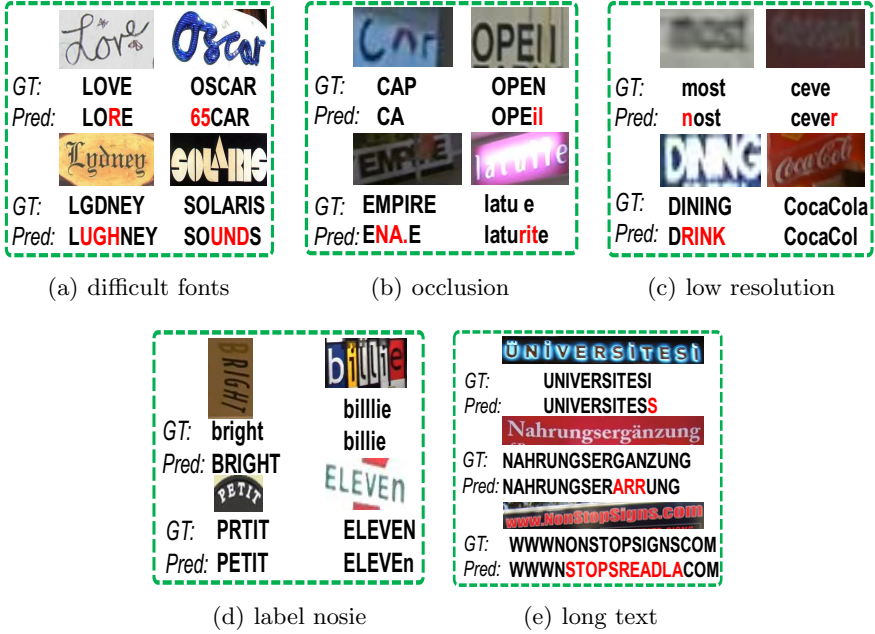


Fig. 5. Some failed cases of our method.

4.6 Failure Cases

Although the proposed method performs well when recognizing scene texts with arbitrary shapes, it still fail in some extreme cases. Here, we present some failure cases of our method in Figure 5, from which we can see that our method fails in some challenging cases such as difficult fonts, occlusion or low resolution. We also find there are more or less label nosies in the test sets of all datasets. In addition, our method also struggles to recognize the long texts. The main reasons are in three folder. Firstly, there are less long text images in the training set. Secondly, resize the long text images will result in lower resolution. Thirdly, the false former decoded character will mislead the latter decodings.

5 Conclusions

In this paper, we propose a simple but extremely effective scene text recognition method based on transformer [50]. To demonstrate the effectiveness of the proposed method, we conduct extensive experiments on five benchmark datasets including three irregular text benchmarks. Experimental results indicate that the proposed method achieves very surprising performance. In particular, the proposed method performs the best on two regular text benchmarks. On irregular text benchmarks, the proposed method shows its powerful ability to recognize

irregular texts. Surprisingly, we beat 60%, 58.3%, and 75% models on the IC15, SVTP and CUTE dataset, respectively. As for future work, we would like to extend the proposed method to multi-line text recognition.

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