Robust Scene Text Recognition with Automatic Rectification

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Abstract

Recognizing texts in natural images is a challenging task with many unsolved problems. Different from texts in printed documents, scene texts are often in irregular arrangements, or are seriously distorted. In this paper, we propose a recognition method that is robust to irregular texts, such as perspective texts and curved texts. Specifically, we construct a deep neural network model, which consists of a spatial transformer network (STN) and a sequence recognition network (SRN). The network can be trained end-to-end using only images and text labels, thus the spatial transformation is learned using the supervision of the recognition loss, rather than humanlabeled geometric ground truth. In testing, the image is firstly automatically rectified via a predicted thin-platespline transformation, into a more "readable" image for the followed SRN. We show that the model is able to read word images containing several types of irregular texts, including perspective texts, curved texts and multi-oriented texts. Requiring minimal labels, the model is easy to train and deploy in a practical system. The state-of-the-art or highly competitive performance on several benchmarks for scene text recognition demonstrates the effectiveness of the proposed method.

1. Introduction

In natural scenes, texts appear on various kinds of objects, *e.g.* road signs, bill boards and product packaging. They carry rich, high level semantics that are important cues for image understanding. Recognizing texts from images facilitates many real world applications, such as geolocation, driverless car and image-based machine translator. For these reasons, scene text recognition have attracted great interests of the computer vision community [25], [36], [14], [30]. Despite the maturity of the Optical Charac-

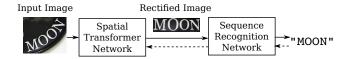


Figure 1. Semantic overview of the proposed model. The model consists of two parts, namely the spatial transformer network (STN) and sequence recognition network (SRN). The STN transforms the input image to a new image, which we call the *rectified image*. The SRN takes the rectified image as the input and recognizes the text. The two networks can be trained jointly by back-propagation (represented by dashed arrows).

ter Recognition (OCR) research [23], recognizing texts in the form of natural images, rather than scanned documents, is still challenging. Taken by cameras under uncontrolled environments, text images exhibit large variations due to several factors of illumination change, blur, fonts, colors, *etc*. Besides, there exists several types of *irregular texts*. For example, some texts have irregular character placements, such as the curved texts. Some texts are perspective texts, *i.e.* texts that are distorted by perspective projections.

Usually, a text recognizer works the best when the input texts are tightly-bounded, horizontal and frontal. We call them *regular texts*. This motivates us to apply a spatial transformation prior to recognizing the text. In this paper, we propose a recognition method that is robust to irregular texts. Specifically, we construct a deep neural network that combines a spatial transformer network [17] (STN) and a sequence recognition network (SRN). An overview of the network architecture is shown in Fig. 1. The network can be trained end-to-end, using only word images and their corresponding text labels.

In the STN part, the input image is spatially transformed into a new image which we call the *rectified image*. This part can be seen as an image preprocessor. Ideally, given the input image, the STN produces an image that contains a piece of regular text, which is a more appropriate input for a text recognition system than the original input image. The

transformation we use is a non-linear thin-plate-spline [6] (TPS) transformation configured by a set of fiducial points. The coordinates of the fiducial points are regressed from the input image, using a convolutional neural network. Due to the flexibility of TPS, we are able to transform several types of irregular texts to horizontal and frontal ones, including multi-oriented texts, perspective texts and curved texts.

The SRN recognizes the rectified image in a sequence-to-sequence manner, *i.e.* from the sequence-based representation of the image, to the character sequence. Specifically, we build the SRN as an *attention-based* model [4], which consists of an encoder and a decoder. The encoder generates the sequence-based representation from the image. In our case, it is a network that combines several convolution layers and a recurrent network. The decoder is a recurrent sequence generator. At each step of the generation process, the decoder outputs a character prediction, based on the encoder output and its stored memory state. Both the encoder and the decoder leverage the rich context information on the image. Consequently, the SRN is able to produce accurate predictions.

We show that, with some proper initialization strategies, one can train the whole network end-to-end, jointly optimizing the spatial transformer network and the sequence recognition network. Therefore, in the STN part, we do not need to label any geometric ground truth, *e.g.* the locations of the fiducial points, but let it automatically adjust its weights with respect to the gradients. In practice, we observe that the training eventually makes the STN tend to produce frontal and horizontal text images, which are desirable inputs for the SRN.

The contributions of this paper are as followed: Firstly, we propose a scene text recognition method that is robust to irregular texts. Secondly, the proposed network is an extension to the recently proposed spatial transformer network [17], which was deployed into convolutional neural networks for object recognition tasks. We further connect it with the recurrent neural networks. Thirdly, we extend the attention-based model proposed in [4] with the convolution layers, and apply it to the image-based sequence recognition problem. Finally, we quantitatively validate the effectiveness of the proposed method with state-of-the-art performances on several public benchmarks.

2. Related Work

In recent years, a rich body of works concerning scene text recognition has been published. A comprehensive review is provided in [39]. Among the traditional methods, many adopt the bottom-up approaches, where individual characters are firstly detected by methods based on sliding window [35], [34], connected components [25], or Hough voting [38]. The recognized text is then the integration of

the character predictions. Other methods can be categorized as the top-down approaches, where texts are directly predicted from the entire image without detecting the characters. Almázan et al. [2] propose to predict the label embedding vectors from the the input images. In [16], the recognition is handled by a 90k-class convolutional neural network, where each class represents an English word. In [15], a CNN with structured output layer is used for unconstrained recognition. Some recent works model the problem as a sequence recognition problem, where images and texts are modeled as patch sequences and character sequences respectively. Su and Lu [32] represent images by sequences of HOG features, and predict the character sequence with the recurrent neural network (RNN). Shi et al. [30] propose an end-to-end neural network that combines CNN and RNN. Our model also treats the recognition as sequence recognition problem, but it has a spatial transformation network which can rectify the input image before recognition. Additionally, our model is able to map an input sequence of arbitrary length to the output sequence, both have arbitrary lengths, and is thus more flexible than [30].

Irregular text is a usual situation during text detection and text recognition in photo OCR. Various methods have been proposed to address this problem. To name a few, in the text detection stage, Yao et al. [37] firstly propose the irregular text problem and provide a solution by carefully designing rotation invariant low-level image features. In the text recognition stage. Zhang et al. [41] propose a char rectification method according to the low-rank structure of text. Phan et al. propose to explicitly rectify the perspective distortions via SIFT [20] descriptor matching. In all of the above-mentioned methods, text rectification is regarded as a standalone component that is separated from the recognition and detection processes. Our method treats irregular problem from a totally different view, we are aiming to get a rectified image, which is more suitable for neural network to recognize. Thus, text rectification is built together with recognition, and directly guided by recognition in the training process.

3. Proposed Model

In this section we formulate the proposed model. The model takes an input image I and predicts a sequence $\mathcal{L} = \{l_1, \ldots, l_T\}$, where l_t represents the t-th character, T is the text length. The model consists of two parts, the spatial transformer network (STN) and the sequence recognition network (SRN).

3.1. Spatial Transformer Network

The STN transforms the input image I to the rectified image I'. It first regresses a set of fiducial points from I, then transforms I using the TPS transformation with

respect to the fiducial points. The structure of the STN is illustrated in Fig. 2. The localization network regresses a set of fiducial points, while the grid generator produces a sampling grid on the input image I. The sampler takes the sampling grid and the input image I, it produce the new image I'.

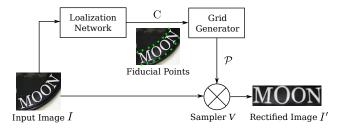


Figure 2. The structure of the spatial transformer network. The localization network regresses a set of fiducial points C, with which the grid generator produces the sampling grid \mathcal{P} . The sampler produces the rectified image I', given I and \mathcal{P} .

A distinctive property of the STN is that the sampler is differentiable, thus, if we create a differentiable localization network and a differentiable grid generator, the STN can back-propagate error differentials in the direction opposite to the arrows in Fig. 2. We can hence integrate the STN with other networks, and jointly train them.

3.1.1 Localization Network

The localization network regresses the coordinates of the fiducial points, which are denoted by $\mathbf{C} = [\mathbf{c}_1, \dots, \mathbf{c}_K] \in \Re^{2 \times K}$, whose k-th column $\mathbf{c}_k = [x_k, y_k]^\mathsf{T}$ contains the 2-D coordinates of the fiducial point. We use a normalized coordinate system whose origin is the center of the image. x, y coordinates are within the range [-1, 1]. The localization network is a convolutional neural network, it regresses the coordinates \mathbf{C} directly from the input image I:

$$\mathbf{C} = \text{CNN}(I, \boldsymbol{\theta}_{\text{loc}}) \tag{1}$$

where $\theta_{\rm loc}$ is the parameters of the CNN. The CNN we use contains four convolution+maxpooling layers, followed by two fully-connected layers. On its top, we use a $\tanh(\cdot)$ output layer to constrain the output within the range (-1,1), so that fiducial points do not fall outside the image. Being a CNN, the localization network is obviously differentiable. We jointly train it with other networks, so that we do not need to label the fiducial points C for training.

3.1.2 Grid Generator

The grid generator generates a sampling grid. We first define another set of fiducial points, called the *base fiducial points* $\mathbf{C}' = [\mathbf{c}_1', \dots, \mathbf{c}_K'] \in \Re^{2 \times K}$. As illustrated in Fig. 3

(right). The base fiducial points are evenly distributed along the top and bottom of the rectified image I'. Since we use normalized coordinates, \mathbf{C}' is a constant.

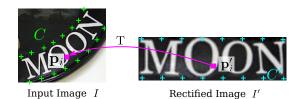


Figure 3. Fiducial points and the transformation. The cross markers on the images are the predicted fiducial points \mathbf{C} (in green) and the base fiducial points \mathbf{C}' (in cyan). The transformation \mathbf{T} is illustrated by the pink arrow. For each point (x_i', y_i') on I', the transformation \mathbf{T} finds the corresponding point (x_i, y_i) on I.

To generate the sampling grid on the input image I, firstly we calculate the TPS transformation, represented by $\mathbf{T} \in \Re^{2 \times (K+3)}$:

$$\mathbf{T} = \left(\mathbf{\Delta}_{\mathbf{C}'}^{-1} \begin{bmatrix} \mathbf{C}^{\mathsf{T}} \\ \mathbf{0}^{3 \times 2} \end{bmatrix} \right)^{\mathsf{T}}.$$
 (2)

where $\Delta_{\mathbf{C}'} \in \Re^{(K+3) \times (K+3)}$ is a matrix determined only by \mathbf{C}' , thus it is also a constant. The grid of pixels on the rectified image I' is denoted by $\mathcal{P}' = \{\mathbf{p}_i'\}_{i=1,\dots,N}$, where $\mathbf{p}_i' = [x_i', y_i']^\mathsf{T}$ is the x,y-coordinates of the i-th pixel, and N is the number of pixels. As illustrated in Fig. 3, for each point \mathbf{p}_i' , we find the corresponding point $\mathbf{p}_i = [x_i, y_i]^\mathsf{T}$ on the input image I, by applying the transformation:

$$\mathbf{p}_i = \mathbf{T}\hat{\mathbf{p}}_i' \tag{3}$$

$$\hat{\mathbf{p}}_{i}' = [1, x_{i}', y_{i}', r_{i,1}', \dots, r_{i,K}']^{\mathsf{T}}$$
(4)

Here, $r'_{i,k} = d^2_{i,k} \ln d^2_{i,k}$, where $d_{i,k}$ is the euclidean distance between \mathbf{p}'_i and the k-th base fiducial point \mathbf{c}'_k . By iterating over all points in the grid \mathcal{P}' , we generate the grid $\mathcal{P} = \{\mathbf{p}_i\}_{i=1,\dots,N}$. The grid generation involves two matrix productions, Eq. 2 and Eq. 3. Therefore, the grid generator is also differentiable.

3.1.3 Sampler

Lastly, in the sampler, the pixel value of I' on \mathbf{p}'_i is bilinearly interpolated from the pixels near \mathbf{p}_i on the input image. Setting all the pixels in I', we get the rectified image I':

$$I' = V(\mathcal{P}, I) \tag{5}$$

where V represents the bi-linear sampler [17], which is also a differentiable function.

The flexibility of the TPS transformation allows the STN to transform irregular text images into rectified

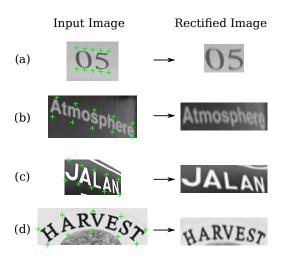


Figure 4. Examples of the spatial transformation. We regress the fiducial points (green crosses) from the input image (left column), and transform the image into the rectified image (right column) using TPS transform. The TPS is able to transform several types of irregular text images into the rectified regular text images, including (a) loosely-bounded text; (b) multi-oriented text; (c) perspective text and (d) curved text.

images that contain regular texts. Illustrated in Fig. 4, some common types of irregular texts include (a) loosely-bounded text, caused by imperfect cropping or bounding box detection; (b) multi-oriented texts, caused by non-horizontal shooting; (c) perspective texts, caused by non-frontal view; (d) curved texts, a common artistic style.

3.2. Sequence Recognition Network

The input to the SRN is the rectified image I'. Ideally, the image contains a piece of text that is written horizontally from left to right. It is natural to model I' as a sequence. Also, texts are inherently sequences of characters. Therefore, we can model the recognition problem as a *sequence-to-sequence* [33] learning problem, where the input sequence is the sequence-based representation of I', and the output sequence is the character predictions $\mathcal{L} = \{l_1, \ldots, l_T\}$. Specifically, the SRN is an *attention-based* model [4], [8], which consists of an encoder and a

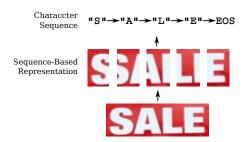


Figure 5. The SRN recognizes in a sequence-to-sequence manner. It maps the sequence-based representation of I', to the character sequence. "EOS" is the end-of-sequence symbol.

decoder. The encoder produces the sequence-based representation for the image I', while the decoder generates the prediction sequence conditioned on the encoder output.

3.2.1 Encoder: Convolution-Recurrent Network

A naïve approach for representing I' as a sequence is to take columns of raw pixels on the image from left to right. However, raw pixels are noisy and may not be the optimal choice for representation. Instead, following [30], in the encoder part, we build a robust and learnable sequence-based representation, using a network that combines convolution layer and recurrent network. As illustrated in 6, on the bottom of the encoder is several convolution layers. These layers provide the image representation that is robust to noise and distortions. The convolution layers output $d_{\rm conv}$ maps of size $W_{\rm conv} \times H_{\rm conv}$. We take out the columns of these maps, from left to right, resulting in a sequence with $W_{\rm conv}$ items, each a feature vector with $d_{\rm conv}H_{\rm conv}$ dimensions ("map-to-sequence" in Fig. 6).

We further use a two-layer Bi-directional Long-Short Term Memory (BLSTM) [13], [12] network to model the long-range dependencies within the sequence. The BLSTM outputs a sequence, whose length is also $W_{\rm conv}$. The vectors in this sequence capture long-range, bidirectional context information, and is the strong representation for the image. We denote the sequence by $\{\mathbf{x}_1,\ldots,\mathbf{x}_{W_{\rm conv}}\}$, it is the output of the encoder.

3.2.2 Decoder: Recurrent Character Generator

The decoder is another recurrent neural network. The decoding is a T-step process: at step t, the decoder firstly calculates the *alignment weights* $\alpha_t \in \Re^{W_{\text{conv}}}$. Then a *context vector* is calculated as the weighted sum of the encoder output: $\mathbf{o}_t = \sum_{i=1}^{W_{\text{conv}}} \alpha_{ti} \mathbf{x}_i$. The decoder predicts a character conditioned on the context vector \mathbf{o}_t , the last ground truth character \hat{l}_{t-1} (during test, it is the last character predicted), and the memory state \mathbf{s}_{t-1} it stored:

$$\mathbf{s}_t = GRU(\hat{l}_{t-1}, \mathbf{o}_t, \mathbf{s}_{t-1}) \tag{6}$$

$$\mathbf{y}_t = softmax(\mathbf{W}^{\mathsf{T}}\mathbf{s}_t) \tag{7}$$

Here, GRU stands for Gated Recurrent Unit [7]. Similar to LSTM, GRU also has the capability of capturing long-range dependencies. We choose GRU as the generator because it has a simpler structure than LSTM. \mathbf{y}_t is the predicted label distribution, and \mathbf{W} is the classification weights. The decoder needs to generate sequences of variable lengths. Following [33], a special "end-of-sequence" (EOS) symbol is added to the label space. Once the EOS symbol is predicted by the decoder, the decoding process terminates.

The encoder-decoder structure allows us to map a sequence of arbitrary length to another sequence of arbitrary

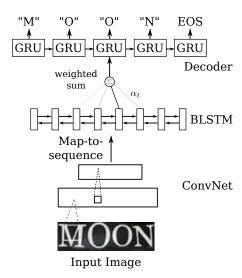


Figure 6. The structure of the sequence recognition network. The network consists of an encoder and a decoder. The encoder uses the convolution layers (ConvNet) and the BLSTM to extract a robust sequence-based representation for the input image. The decoder generates the prediction sequence conditioned on the sequence produced by the encoder.

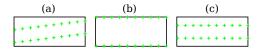


Figure 7. Some initialization patterns for the fiducial points.

length, with a differentiable function. With this structure, we can train the recognition model directly using only the images and the text labels.

3.3. Network Training

The STN and the SRN can be cascaded into one network. During training, we minimize the negative log-likelihood on the training set \mathcal{X} :

$$E = \sum_{I^{(i)}, \mathcal{L}^{(i)} \in \mathcal{X}} \log \prod_{t=1}^{T^{(i)}} p(l_t^{(i)} | I^{(i)}, \boldsymbol{\theta})$$

The superscript (i) denotes the i-th training sample. θ is a vector that combines all the network parameters. The network is trained by standard back-propagation [29]. However, in practice, directly training the whole network with random initialization results in poor performance. Some special initialization tricks for the STN are necessary. We initialize the STN parameters to make the initially regressed fiducial points on the locations shown in Fig. 7.a. We have also tested the other two patterns, namely Fig. 7.b and Fig. 7.c, but end with relatively poorer performance.

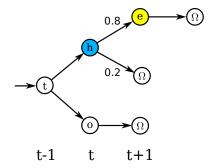


Figure 8. Illustration of the decoding with a prefix tree. Ω is the end-of-sequence symbol. Refer to the text for detailed explanation.

3.4. Decoding

Decoding is the process of converting the sequence of probability distributions, *i.e.* $\{y_t\}$, into the sequence of characters $\{l_t\}$. In the case of unconstrained recognition, we simply take the character with the highest probability at each t. In the case of constrained recognition, the output is constrained to a lexicon. For small or medium lexicons, we calculate the conditional sequence probabilities for all lexicon words and pick the one with the highest probability.

On a very large lexicon, e.g. the Hunspell [1] which contains more than 50k words, calculating the conditional probabilities for all lexicon words would be computationally expensive. Instead, we propose an approximate decoding method. First we construct a prefix tree for the lexicon. As illustrated in Fig. 8, the prefix tree compactly represents the lexicon. The decoding process starts from the root node. At each step, the decoder predicts a distribution y_t conditioned on the previously predicted characters. The node with the highest conditional probability, among the child nodes of the current node, is taken as the next node. When a leaf node, i.e. the EOS node, is reached, the decoding process terminates. As an example, Fig. 8 shows a part of a prefix tree. The blue node "h" is the current node. The decoder predicts the next-character probabilities, namely 0.8 for "e" and 0.2 for Ω (end-ofsequence). Then the node "e" is taken as the next node. We can further extend this decoding process with a beamsearch scheme, by recording the top-B nodes with the highest path probabilities, B is the beam width.

4. Experiments

We conduct several experiments to validate the effectiveness of the proposed model, especially on recognizing irregular texts. First, we evaluate our model on some general recognition benchmarks. These datasets mainly consists of frontal and horizontal texts. But still, many irregular texts exist. Next, we evaluate our model on

Table 1. Recognition accuracies	on general recognition datasets	s. The "50", "1k" and "50k"	" are the lexicon sizes. "Fu	ıll" lexicon is the
combined lexicon of all images	n the dataset. "None" means l	exicon-free recognition.		

Method		IIIT5k		S	VT		I	C 03		IC13
	50	1k	None	50	None	50	Full	50k	None	None
ABBYY [34]	24.3	-	-	35.0	-	56.0	55.0	-	-	-
Wang et al. [34]	-	-	-	57.0	-	76.0	62.0	-	-	-
Mishra et al. [22]	64.1	57.5	-	73.2	-	81.8	67.8	-	-	-
Wang et al. [36]	-	-	-	70.0	-	90.0	84.0	-	-	-
Goel <i>et al</i> . [10]	-	-	-	77.3	-	89.7	-	-	- 1	-
Bissacco et al. [5]	-	-	-	90.4	78.0	-	-	-	- 1	87.6
Alsharif and Pineau [3]	-	-	-	74.3	-	93.1	88.6	85.1	- 1	-
Almazán <i>et al</i> . [2]	91.2	82.1	-	89.2	-	-	-	-	- 1	-
Yao et al. [38]	80.2	69.3	-	75.9	-	88.5	80.3	-	-	-
Rodríguez-Serrano et al. [28]	76.1	57.4	-	70.0	-	-	-	-	-	-
Jaderberg et al. [18]	-	-	-	86.1	-	96.2	91.5	-	-	-
Su and Lu [32]	-	-	-	83.0	-	92.0	82.0	-	-	-
Gordo [11]	93.3	86.6	-	91.8	-	-	-	-	-	-
Jaderberg et al. [16]	97.1	92.7	-	95.4	80.7	98.7	98.6	93.3	93.1	90.8
Jaderberg et al. [15]	95.5	89.6	-	93.2	71.7	97.8	97.0	93.4	89.6	81.8
Shi <i>et al</i> . [30]	97.6	94.4	78.2	96.4	80.8	98.7	97.6	95.5	89.4	86.7
Ours	96.2	93.8	81.9	95.5	81.9	98.3	96.2	94.8	90.1	88.6
Ours (SRN only)	96.5	92.8	79.7	96.1	81.5	97.8	96.4	93.7	88.7	87.5

some datasets that are specially designed for irregular text recognition. In these datasets, the majority of the test images contain irregular texts.

4.1. Implementation Details

Spatial Transformer Network: The localization network of STN has 4 convolution layers, each followed by a 2×2 max-pooling layer. The filter size, padding size and stride are 3, 1, 1 respectively, for all convolution layers. The number of filters are respectively 64, 128, 256 and 512. Following the convolution and the max-pooling layers is a fully-connected layers with 1024 hidden units. The localization network regresses the coordinates of 20 fiducial points, meaning that the output of the network is a vector with 40 dimensions. For all non-linearities we use the ReLU [24], except the output layer, where $\tanh(\cdot)$ is used, as we have mentioned.

Sequence Recognition Network: For the encoder, we use 7 convolutional layers, similar as the structure proposed in [31]. The {filter size, number of filters, stride, padding size} for them are $\{3,64,1,1\}$, $\{3,128,1,1\}$, $\{3,256,1,1\}$, $\{3,512,1,1\}$, $\{3,512,1,1\}$ and $\{2,512,1,0\}$. The 1st, 2nd, 4th, 6th convolution layers are each followed by a 2×2 max-pooling layer. On the top of the convolution layers is a two-layer BLSTM network. Each LSTM has 256 hidden units. For the decoder, we use a GRU that has 256 memory blocks and 37 output units (26 letters, 10 digits, and 1 EOS symbol).

Model Training: We train our model on the 8-million synthetic data released by Jaderberg *et al.* [14]. No extra data is used. Many samples in the synthetic dataset are irregular texts. We train the model with the ADADELTA [40] optimization method. The batch size is set to 64 in training. Since most of the tested datasets contain only word images

that have limited lengths, for simplicity, we scale the images to 100×32 in both training and testing. The output size of the spatial transformer network is also 100×32 . In training, our model processes about 160 samples per second, and converges in 2 days after about 3 epochs over the training set.

Implementation: Our method is implemented under the Torch7 framework [9]. We use the CUDA backend extensively in our implementation, so that most modules in our model are GPU-accelerated. Our experiments are carried out on a workstation with one Intel Xeon(R) E5-2620 2.40GHz CPU, an NVIDIA GTX-Titan GPU, and 64GB RAM.

Running Speed: The recognition speed depends on the size of the associated lexicon. Without a lexicon, the model takes less than 2ms per image. With a lexicon that contains 1k words, the precise decoding scheme takes 100ms per image. On the 50k-words lexicon of IC03, we adopt the approximate decoding scheme with the beam width set to 7. The recognition process takes about 200ms per image.

4.2. Results on General Recognition Datasets

Our model is firstly evaluated on several general recognition benchmarks. These datasets mainly consist of horizontal and frontal texts. But still, irregular texts exist. Our rectification scheme may improve the recognition performance on these samples. The datasets include:

- IIIT 5K-Words [22] (IIIT5K) contains 3000 cropped word images in its test set. The images are collected from the Internet. For each image, there is a 50-word lexicon and a 1000-word lexicon. The lexicons contain the ground truth words as well as other randomly picked words.
- Street View Text [34] (SVT) is collected from the

Google Street View. Its test dataset consists of 647 word images. Many images of SVT are severely corrupted by noise and blur, or have very low resolutions. Each image is associated with a 50-word lexicon.

- ICDAR 2003 [21] (ICO3) contains 251 scene images, labeled with text bounding boxes. Each image is associated with a 50-word lexicon defined by Wang et al. [34]. For fair comparison, we discard images that contain non-alphanumeric characters or have less than three characters, following [34]. The resulting dataset contains 860 cropped images. The lexicons include the 50-word lexicons, the full lexicon which combines all lexicon words, and the Hunspell [1] 50k lexicon.
- ICDAR 2013 [19] (IC13) is the successor of IC03, from which most of its data is inherited. It contains 1015 cropped text images. No lexicon is associated.

Tab. 1 lists the results produced by our method, and the previous methods. In the unconstrained recognition benchmarks (where the lexicon is "None" in Tab. 1), our model outperforms all the other methods. On IIIT5k, our outperforms the previous art [30] by nearly 4 percentages, a clear improvement. We observe that IIIT5k contains a lot of irregular texts such as curved texts, which explain for the improvement, since our model rectifies texts before recognition. On the other datasets, our method achieves state-of-the-art or highly competitive accuracies. It is worth mentioning that, although our method falls behind [16] on some datasets, it differs from [16] in that our model is not constrained to a particular lexicon or dictionary. Thus, it is able to recognize random strings such as telephone numbers. In the constrained cases, our method also achieves competitive results. On IIIT5k, SVT and IC03, the lexicon-based recognition accuracies are on par with [16], and are slightly lower than [30].

We also train a model that contains only the SRN. The recognition accuracies of this model are listed in the last row of Tab. 1. One can see that the SRN alone is already a very strong recognizer. Comparing it with another RNN-based model [30], we see that the SRN achieves higher or highly competitive performance on most of the benchmarks. Moreover, we emphasize that the SRN is more flexible than the model proposed in [30], in that the lengths of both the input sequence and the output sequence are arbitrary. In [30], the input sequence must be longer than the output sequence, limiting the maximum length of the the output sequence.

Lastly, by comparing the SRN model with the proposed STN+SRN model, we observe that, on the majority of the benchmarks, the STN+SRN model outperforms the SRN model. This further validates the effectiveness of the STN.



Figure 9. Examples of irregular texts. (a) Perspective texts. The images contain texts that are taken from a non-frontal view angle. The images are from the SVT-Perspective [26] dataset; (b) Curved texts. The characters are placed in a curve or an arc. The images are from the CUTE [27] dataset.

4.3. Recognizing Perspective Texts

We further evaluate our model on the task of perspective text recognition, in order to validate the effectiveness of the rectification scheme we adopt. **SVT-Perspective** [26] is specifically designed for evaluating perspective text recognition algorithms. The dataset is constructed by picking the side-view angles in Google Street View. Some examples of this dataset are shown in Fig. 9.a. Most images in this dataset are heavily distorted by perspective projections. The dataset consists of 639 cropped images for testing. Each image is associated with a 50-word lexicon. The lexicons are inherited from the SVT [34] dataset. In addition, there is a "Full" lexicon which contains all the lexicon words.

We evaluate our trained model on this dataset, and compare the recognition accuracies with other methods. For [30], we obtain the trained models and test it on this dataset directly. Our method, together with [30], are evaluated with and without lexicons. For the other methods, including [34], [22], [36], [26], we report the lexicon-based recognition accuracies reported in [26].

Tab. 2 summarizes the results. In the second and third columns, we compare the recognition accuracies using the 50-word lexicon and the full lexicon. Our method outperforms [26], a perspective text recognition method, by a large margin on both lexicons. However, that may be explained by that we use a much larger training set than [26]. In the comparisons with [30], which uses the same training set as our method, we still observe significant

Table 2. Recognition accuracies on SVT-Perspective [26]. "50" and "Full" means 50-word lexicon and full lexicon respectively. "None" means recognition without a lexicon.

Method	50	Full	None
Wang et al. [34]	40.5	26.1	-
Mishra et al. [22]	45.7	24.7	-
Wang et al. [36]	40.2	32.4	-
Phan <i>et al</i> . [26]	75.6	67.0	-
Shi et al. [30]	92.6	72.6	66.8
Ours	91.2	77.4	71.8

improvements, on both the Full lexicon and the lexicon-free benchmarks. Furthermore, recall the comparisons we made in Tab. 1, on this dataset we outperforms [30] by a even larger margin on the lexicon free benchmark. The reason is that the SVT-perspective dataset mainly consists of perspective texts, which may be inappropriate for direct recognition. Our rectification scheme can significantly alleviate this problem. In Fig. 10 we make some qualitative analysis. From the fiducial points (green crosses), we see that the STN tends to place the fiducial points along the upper and lower edges of the text lines, so that the transformation results in horizontal and frontal texts. However, it fails sometimes, in the case of heavy perspective distortion.

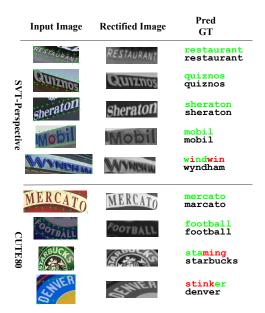


Figure 10. Examples showing the rectifications our model makes, and the recognition results. The left column is the input image, where green crosses are the regressed fiducial points. The middle column is the rectified images, we use gray-scale images for recognition. The right column is the predictions and the ground truth texts. Green and red characters are correctly and mistakenly recognized characters, respectively. The first five rows of images are from SVT-Perspective [26], the rest are from CUTE80 [27].

Table 3. Recognition accuracies on CUTE80 [26].

Method	Accuracy
Jaderberg et al. [16]	42.7
Shi et al. [30]	54.9
Ours	59.2

4.4. Recognizing Curved Texts

Our model is also able to recognize curved texts, whose characters are placed along curves or arcs. Curved texts frequently appear as artistic-style texts in natural scenes. Due to the irregular character placements, recognizing curved texts is very challenging. **CUTE80** [27] is a dataset that mainly consists of curved texts. The dataset contains 80 high-resolution images taken in natural scenes. Originally, the dataset is proposed for detection tasks. We manually crop the words in the images, resulting in 288 word images for testing. For comparisons, we evaluate the trained models of [16] and [30]. All methods are evaluated without any lexicon.

From the results summarized in Tab. 3, we see that our method outperforms the other two methods by a large margin. [16] is a constrained recognition model, it cannot recognize the words that are not in its dictionary. [30] can recognize arbitrary text strings, but it does not have a specific mechanism to handle the curved texts. Our model tries to rectify the curved texts before recognizing them. Therefore, it takes advantages on the task of recognizing curved texts.

In Fig. 10 we show some examples of the rectifications our model makes on this dataset. Although the rectifications are generally not perfect generally, they alleviate the recognition difficulties to some extent. Our method tends to fail in the case that the angle of the arc is too large, shown in the last two rows in In Fig. 10.

5. Conclusion

We study a common but difficult problem in scene text recognition, called irregular texts problem. Traditional solutions either use a separate text rectification component or overfit deep neural networks using a huge number of synthetic irregular texts. We deal with this problem in a more feasible and elegant way by adopting a differentiable spatial transformer network module. In addition, the spatial transformer network is connected with an attention based sequence recognizer, for end-to-end training through back-propagation. The extensive experiment results show that (1) without geometric supervision, the learned network can automatically generate more "readable" image for both human and the sequence recognition network; (2) the proposed text rectification method can significantly

improve irregular scene text recognition accuracy and obvious better than the competitors; and (3) the proposed scene text recognition system is competitive with the state-of-the-arts. In the future, we plan to extent the proposed method for irregular text detection and other alignment tasks, such as face alignment.

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